Credit Risk Analysis Using Machine Learning Models

Business Objective: The project's primary goal is to predict credit defaulters as loan providers find it difficult to give loans due to inconsistencies in credit histories. As a result, the majority of clients accept the risk of defaulting, and loan providers struggle to find the proper customer.

The project highlights that it's critical to check data quality (by excluding redundant variables during the preparation and cleaning phase) and to deal with an imbalanced training dataset to avoid bias in majority class.
We shall also indicate that the features chosen to meet the business objective (Can we make this decision with only a few features to save time?) and the algorithm applied to make the decision (whether the borrower defaults or not) are two important keys in the decision management processing when issuing a loan (here, the bank).

In [1]:

```
''' IMPORT REQUIRED LIBRARIES '''

''' Numpy '''
import numpy as np
##-------------------------------------------------------------------------------------------
''' Pandas '''
import pandas as pd
##-------------------------------------------------------------------------------------------
''' Matplotlib '''
# import pyplot subpackage
import matplotlib.pyplot as plt
from matplotlib import colors
import matplotlib as mpl
##-------------------------------------------------------------------------------------------
''' Seaborn '''
import seaborn as sns
##-------------------------------------------------------------------------------------------
''' Scipy '''
# import 'stats' module
import scipy.stats as st
##-------------------------------------------------------------------------------------------
''' Sklearn '''
# import SimpleImputer
from sklearn.impute import SimpleImputer
# import the LabelEncoder
from sklearn.preprocessing import LabelEncoder
# import PowerTransformer
from sklearn.preprocessing import PowerTransformer
# import Kfold cross-validator
from sklearn.model_selection import KFold
# import cross_val_score
from sklearn.model_selection import cross_val_score
# import RepeatedStratifiedKFold
from sklearn.model_selection import RepeatedStratifiedKFold
# import RFE abd RFECV
from sklearn.feature_selection import RFE,RFECV
# import LogisticRegression
from sklearn.linear_model import LogisticRegression
# import DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier
# import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier
# import XGBClassifier
from xgboost import XGBClassifier
# import GaussianNB
from sklearn.naive_bayes import GaussianNB
# import Pipeline
from sklearn.pipeline import Pipeline
# import train_test_split
from sklearn.model_selection import train_test_split
# import different scalers
from sklearn.preprocessing import StandardScaler, MinMaxScaler, Normalizer, MaxAbsScaler, R
# import GridSearchCV
from sklearn.model_selection import GridSearchCV
# import elastic net regularization function
from sklearn.linear_model import ElasticNet
# import VarianceThreshold
from sklearn.feature_selection import VarianceThreshold
# import metrics from sklearn
```

```
from sklearn import metrics
# import classification_report
from sklearn.metrics import classification_report
# import cohen_kappa_score
from sklearn.metrics import cohen_kappa_score
# import confusion_matrix
from sklearn.metrics import confusion_matrix
# import roc_curve
from sklearn.metrics import roc_curve
# import accuracy_score
from sklearn.metrics import accuracy_score
# import tree
from sklearn import tree
##-------------------------------------------------------------------------------------------------
''' Pydotplus '''
import pydotplus
##-------------------------------------------------------------------------------------------------
''' IPython '''
from IPython.display import Image
##-------------------------------------------------------------------------------------------------
''' Imblearn '''
# import 'SMOTE'
from imblearn.over_sampling import SMOTE

##-------------------------------------------------------------------------------------------------
''' Statsmodels '''
# import variance_inflation_factor
from statsmodels.stats.outliers_influence import variance_inflation_factor
# import statsmodels api module
import statsmodels.api as sm

##-------------------------------------------------------------------------------------------------
''' Configurations '''
## display all rows of the dataframe
pd.set_option("display.max_rows",200)
## display all columns of the dataframe
pd.set_option("display.max_columns",None)
## set the plot size using 'rcParams'
plt.rcParams["figure.figsize"] = [15,10]

# to suppress warnings
import warnings
warnings.filterwarnings('ignore')

# import random
import random

# define class to customize print statements
class style:
    PURPLE = '\033[95m'
    CYAN = '\033[96m'
    DARKCYAN = '\033[36m'
    BLUE = '\033[94m'
    GREEN = '\033[92m'
    YELLOW = '\033[93m'
    RED = '\033[91m'
    BOLD = '\033[1m'
    UNDERLINE = '\033[4m'
    END = '\033[0m'

# create & store random colors for 'color' parameter in visualization
```

```
color_codes = ["#"+''.join([random.choice('0123456789ABCDEF') for j in range(6)]) for i in

##-------------------------------------------------------------------------------------
```

