1 Home Credit Default Risk (HCDR)

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

1.1 Some of the challenges

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

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

2 Kaggle API setup

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

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

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

1. Install library

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

For more detailed information on setting the Kaggle API see here (https://medium.com/@nokkk/make-your-kaggle-submissions-with-kaggle-official-api-f49093c04f8a) and here (https://github.com/Kaggle/kaggle-api).

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

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.7/sit
e-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: urllib3 in /usr/local/lib/python3.7/si
te-packages (from kaggle) (1.26.6)
Requirement already satisfied: requests in /usr/local/lib/python3.7/s
ite-packages (from kaggle) (2.25.1)
Requirement already satisfied: python-dateutil in /usr/local/lib/pyth
on3.7/site-packages (from kaggle) (2.8.2)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/si
te-packages (from kaggle) (2021.5.30)
Requirement already satisfied: python-slugify in /usr/local/lib/pytho
n3.7/site-packages (from kaggle) (5.0.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/site-
packages (from kaggle) (4.62.1)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/
python3.7/site-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: chardet<5,>=3.0.2 in /usr/local/lib/py
thon3.7/site-packages (from requests->kaggle) (4.0.0)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3
.7/site-packages (from requests->kaggle) (2.10)
WARNING: Running pip as the 'root' user can result in broken permissi
ons and conflicting behaviour with the system package manager. It is
recommended to use a virtual environment instead: https://pip.pypa.io
/warnings/venv (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 i
nstall --upgrade pip' command.
```

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

```
/root/shared/AML/I526_AML_Student/Assignments/Unit-Project-Home-Credi
t-Default-Risk/Phase2
```

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

```
/root/shared/AML/I526_AML_Student/Assignments/Unit-Project-Home-Credi
t-Default-Risk/Phase2
```

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

```
-rw------- 1 root root 62 Nov 22 17:40 /root/.kaggle/kaggle.json
```

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

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

```
name                                  size  creationDate
-----------------------------------  -----  -------------------
installments_payments.csv            690MB  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_train.csv                158MB  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
sample_submission.csv                524KB  2019-12-11 02:55:35
bureau.csv                           162MB  2019-12-11 02:55:35
bureau_balance.csv                   358MB  2019-12-11 02:55:35
application_test.csv                  25MB  2019-12-11 02:55:35
```

3 Dataset and how to download

3.1 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.

3.1.1 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.

3.2 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.

3.3 Data files overview

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

There are 7 different sources of data:

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

- **installments_payment (13.6 Million rows):** payment history for previous loans at Home Credit. There is one row for every made payment and one row for every missed payment.

3.3.1 Table sizes

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

3.4 Downloading the files via Kaggle API

Create a base directory:

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

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

1. Click on the `Download` button on the following [Data Webpage (https://www.kaggle.com/c/home-credit-default-risk/data)](https://www.kaggle.com/c/home-credit-default-risk/data) and unzip the zip file to the `BASE_DIR`
2. If you plan to use the Kaggle API, please use the following steps.

In [7]:
```
DATA_DIR = "/root/shared/AML/I526_AML_Student/Assignments/Unit-Project
#DATA_DIR = os.path.join('./ddddd/')
# !mkdir DATA_DIR
```

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

```
total 2621364
-rw-r--r-- 1 root root     37383 Nov 25 21:45 HomeCredit_columns_desc
ription.csv
-rw-r--r-- 1 root root 392703158 Nov 25 21:45 POS_CASH_balance.csv
-rw-r--r-- 1 root root  26567651 Nov 25 21:45 application_test.csv
-rw-r--r-- 1 root root 166133370 Nov 25 21:45 application_train.csv
-rw-r--r-- 1 root root 170016717 Nov 25 21:45 bureau.csv
-rw-r--r-- 1 root root 375592889 Nov 25 21:45 bureau_balance.csv
-rw-r--r-- 1 root root 424582605 Nov 25 21:45 credit_card_balance.csv
-rw-r--r-- 1 root root 723118349 Nov 25 21:45 installments_payments.c
sv
-rw-r--r-- 1 root root 404973293 Nov 25 21:45 previous_application.cs
v
-rw-r--r-- 1 root root    536202 Nov 25 21:45 sample_submission.csv
```

In [9]:
```
# ! kaggle competitions download home-credit-default-risk -p $DATA_DIR
```

```
Downloading home-credit-default-risk.zip to /root/shared/AML/I526_AML
_Student/Assignments/Unit-Project-Home-Credit-Default-Risk/Phase2
 13%|█████                                  | 87.0M/688M [00:04<00:33
, 18.6MB/s]^C
 13%|█████                                  | 87.0M/688M [00:04<00:34
, 18.4MB/s]
User cancelled operation
```

In [10]:
```
!pwd
```

```
/root/shared/AML/I526_AML_Student/Assignments/Unit-Project-Home-Credi
t-Default-Risk/Phase2
```

In [11]:
```
!ls -l $DATA_DIR
```

```
total 831304
drwxr-xr-x 1 root root      4096 Nov 25 21:45 DATA_DIR
-rwxrwxrwx 1 root root   4988449 Nov 29 20:34 HCDR_baseLine_submissio
n_with_numerical_and_cat_features_to_kaggle_v1.ipynb
-rwxrwxrwx 1 root root   2215207 Nov 29 20:47 HCDR_baseLine_submissio
n_with_numerical_and_cat_features_to_kaggle_v2.ipynb
-rwxrwxrwx 1 root root        10 Nov 25 21:34 Phase2.md
-rw-r--r-- 1 root root  91226112 Nov 29 20:47 home-credit-default-ris
k.zip
-rwxrwxrwx 1 root root     66899 Nov 25 21:34 home_credit.png
-rw-r--r-- 1 root root 375168662 Nov 29 00:41 merged_data_test.csv
-rw-r--r-- 1 root root 375168662 Nov 29 00:41 merged_data_train.csv
-rwxrwxrwx 1 root root   1320236 Nov 25 21:34 submission.csv
-rwxrwxrwx 1 root root   1091396 Nov 25 21:35 submission.png
```

In [12]:
```
#!rm -r  DATA_DIR
```

3.4.1 Imports

In [4]:
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import os
import zipfile
from sklearn.base import BaseEstimator, TransformerMixin
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline, FeatureUnion
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import warnings
warnings.filterwarnings('ignore')
```

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

3.5 Data files overview

3.5.1 Data Dictionary

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

3.5.2 Application train

In [13]:
```
ls -l /root/shared/AML/I526_AML_Student/Assignments/Unit-Project-Home-
```

```
-rw-r--r-- 1 root root 166133370 Nov 25 21:45 /root/shared/AML/I526_A
ML_Student/Assignments/Unit-Project-Home-Credit-Default-Risk/Phase2/D
ATA_DIR/application_train.csv
```

In [ ]:

In [1]:

```
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')
%matplotlib inline


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
ds_name = 'application_train'
DATA_DIR='/root/shared/AML/I526_AML_Student/Assignments/Unit-Project-H
datasets[ds_name] = load_data(os.path.join(DATA_DIR, f'{ds_name}.csv')

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_(
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	

2	100004	0	Revolving loans	M	Y
3	100006	0	Cash loans	F	N
4	100007	0	Cash loans	M	N

5 rows × 122 columns

Out[1]:
```
(307511, 122)
```

In [2]:
```
datasets.keys()
```

Out[2]:
```
dict_keys(['application_train'])
```

In [3]:
```
DATA_DIR
```

Out[3]:
```
'/root/shared/AML/I526_AML_Student/Assignments/Unit-Project-Home-Cred
it-Default-Risk/Phase2/DATA_DIR/'
```

3.5.3 Application test

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

In [41]:
```
ds_name = 'application_test'
datasets[ds_name] = load_data(os.path.join(DATA_DIR, f'{ds_name}.csv')
```

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

5 rows × 121 columns

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

3.5.4 The Other datasets

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

In [42]:
```
ds_names = ("application_train", "application_test", "bureau","bureau_
            "previous_application","POS_CASH_balance")
```

In [43]:
```
%%time
ds_names = ("application_train", "application_test", "bureau","bureau_
            "previous_application","POS_CASH_balance")

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

```
 #   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_FU
0	1803195	182943	-31	48.0	
1	1715348	367990	-33	36.0	

In [44]:
```
for ds_name in datasets.keys():
    print(f'dataset {ds_name:24}: [ {datasets[ds_name].shape[0]:10,},
```

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

$$BinaryCrossEntropy = H_p(q) = -\frac{1}{N}\sum_{i=1}^{n} y_i.\,log(p(y_i)) + (1-y_i).\,log(1-p(y_i))$$

- We primarily focus on these two performance metrics and loss functions:

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN}$$

$$Sensitivity = Recall = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{FP + TN}$$

4 Exploratory Data Analysis

4.1 Summary of Application train

In [22]:
```
datasets["application_train"].info()
```

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

In [23]:
```
datasets["application_train"].describe() #numerical only features
```

Out[23]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AN
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	30
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	2
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	1
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	1
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	2
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	3
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	25

8 rows × 106 columns

In [24]:
```
datasets["application_test"].describe() #numerical only features
```

Out[24]:

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

8 rows × 105 columns

In [25]:
```
datasets["application_train"].describe(include='all') #look at all cat
```

Out[25]:

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

11 rows × 122 columns

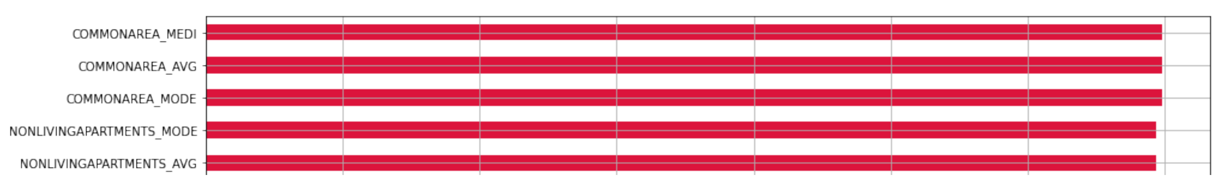
4.2 Missing data for application train

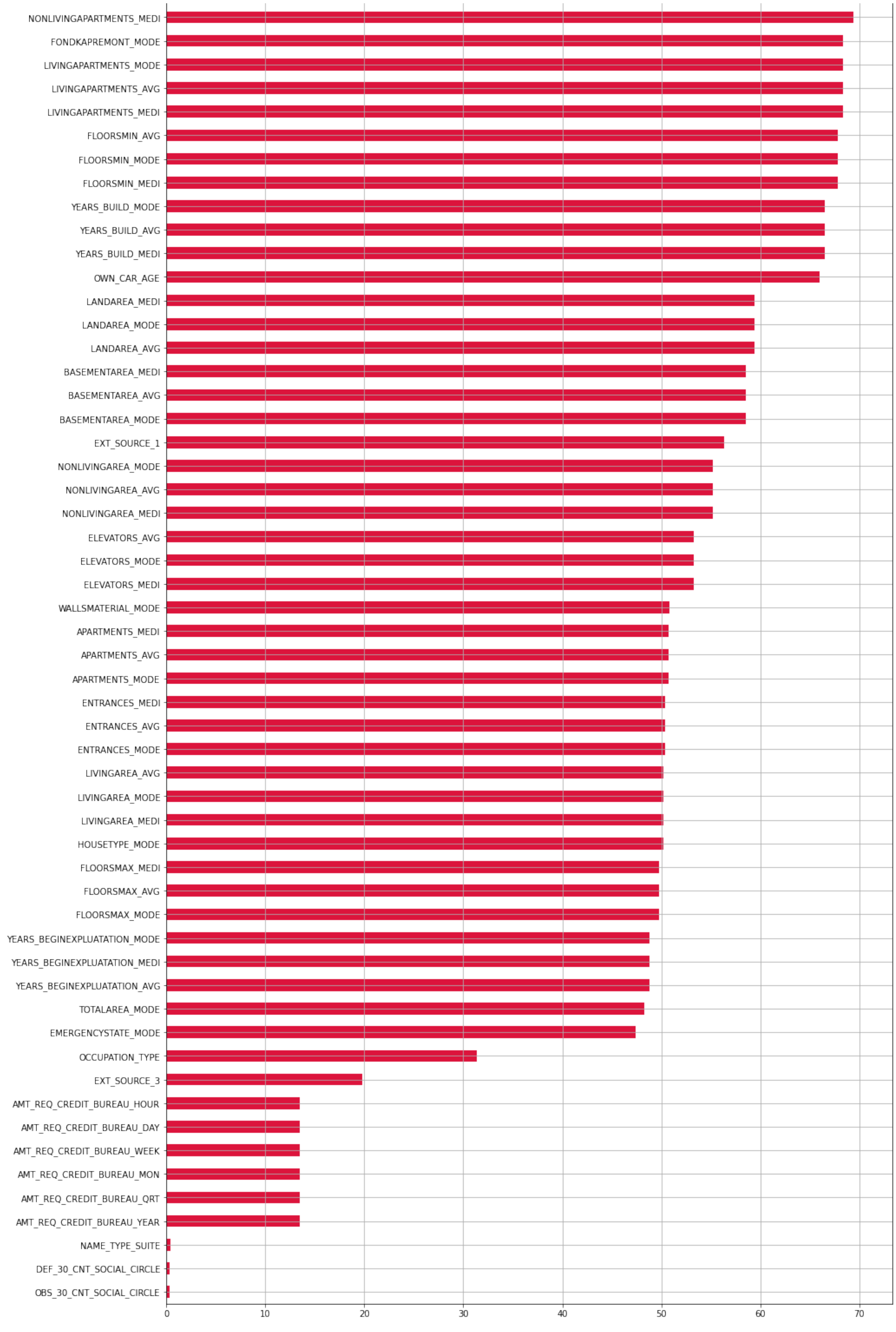
In [26]:
```
percent = (datasets["application_train"].isnull().sum()/datasets["appl
sum_missing = datasets["application_train"].isna().sum().sort_values(a
missing_application_train_data  = pd.concat([percent, sum_missing], ax
missing_application_train_data.head(20)
```

Out[26]:

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

In [27]:
```
plt.figure(figsize=(15, 7))
missing_application_train_data['Percent'].sort_values().tail(60).plot.
plt.grid(b=True)
plt.show();
```



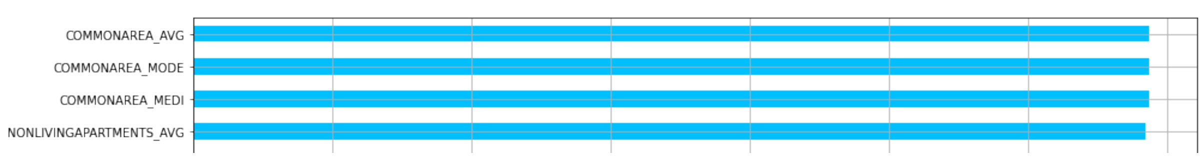

NONLIVINGAPARTMENTS_MEDI
FONDKAPREMONT_MODE
LIVINGAPARTMENTS_MODE
LIVINGAPARTMENTS_AVG
LIVINGAPARTMENTS_MEDI
FLOORSMIN_AVG
FLOORSMIN_MODE
FLOORSMIN_MEDI
YEARS_BUILD_MODE
YEARS_BUILD_AVG
YEARS_BUILD_MEDI
OWN_CAR_AGE
LANDAREA_MEDI
LANDAREA_MODE
LANDAREA_AVG
BASEMENTAREA_MEDI
BASEMENTAREA_AVG
BASEMENTAREA_MODE
EXT_SOURCE_1
NONLIVINGAREA_MODE
NONLIVINGAREA_AVG
NONLIVINGAREA_MEDI
ELEVATORS_AVG
ELEVATORS_MODE
ELEVATORS_MEDI
WALLSMATERIAL_MODE
APARTMENTS_MEDI
APARTMENTS_AVG
APARTMENTS_MODE
ENTRANCES_MEDI
ENTRANCES_AVG
ENTRANCES_MODE
LIVINGAREA_AVG
LIVINGAREA_MODE
LIVINGAREA_MEDI
HOUSETYPE_MODE
FLOORSMAX_MEDI
FLOORSMAX_AVG
FLOORSMAX_MODE
YEARS_BEGINEXPLUATATION_MODE
YEARS_BEGINEXPLUATATION_MEDI
YEARS_BEGINEXPLUATATION_AVG
TOTALAREA_MODE
EMERGENCYSTATE_MODE
OCCUPATION_TYPE
EXT_SOURCE_3
AMT_REQ_CREDIT_BUREAU_HOUR
AMT_REQ_CREDIT_BUREAU_DAY
AMT_REQ_CREDIT_BUREAU_WEEK
AMT_REQ_CREDIT_BUREAU_MON
AMT_REQ_CREDIT_BUREAU_QRT
AMT_REQ_CREDIT_BUREAU_YEAR
NAME_TYPE_SUITE
DEF_30_CNT_SOCIAL_CIRCLE
OBS_30_CNT_SOCIAL_CIRCLE
0
10
20
30
40
50
60
70

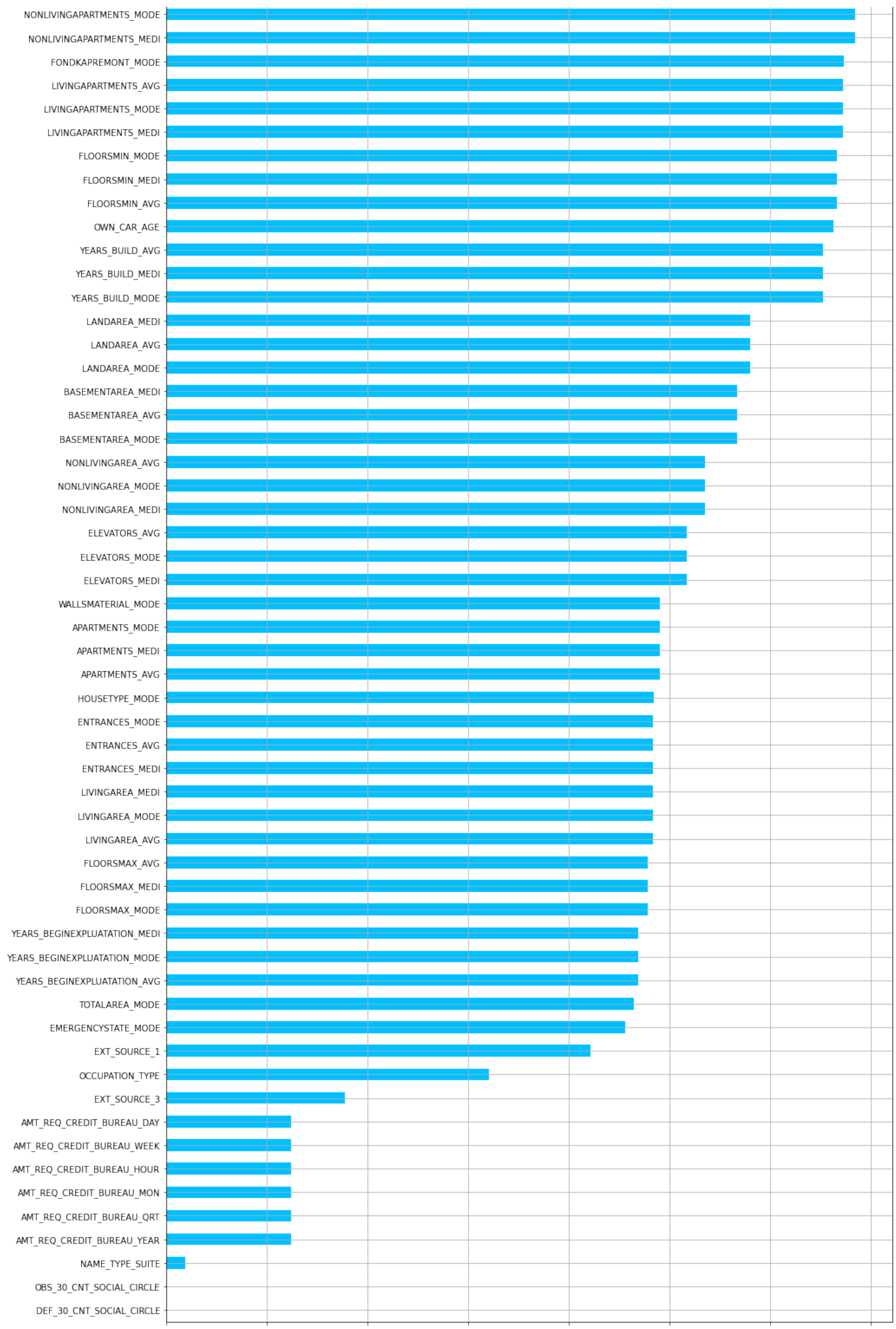
In [28]:
```
percent = (datasets["application_test"].isnull().sum()/datasets["appli
sum_missing = datasets["application_test"].isna().sum().sort_values(as
missing_application_test_data  = pd.concat([percent, sum_missing], axi
missing_application_test_data.head(20)
```

Out[28]:

	Percent	Test Missing Count
COMMONAREA_AVG	68.72	33495
COMMONAREA_MODE	68.72	33495
COMMONAREA_MEDI	68.72	33495
NONLIVINGAPARTMENTS_AVG	68.41	33347
NONLIVINGAPARTMENTS_MODE	68.41	33347
NONLIVINGAPARTMENTS_MEDI	68.41	33347
FONDKAPREMONT_MODE	67.28	32797
LIVINGAPARTMENTS_AVG	67.25	32780
LIVINGAPARTMENTS_MODE	67.25	32780
LIVINGAPARTMENTS_MEDI	67.25	32780
FLOORSMIN_MEDI	66.61	32466
FLOORSMIN_AVG	66.61	32466
FLOORSMIN_MODE	66.61	32466
OWN_CAR_AGE	66.29	32312
YEARS_BUILD_AVG	65.28	31818
YEARS_BUILD_MEDI	65.28	31818
YEARS_BUILD_MODE	65.28	31818
LANDAREA_MEDI	57.96	28254
LANDAREA_AVG	57.96	28254
LANDAREA_MODE	57.96	28254

In [29]:
```
plt.figure(figsize=(15, 7))
missing_application_test_data['Percent'].sort_values().tail(60).plot.b
plt.grid(b=True)
plt.show();
```




NONLIVINGAPARTMENTS_MODE
NONLIVINGAPARTMENTS_MEDI
FONDKAPREMONT_MODE
LIVINGAPARTMENTS_AVG
LIVINGAPARTMENTS_MODE
LIVINGAPARTMENTS_MEDI
FLOORSMIN_MODE
FLOORSMIN_MEDI
FLOORSMIN_AVG
OWN_CAR_AGE
YEARS_BUILD_AVG
YEARS_BUILD_MEDI
YEARS_BUILD_MODE
LANDAREA_MEDI
LANDAREA_AVG
LANDAREA_MODE
BASEMENTAREA_MEDI
BASEMENTAREA_AVG
BASEMENTAREA_MODE
NONLIVINGAREA_AVG
NONLIVINGAREA_MODE
NONLIVINGAREA_MEDI
ELEVATORS_AVG
ELEVATORS_MODE
ELEVATORS_MEDI
WALLSMATERIAL_MODE
APARTMENTS_MODE
APARTMENTS_MEDI
APARTMENTS_AVG
HOUSETYPE_MODE
ENTRANCES_MODE
ENTRANCES_AVG
ENTRANCES_MEDI
LIVINGAREA_MEDI
LIVINGAREA_MODE
LIVINGAREA_AVG
FLOORSMAX_AVG
FLOORSMAX_MEDI
FLOORSMAX_MODE
YEARS_BEGINEXPLUATATION_MEDI
YEARS_BEGINEXPLUATATION_MODE
YEARS_BEGINEXPLUATATION_AVG
TOTALAREA_MODE
EMERGENCYSTATE_MODE
EXT_SOURCE_1
OCCUPATION_TYPE
EXT_SOURCE_3
AMT_REQ_CREDIT_BUREAU_DAY
AMT_REQ_CREDIT_BUREAU_WEEK
AMT_REQ_CREDIT_BUREAU_HOUR
AMT_REQ_CREDIT_BUREAU_MON
AMT_REQ_CREDIT_BUREAU_QRT
AMT_REQ_CREDIT_BUREAU_YEAR
NAME_TYPE_SUITE
OBS_30_CNT_SOCIAL_CIRCLE
DEF_30_CNT_SOCIAL_CIRCLE

4.2.1 Observation:

- We can see that a large portion of the data is missing from train and test sets

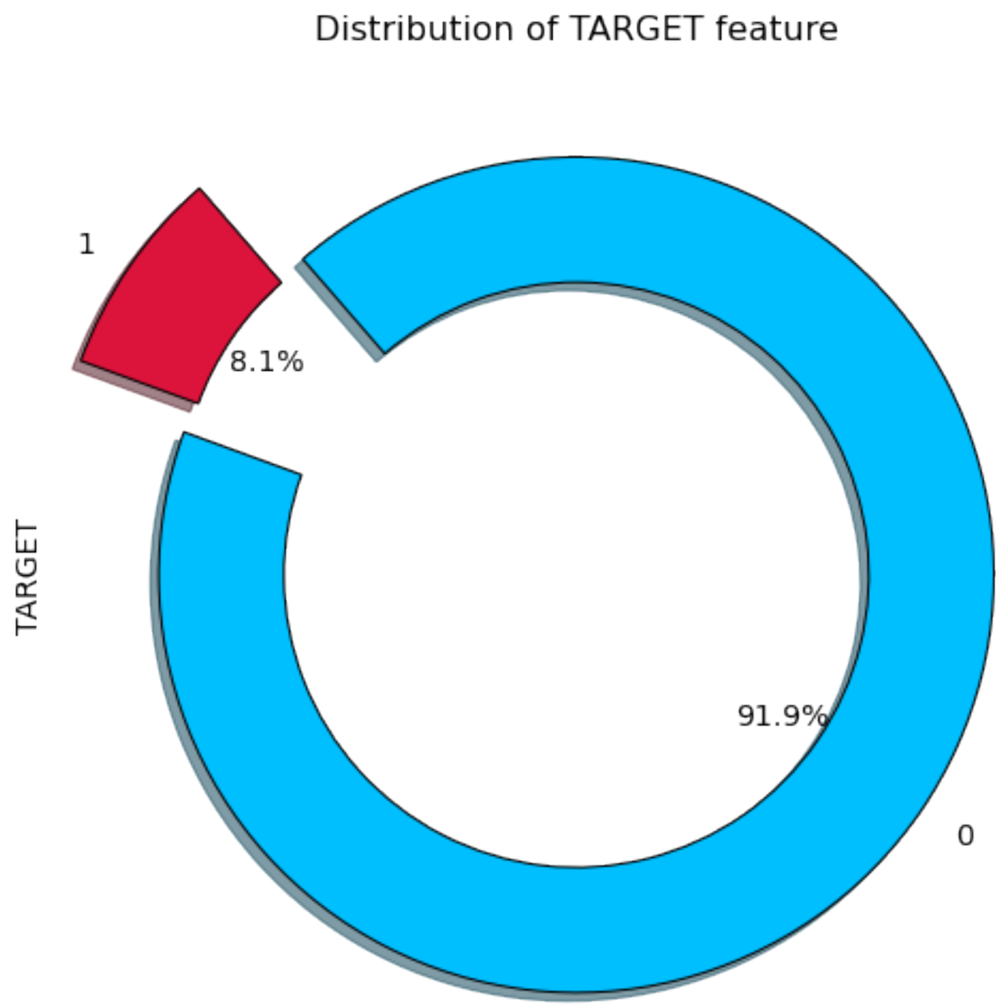
In [30]:
```
# Setting up the train and test datasets

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

4.3 Distribution of the target column

In [31]:
```
app_train['TARGET'].value_counts()
```

Out[31]:
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

In [32]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=app_train['TARGET'].value_counts(),
        radius=1.3-0.3,
        labels=app_train['TARGET'].value_counts().index,
        autopct='%1.1f%%',
        colors=['deepskyblue', 'crimson'],
        explode=[0,0.3],
        wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=160,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('TARGET', fontsize=14)
plt.title('Distribution of TARGET feature', fontsize=16)
plt.show()
```



4.3.1 Observation:

- We can observe a high amount of imbalance in the TARGET feature.
- This will cause issues when measuring the accuracy performance metric.

4.4 Correlation with the target column

In [33]:
```
correlations = datasets["application_train"].corr()['TARGET'].sort_val
print('Most Positive Correlations:\n', correlations.tail(10))
print('\nMost Negative Correlations:\n', correlations.head(10))
```

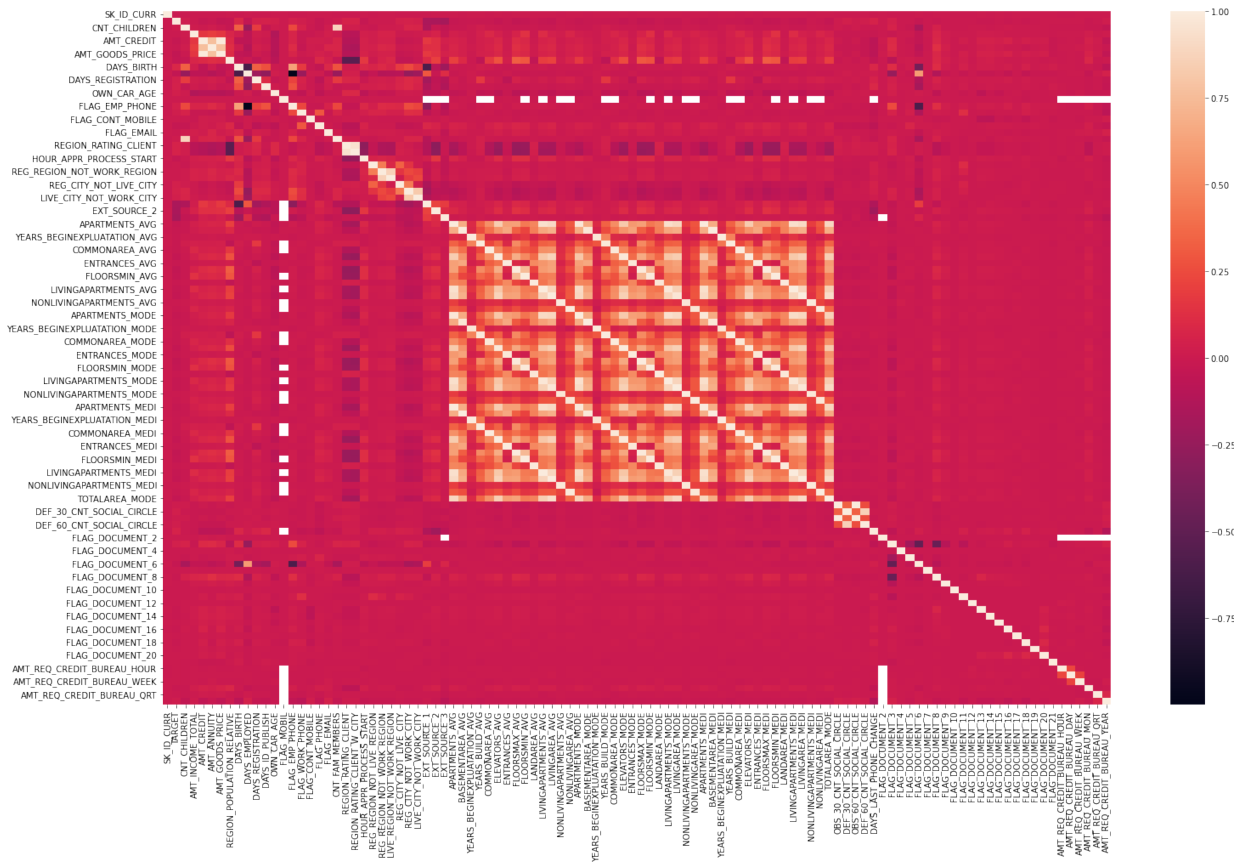
```
Most Positive Correlations:
 ELEVATORS_AVG                 -0.034199
REGION_POPULATION_RELATIVE   -0.037227
AMT_GOODS_PRICE              -0.039645
FLOORSMAX_MODE               -0.043226
FLOORSMAX_MEDI               -0.043768
FLOORSMAX_AVG                -0.044003
DAYS_EMPLOYED                -0.044932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

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

4.4.1 Observation:

- The maximum positive correlation with TARGET feature is observed as 0.0782 with DAYS_BIRTH feature. We will obeserve that in the coming sections.
- This is followed by REGION_RATING, DAYS_LAST_PHONE_CHANGE, DAYS_ID_PUBLISH, and REG_CITY_NOT_WORK_CITY features.
- High indirect correlation is observed between TARGET and FLOORS features, External Sources, AMT_GOODS_PRICE, and relative population features.

In [34]:
```
train_corr = datasets["application_train"].corr()
```

In [35]:
```
plt.figure(figsize=(25, 15))
sns.heatmap(train_corr, cmap='rocket')
plt.plot();
```



4.4.2 Observation:

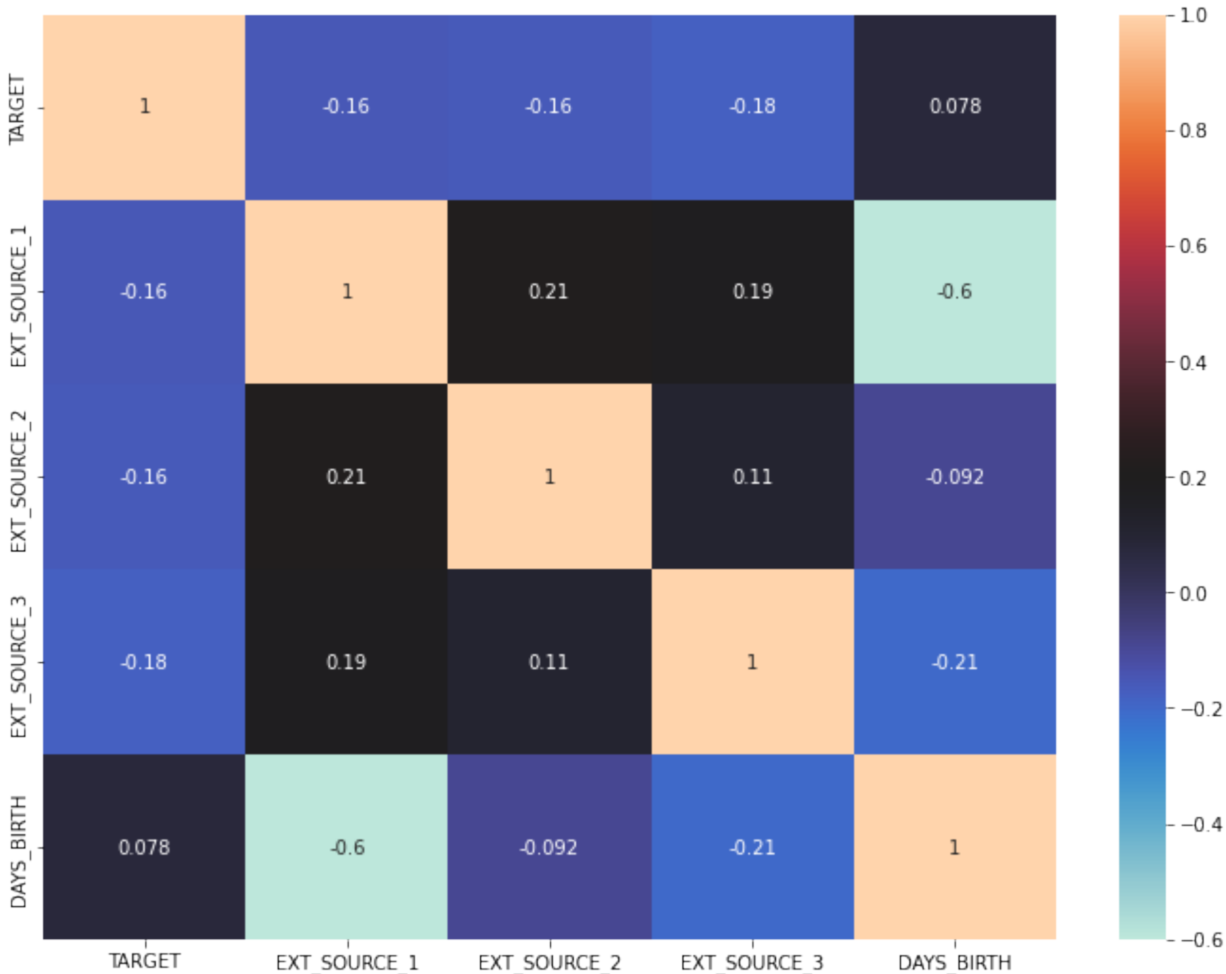
- The heatmap can't be made sense of as of now since we have 120+ columns to compare from.

In [36]:
```
# Extract the EXT_SOURCE variables and show correlations
ext_source_data = app_train[['TARGET', 'EXT_SOURCE_1', 'EXT_SOURCE_2',
ext_source_data_corrs = ext_source_data.corr()
ext_source_data_corrs
```

Out[36]:

	TARGET	EXT_SOURCE_1	EXT_SOURCE_2	EXT_SOURCE_3	DAYS_BIRTH
TARGET	1.000000	-0.155317	-0.160472	-0.178919	0.078239
EXT_SOURCE_1	-0.155317	1.000000	0.213982	0.186846	-0.600610
EXT_SOURCE_2	-0.160472	0.213982	1.000000	0.109167	-0.091996
EXT_SOURCE_3	-0.178919	0.186846	0.109167	1.000000	-0.205478
DAYS_BIRTH	0.078239	-0.600610	-0.091996	-0.205478	1.000000

In [37]:
```
plt.figure(figsize=(12, 9))
sns.heatmap(ext_source_data_corrs, annot=True, cmap='icefire')
plt.plot();
```



4.4.3 Observation:

- The heatmap shows us that external sources indirectly affect the TARGET feature.
- But we can also see that they are correlated to each other as well i.e. multicollinearity is present.

In [38]:
```
app_train.describe()
```

Out[38]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AI
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	3(
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	2
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	1
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	1
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	2
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	3
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	25

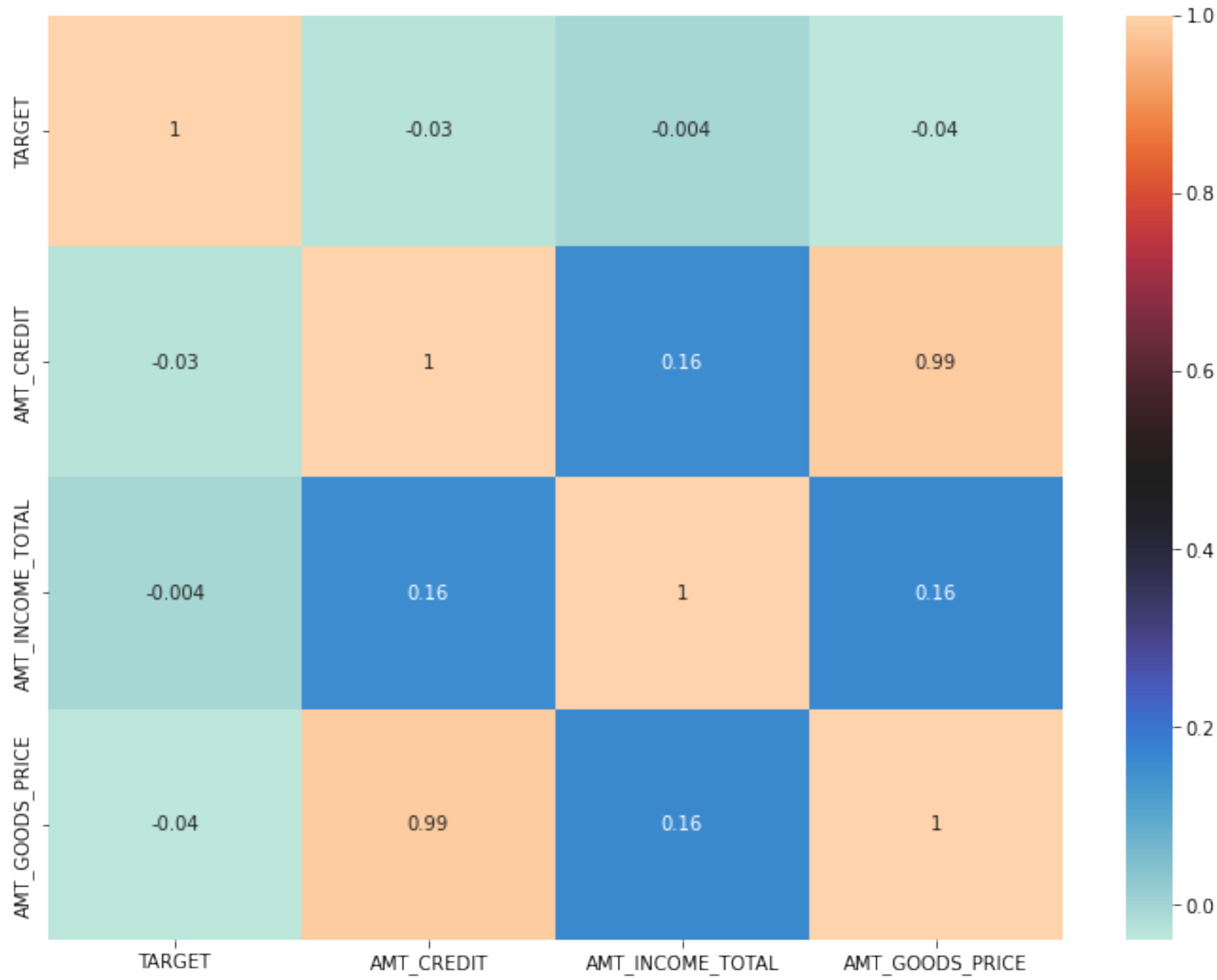
8 rows × 106 columns

In [39]:
```
# Extract the AMOUNT variables and show correlations
amount_data = app_train[['TARGET', 'AMT_CREDIT', 'AMT_INCOME_TOTAL', '
amount_data_corrs = amount_data.corr()
amount_data_corrs
```

Out[39]:

	TARGET	AMT_CREDIT	AMT_INCOME_TOTAL	AMT_GOODS_PRICE
TARGET	1.000000	-0.030369	-0.003982	-0.039645
AMT_CREDIT	-0.030369	1.000000	0.156870	0.986968
AMT_INCOME_TOTAL	-0.003982	0.156870	1.000000	0.159610
AMT_GOODS_PRICE	-0.039645	0.986968	0.159610	1.000000

In [40]:
```
plt.figure(figsize=(12, 9))
sns.heatmap(amount_data_corrs, annot=True, cmap='icefire')
plt.plot();
```



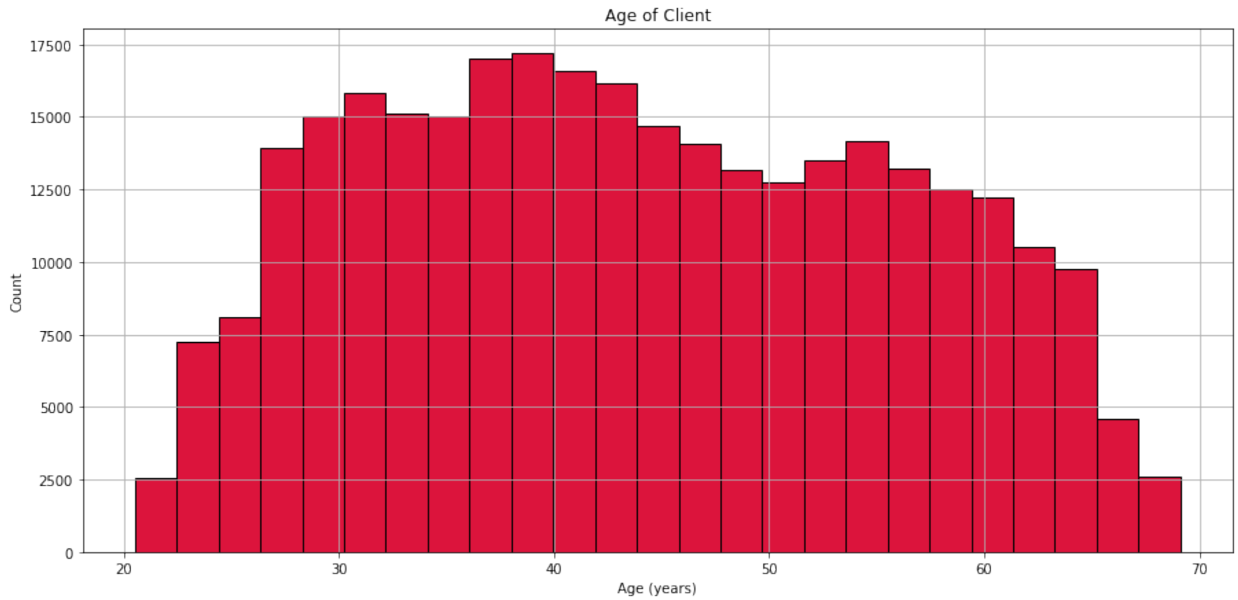
4.4.4 Observation:

- The heatmap shows us yet again a case of multicollinearity among the AMT featurs.
- We may have to deal with these features while proceeding with the modelling.

4.5 Exploratory Data Analysis on Categorical Features

4.6 Applicants Age

In [41]:
```
plt.figure(figsize=(15, 7))
plt.hist(datasets["application_train"]['DAYS_BIRTH'] / -365, edgecolor
plt.title('Age of Client')
plt.xlabel('Age (years)')
plt.ylabel('Count')
plt.grid(b=True)
plt.show()
```



4.6.1 Observation:

- Age is obtained by the DAYS_BIRTH feature which has negative values. This is inconsistent and should be taken care of.
- On plotting the age as number of years, we see a fairly standard distribution which is a good sign in such a complicated dataset as we have DAYS_BIRTH highly correlated with TARGET feature.