1) EXPLORATORY DATA ANALYSIS (EDA)

In [17]:

```
%%time
''' ## CUSTOM FUNCTIONS '''

def fetch_raw_data():
    # import dataset
    return pd.read_csv('application_train.csv')

##-------------------------------------------------------------------------------------
# define function to categorize into numerical and categorical features
def categorize_features(df):
    #create a list to select categorical features which start with the string
    categorical_like_list = ['TARGET','NAME','CODE','FLAG','CNT','REGION_RATING','OCCUPATIO
                      'REG_REGION','LIVE_REGION','REG_CITY','LIVE_CITY','ORGANIZATION', 'CA
    #create a list to select numerical features which start or end with the string
    numerical_like_list = ['AMT','REGION_POPULATION','DAYS','HOUR_APPR','EXT_SOURCE','OBS',
                           'CAR_AGE','_AVG','_MEDI','_MODE','SCORE_', 'RATIO_']

    global categorical_columns
    categorical_columns = [feature for feature in df.columns for string in categorical_like
    categorical_columns.sort()
    global numerical_columns
    numerical_columns = [feature for feature in df.columns for string in numerical_like_lis
                         if feature.startswith(string) | feature.endswith(string)]
    numerical_columns.sort()
    #select document submission features
    global document_features
    document_features = [feature for feature in df.columns if feature.startswith('FLAG_DOCU
##-------------------------------------------------------------------------------------
# define function to clean data
def cleanse_dataset(df):

    # drop the feature 'SK_ID_CURR'
    if 'SK_ID_CURR' in df.columns:
         df.drop('SK_ID_CURR',axis=1, inplace=True)
    ##-------------------------------------------------------------------------------------
    print(style.BOLD+style.RED+"Cleansing the dataset"+style.END)
    print('Shape before dropping columns having more than 40% missing data:', df.shape)
    # calculate missing value percentage
    missing_data_percentage = ((df.isna().sum()*100)/len(df)).sort_values(ascending=False)
    print('Missing value Percentage')
    display(pd.DataFrame(missing_data_percentage).T)
    # select columns having more than 40% missing data
    missing_above_40_percentage_cols = list(missing_data_percentage[missing_data_percentage
    # display details
    print("No.of columns with more than 40% missing values:", len(missing_above_40_percenta
    # dropping columns having more than 40% missing data
    df.drop(missing_above_40_percentage_cols,axis=1, inplace=True)
    print('Shape after dropping columns having more than 40% missing data:', df.shape)
    ##-------------------------------------------------------------------------------------
    #Checking for duplicates in the data.
    df[df.duplicated(subset = list(df.columns), keep=False)]
    print('No.of duplicates in the data:',df[df.duplicated(subset = list(df.columns), keep=
    ##-------------------------------------------------------------------------------------
    # Observe that the values in the below features are negative.
    # Since days count cannot be negative, let's convert the data into positive values.
    df['DAYS_LAST_PHONE_CHANGE'] = np.abs(df['DAYS_LAST_PHONE_CHANGE'])
    df['DAYS_BIRTH'] = np.abs(df['DAYS_BIRTH'])
    df['DAYS_REGISTRATION'] = np.abs(df['DAYS_REGISTRATION'])
    df['DAYS_ID_PUBLISH'] = np.abs(df['DAYS_ID_PUBLISH'])
```

```
    df['DAYS_EMPLOYED'] = np.abs(df['DAYS_EMPLOYED'])
    ##--------------------------------------------------------------------------------------
    # Update numerical and categorical columns lists
    categorize_features(df)
    print("Total number of categorical features after cleansing the data: ", len(categorica
    print("Total number of numerical features after cleansing the data: ", len(numerical_co

    return df
##--------------------------------------------------------------------------------------

# define a function to start EDA
def init():
## Initialize df_credit (dataframe used for EDA in this project)
    global df_credit
    df_credit = fetch_raw_data()

## Check Shape
    print(style.BOLD+style.RED+"Shape of the dataset: "+style.END)
    print(df_credit.shape)
## Check head
    print(style.BOLD+style.RED+"View first five observations"+style.END)
    display(df_credit.head())
## Check data types
    print(style.BOLD+style.RED+"Check data types: "+style.END)
    #use info() to understand the dataset
    display(df_credit.select_dtypes(np.number).dtypes)
    display(df_credit.select_dtypes(object).dtypes)
## Descriptive Statistics
    #use describe to display descriptive statistics
    print(style.BOLD+style.RED+"Descriptive statistics "+style.END)
    display(df_credit.describe(include='all'))
## Clean the dataset
    cleanse_dataset(df_credit)

init()
```