In [42]:
```
# Age information into a separate dataframe
age_data = app_train[['TARGET', 'DAYS_BIRTH']]
age_data['YEARS_BIRTH'] = age_data['DAYS_BIRTH'] / -365

# Bin the age data
age_data['GROUPED_YEARS_BIRTH'] = pd.cut(age_data['YEARS_BIRTH'], bins
age_data.head(10)
```

Out[42]:

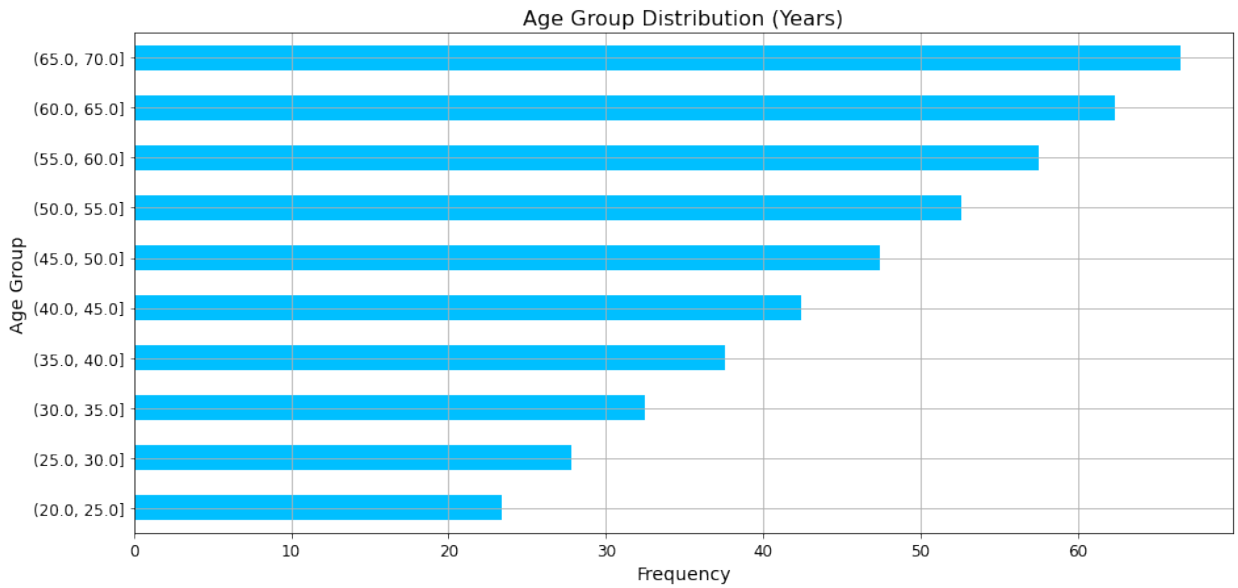
	TARGET	DAYS_BIRTH	YEARS_BIRTH	GROUPED_YEARS_BIRTH
0	1	-9461	25.920548	(25.0, 30.0]
1	0	-16765	45.931507	(45.0, 50.0]
2	0	-19046	52.180822	(50.0, 55.0]
3	0	-19005	52.068493	(50.0, 55.0]
4	0	-19932	54.608219	(50.0, 55.0]
5	0	-16941	46.413699	(45.0, 50.0]
6	0	-13778	37.747945	(35.0, 40.0]
7	0	-18850	51.643836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

In [43]:
```
age_groups  = age_data.groupby('GROUPED_YEARS_BIRTH').mean()
age_groups
```

Out[43]:

	TARGET	DAYS_BIRTH	YEARS_BIRTH
GROUPED_YEARS_BIRTH			
(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

In [44]:
```
age_groups['YEARS_BIRTH'].plot.barh(figsize=(15, 7), color='deepskyblu
plt.title('Age Group Distribution (Years)', fontsize=16)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.xlabel('Frequency', fontsize=14)
plt.ylabel('Age Group', fontsize=14)
plt.grid(b=True)
plt.show()
```

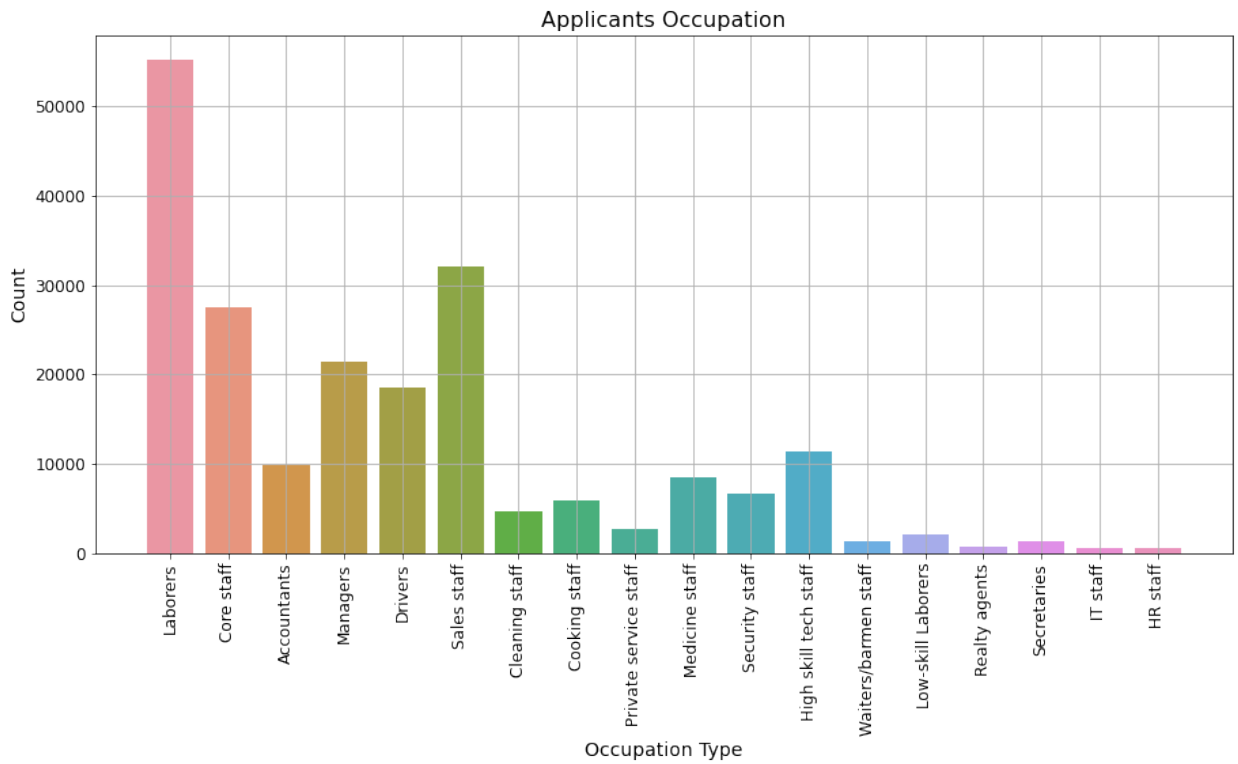


4.6.2 Observation:

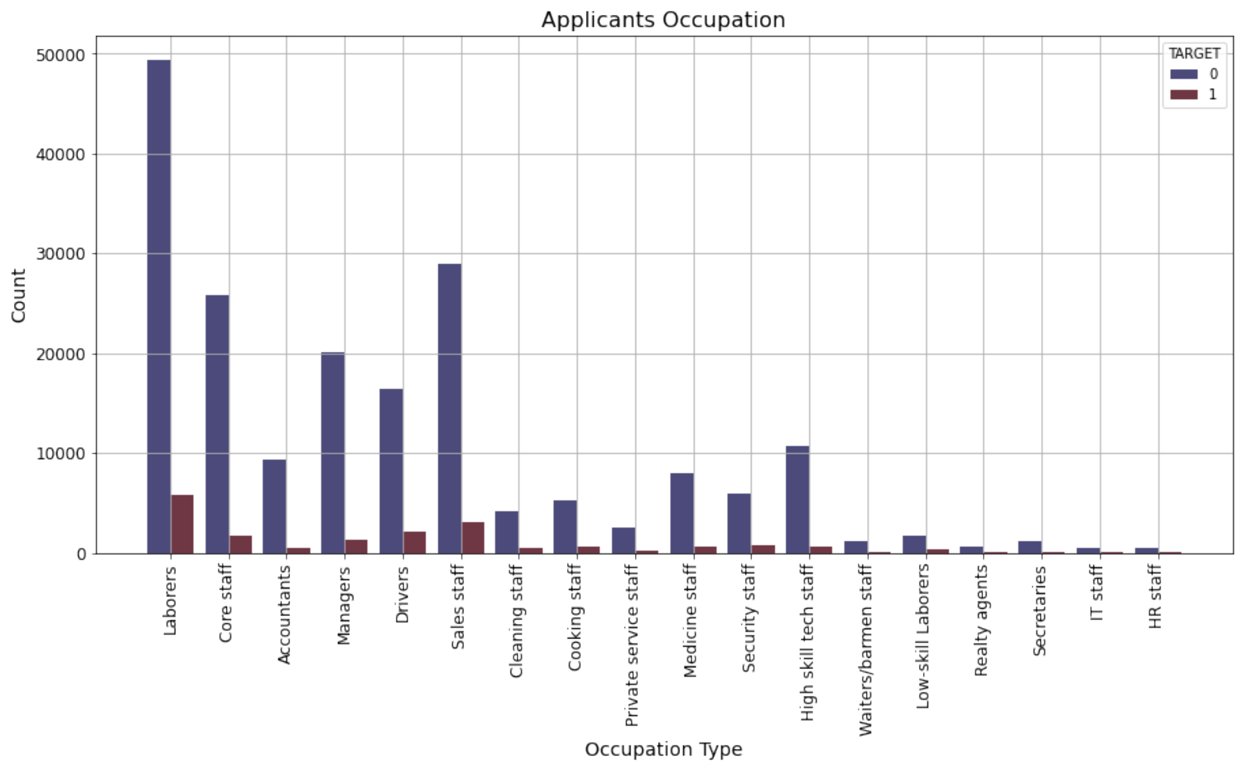
- After performing binning, we can observe that older people tend to take more loans than younger people.

4.7 Applicants occupations

In [45]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='OCCUPATION_TYPE', data=datasets["application_train"])
plt.title('Applicants Occupation', fontsize=16)
plt.xlabel('Occupation Type', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(rotation=90, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```



In [46]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='OCCUPATION_TYPE', data=datasets["application_train"],
plt.title('Applicants Occupation', fontsize=16)
plt.xlabel('Occupation Type', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(rotation=90, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```



4.7.1 Observation:

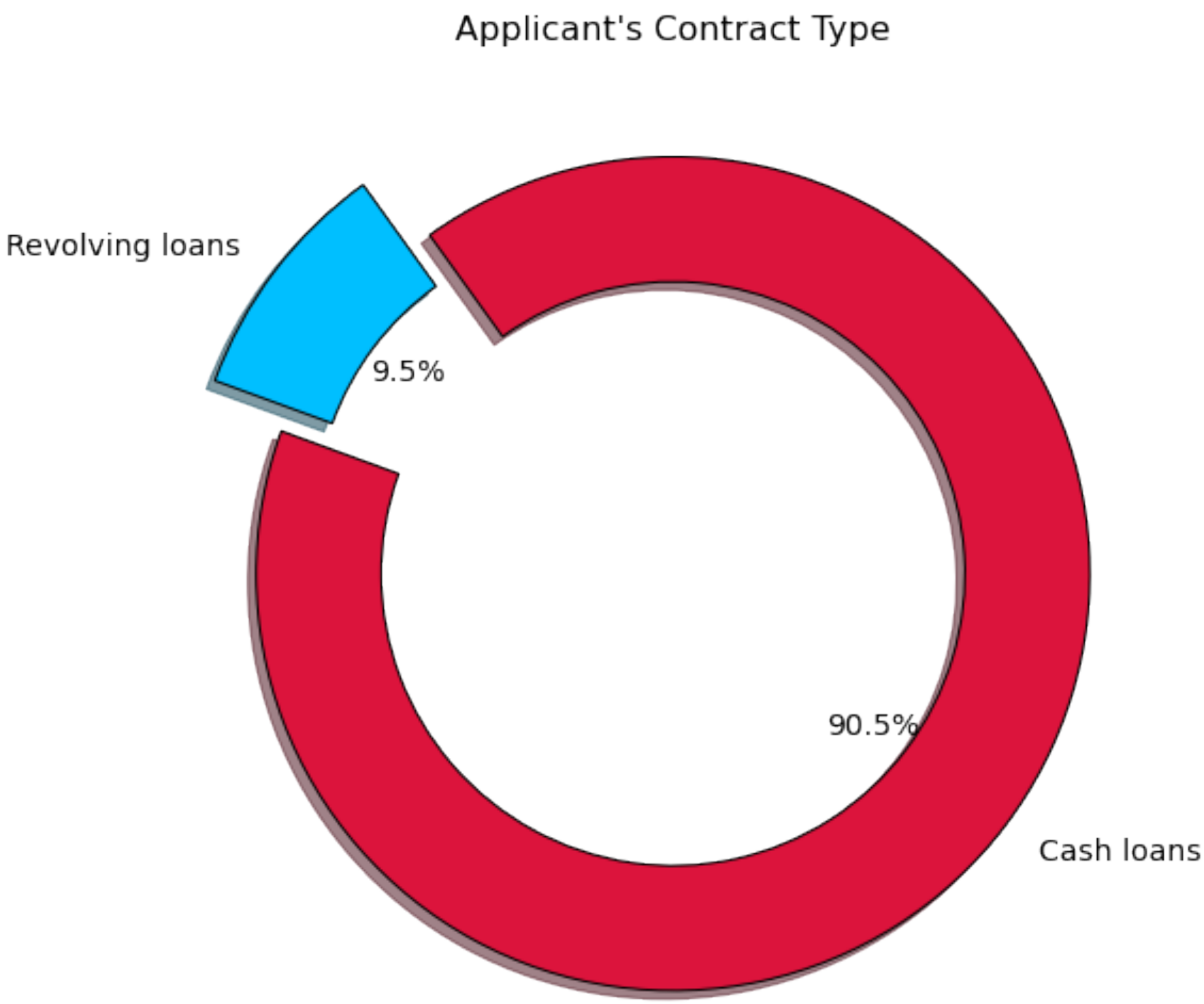
- We see 18 different occupations among the borrowers, led by Laborers, Sales staff, Core staff, Managers and Drivers.
- We can't observe any specific trend as to which occupation class successfully pays back their loan.

4.8 Applicant Contract Type

In [47]:
```
app_train['NAME_CONTRACT_TYPE'].value_counts()
```

Out[47]:
```
Cash loans         278232
Revolving loans     29279
Name: NAME_CONTRACT_TYPE, dtype: int64
```

In [48]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=app_train['NAME_CONTRACT_TYPE'].value_counts(),
        radius=1.3-0.3,
        labels=app_train['NAME_CONTRACT_TYPE'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue'],
        explode=[0,0.2],
        wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=160,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.title("Applicant's Contract Type", fontsize=16)
plt.show()
```



4.8.1 Observation:

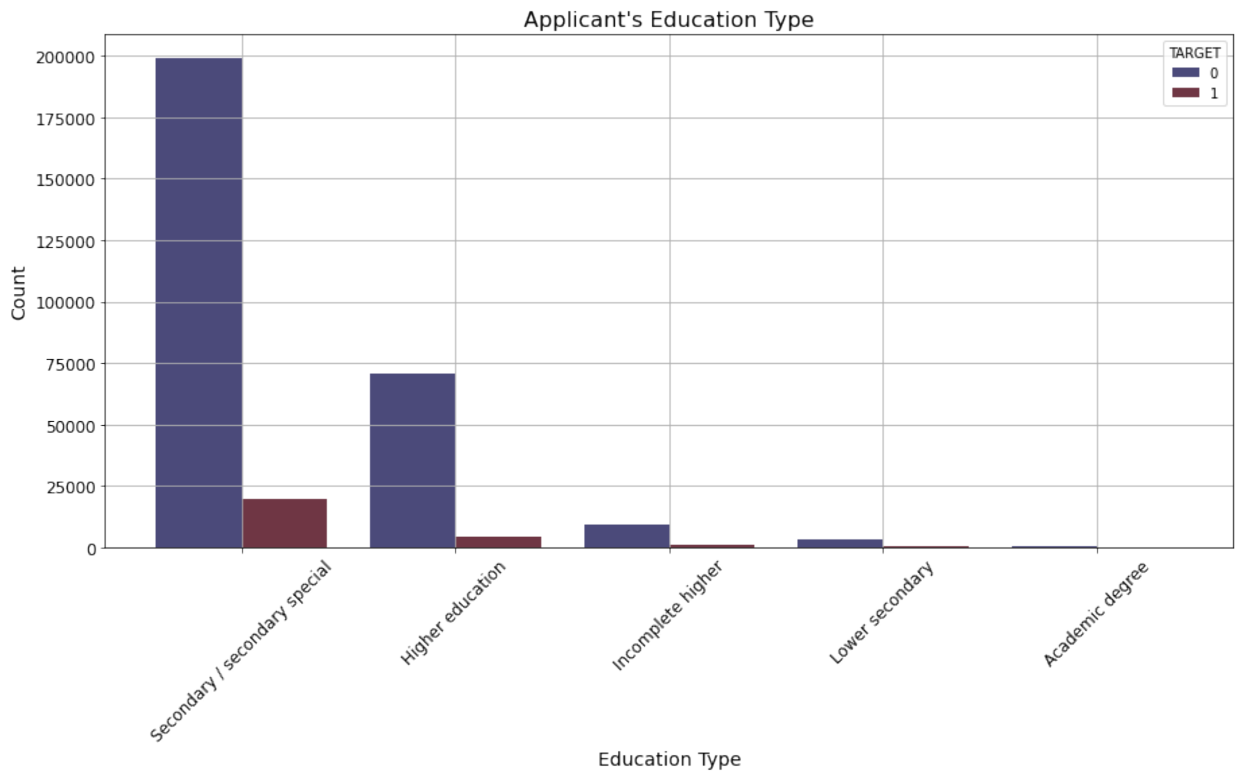
- There are two type of loan contracts - Cash loans (90.5%) and Revolving (re-pay and re-borrow again and again) loans (9.5%)

4.9 Applicant Education Type v/s TARGET

In [49]:
```
app_train['NAME_EDUCATION_TYPE'].value_counts()
```

Out[49]:
```
Secondary / secondary special    218391
Higher education                  74863
Incomplete higher                 10277
Lower secondary                    3816
Academic degree                     164
Name: NAME_EDUCATION_TYPE, dtype: int64
```

In [50]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='NAME_EDUCATION_TYPE', data=app_train, palette='icefir
plt.title("Applicant's Education Type", fontsize=16)
plt.xlabel('Education Type', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(rotation=45, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```



4.9.1 Observation:

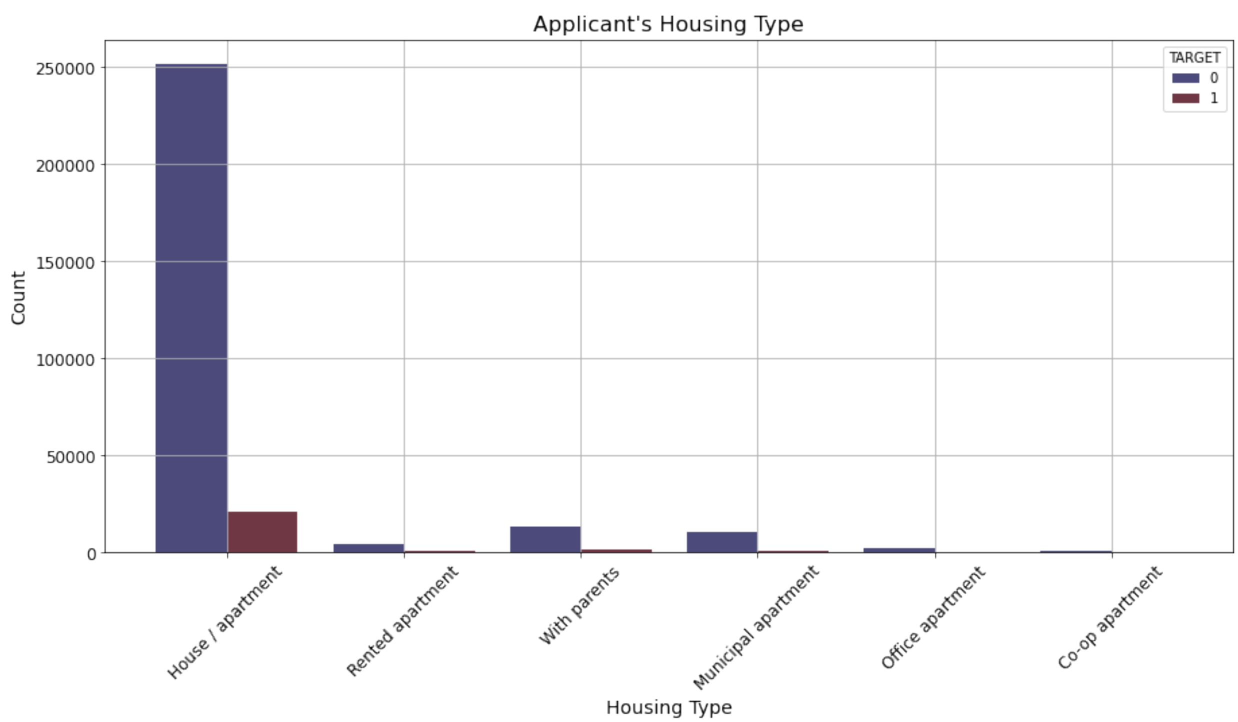
- We see most of the applicants have highest education of secondary and higher education with the lowest being Academic degree.

4.10 Applicant Housing Type v/s TARGET

In [51]:
```
app_train['NAME_HOUSING_TYPE'].value_counts()
```

Out[51]:
```
House / apartment      272868
With parents            14840
Municipal apartment     11183
Rented apartment         4881
Office apartment         2617
Co-op apartment          1122
Name: NAME_HOUSING_TYPE, dtype: int64
```

In [52]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='NAME_HOUSING_TYPE', data=app_train, palette='icefire'
plt.title("Applicant's Housing Type", fontsize=16)
plt.xlabel('Housing Type', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(rotation=45, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```

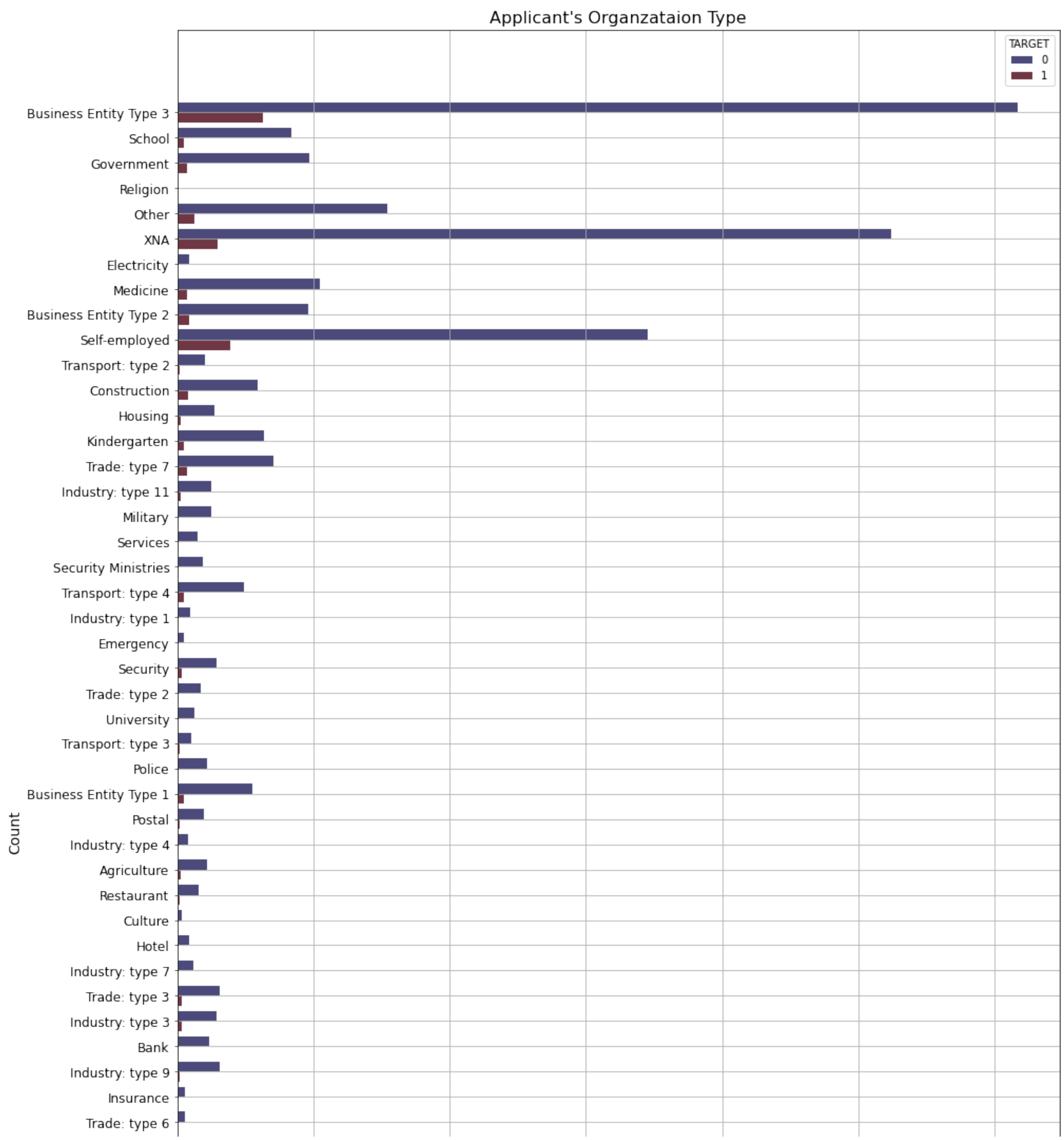


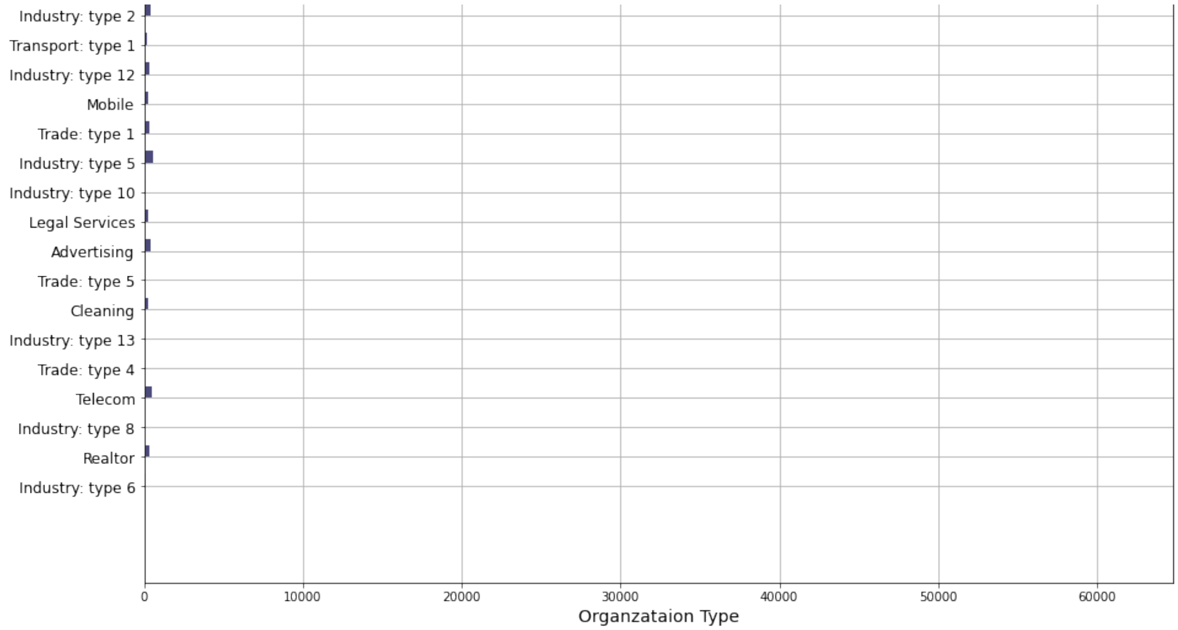
4.10.1 Observation:

- Most of the applicant's current house type is a house or an apartment followed by living with parents (searching for a new home for themselves) and municipal apartment.

4.11 Applicant Organization Type

In [53]:
```
plt.figure(figsize=(15, 28))
sns.countplot(y='ORGANIZATION_TYPE', data=app_train, palette='icefire'
plt.title("Applicant's Organzataion Type", fontsize=16)
plt.xlabel('Organzataion Type', fontsize=14)
plt.ylabel('Count', fontsize=14)
# plt.xticks(rotation=45, fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```





4.11.1 Observation:

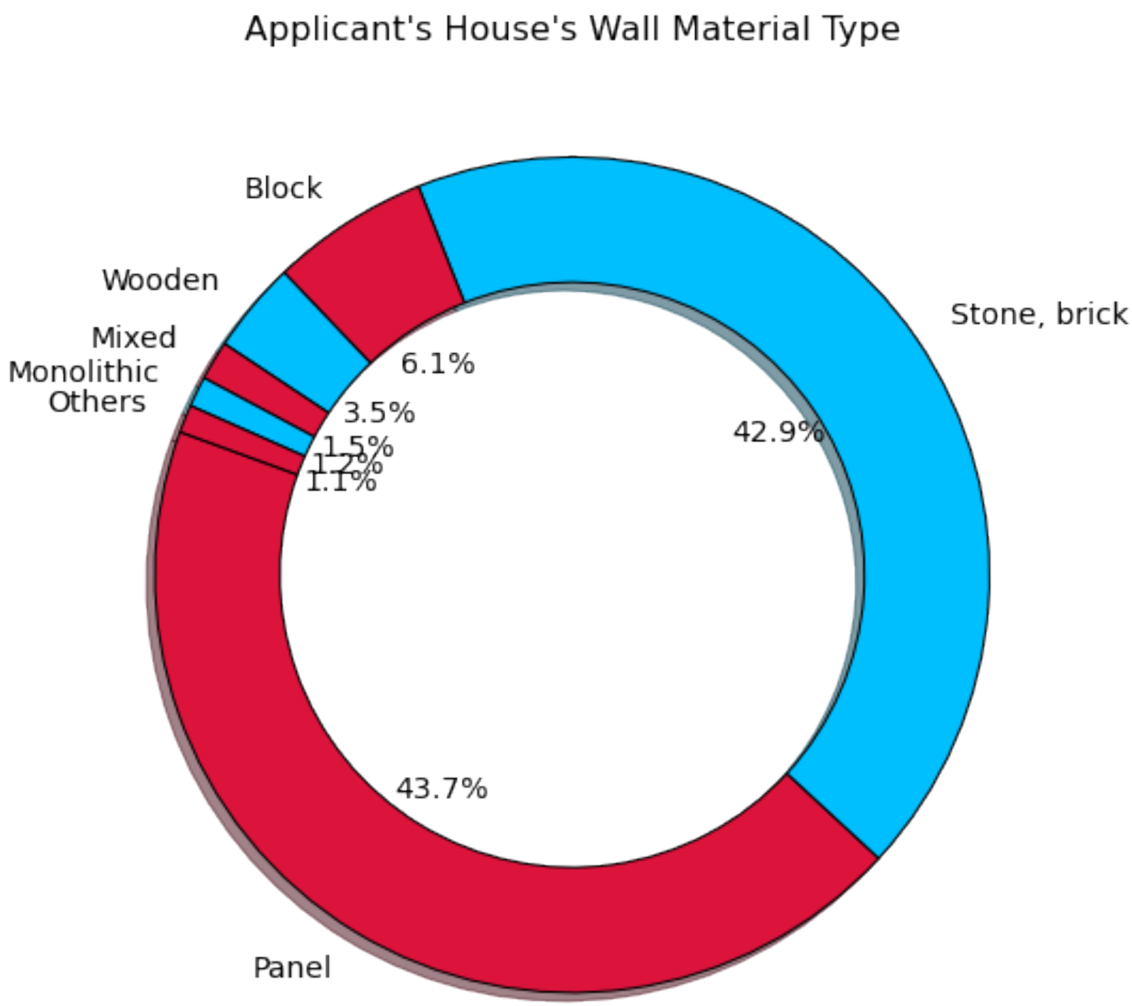
- There are several organization types across various applicants predominantly from Type 3 business entities and self-employement.

4.12 Applicant's House Wall Material Type

In [54]:
```
app_train['WALLSMATERIAL_MODE'].value_counts()
```

Out[54]:
```
Panel           66040
Stone, brick    64815
Block            9253
Wooden           5362
Mixed            2296
Monolithic       1779
Others           1625
Name: WALLSMATERIAL_MODE, dtype: int64
```

In [55]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=app_train['WALLSMATERIAL_MODE'].value_counts(),
        radius=1.3-0.3,
        labels=app_train['WALLSMATERIAL_MODE'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue'],
        # explode=[0.2,0.2,0,0.2,0,0.2,0],
        wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=160,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.title("Applicant's House's Wall Material Type", fontsize=16)
plt.show()
```



4.12.1 Observation:

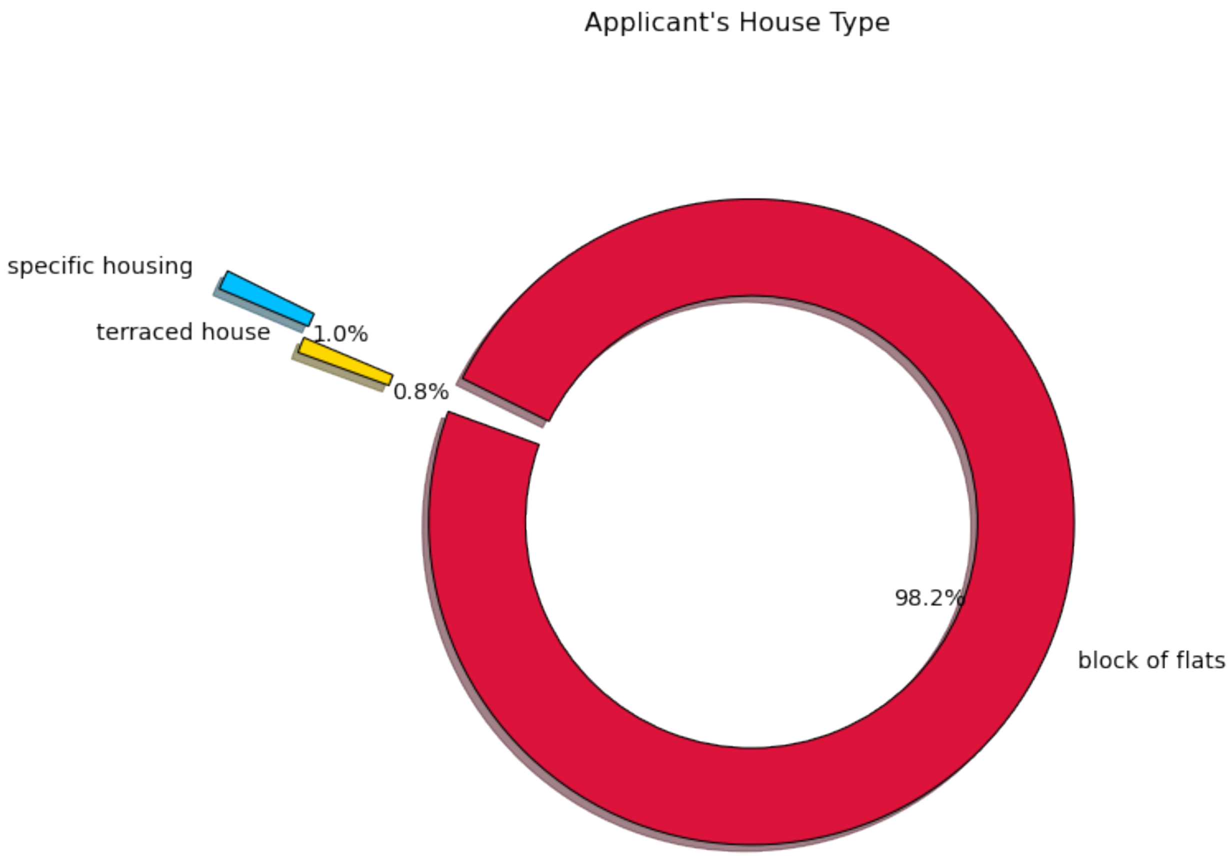
- Most Applicant's house's wall material are made of panels or stones and bricks, followed by cement blocks, wood or a mix of the earlier mentioned.

4.13 Applicant's House Type Part 2

In [56]:
```
app_train['HOUSETYPE_MODE'].value_counts()
```

Out[56]:
```
block of flats      150503
specific housing      1499
terraced house        1212
Name: HOUSETYPE_MODE, dtype: int64
```

In [57]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=app_train['HOUSETYPE_MODE'].value_counts(),
        radius=1.3-0.3,
        labels=app_train['HOUSETYPE_MODE'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue', 'gold'],
        explode=[0,0.8,0.5],
        wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=160,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.suptitle("Applicant's House Type", fontsize=16)
plt.show()
```



4.13.1 Observation:

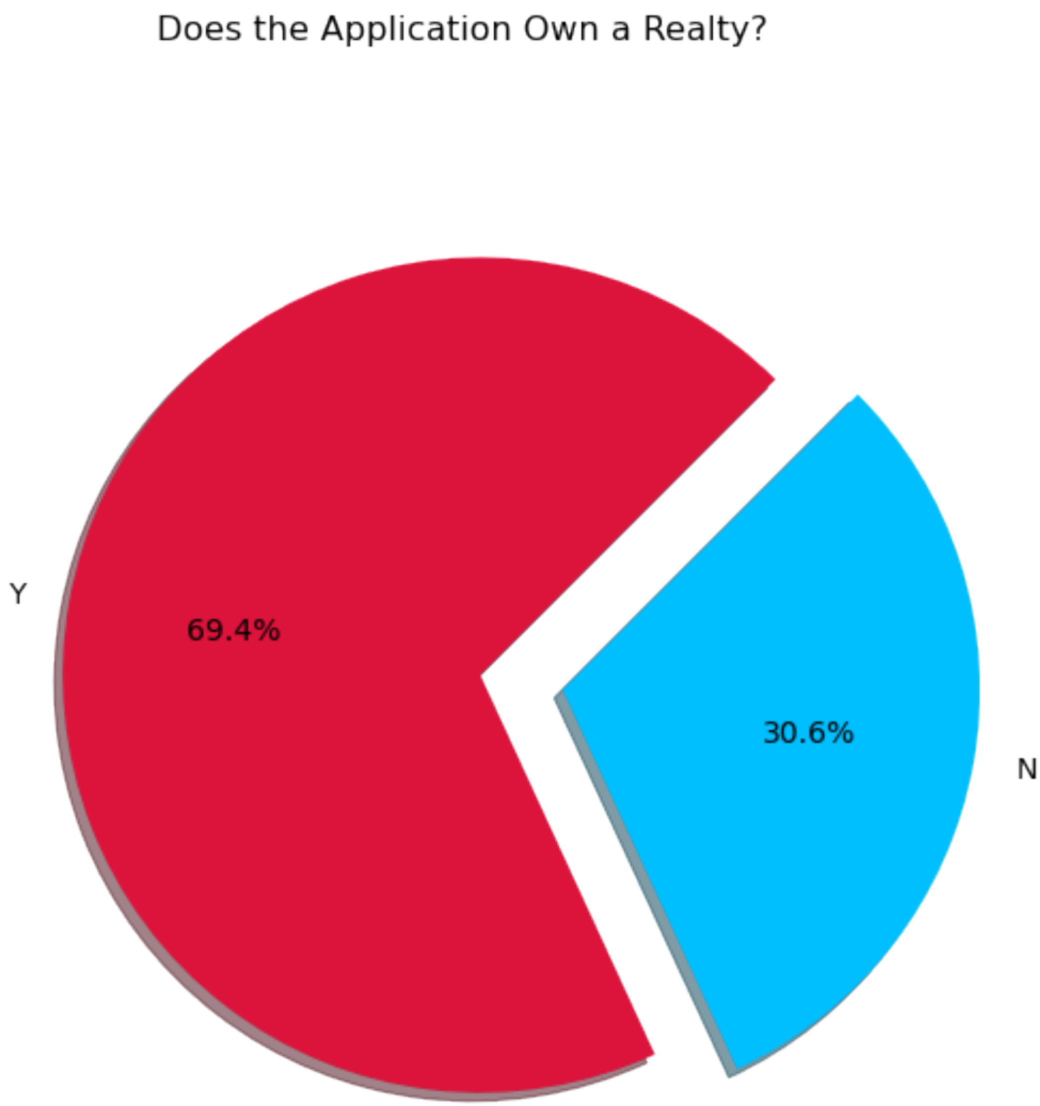
- Applicants mostly reside in flats (more than 98%) while the remaining either live in terraced or other specific house types.