Shape of the dataset:

(307511, 122)

View first five observations

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_C
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	

Check data types:

```
SK_ID_CURR                      int64
```

```
TARGET                          int64
CNT_CHILDREN                    int64
AMT_INCOME_TOTAL              float64
AMT_CREDIT                    float64
AMT_ANNUITY                   float64
AMT_GOODS_PRICE               float64
REGION_POPULATION_RELATIVE    float64
DAYS_BIRTH                      int64
DAYS_EMPLOYED                   int64
DAYS_REGISTRATION             float64
DAYS_ID_PUBLISH                 int64
OWN_CAR_AGE                   float64
FLAG_MOBIL                      int64
FLAG_EMP_PHONE                  int64
FLAG_WORK_PHONE                 int64
FLAG_CONT_MOBILE                int64
FLAG_PHONE                      int64
FLAG_EMAIL                      int64
CNT_FAM_MEMBERS               float64
REGION_RATING_CLIENT            int64
REGION_RATING_CLIENT_W_CITY     int64
HOUR_APPR_PROCESS_START         int64
REG_REGION_NOT_LIVE_REGION      int64
REG_REGION_NOT_WORK_REGION      int64
LIVE_REGION_NOT_WORK_REGION     int64
REG_CITY_NOT_LIVE_CITY          int64
REG_CITY_NOT_WORK_CITY          int64
LIVE_CITY_NOT_WORK_CITY         int64
EXT_SOURCE_1                  float64
EXT_SOURCE_2                  float64
EXT_SOURCE_3                  float64
APARTMENTS_AVG                float64
BASEMENTAREA_AVG              float64
YEARS_BEGINEXPLUATATION_AVG   float64
YEARS_BUILD_AVG               float64
COMMONAREA_AVG                float64
ELEVATORS_AVG                 float64
ENTRANCES_AVG                 float64
FLOORSMAX_AVG                 float64
FLOORSMIN_AVG                 float64
LANDAREA_AVG                  float64
LIVINGAPARTMENTS_AVG          float64
LIVINGAREA_AVG                float64
NONLIVINGAPARTMENTS_AVG       float64
NONLIVINGAREA_AVG             float64
APARTMENTS_MODE               float64
BASEMENTAREA_MODE             float64
YEARS_BEGINEXPLUATATION_MODE  float64
YEARS_BUILD_MODE              float64
COMMONAREA_MODE               float64
ELEVATORS_MODE                float64
ENTRANCES_MODE                float64
FLOORSMAX_MODE                float64
FLOORSMIN_MODE                float64
LANDAREA_MODE                 float64
LIVINGAPARTMENTS_MODE         float64
LIVINGAREA_MODE               float64
NONLIVINGAPARTMENTS_MODE      float64
NONLIVINGAREA_MODE            float64
APARTMENTS_MEDI               float64
BASEMENTAREA_MEDI             float64
```

```
YEARS_BEGINEXPLUATATION_MEDI    float64
YEARS_BUILD_MEDI                float64
COMMONAREA_MEDI                 float64
ELEVATORS_MEDI                  float64
ENTRANCES_MEDI                  float64
FLOORSMAX_MEDI                  float64
FLOORSMIN_MEDI                  float64
LANDAREA_MEDI                   float64
LIVINGAPARTMENTS_MEDI           float64
LIVINGAREA_MEDI                 float64
NONLIVINGAPARTMENTS_MEDI        float64
NONLIVINGAREA_MEDI              float64
TOTALAREA_MODE                  float64
OBS_30_CNT_SOCIAL_CIRCLE        float64
DEF_30_CNT_SOCIAL_CIRCLE        float64
OBS_60_CNT_SOCIAL_CIRCLE        float64
DEF_60_CNT_SOCIAL_CIRCLE        float64
DAYS_LAST_PHONE_CHANGE          float64
FLAG_DOCUMENT_2                   int64
FLAG_DOCUMENT_3                   int64
FLAG_DOCUMENT_4                   int64
FLAG_DOCUMENT_5                   int64
FLAG_DOCUMENT_6                   int64
FLAG_DOCUMENT_7                   int64
FLAG_DOCUMENT_8                   int64
FLAG_DOCUMENT_9                   int64
FLAG_DOCUMENT_10                  int64
FLAG_DOCUMENT_11                  int64
FLAG_DOCUMENT_12                  int64
FLAG_DOCUMENT_13                  int64
FLAG_DOCUMENT_14                  int64
FLAG_DOCUMENT_15                  int64
FLAG_DOCUMENT_16                  int64
FLAG_DOCUMENT_17                  int64
FLAG_DOCUMENT_18                  int64
FLAG_DOCUMENT_19                  int64
FLAG_DOCUMENT_20                  int64
FLAG_DOCUMENT_21                  int64
AMT_REQ_CREDIT_BUREAU_HOUR      float64
AMT_REQ_CREDIT_BUREAU_DAY       float64
AMT_REQ_CREDIT_BUREAU_WEEK      float64
AMT_REQ_CREDIT_BUREAU_MON       float64
AMT_REQ_CREDIT_BUREAU_QRT       float64
AMT_REQ_CREDIT_BUREAU_YEAR      float64
dtype: object
```

```
NAME_CONTRACT_TYPE           object
CODE_GENDER                  object
FLAG_OWN_CAR                 object
FLAG_OWN_REALTY              object
NAME_TYPE_SUITE              object
NAME_INCOME_TYPE             object
NAME_EDUCATION_TYPE          object
NAME_FAMILY_STATUS           object
NAME_HOUSING_TYPE            object
OCCUPATION_TYPE              object
WEEKDAY_APPR_PROCESS_START   object
ORGANIZATION_TYPE            object
FONDKAPREMONT_MODE           object
HOUSETYPE_MODE               object
WALLSMATERIAL_MODE           object
```

```
EMERGENCYSTATE_MODE            object
dtype: object
```