4.14 Does an Applicant already own Realty?

In [58]:
```
app_train['FLAG_OWN_REALTY'].value_counts()
```

Out[58]:
```
Y    213312
N     94199
Name: FLAG_OWN_REALTY, dtype: int64
```

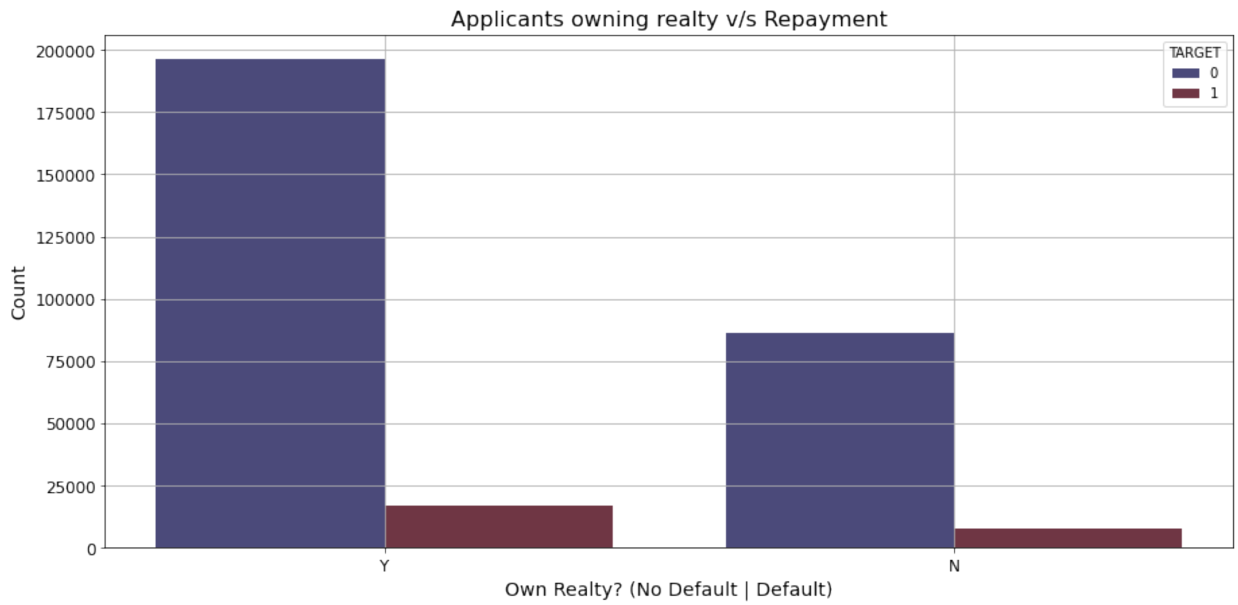
In [59]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=app_train['FLAG_OWN_REALTY'].value_counts(),
        radius=1.3-0.3,
        labels=app_train['FLAG_OWN_REALTY'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue'],
        explode=[0,0.2],
        # wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=45,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.suptitle("Does the Application Own a Realty?", fontsize=16)
plt.show()
```



4.14.1 Observation:

- 69.4% Applicants already own a realty. Let's see the distribution of the repayment.

In [60]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='FLAG_OWN_REALTY', data=app_train, palette='icefire',
plt.title("Applicants owning realty v/s Repayment", fontsize=16)
plt.xlabel('Own Realty? (No Default | Default)', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```



4.14.2 Observation:

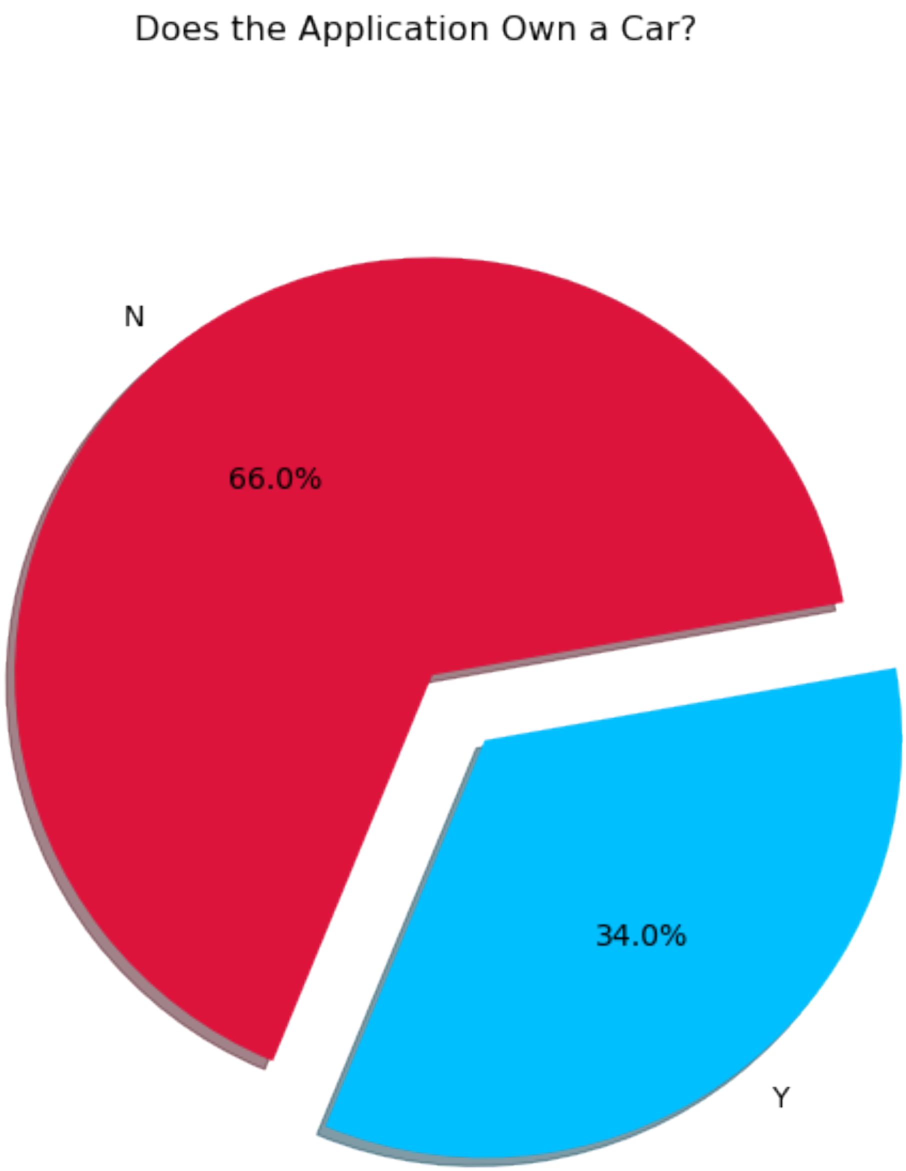
- Most of the applicants in either class are not in default. Less than 25000 applicants own a realty and are in default for their repayment.

4.15 Does an Applicant own cars?

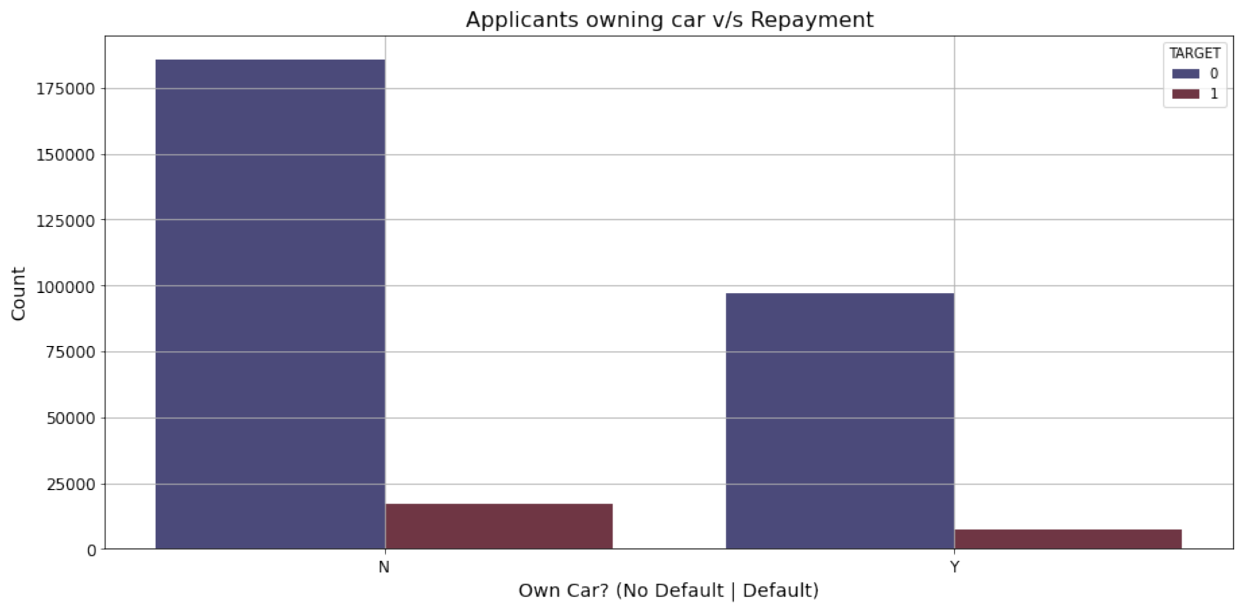
In [61]:
```
app_train['FLAG_OWN_CAR'].value_counts()
```

Out[61]:
```
N    202924
Y    104587
Name: FLAG_OWN_CAR, dtype: int64
```

In [62]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=app_train['FLAG_OWN_CAR'].value_counts(),
        radius=1.3-0.3,
        labels=app_train['FLAG_OWN_CAR'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue'],
        explode=[0,0.2],
        # wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=10,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.suptitle("Does the Application Own a Car?", fontsize=16)
plt.show()
```



In [63]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='FLAG_OWN_CAR', data=app_train, palette='icefire', hue
plt.title("Applicants owning car v/s Repayment", fontsize=16)
plt.xlabel('Own Car? (No Default | Default)', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```

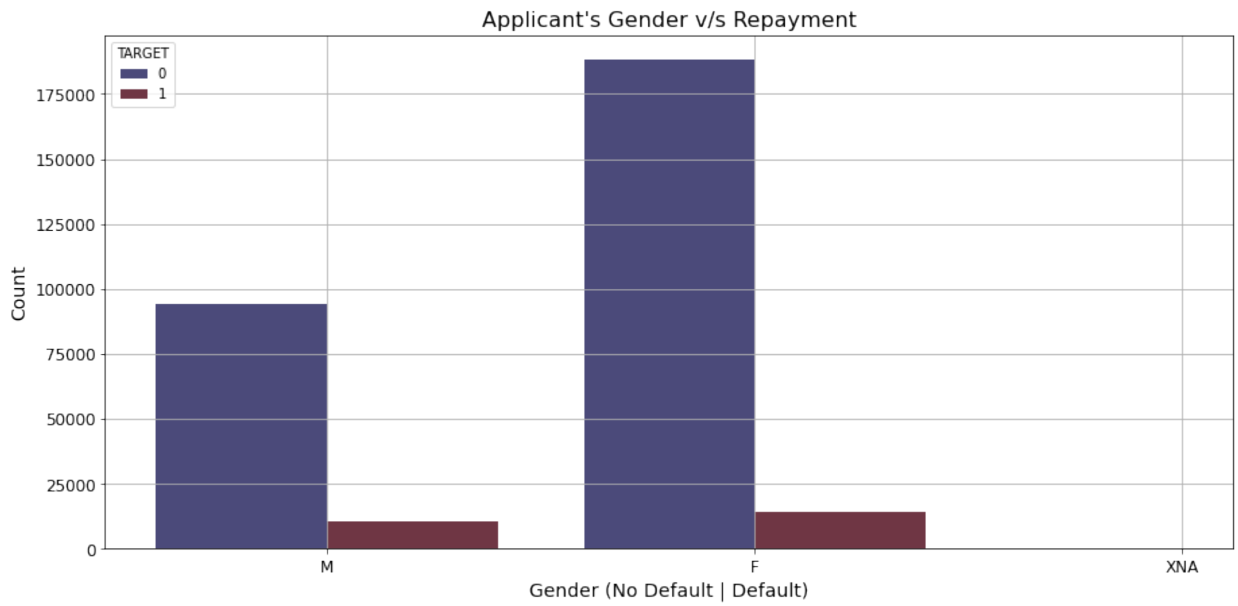


4.15.1 Observation:

- 34% applicants own atleast one car.
- No specific relation to be noted here when it comes to finding a relation between car ownership and loan repayment.

4.16 Which Gender seems more likely to take and re-pay loans?

In [64]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='CODE_GENDER', data=app_train, palette='icefire', hue=
plt.title("Applicant's Gender v/s Repayment", fontsize=16)
plt.xlabel('Gender (No Default | Default)', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```



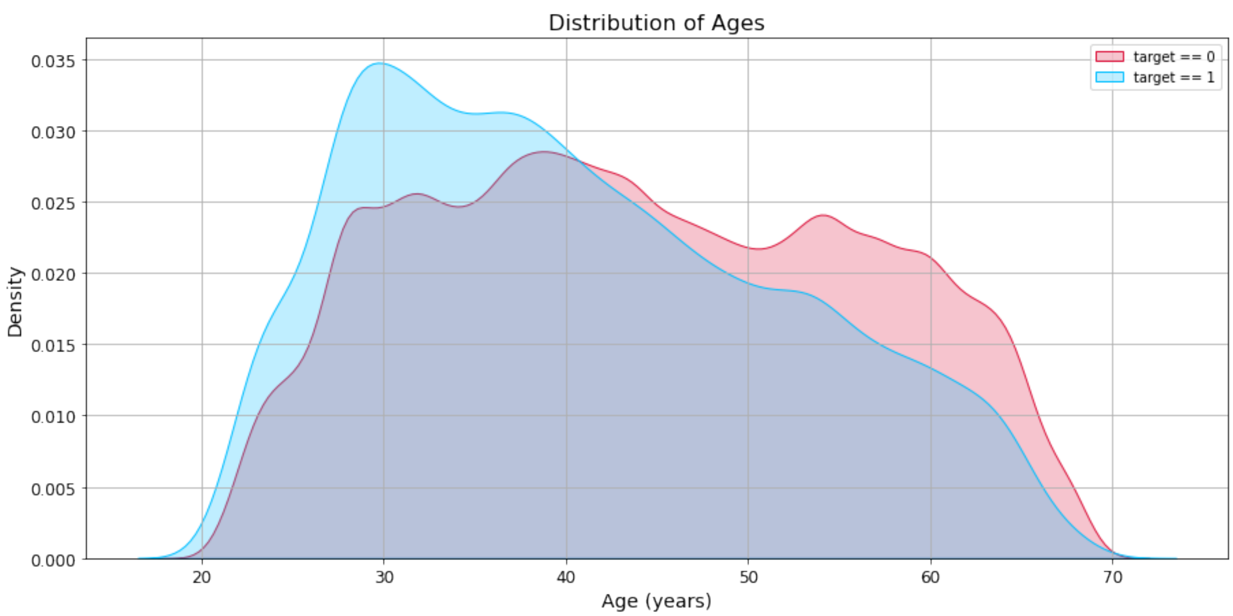
4.16.1 Observation:

- Most of the applicants are females and most of them have no default in their history.
- In case of male applicants, we can see that relatively higher number of applicants are in default.

4.17 Exploratory Data Analysis on Numeric/Continuous Features

4.18 Target v/s Age (in years)

In [65]:
```
plt.figure(figsize = (15, 7))

# KDE plot of loans that were repaid on time
sns.kdeplot(app_train.loc[app_train['TARGET'] == 0, 'DAYS_BIRTH'] / -3

# KDE plot of loans which were not repaid on time
sns.kdeplot(app_train.loc[app_train['TARGET'] == 1, 'DAYS_BIRTH'] / -3

# Labeling of plot
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.xlabel('Age (years)', fontsize=14)
plt.ylabel('Density', fontsize=14)
plt.title('Distribution of Ages', fontsize=16)

plt.legend()
plt.grid(b=True)
plt.show()
```

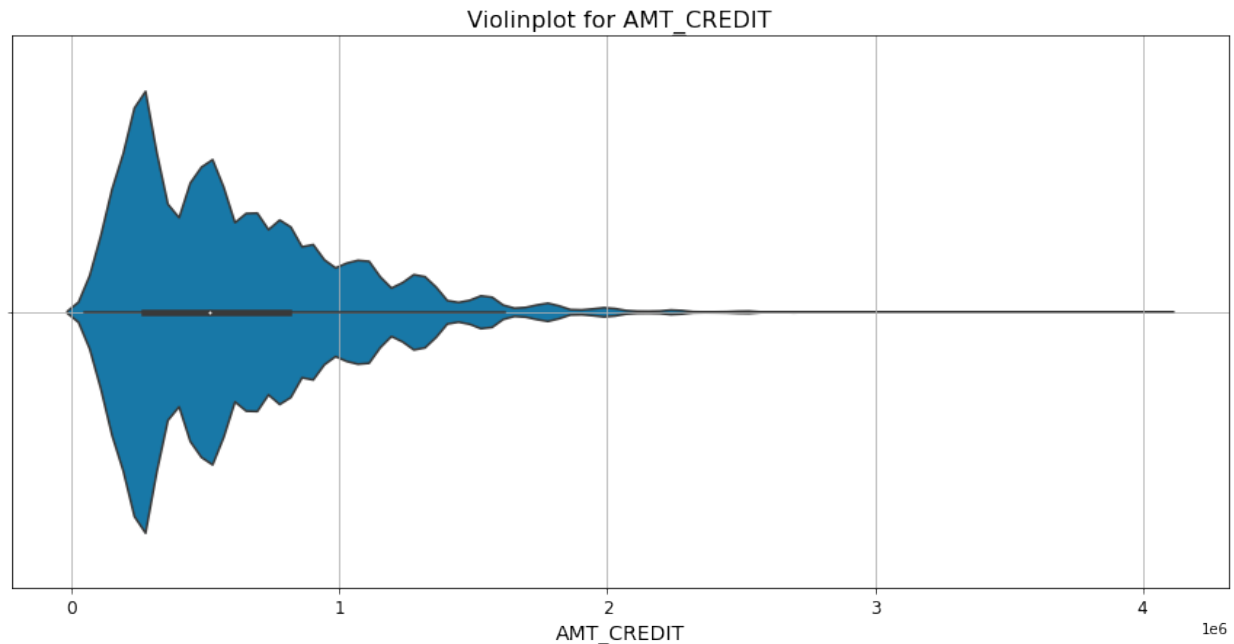


4.18.1 Observation

- We can observe a skew of defaults towards the younger applicants.
- This indicates that older applicants repaid their loans in a more timely/efficient manner.

4.18.2 Checking the distribution of AMT_CREDIT feature

In [66]:
```
plt.figure(figsize=(15, 7))
sns.violinplot(x=app_train['AMT_CREDIT'], palette='winter')
plt.xticks(size=12)
plt.yticks(size=12)
plt.xlabel('AMT_CREDIT', size=14)
plt.title('Violinplot for AMT_CREDIT', size=16)
plt.grid(b=True)
```

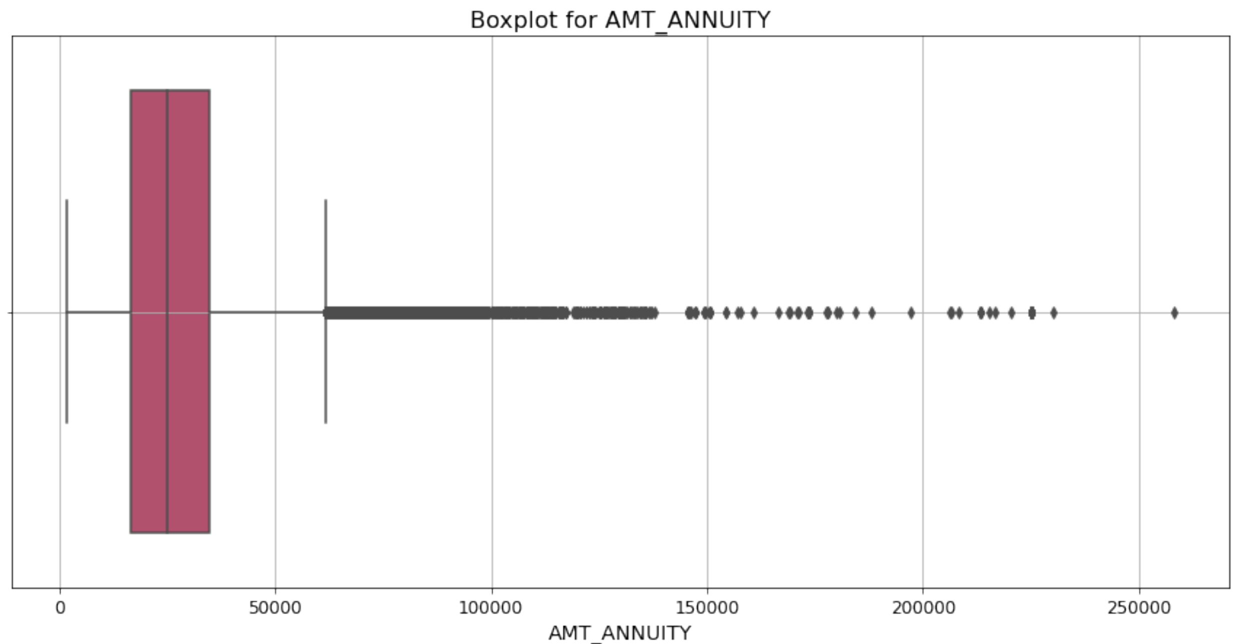


4.18.3 Observation

- We can observe that the feature is right skewed.
- Scaling might help us use this feature appropriately

4.18.4 Checking the distribution of AMT_ANNUITY feature

In [67]:
```
plt.figure(figsize=(15, 7))
sns.boxplot(x=app_train['AMT_ANNUITY'], palette='flare')
plt.xticks(size=12)
plt.yticks(size=12)
plt.xlabel('AMT_ANNUITY', size=14)
plt.title('Boxplot for AMT_ANNUITY', size=16)
plt.grid(b=True)
```

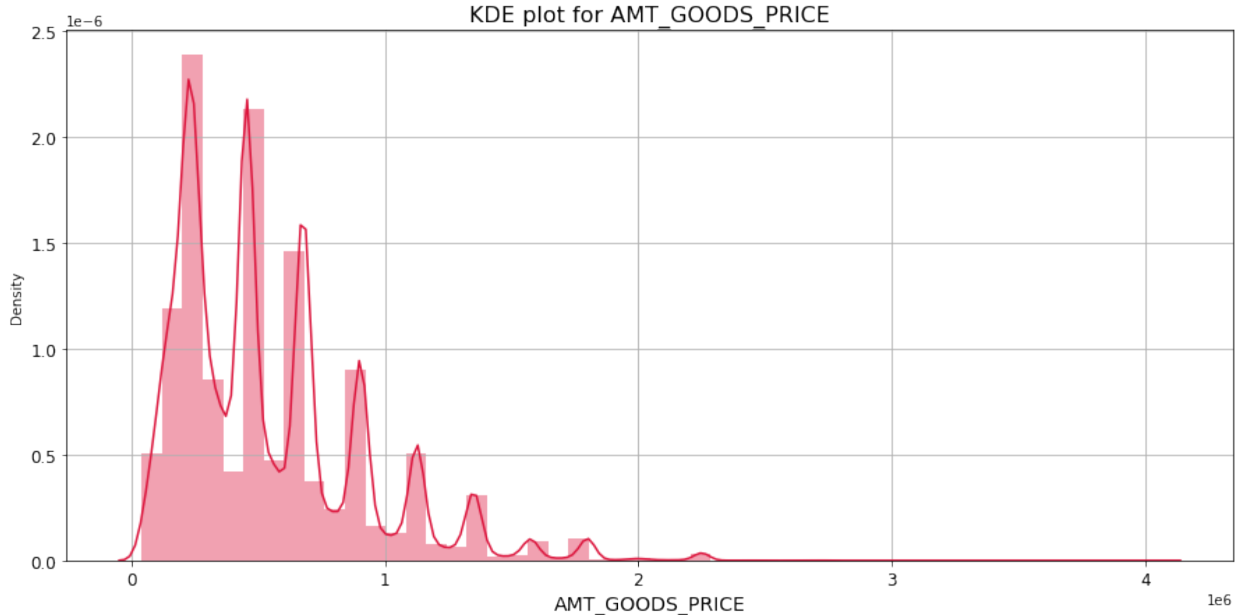


4.18.5 Observation

- We observe yet again a right skewed feature with a lot of outliers.
- We can't remove these outliers since we might lose important information.

4.18.6 Checking the distribution of AMT_GOODS_PRICE feature

In [68]:
```
plt.figure(figsize=(15, 7))
sns.distplot(x=app_train['AMT_GOODS_PRICE'], color='crimson')
plt.xticks(size=12)
plt.yticks(size=12)
plt.xlabel('AMT_GOODS_PRICE', size=14)
plt.title('KDE plot for AMT_GOODS_PRICE', size=16)
plt.grid(b=True)
```



4.18.7 Observation

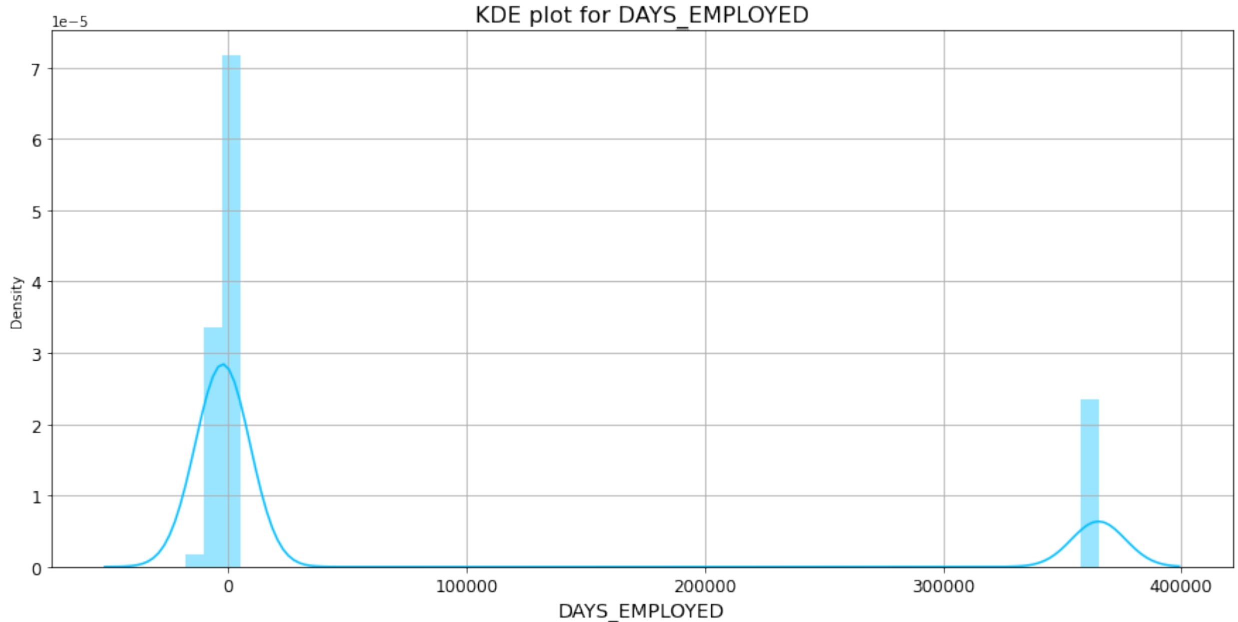
- We see yet another skewed distribution which is multi-modal in nature.
- Binning might help to make an efficient use of this feature.