Descriptive statistics

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

Cleansing the dataset

```
Shape before dropping columns having more than 40% missing data: (307511, 12
1)
Missing value Percentage
```

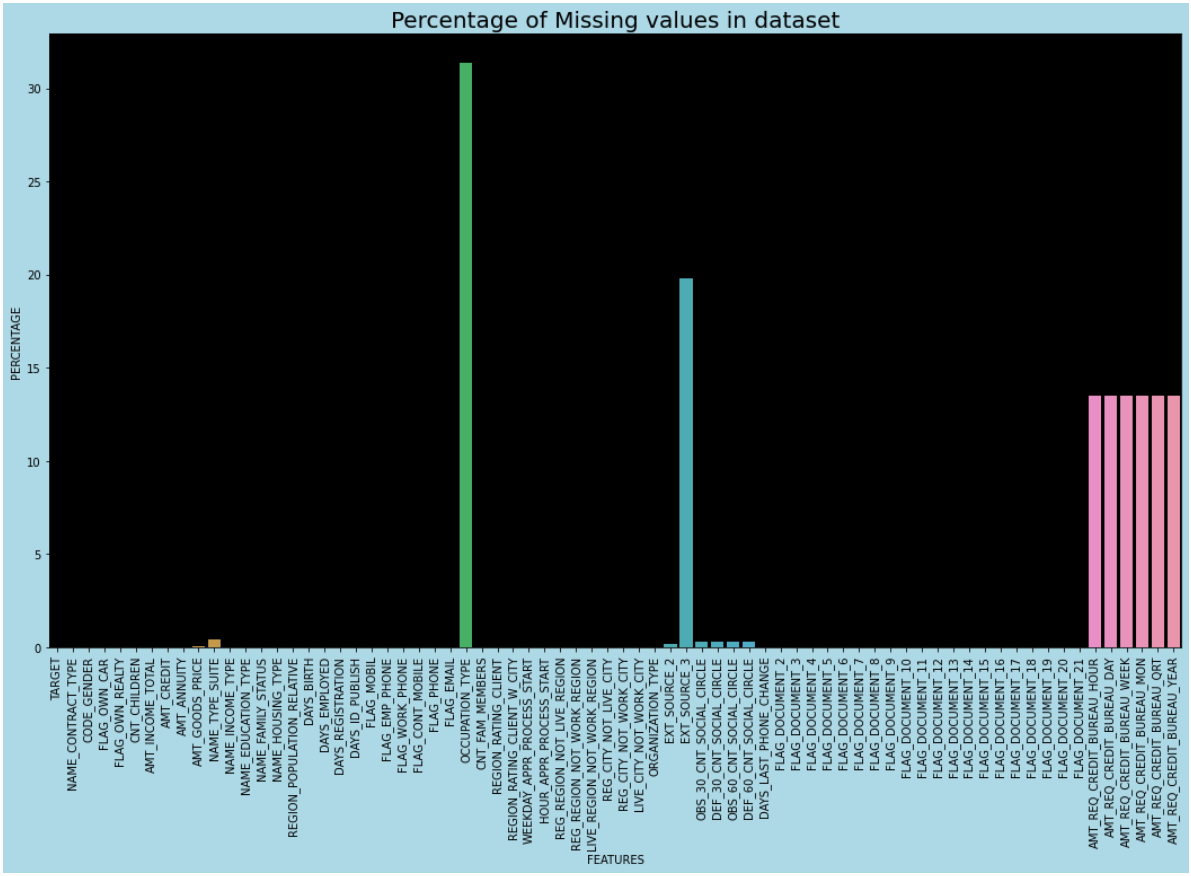
	COMMONAREA_MEDI	COMMONAREA_AVG	COMMONAREA_MODE	NONLIVINGAPARTMENTS_
0	69.872297	69.872297	69.872297	69.4

```
No.of columns with more than 40% missing values: 49
Shape after dropping columns having more than 40% missing data: (307511, 72)
No.of duplicates in the data: 0
Total number of categorical features after cleansing the data:  49
Total number of numerical features after cleansing the data:  23
Wall time: 8.95 s
```