4.18.8 Checking the distribution of DAYS_EMPLOYED feature

In [69]:
```
app_train['DAYS_EMPLOYED'].describe()
```

Out[69]:
```
count    307511.000000
mean      63815.045904
std      141275.766519
min      -17912.000000
25%       -2760.000000
50%       -1213.000000
75%        -289.000000
max      365243.000000
Name: DAYS_EMPLOYED, dtype: float64
```

In [70]:
```
plt.figure(figsize=(15, 7))
sns.distplot(x=app_train['DAYS_EMPLOYED'], color='deepskyblue')
plt.xticks(size=12)
plt.yticks(size=12)
plt.xlabel('DAYS_EMPLOYED', size=14)
plt.title('KDE plot for DAYS_EMPLOYED', size=16)
plt.grid(b=True)
```

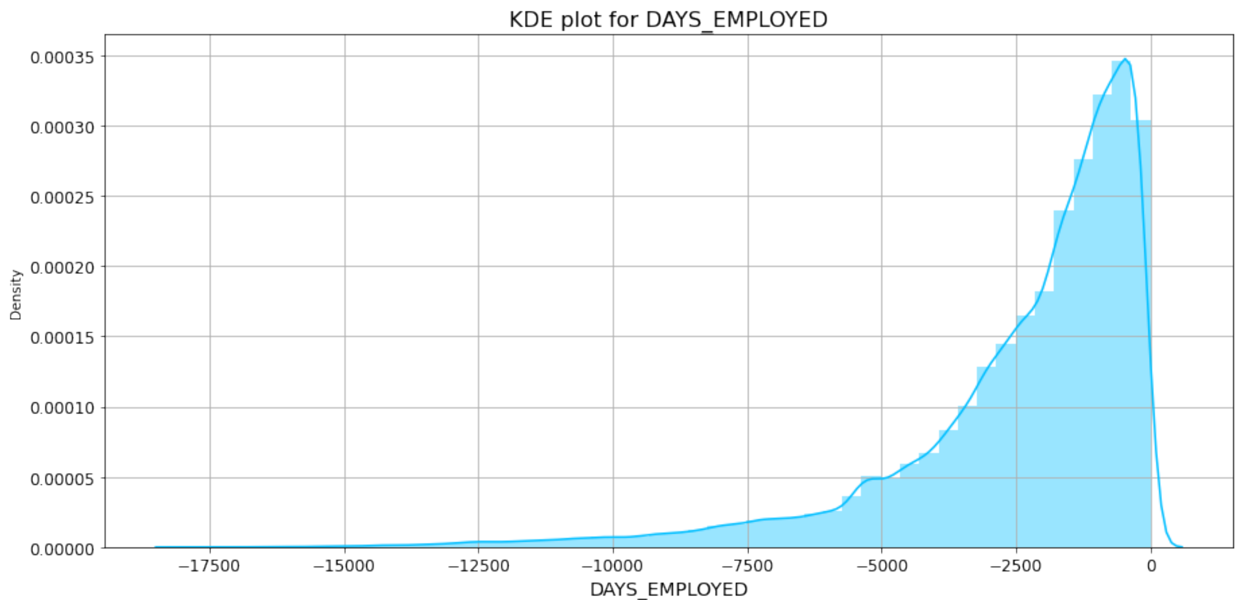


4.18.9 Observation

- Just like DAYS_BIRTH, this feature has negative days values.
- But we observe a weird anomaly here - max days employed is 365243 days which is a thousand years.
- We will simply ignore this anomaly (replace with appropriate values) and check the distribution of the feature again.

4.18.10 Checking the distribution of DAYS_EMPLOYED feature after removing the inconsistent value

In [71]:
```
days_employed = app_train['DAYS_EMPLOYED']
days_employed = days_employed[days_employed<365243]
plt.figure(figsize=(15, 7))
sns.distplot(x=days_employed, color='deepskyblue')
plt.xticks(size=12)
plt.yticks(size=12)
plt.xlabel('DAYS_EMPLOYED', size=14)
plt.title('KDE plot for DAYS_EMPLOYED', size=16)
plt.grid(b=True)
```



4.18.11 Observation

- We observe a left skewed data in this plot which in turn would form a right skewed distribution if we flip the days to the positive side.

4.18.12 Fixing DAYS_EMPLOYES and DAYS_BIRTH features

In [21]:
```
app_train['DAYS_BIRTH'] = app_train['DAYS_BIRTH'] / -1
app_test['DAYS_BIRTH'] = app_test['DAYS_BIRTH'] / -1

app_train['DAYS_EMPLOYED'] = app_train['DAYS_EMPLOYED'][app_train['DAY
app_test['DAYS_EMPLOYED'] = app_test['DAYS_EMPLOYED'][app_test['DAYS_E
app_train['DAYS_EMPLOYED'] = app_train['DAYS_EMPLOYED']/-1
app_test['DAYS_EMPLOYED'] = app_test['DAYS_EMPLOYED']/-1

app_train['DAYS_BIRTH'].head()
```

Out[21]:
```
0    -9461.0
1   -16765.0
2   -19046.0
3   -19005.0
4   -19932.0
Name: DAYS_BIRTH, dtype: float64
```

In [22]:
```
app_test['DAYS_BIRTH'].head()
```

Out[22]:
```
0   -19241.0
1   -18064.0
2   -20038.0
3   -13976.0
4   -13040.0
Name: DAYS_BIRTH, dtype: float64
```

In [23]:
```
app_train['DAYS_EMPLOYED'].head()
```

Out[23]:
```
0    -637.0
1   -1188.0
2    -225.0
3   -3039.0
4   -3038.0
Name: DAYS_EMPLOYED, dtype: float64
```

In [24]:
```
app_test['DAYS_EMPLOYED'].head()
```

Out[24]:
```
0   -2329.0
1   -4469.0
2   -4458.0
3   -1866.0
4   -2191.0
Name: DAYS_EMPLOYED, dtype: float64
```

5 Dataset questions

5.1 Unique record for each SK_ID_CURR

In [25]:
```
list(datasets.keys())
```

Out[25]:
```
['application_train',
 'application_test',
 'bureau',
 'bureau_balance',
 'credit_card_balance',
 'installments_payments',
 'previous_application',
 'POS_CASH_balance']
```

In [26]:
```
len(datasets["application_train"]["SK_ID_CURR"].unique()) == datasets[
```

Out[26]:
```
True
```

In [27]:
```
# is there an overlap between the test and train customers
np.intersect1d(datasets["application_train"]["SK_ID_CURR"], datasets["
```

Out[27]:
```
array([], dtype=int64)
```

In [28]:
```
datasets["application_test"].shape
```

Out[28]:
```
(48744, 121)
```

In [29]:
```
datasets["application_train"].shape
```

Out[29]:
```
(307511, 122)
```

5.2 previous applications for the submission file

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

In [4]:
```
appsDF = pd.read_csv('/root/shared/AML/I526_AML_Student/Assignments/Ur
display(appsDF.head())
print(f"{appsDF.shape[0]:,} rows, {appsDF.shape[1]:,} columns")
```

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

5 rows × 37 columns

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

In [4]:
```
print(f"There are  {appsDF.shape[0]:,} previous applications")
```

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

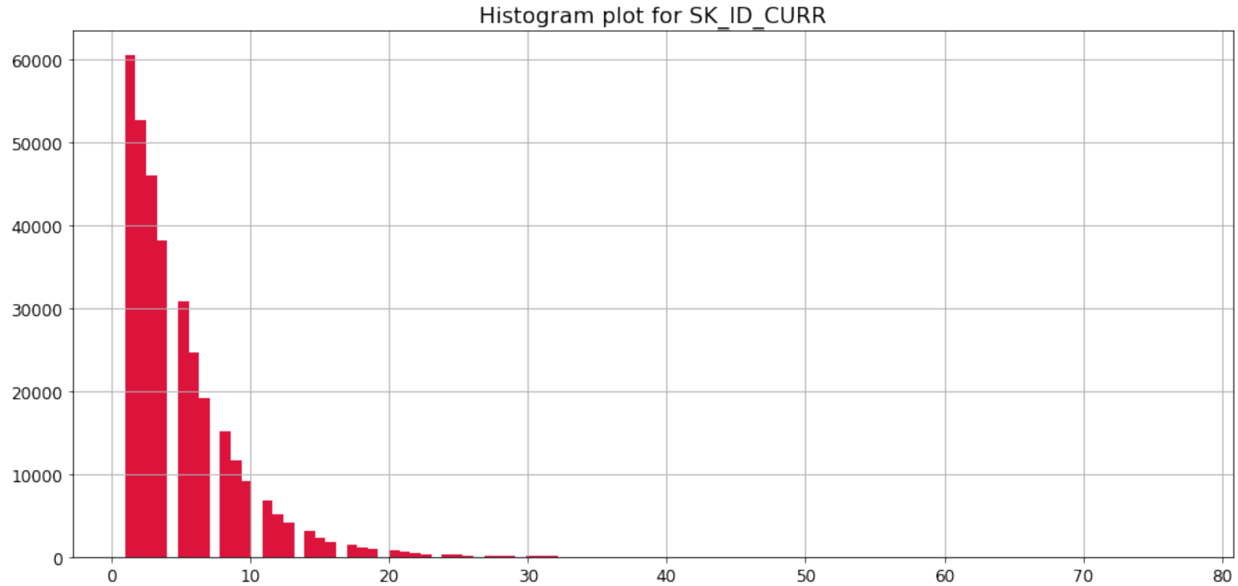
In [12]:
```
#Find the intersection of two arrays.
print(f'Number of train applicants with previous applications is {len(
```

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

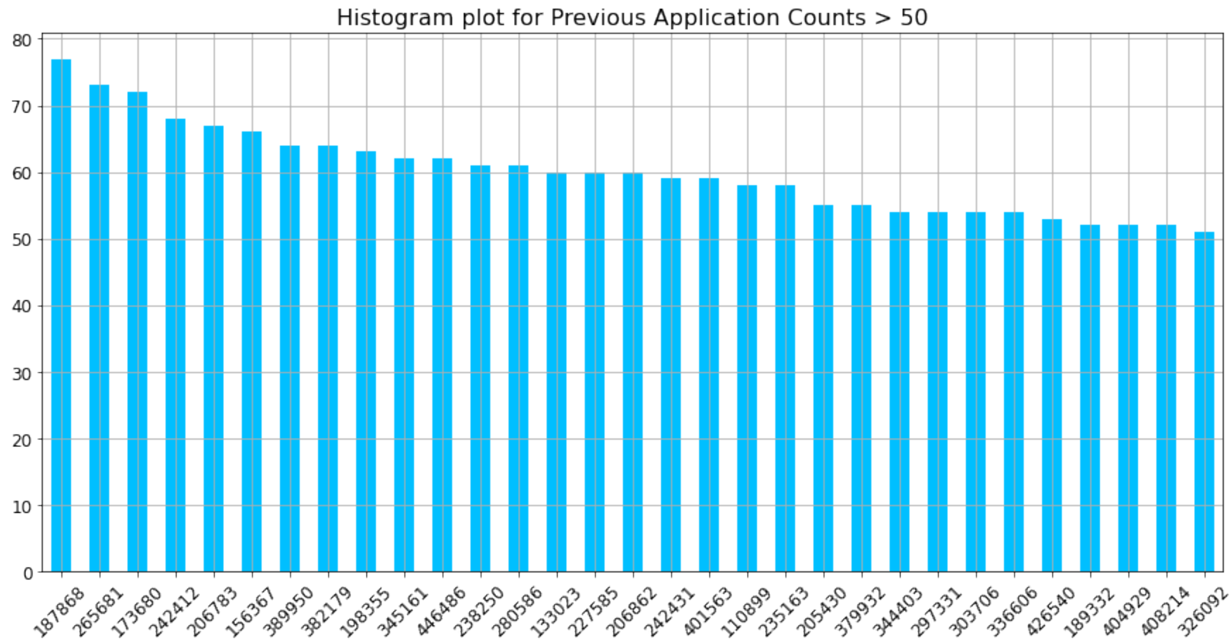
In [13]:
```
#Find the intersection of two arrays.
print(f'Number of test applicants with previous applications is {len(r
```

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

In [14]:
```
# How many previous applciations  per applicant in the previous_applic
plt.figure(figsize=(15,7))
prevAppCounts = appsDF['SK_ID_CURR'].value_counts(dropna=False)
len(prevAppCounts[prevAppCounts >40])  #more that 40 previous applicat
plt.hist(prevAppCounts[prevAppCounts>=0], bins=100, color='crimson')
plt.xticks(size=12)
plt.yticks(size=12)
plt.xlabel('', size=14)
plt.ylabel('', size=14)
plt.title('Histogram plot for SK_ID_CURR', size=16)
plt.grid(b=True)
```



In [15]:
```
plt.figure(figsize=(15,7))
prevAppCounts[prevAppCounts > 50].plot(kind='bar', color='deepskyblue'
plt.xticks(size=12, rotation=45)
plt.yticks(size=12)
plt.xlabel('', size=14)
plt.ylabel('', size=14)
plt.title('Histogram plot for Previous Application Counts > 50', size=
plt.grid(b=True)
```

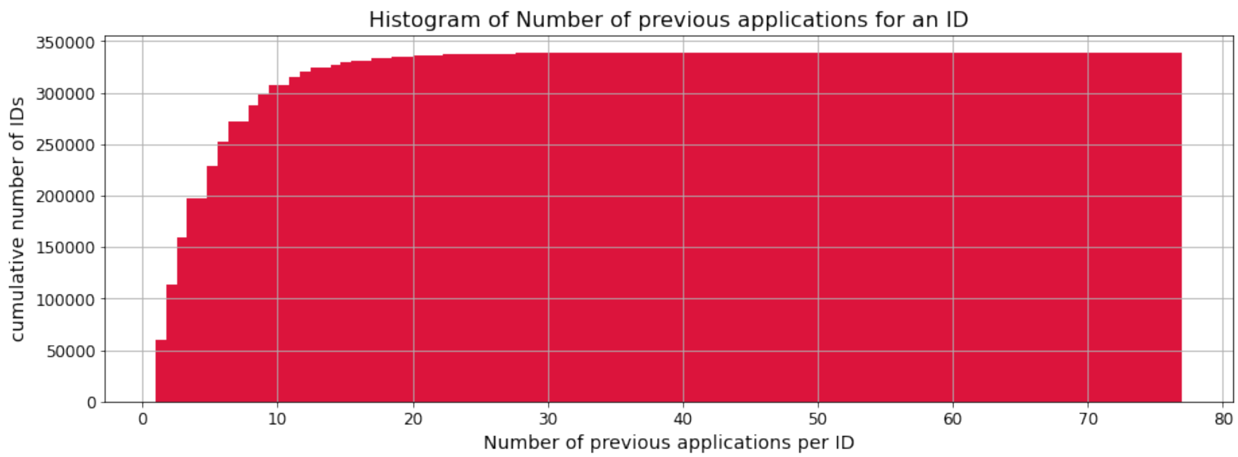


5.2.1 Histogram of Number of previous applications for an ID

In [16]:
```
sum(appsDF['SK_ID_CURR'].value_counts()==1)
```

Out[16]: 60458

In [17]:
```
plt.figure(figsize=(15,5))
plt.hist(appsDF['SK_ID_CURR'].value_counts(), cumulative =True, bins =
plt.xticks(size=12)
plt.yticks(size=12)
plt.ylabel('cumulative number of IDs', size=14)
plt.xlabel('Number of previous applications per ID', size=14)
plt.title('Histogram of Number of previous applications for an ID', si
plt.grid()
plt.show()
```



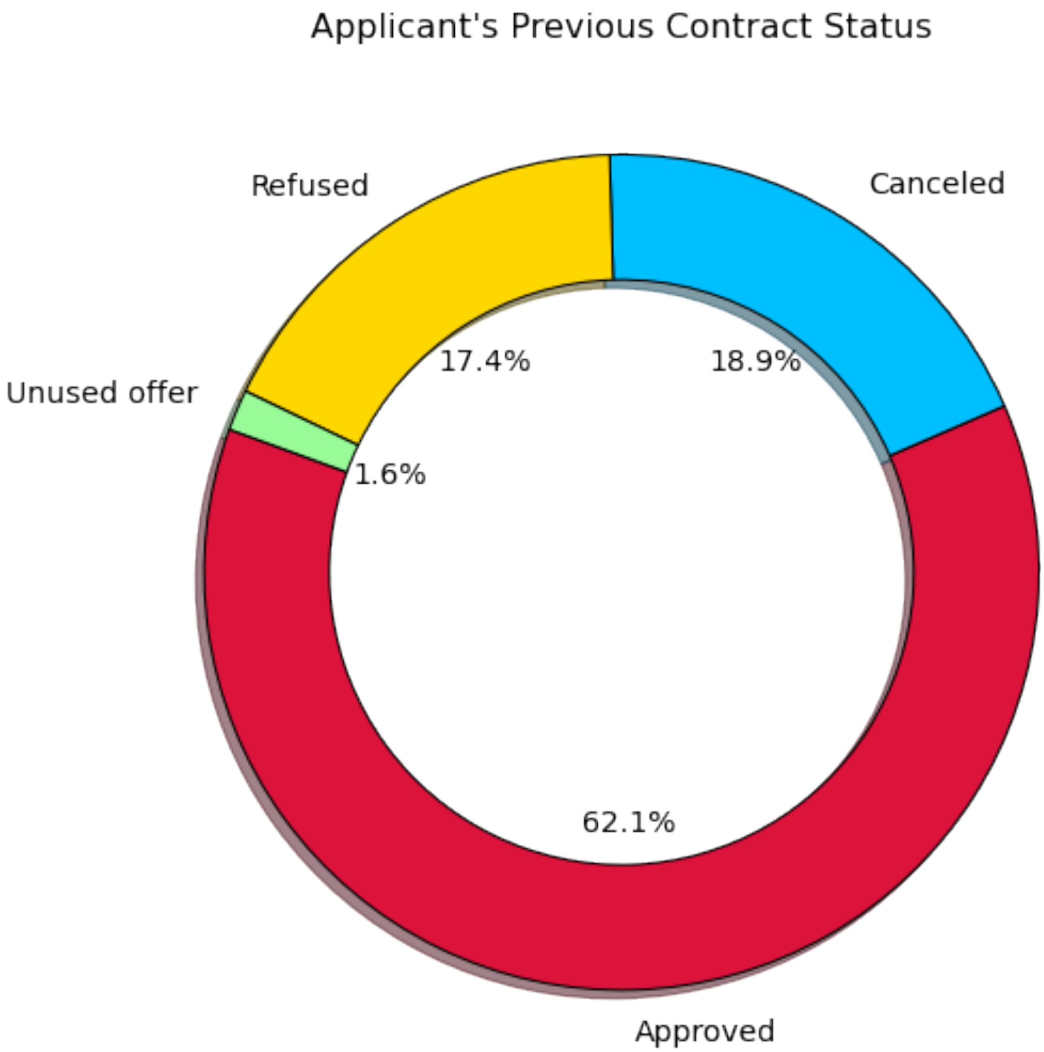
Can we differentiate applications by low, medium and high previous apps?