Univariate Analysis

In [6]:

```
%%time
# set figuresize
fig = plt.figure(figsize=(18,10))

# calculate & store missing data percentage in a dataframe
df_missing_data = pd.DataFrame((df_credit.isnull().sum())*100/df_credit.shape[0]).reset_ind

# create barplot
ax = sns.barplot("index",0,data=df_missing_data)
plt.xticks(rotation =90,fontsize =10)
plt.title("Percentage of Missing values in dataset", fontdict={'fontsize':20})
plt.ylabel("PERCENTAGE")
plt.xlabel("FEATURES")
ax.set_facecolor("black")
fig.set_facecolor("lightblue")
plt.show()
```

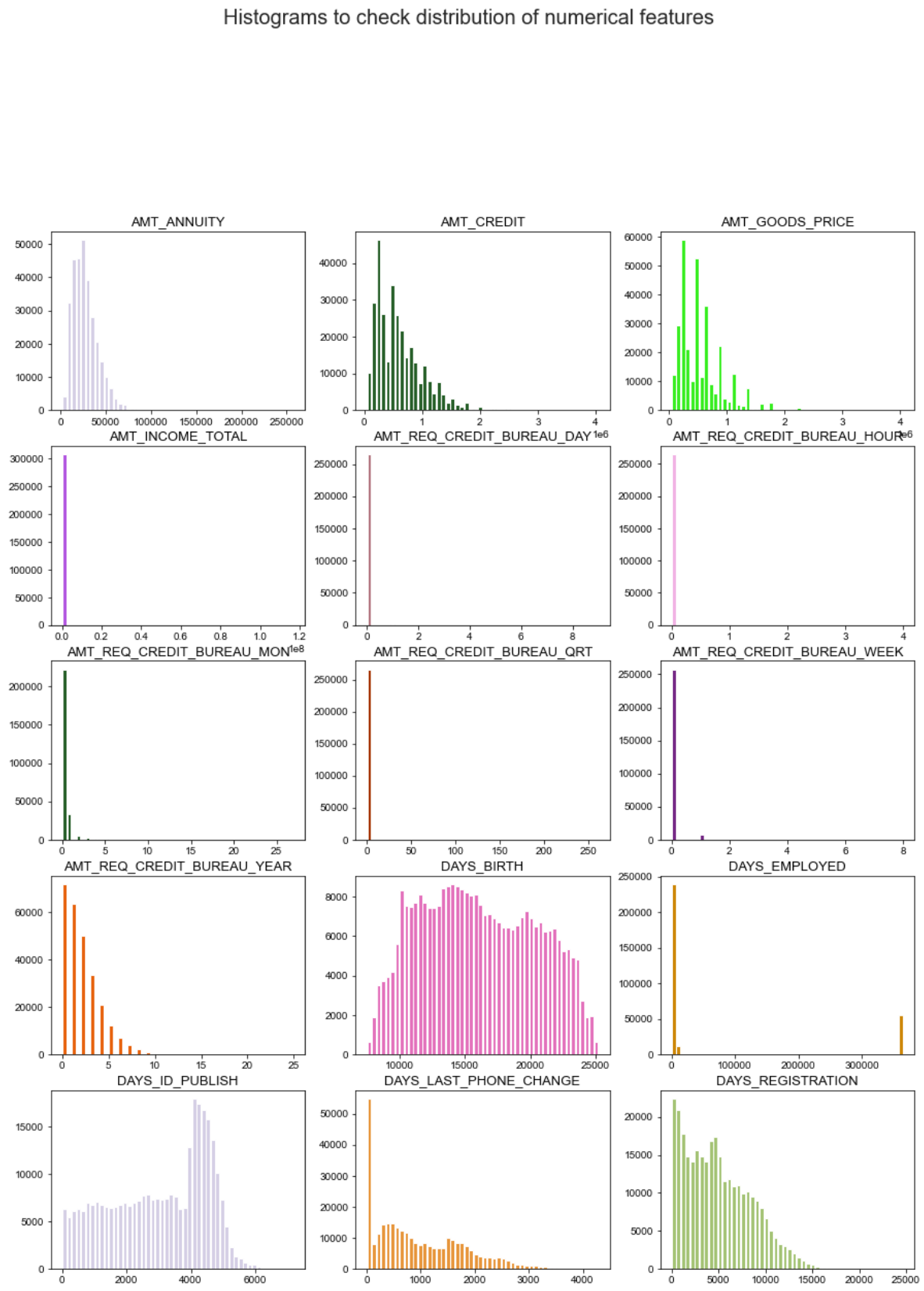


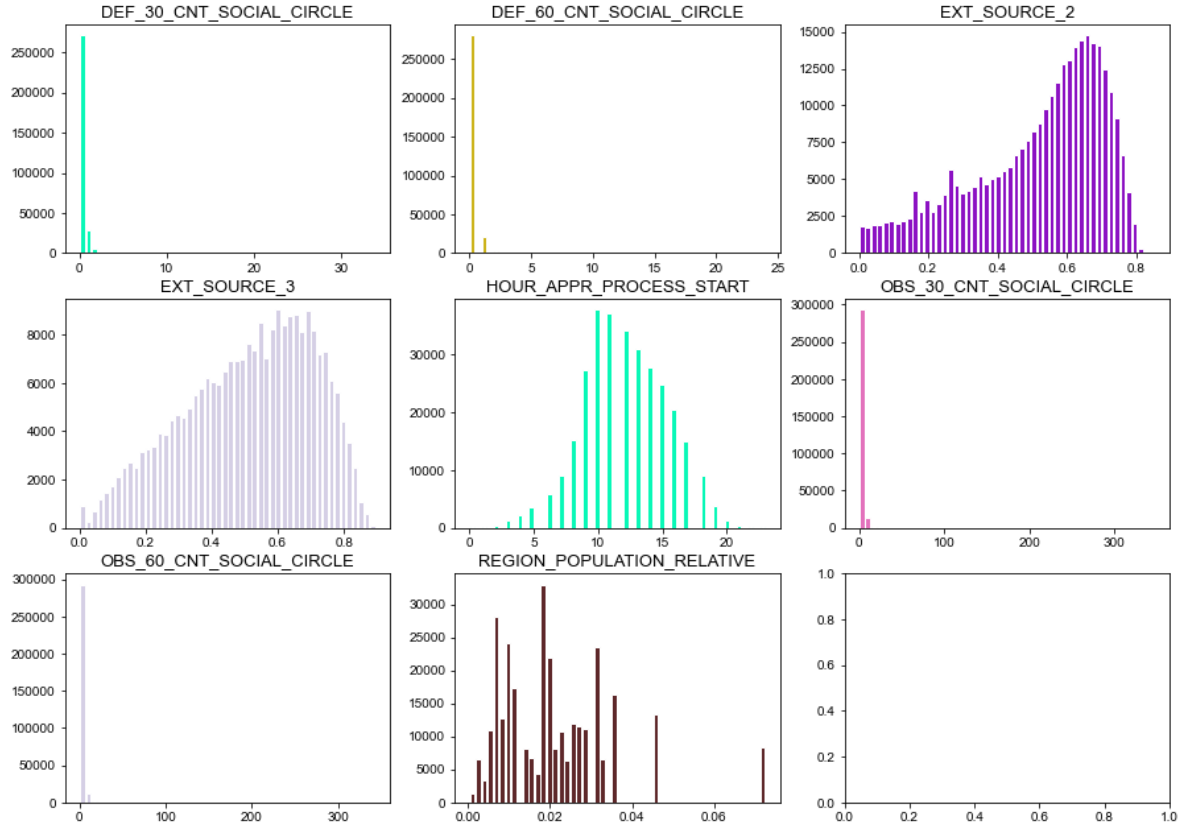

```
Wall time: 4.99 s
```

Observations: The above visualization shows us that after the removal of null values above 40% then the feature with maximum null value % is OCCUPATION_TYPE feature. Features like EXT_SOURCE_3 too has null values around 20% Features like 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' also show around 13% of missing values.