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

In [38]:
```
apps_all = appsDF['SK_ID_CURR'].nunique()
apps_5plus = appsDF['SK_ID_CURR'].value_counts()>=5
apps_40plus = appsDF['SK_ID_CURR'].value_counts()>=40
print('Percentage with 10 or more previous apps:', np.round(100.*(sum(
print('Percentage with 40 or more previous apps:', np.round(100.*(sum(
```

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

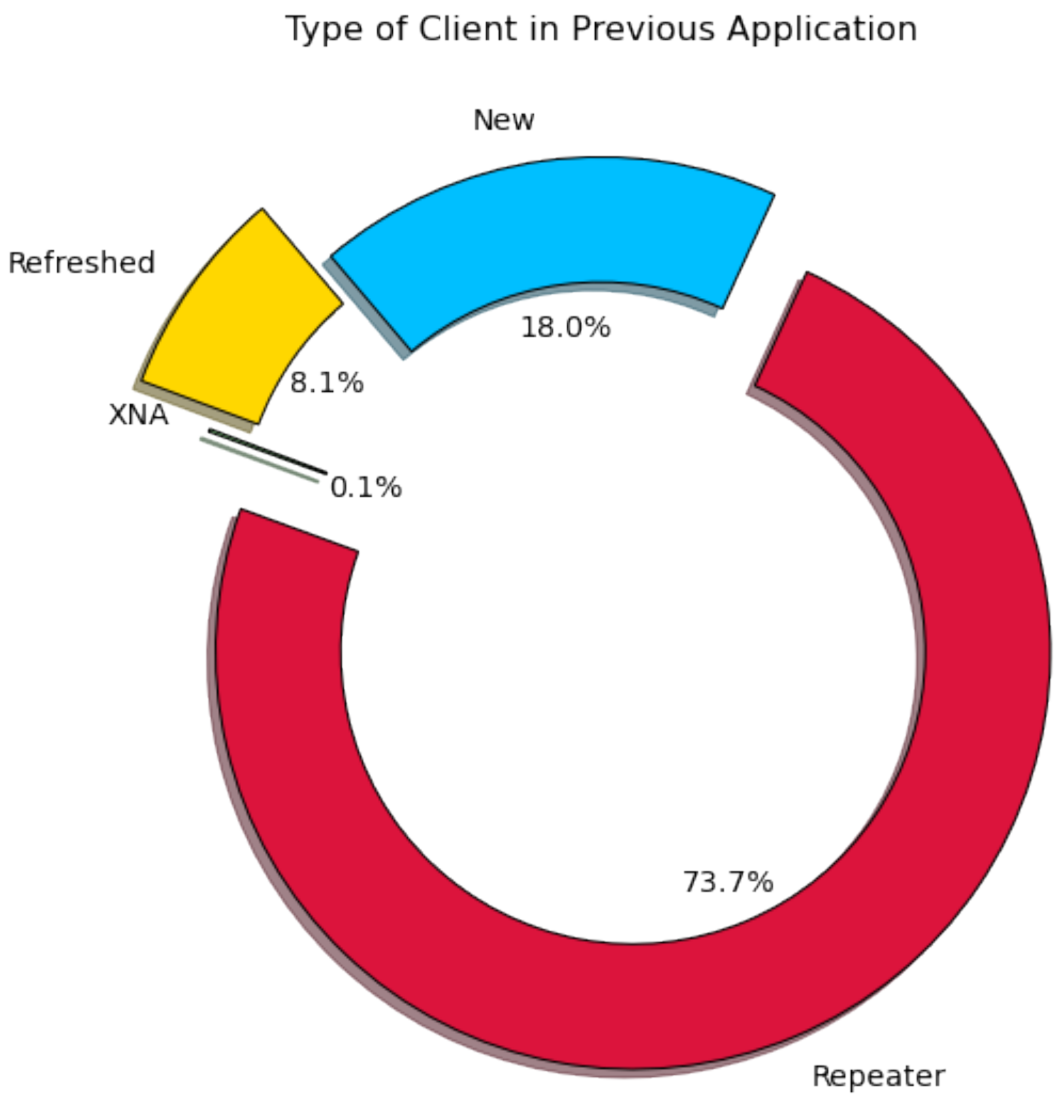
In [39]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=appsDF['NAME_CONTRACT_STATUS'].value_counts(),
        radius=1.3-0.3,
        labels=appsDF['NAME_CONTRACT_STATUS'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue', 'gold', 'palegreen'],
        wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=160,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.title("Applicant's Previous Contract Status", fontsize=16)
plt.show()
```



5.2.2 Observation

- In previous applications, most of the applicants had their contracts approved.
- 36% of applicants had their contracts either rejected or cancelled and the rest 1.6% didn't use their contracts at all.

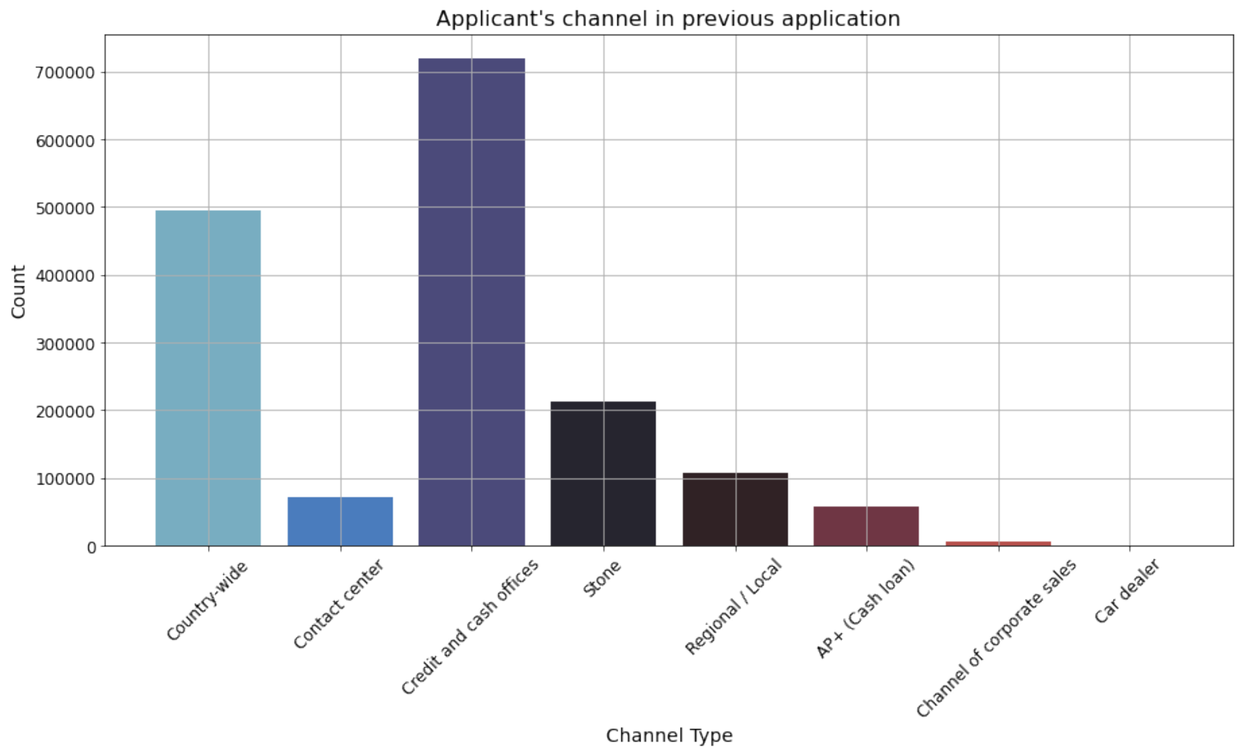
In [ ]:
```
plt.figure(figsize=(9, 9))
plt.pie(x=appsDF['NAME_CLIENT_TYPE'].value_counts(),
        radius=1.3-0.3,
        labels=appsDF['NAME_CLIENT_TYPE'].value_counts().index,
        autopct='%1.1f%%',
        colors=['crimson', 'deepskyblue', 'gold', 'palegreen'],
        explode=[0.2,0,0.2,0],
        wedgeprops={"edgecolor":"0", "width":0.3},
        startangle=160,
        shadow=True,
        textprops={'fontsize': 14})
plt.ylabel('', fontsize=14)
plt.title("Type of Client in Previous Application", fontsize=16)
plt.show()
```



5.2.3 Observation

- Most of the applicants are repeaters, followed by new applicants and refreshed applicants.

In [ ]:
```
plt.figure(figsize=(15, 7))
sns.countplot(x='CHANNEL_TYPE', data=appsDF, palette='icefire')
plt.title("Applicant's channel in previous application", fontsize=16)
plt.xlabel('Channel Type', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(fontsize=12, rotation=45)
plt.yticks(fontsize=12)
plt.grid(b=True)
plt.plot();
```



5.2.4 Observation

- Previous applicants primarily came through credit and cash offices and least via car dealers.

5.3 Feature Engineering

5.3.1 Performing Encoding on the Categorical Features of application_train and application_test

In [40]:
```
# Label Encoding
# Create a label encoder object
le = LabelEncoder()
le_count = 0

# Iterate through the columns
for col in app_train:
    if app_train[col].dtype == 'object':
        # If 2 or fewer unique categories
        if len(list(app_train[col].unique())) <= 2:
            # Train on the training data
            le.fit(app_train[col])
            # Transform both training and testing data
            app_train[col] = le.transform(app_train[col])
            app_test[col] = le.transform(app_test[col])

            # Keep track of how many columns were label encoded
            le_count += 1

print('%d columns were label encoded.' % le_count)
```

```
0 columns were label encoded.
```

In [43]:
```
# one-hot encoding of features
app_train = pd.get_dummies(app_train)
app_test = pd.get_dummies(app_test)

print('Training Features shape: ', app_train.shape)
print('Testing Features shape: ', app_test.shape)
```

```
Training Features shape:  (307511, 240)
Testing Features shape:  (48744, 239)
```

In [44]:
```
train_labels = app_train['TARGET']

# Align the training and testing data, keep only columns present in bo
app_train, app_test = app_train.align(app_test, join = 'inner', axis =

# Add the target back in
app_train['TARGET'] = train_labels

print('Training Features shape: ', app_train.shape)
print('Testing Features shape: ', app_test.shape)
```

```
Training Features shape:  (307511, 240)
Testing Features shape:  (48744, 239)
```

5.4 Saving the cleaned train and test file for easy future access

In [91]:
```
# app_train.to_csv('app_train.csv', index=False)
```

In [92]:
```
# app_test.to_csv('app_test.csv', index=False)
```

6 Joining secondary tables with the primary table

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

6.1 Joining `previous_application` with `application_x`

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

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

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

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

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

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

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

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

6.2 Roadmap for secondary table processing

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

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

In [45]:
```
!pwd
```

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

In [5]:
```
app_train = pd.read_csv('/root/shared/AML/I526_AML_Student/Assignments
app_train.head()
```

Out[5]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDF
0	100002	0	0	1	
1	100003	0	0	0	
2	100004	1	1	1	
3	100006	0	0	1	
4	100007	0	0	1	

5 rows × 240 columns

In [6]:
```
app_test = pd.read_csv('/root/shared/AML/I526_AML_Student/Assignments/
app_test.head()
```

Out[6]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDF
0	100001	0	0	1	
1	100005	0	0	1	
2	100013	0	1	1	
3	100028	0	0	1	
4	100038	0	1	0	

5 rows × 239 columns

In [46]:
```
appsDF.columns
```

Out[46]:
```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'AMT_ANNUITY
',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOOD
S_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VER
SION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION', 'NFLAG_INSURED_ON_APPROVA
L'],
      dtype='object')
```

In [47]:
```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]
```

Out[47]:

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

In [48]:
```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704)]["AMT_CREDIT"]
```

Out[48]:
```
6    0.0
Name: AMT_CREDIT, dtype: float64
```

In [49]:
```
appsDF[0:50][(appsDF["SK_ID_CURR"]==175704) & ~(appsDF["AMT_CREDIT"]==
```

Out[49]:

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

6.3 Missing values in prevApps

In [7]:
```
appsDF.isna().sum()
```

Out[7]:
```
SK_ID_PREV                           0
SK_ID_CURR                           0
NAME_CONTRACT_TYPE                   0
AMT_ANNUITY                     372235
AMT_APPLICATION                      0
AMT_CREDIT                           1
AMT_DOWN_PAYMENT                895844
AMT_GOODS_PRICE                 385515
WEEKDAY_APPR_PROCESS_START           0
HOUR_APPR_PROCESS_START              0
FLAG_LAST_APPL_PER_CONTRACT          0
NFLAG_LAST_APPL_IN_DAY               0
RATE_DOWN_PAYMENT               895844
RATE_INTEREST_PRIMARY          1664263
RATE_INTEREST_PRIVILEGED       1664263
NAME_CASH_LOAN_PURPOSE               0
NAME_CONTRACT_STATUS                 0
DAYS_DECISION                        0
NAME_PAYMENT_TYPE                    0
CODE_REJECT_REASON                   0
NAME_TYPE_SUITE                 820405
NAME_CLIENT_TYPE                     0
NAME_GOODS_CATEGORY                  0
NAME_PORTFOLIO                       0
NAME_PRODUCT_TYPE                    0
CHANNEL_TYPE                         0
SELLERPLACE_AREA                     0
NAME_SELLER_INDUSTRY                 0
CNT_PAYMENT                     372230
NAME_YIELD_GROUP                     0
PRODUCT_COMBINATION                346
DAYS_FIRST_DRAWING              673065
DAYS_FIRST_DUE                  673065
DAYS_LAST_DUE_1ST_VERSION       673065
DAYS_LAST_DUE                   673065
DAYS_TERMINATION                673065
NFLAG_INSURED_ON_APPROVAL       673065
dtype: int64
```

In [51]:
```
appsDF.columns
```

Out[51]:
```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'AMT_ANNUITY
',
       'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT', 'AMT_GOOD
S_PRICE',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
       'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
       'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
       'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
       'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
       'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
       'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
       'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE_1ST_VER
SION',
       'DAYS_LAST_DUE', 'DAYS_TERMINATION', 'NFLAG_INSURED_ON_APPROVA
L'],
      dtype='object')
```

6.4 feature engineering for prevApp table

In [8]:
```
features = ['AMT_ANNUITY', 'AMT_APPLICATION']
print(f"{appsDF[features].describe()}")
agg_ops = ["min", "max", "mean"]
result = appsDF.groupby(["SK_ID_CURR"], as_index=False).agg("mean") #g
display(result.head())
print("-"*50)
result = appsDF.groupby(["SK_ID_CURR"], as_index=False).agg({'AMT_ANNU
result.columns = result.columns.map('_'.join)
display(result)
result['range_AMT_APPLICATION'] = result['AMT_APPLICATION_max'] - resu
print(f"result.shape: {result.shape}")
result[0:10]
```

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

SK_ID_CURR	SK_ID_PREV	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_

0	100001	1.369693e+06	3951.000	24835.50	23787.00
1	100002	1.038818e+06	9251.775	179055.00	179055.00
2	100003	2.281150e+06	56553.990	435436.50	484191.00
3	100004	1.564014e+06	5357.250	24282.00	20106.00
4	100005	2.176837e+06	4813.200	22308.75	20076.75

5 rows × 21 columns

	SK_ID_CURR_	AMT_ANNUITY_min	AMT_ANNUITY_max	AMT_ANNUITY_mean	AMT_AF
0	100001	3951.000	3951.000	3951.000000	
1	100002	9251.775	9251.775	9251.775000	
2	100003	6737.310	98356.995	56553.990000	
3	100004	5357.250	5357.250	5357.250000	
4	100005	4813.200	4813.200	4813.200000	
...	...	...	...	...	
338852	456251	6605.910	6605.910	6605.910000	
338853	456252	10074.465	10074.465	10074.465000	
338854	456253	3973.095	5567.715	4770.405000	
338855	456254	2296.440	19065.825	10681.132500	
338856	456255	2250.000	54022.140	20775.391875	

338857 rows × 7 columns

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

Out[8]:

	SK_ID_CURR_	AMT_ANNUITY_min	AMT_ANNUITY_max	AMT_ANNUITY_mean	AMT_APPLICA
0	100001	3951.000	3951.000	3951.000000	
1	100002	9251.775	9251.775	9251.775000	
2	100003	6737.310	98356.995	56553.990000	
3	100004	5357.250	5357.250	5357.250000	
4	100005	4813.200	4813.200	4813.200000	
5	100006	2482.920	39954.510	23651.175000	
6	100007	1834.290	22678.785	12278.805000	

7	100008	8019.090	25309.575	15839.696250
8	100009	7435.845	17341.605	10051.412143
9	100010	27463.410	27463.410	27463.410000

In [19]:
```
result.isna().sum()
```

Out[19]:
```
SK_ID_CURR_                0
AMT_ANNUITY_min          480
AMT_ANNUITY_max          480
AMT_ANNUITY_mean         480
AMT_APPLICATION_min        0
AMT_APPLICATION_max        0
AMT_APPLICATION_mean       0
range_AMT_APPLICATION      0
dtype: int64
```

6.5 feature transformer for prevApp table

In [98]:

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

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

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

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

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

# features = ['AMT_ANNUITY', 'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOW
#             'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
#             'RATE_INTEREST_PRIVILEGED', 'DAYS_DECISION', 'NAME_PAYME
#             'CNT_PAYMENT', 'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', '
#             'DAYS_LAST_DUE', 'DAYS_TERMINATION']

# res = test_driver_prevAppsFeaturesAggregater(appsDF, features)
# print(f"HELLO")
# print(f"Test driver: \n{res[0:10]}")
# print(f"input[features][0:10]: \n{appsDF[0:10]}")
```

In [9]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.impute import SimpleImputer

# Make a new dataframe for polynomial features
poly_features = app_train[['EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SOURCE
poly_features_test = app_test[['EXT_SOURCE_1', 'EXT_SOURCE_2', 'EXT_SC

# imputer for handling missing values
# from sklearn.preprocessing import Imputer
imputer = SimpleImputer(strategy = 'median')

poly_target = poly_features['TARGET']

poly_features = poly_features.drop(columns = ['TARGET'])

# Need to impute missing values
poly_features = imputer.fit_transform(poly_features)
poly_features_test = imputer.transform(poly_features_test)

# Create the polynomial object with specified degree
poly_transformer = PolynomialFeatures(degree = 3)
```

In [10]:
```
# Train the polynomial features
poly_transformer.fit(poly_features)

# Transform the features
poly_features = poly_transformer.transform(poly_features)
poly_features_test = poly_transformer.transform(poly_features_test)
print('Polynomial Features shape: ', poly_features.shape)
```

```
Polynomial Features shape:  (307511, 35)
```

In [11]:
```
poly_transformer.get_feature_names(input_features = ['EXT_SOURCE_1', '
```

Out[11]:
```
['1',
 'EXT_SOURCE_1',
 'EXT_SOURCE_2',
 'EXT_SOURCE_3',
 'DAYS_BIRTH',
 'EXT_SOURCE_1^2',
 'EXT_SOURCE_1 EXT_SOURCE_2',
 'EXT_SOURCE_1 EXT_SOURCE_3',
 'EXT_SOURCE_1 DAYS_BIRTH',
 'EXT_SOURCE_2^2',
 'EXT_SOURCE_2 EXT_SOURCE_3',
 'EXT_SOURCE_2 DAYS_BIRTH',
 'EXT_SOURCE_3^2',
 'EXT_SOURCE_3 DAYS_BIRTH',
 'DAYS_BIRTH^2',
 'EXT_SOURCE_1^3',
 'EXT_SOURCE_1^2 EXT_SOURCE_2',
 'EXT_SOURCE_1^2 EXT_SOURCE_3',
 'EXT_SOURCE_1^2 DAYS_BIRTH',
 'EXT_SOURCE_1 EXT_SOURCE_2^2']
```

In [12]:
```
# Create a dataframe of the features
poly_features = pd.DataFrame(poly_features,
                             columns = poly_transformer.get_feature_na


# Add in the target
poly_features['TARGET'] = poly_target

# Find the correlations with the target
poly_corrs = poly_features.corr()['TARGET'].sort_values()

# Display most negative and most positive
print(poly_corrs.head(10))
print(poly_corrs.tail(5))
```

```
EXT_SOURCE_2 EXT_SOURCE_3                -0.193939
EXT_SOURCE_1 EXT_SOURCE_2 EXT_SOURCE_3   -0.189605
EXT_SOURCE_2 EXT_SOURCE_3 DAYS_BIRTH     -0.181283
EXT_SOURCE_2^2 EXT_SOURCE_3              -0.176428
EXT_SOURCE_2 EXT_SOURCE_3^2              -0.172282
EXT_SOURCE_1 EXT_SOURCE_2                -0.166625
EXT_SOURCE_1 EXT_SOURCE_3                -0.164065
EXT_SOURCE_2                             -0.160295
EXT_SOURCE_2 DAYS_BIRTH                  -0.156873
EXT_SOURCE_1 EXT_SOURCE_2^2              -0.156867
Name: TARGET, dtype: float64
DAYS_BIRTH     -0.078239
DAYS_BIRTH^2   -0.076672
DAYS_BIRTH^3   -0.074273
TARGET          1.000000
1                    NaN
Name: TARGET, dtype: float64
```

In [13]:
```
# Put test features into dataframe
poly_features_test = pd.DataFrame(poly_features_test,
                                  columns = poly_transformer.get_featu



# Merge polynomial features into training dataframe
poly_features['SK_ID_CURR'] = app_train['SK_ID_CURR']
app_train_poly = app_train.merge(poly_features, on = 'SK_ID_CURR', how

# Merge polnomial features into testing dataframe
poly_features_test['SK_ID_CURR'] = app_test['SK_ID_CURR']
app_test_poly = app_test.merge(poly_features_test, on = 'SK_ID_CURR',

# Align the dataframes
app_train_poly, app_test_poly = app_train_poly.align(app_test_poly, jo

# Print out the new shapes
print('Training data with polynomial features shape: ', app_train_poly
print('Testing data with polynomial features shape:  ', app_test_poly.
```

```
Training data with polynomial features shape:  (307511, 274)
Testing data with polynomial features shape:   (48744, 274)
```

In [14]:
```
app_train_poly['TARGET'] = app_train['TARGET']
app_train_poly.head()
```

Out[14]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDF
0	100002	0	0	1	
1	100003	0	0	0	
2	100004	1	1	1	
3	100006	0	0	1	
4	100007	0	0	1	

5 rows × 275 columns

In [15]:
```
app_train_poly['TARGET'].head()
```

Out[15]:
```
0    1
1    0
2    0
3    0
4    0
Name: TARGET, dtype: int64
```

In [16]:
```
app_test_poly.head()
```

Out[16]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDF
0	100001	0	0	1	
1	100005	0	0	1	
2	100013	0	1	1	
3	100028	0	0	1	
4	100038	0	1	0	

5 rows × 274 columns

6.6 Feature Aggregating

In [ ]:
```
```

6.7 Join the labeled dataset

In [51]:
```
datasets.keys()
```

Out[51]:
```
dict_keys(['application_train', 'application_test', 'bureau', 'bureau
_balance', 'credit_card_balance', 'installments_payments', 'previous_
application', 'POS_CASH_balance'])
```

In [52]:
```
```

```
# features = ['AMT_ANNUITY', 'AMT_APPLICATION']
# prevApps_feature_pipeline = Pipeline([
#         ('prevApps_add_features1', prevApps_add_features1()),  # adc
#         ('prevApps_add_features2', prevApps_add_features2()),  # adc
#         ('prevApps_aggregater', prevAppsFeaturesAggregater()), # Agg
#     ])


merged_data = app_train_poly #primary dataset
appsDF = datasets["previous_application"] #prev app


merge_all_data = False

# transform all the secondary tables
# 'bureau', 'bureau_balance', 'credit_card_balance', 'installments_pay
# 'previous_application', 'POS_CASH_balance'

if merge_all_data:
    prevApps_aggregated = prevApps_feature_pipeline.transform(appsDF)

    #'bureau', 'bureau_balance', 'credit_card_balance', 'installments_
    # 'previous_application', 'POS_CASH_balance'

# merge primary table and secondary tables using features based on met
if merge_all_data:
    # 1. Join/Merge in prevApps Data
    merged_data = merged_data.merge(prevApps_aggregated, how='left', c
    # merged_data = merged_data.merge(bureau_aggregated, how='left', c
    # merged_data = merged_data.merge(ccblance_aggregated, how='left',
    # merged_data = merged_data.merge(installments_pmnts_aggregated, h

    # 2. Join/Merge in ...... Data
    #X_train = X_train.merge(...._aggregated, how='left', on="SK_ID_CU

    # 3. Join/Merge in .....Data
    #dX_train = X_train.merge(...._aggregated, how='left', on="SK_ID_C

    # 4. Join/Merge in Aggregated ...... Data
    #X_train = X_train.merge(...._aggregated, how='left', on="SK_ID_CU

    # ......
merged_data.head()
```

Out[52]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDF
0	100002	0	0	1	

1	100003	0	0	0
2	100004	1	1	1
3	100006	0	0	1
4	100007	0	0	1

5 rows × 275 columns

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

In [17]:
```
# X_kaggle_test= app_test_poly
# X_kaggle_test = appln_feature_pipeline.fit_transform(X_kaggle_test)

# merge_all_data = True
# if merge_all_data:
#     X_kaggle_test = X_kaggle_test.merge(prevApps_aggregated, how='le
#     # X_kaggle_test = X_kaggle_test.merge(bureau_aggregated, how='le
#     # X_kaggle_test = X_kaggle_test.merge(ccblance_aggregated, how='
#     # X_kaggle_test = X_kaggle_test.merge(installments_pmnts_aggrega
```

In [31]:
```
app_train_poly.to_csv('app_train_poly.csv', index=False)
app_test_poly.to_csv('app_test_poly.csv', index=False)
```

7 Processing pipeline

In [3]:
```
# merged_data = pd.read_csv('merged_data_train.csv')
# merged_data.head()
```

Out[3]:

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

5 rows × 160 columns

In [4]:
```
# pd.set_option('display.max_columns', None)
# pd.set_option('display.max_rows', None)
# list(merged_data.columns)
```

Out[4]:
```
['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',
 'NAME_TYPE_SUITE',
 'NAME_INCOME_TYPE',
 'NAME_EDUCATION_TYPE',
 'NAME_FAMILY_STATUS',
 'NAME_HOUSING_TYPE',
 'REGION_POPULATION_RELATIVE',
 'DAYS_BIRTH_x',
 'DAYS_EMPLOYED',
 'DAYS_REGISTRATION',
```

Please [this blog (https://medium.com/hugo-ferreiras-blog/dealing-with-categorical-features-in-machine-learning-1bb70f07262d)](https://medium.com/hugo-ferreiras-blog/dealing-with-categorical-features-in-machine-learning-1bb70f07262d) for more details of OHE when the validation/test have previously unseen unique values.

In [18]:
```
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 [22]:
```
# # Split the provided training data into training and validationa and
# # The kaggle evaluation test set has no labels

train_dataset=app_train_poly
class_labels = ["No Default","Default"]

from sklearn.model_selection import train_test_split

num_attribs = [
'AMT_INCOME_TOTAL',
'AMT_CREDIT',
'EXT_SOURCE_3_x',
```

```
'EXT_SOURCE_2_x',
'EXT_SOURCE_1_x',
'EXT_SOURCE_3_y',
'EXT_SOURCE_2_y',
'EXT_SOURCE_1_y',
'DAYS_EMPLOYED',
'FLOORSMAX_AVG',
'FLOORSMAX_MEDI',
'FLOORSMAX_MODE',
'AMT_GOODS_PRICE',
'REGION_POPULATION_RELATIVE',
'ELEVATORS_AVG',
'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',
'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',
'1',
'EXT_SOURCE_1_y',
'EXT_SOURCE_2_y',
'EXT_SOURCE_3_y',
'DAYS_BIRTH_y',
'EXT_SOURCE_1^2',
'EXT_SOURCE_1 EXT_SOURCE_2',
'EXT_SOURCE_1 EXT_SOURCE_3',
'EXT_SOURCE_1 DAYS_BIRTH',
'EXT_SOURCE_2^2',
'EXT_SOURCE_2 EXT_SOURCE_3',
'EXT_SOURCE_2 DAYS_BIRTH',
'EXT_SOURCE_3^2',
'EXT_SOURCE_3 DAYS_BIRTH',
'DAYS_BIRTH^2',
'EXT_SOURCE_1^3',
'EXT_SOURCE_1^2 EXT_SOURCE_2',
'EXT_SOURCE_1^2 EXT_SOURCE_3',
'EXT_SOURCE_1^2 DAYS_BIRTH',
'EXT_SOURCE_1 EXT_SOURCE_2^2',
'EXT_SOURCE_1 EXT_SOURCE_2 EXT_SOURCE_3',
'EXT_SOURCE_1 EXT_SOURCE_2 DAYS_BIRTH',
'EXT_SOURCE_1 EXT_SOURCE_3^2',
'EXT_SOURCE_1 EXT_SOURCE_3 DAYS_BIRTH',
'EXT_SOURCE_1 DAYS_BIRTH^2',
'EXT_SOURCE_2^3'
```

```
'EXT_SOURCE_2^2 EXT_SOURCE_3',
'EXT_SOURCE_2^2 DAYS_BIRTH',
'EXT_SOURCE_2 EXT_SOURCE_3^2',
'EXT_SOURCE_2 EXT_SOURCE_3 DAYS_BIRTH',
'EXT_SOURCE_2 DAYS_BIRTH^2',
'EXT_SOURCE_3^3',
'EXT_SOURCE_3^2 DAYS_BIRTH',
'EXT_SOURCE_3 DAYS_BIRTH^2',
'DAYS_BIRTH^3']

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


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

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

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

selected_features = num_attribs + cat_attribs
total_features = f"{len(selected_features)}:   Num:{len(num_attribs)},
#Total Feature selected for processing
total_features

# 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_EMP
#         'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER', 'FLAG_OWN_REALT
#                    'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INC
#     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
#     X_train, X_test, y_train, y_test = train_test_split(X_train, y_t
#     X_kaggle_test= datasets["application_test"][selected_features]
#     # y_test = datasets["application_test"]['TARGET']   #why no  TAR

# selected_features = ['AMT_INCOME_TOTAL',  'AMT_CREDIT','DAYS_EMPLOYE
```

```
#         'EXT_SOURCE_2','EXT_SOURCE_3','CODE_GENDER', 'FLAG_OWN_REALT
#                    'NAME_EDUCATION_TYPE','OCCUPATION_TYPE','NAME_INC
# y_train = X_train['TARGET']
# X_train = X_train[selected_features]
# X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_tra
# X_train, X_test, y_train, y_test = train_test_split(X_train, y_train
# X_kaggle_test= X_kaggle_test[selected_features]
# # y_test = datasets["application_test"]['TARGET']   #why no  TARGET?


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

Out[22]: '67:   Num:63,   Cat:4'

In [23]:
```
# list(train_dataset.columns)
```

In [26]:
```
X_train = train_dataset[selected_features]
y_train = app_train_poly["TARGET"]
X_kaggle_test = app_test_poly[selected_features]

subsample_rate = 0.3

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

X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_trair
                                                      test_size=0.15,

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

```
X train           shape: (182968, 67)
X validation      shape: (32289, 67)
X test            shape: (92254, 67)
X X_kaggle_test   shape: (48744, 67)
```

In [ ]:

In [ ]:

In [53]:
```
# from sklearn.base import BaseEstimator, TransformerMixin
# import re

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


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

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


# # QUESTION, should we lower case df['OCCUPATION_TYPE'] as Sales staf
```

In [54]:
```
# # Create a class to select numerical or categorical columns
# # since Scikit-Learn doesn't handle DataFrames yet
# class DataFrameSelector(BaseEstimator, TransformerMixin):
#     def __init__(self, attribute_names):
#         self.attribute_names = attribute_names
#     def fit(self, X, y=None):
#         return self
#     def transform(self, X):
#         return X[self.attribute_names].values
```

In [55]:
```
# # Identify the numeric features we wish to consider.
# num_attribs = [
#     'AMT_INCOME_TOTAL',  'AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','
#     'EXT_SOURCE_2','EXT_SOURCE_3']

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

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

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

In [56]:
```
# list(datasets["application_train"].columns)
```

8 Baseline Model

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

In [27]:
```
def pct(x):
    return round(100*x,3)
```

In [28]:
```
try:
    del expLog
    expLog
except NameError:
    expLog = pd.DataFrame(columns=["exp_name",
                                   "Model name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train AUC",
                                   "Valid AUC",
                                   "Test  AUC",
                                   "Train F1",
                                   "Valid F1",
                                   "Test F1",
                                   "Fit Time"
                                  ])
expLog
```

Out[28]:

exp_name	Model name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1	Valid F1	Test F1	Fit Time

In [29]:
```
import time
np.random.seed(42)
start_time = time.time()
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("linear", LogisticRegression())
    ])
model = full_pipeline_with_predictor.fit(X_train, y_train)
fit_time = time.time() - start_time
```

In [30]:

```
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix

print('Accuracy Score on Train Dataset:', np.round(accuracy_score(y_tr
print('F1 Score on Train Dataset:', np.round(f1_score(y_train, model.p
cf_train = confusion_matrix(y_train, model.predict(X_train))
cf_val = confusion_matrix(y_valid, model.predict(X_valid))
cf_test = confusion_matrix(y_test, model.predict(X_test))
plt.figure(figsize=(8,5))
print('Confusion Matrix for Training Set')
sns.heatmap(cf_train, annot=True, fmt='g')
plt.show()
plt.figure(figsize=(8,5))
print('Confusion Matrix for Validation Set')
sns.heatmap(cf_val, annot=True, fmt='g')
plt.show()
plt.figure(figsize=(8,5))
print('Confusion Matrix for Test Set')
sns.heatmap(cf_test, annot=True, fmt='g')
plt.show()
plt.figure(figsize=(10,8))
print('AUC-ROC for Train Set')
plot_roc_curve(model, X_train, y_train);
plt.show()
plt.figure(figsize=(10,8))
print('AUC-ROC for Valid Set')
plot_roc_curve(model, X_valid, y_valid);
plt.show()
plt.figure(figsize=(10,8))
print('AUC-ROC for Test Set')
plot_roc_curve(model, X_test, y_test);
plt.show()
```

```
Accuracy Score on Train Dataset: 0.919
F1 Score on Train Dataset: 0.008
Confusion Matrix for Training Set
```

8.1 Evaluation metrics

Submissions are evaluated on [area under the ROC curve (http://en.wikipedia.org/wiki/Receiver_operating_characteristic)](http://en.wikipedia.org/wiki/Receiver_operating_characteristic) between the predicted probability and the observed target.

The SkLearn `roc_auc_score` function computes the area under the receiver operating characteristic (ROC) curve, which is also denoted by AUC or AUROC. By computing the area under the roc curve, the curve information is summarized in one number.

```
from sklearn.metrics import roc_auc_score
>>> y_true = np.array([0, 0, 1, 1])
>>> y_scores = np.array([0.1, 0.4, 0.35, 0.8])
>>> roc_auc_score(y_true, y_scores)
0.75
```

In [32]:
```
from sklearn.metrics import roc_auc_score
print('Accuracy Score on Train Dataset:', roc_auc_score(y_train, model
```

```
Accuracy Score on Train Dataset: 0.7376770017713672
```

In [33]:
```
roc_auc_score(y_test, model.predict_proba(X_test)[:, 1])
```

Out[33]:
```
0.7384610162759039
```

In [34]:
```
expLog
```

Out[34]:

exp_name	Model name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1	Valid F1	Test F1	Fit Time

8.1.1 THE BIG RACE (Baseline Models)

In [52]:
```
del expLog
try:
    expLog
except NameError:
    expLog = pd.DataFrame(columns=["exp_name",
                                   "Model name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train AUC",
                                   "Valid AUC",
                                   "Test  AUC",
                                   "Train F1",
                                   "Valid F1",
                                   "Test F1",
                                   "Fit Time (seconds)"
                                  ])
expLog
```

Out[52]:

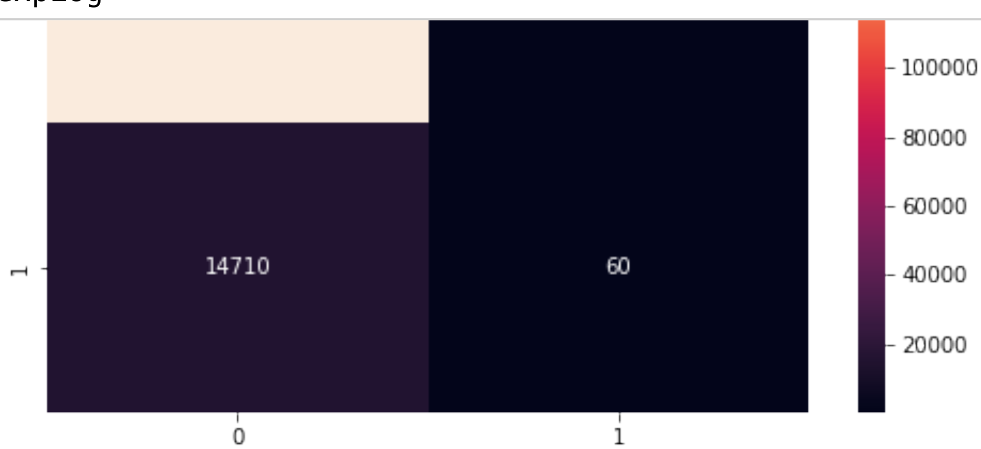
exp_name	Model name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	Train F1	Valid F1	Test F1	Fit Time (seconds)

In [53]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.naive_bayes import GaussianNB
```

8.1.1.1 Using Non-Ensemble Models

In [54]:
```
clfs = [LogisticRegression(penalty='none'),
        LogisticRegression(penalty='l2'),
        DecisionTreeClassifier(),
        GaussianNB()]

for clf in clfs:
    start_time = time.time()
    full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("model", clf)
    ])
    model_name = "Baseline {}".format(type(full_pipeline_with_predicto
    model = full_pipeline_with_predictor.fit(X_train, y_train)
    fit_time = time.time() - start_time
    print('Fit Time for {} is: {} seconds'.format(model_name, fit_time
    exp_name = f"Baseline_{len(selected_features)}_features"
    print(model_name)
    expLog.loc[len(expLog)] = [f"{exp_name}"] + [model_name] + list(np
                   [accuracy_score(y_train, model.predict(X_train)),
```

```
                    [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
                     roc_auc_score(y_valid, model.predict_proba(X_valid
                     roc_auc_score(y_test, model.predict_proba(X_test)[
                     f1_score(y_train, model.predict(X_train)),
                     f1_score(y_valid, model.predict(X_valid)),
                     f1_score(y_test, model.predict(X_test)),
                     fit_time], 4))
    cf_train = confusion_matrix(y_train, model.predict(X_train))
    cf_val = confusion_matrix(y_valid, model.predict(X_valid))
    cf_test = confusion_matrix(y_test, model.predict(X_test))
    plt.figure(figsize=(8,5))
    print('Confusion Matrix for Training Set')
    sns.heatmap(cf_train, annot=True, fmt='g')
    plt.show()
    plt.figure(figsize=(8,5))
    print('Confusion Matrix for Validation Set')
    sns.heatmap(cf_val, annot=True, fmt='g')
    plt.show()
    plt.figure(figsize=(8,5))
    print('Confusion Matrix for Test Set')
    sns.heatmap(cf_test, annot=True, fmt='g')
    plt.show()
    plt.figure(figsize=(10,8))
    print('AUC-ROC for Train Set')
    plot_roc_curve(model, X_train, y_train);
    plt.show()
    plt.figure(figsize=(10,8))
    print('AUC-ROC for Valid Set')
    plot_roc_curve(model, X_valid, y_valid);
    plt.show()
    plt.figure(figsize=(10,8))
    print('AUC-ROC for Test Set')
    plot_roc_curve(model, X_test, y_test);
    plt.show()

expLog
```

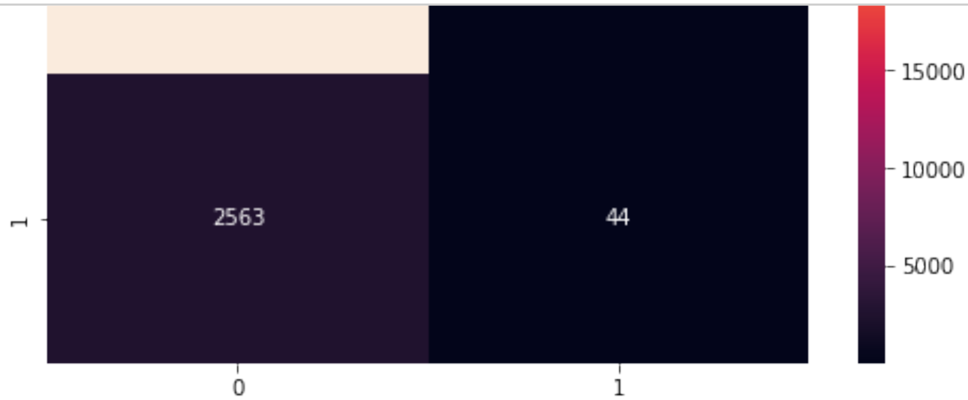


Confusion Matrix for Validation Set

8.1.1.2 Using Ensemble Models

In [55]:
```
clfs = [RandomForestClassifier(), XGBClassifier()]

for clf in clfs:
    start_time = time.time()
    full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("model", clf)
    ])
    model_name = "Baseline {}".format(type(full_pipeline_with_predicto
    model = full_pipeline_with_predictor.fit(X_train, y_train)
    fit_time = time.time() - start_time
    print('Fit Time for {} is: {} seconds'.format(model_name, fit_time
    exp_name = f"Baseline_{len(selected_features)}_features"
    print(model_name)
    expLog.loc[len(expLog)] = [f"{exp_name}"] + [model_name] + list(np
                   [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_trair
                    roc_auc_score(y_valid, model.predict_proba(X_valic
                    roc_auc_score(y_test, model.predict_proba(X_test)[
                    f1_score(y_train, model.predict(X_train)),
                    f1_score(y_valid, model.predict(X_valid)),
                    f1_score(y_test, model.predict(X_test)),
                    fit_time], 4))
    cf_train = confusion_matrix(y_train, model.predict(X_train))
    cf_val = confusion_matrix(y_valid, model.predict(X_valid))
    cf_test = confusion_matrix(y_test, model.predict(X_test))
    plt.figure(figsize=(8,5))
    print('Confusion Matrix for Training Set')
    sns.heatmap(cf_train, annot=True, fmt='g')
    plt.show()
    plt.figure(figsize=(8,5))
    print('Confusion Matrix for Validation Set')
    sns.heatmap(cf_val, annot=True, fmt='g')
    plt.show()
    plt.figure(figsize=(8,5))
    print('Confusion Matrix for Test Set')
```

```
    sns.heatmap(cf_test, annot=True, fmt='g')
    plt.show()
    plt.figure(figsize=(10,8))
    print('AUC-ROC for Train Set')
    plot_roc_curve(model, X_train, y_train);
    plt.show()
    plt.figure(figsize=(10,8))
    print('AUC-ROC for Valid Set')
    plot_roc_curve(model, X_valid, y_valid);
    plt.show()
    plt.figure(figsize=(10,8))
    print('AUC-ROC for Test Set')
    plot_roc_curve(model, X_test, y_test);
    plt.show()
```



Confusion Matrix for Test Set

In [56]:
```
expLog
```

Out[56]:

	exp_name	Model name	Train Acc	Valid Acc	Test Acc	Train AUC	Valid AUC	Test AUC	
0	Baseline_67_features	Baseline LogisticRegression	0.9193	0.9194	0.9195	0.7378	0.7299	0.7386	(
1	Baseline_67_features	Baseline LogisticRegression	0.9193	0.9193	0.9195	0.7377	0.7300	0.7385	(
2	Baseline_67_features	Baseline DecisionTreeClassifier	1.0000	0.8503	0.8512	1.0000	0.5318	0.5387	1
3	Baseline_67_features	Baseline GaussianNB	0.6791	0.6747	0.6812	0.7229	0.7156	0.7225	(
4	Baseline_67_features	Baseline RandomForestClassifier	1.0000	0.9188	0.9192	1.0000	0.6858	0.6958	(
5	Baseline_67_features	Baseline XGBClassifier	0.9231	0.9185	0.9190	0.8586	0.7290	0.7381	(

8.1.1.3 KNeighborsClassifier, SVC, and Logistic Regression with L1 regularization with solver='liblinear' take a lot of time to run and crash the kernel. So we were unable to train the dataset on these models.

In [47]:

```
# from sklearn.svm import SVC
# from sklearn.neighbors import KNeighborsClassifier
# clfs = [SVC(), KNeighborsClassifier()]

# for clf in clfs:
#     start_time = time.time()
#     full_pipeline_with_predictor = Pipeline([
#         ("preparation", data_prep_pipeline),
#         ("model", clf)
#     ])
#     model_name = "Baseline {}".format(type(full_pipeline_with_predic
#     model = full_pipeline_with_predictor.fit(X_train, y_train)
#     fit_time = time.time() - start_time
#     print('Fit Time for {} is: {} seconds'.format(model_name, fit_ti
#     exp_name = f"Baseline_{len(selected_features)}_features"

#     expLog.loc[len(expLog)] = [f"{exp_name}"] + [model_name] + list(
#                     [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_tra
#                      roc_auc_score(y_valid, model.predict_proba(X_val
#                      roc_auc_score(y_test, model.predict_proba(X_test
#                      f1_score(y_train, model.predict(X_train)),
#                      f1_score(y_valid, model.predict(X_valid)),
#                      f1_score(y_test, model.predict(X_test)),
#                      fit_time], 4))
# expLog
```

8.2 Submission File Prep

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

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

8.2.1 Using Logistic Regression (Ridge) for our baseline submission

In [57]:
```
full_pipeline_with_predictor = Pipeline([
        ("preparation", data_prep_pipeline),
        ("linear", LogisticRegression(penalty='l2'))
    ])
model = full_pipeline_with_predictor.fit(X_train, y_train)
```

In [58]:
```
test_class_scores = model.predict_proba(X_kaggle_test)[:, 1]
```

In [59]:
```
test_class_scores[0:10]
```

Out[59]:
```
array([0.06787096, 0.13054041, 0.02292311, 0.03216032, 0.08954263,
       0.02947744, 0.0363267 , 0.08377857, 0.01796927, 0.16895726])
```

In [61]:
```
# Submission dataframe
submit_df = app_test[['SK_ID_CURR']]
submit_df['TARGET'] = test_class_scores

submit_df.head()
```

Out[61]:

	SK_ID_CURR	TARGET
0	100001	0.067871
1	100005	0.130540
2	100013	0.022923
3	100028	0.032160
4	100038	0.089543

In [62]:
```
submit_df.to_csv("submission.csv",index=False)
```

9 Kaggle submission via the command line API

In [63]:
```
! kaggle competitions submit -c home-credit-default-risk -f submission
```

```
100%|██████████████████████████████| 1.26M/1.26M [00:01<00:00
, 1.10MB/s]
Successfully submitted to Home Credit Default Risk
```

9.1 report submission

Click on this [link (https://www.kaggle.com/c/home-credit-default-risk/submissions?sortBy=date&group=all&page=1)](https://www.kaggle.com/c/home-credit-default-risk/submissions?sortBy=date&group=all&page=1)

10 Write-up

For this phase of the project, you will need to submit a write-up summarizing the work you did. The write-up form is available on Canvas (Modules-> Module 12.1 - Course Project - Home Credit Default Risk (HCDR)-> FP Phase 2 (HCDR) : write-up form). It has the following sections:

10.1 Abstract

Please provide an abstract summarizing the work you did (150 words)

10.2 Introduction

10.3 Feature Engineering and transformers

Please explain the work you conducted on feature engineering and transformers. Please include code sections when necessary as well as images or any relevant material

10.4 Pipelines

Please explain the pipelines you created for this project and how you used them Please include code sections when necessary as well as images or any relevant material

10.5 Experimental results

Please present the results of the various experiments that you conducted. The results should be shown in a table or image. Try to include the different details for each experiment.

Please include code sections when necessary as well as images or any relevant material

10.6 Discussion

Discuss & analyze your different experimental results

Please include code sections when necessary as well as images or any relevant material

10.7 Conclusion

10.8 Kaggle Submission

Please provide a screenshot of your best kaggle submission.
The screenshot should show the different details of the submission and not just the score.

11 References

Some of the material in this notebook has been adopted from [here (https://www.kaggle.com/willkoehrsen/start-here-a-gentle-introduction/notebook)](https://www.kaggle.com/willkoehrsen/start-here-a-gentle-introduction/notebook)

In [ ]:

```

```

12 TODO: Predicting Loan Repayment with Automated Feature Engineering in Featuretools

Read the following:

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