In [7]:

```
%%time
# create subplots
fig, axs = plt.subplots(nrows=8, ncols=3, figsize=(15,30))
# create histograms for each numerical feature
for feature, ax in zip(numerical_columns, axs.flatten()):
    sns.set_theme(style="whitegrid")
    ax.hist(df_credit[feature], bins=50, rwidth=0.8, color= random.choice(color_codes))
    ax.set_title(feature,fontsize=13)
plt.suptitle("Histograms to check distribution of numerical features",fontsize=20)
plt.show()
```



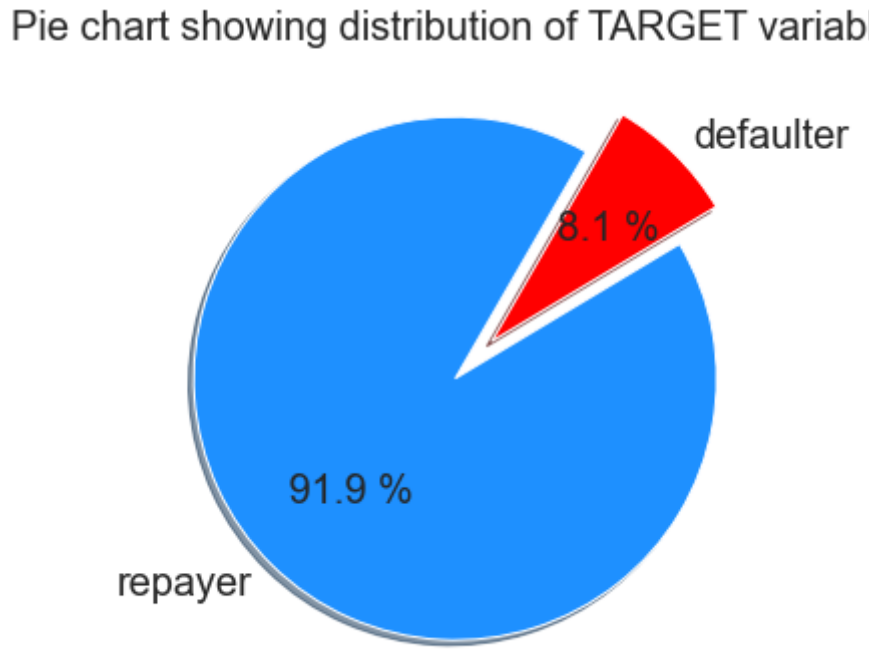



```
Wall time: 8.22 s
```

Observations: The above visualization represents the Histograms to check distribution of numerical features. From the visualization it can be infered that most of the numerical data are skewed in nature. Majority of the skewness is right skewness.

In [8]:

```
%%time
# set figuresize
plt.figure(figsize=(10,6))

# create pie chart
plt.pie(df_credit['TARGET'].value_counts(),autopct ='% 1.1f %%',shadow = True, explode = [0
plt.title("Pie chart showing distribution of TARGET variable", fontdict={'fontsize':20})
plt.show()
```

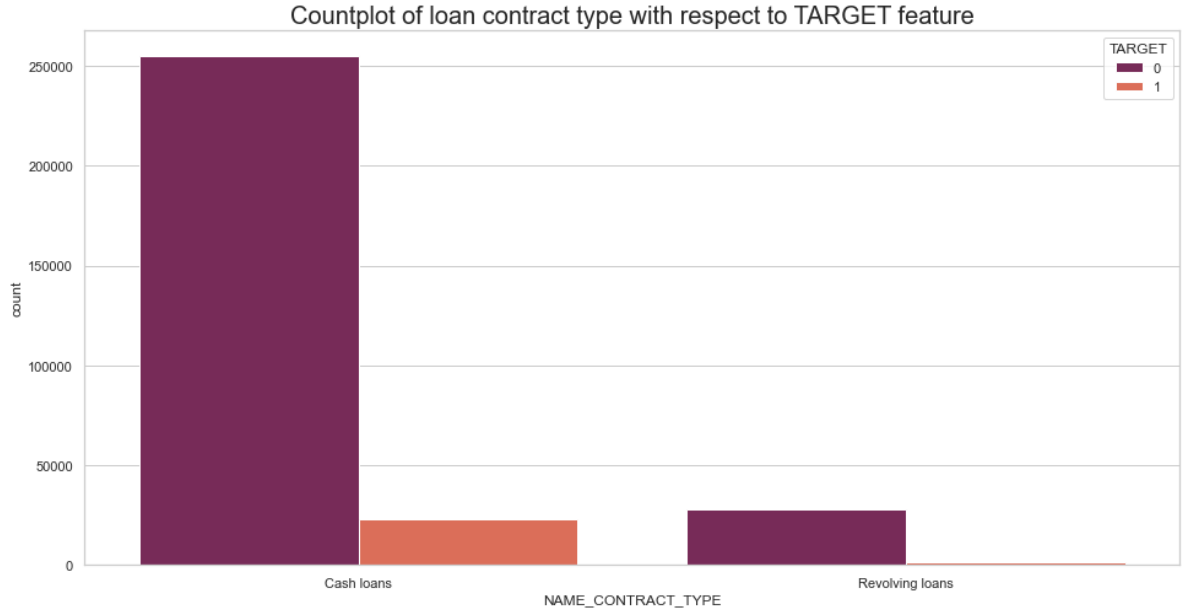



```
Wall time: 204 ms
```

Observations: The above pie chart shows us that 91.9% of people tend to repay the loan amount whereas 8.1% of people were unable to repay the loaned amount.

In [9]:

```
%%time
# set figuresize
plt.figure(figsize=(16,8))

# create countplot
sns.set_theme(style="whitegrid")
sns.countplot(data=df_credit,x='NAME_CONTRACT_TYPE',hue='TARGET',palette='rocket')
plt.title("Countplot of loan contract type with respect to TARGET feature", fontdict={'font
plt.show()
```

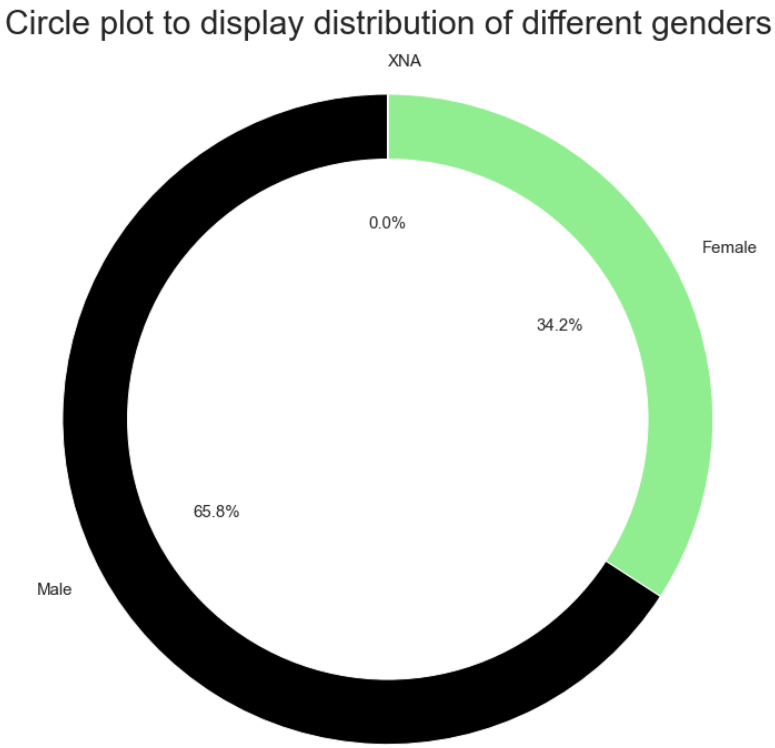



```
Wall time: 560 ms
```

Observations: The number of cash loans are the type of loan that is mostly taken by the people. It could be seen that number of people that were not able to repay the Cash loan were some what same to the number of people payed the Rsvolving loan type. So the number of cash loans are significantly higher than Revolving loans.

In [10]:

```
%%time
# create subplot
fig, ax = plt.subplots()

# create pie chart on the axis
plt.suptitle("Circle plot to display distribution of different genders",fontsize=30)

ax.pie(df_credit.CODE_GENDER.value_counts(),colors=['black','lightgreen','blue'],labels=['M
# draw circle
centre_circle = plt.Circle((0,0),0.80,fc='white')

# get current figure
fig = plt.gcf()

# add artist to current axis
fig.gca().add_artist(centre_circle)

# Equal aspect ratio ensures that pie is drawn as a circle
ax.axis('equal')
plt.tight_layout()
plt.show()
```

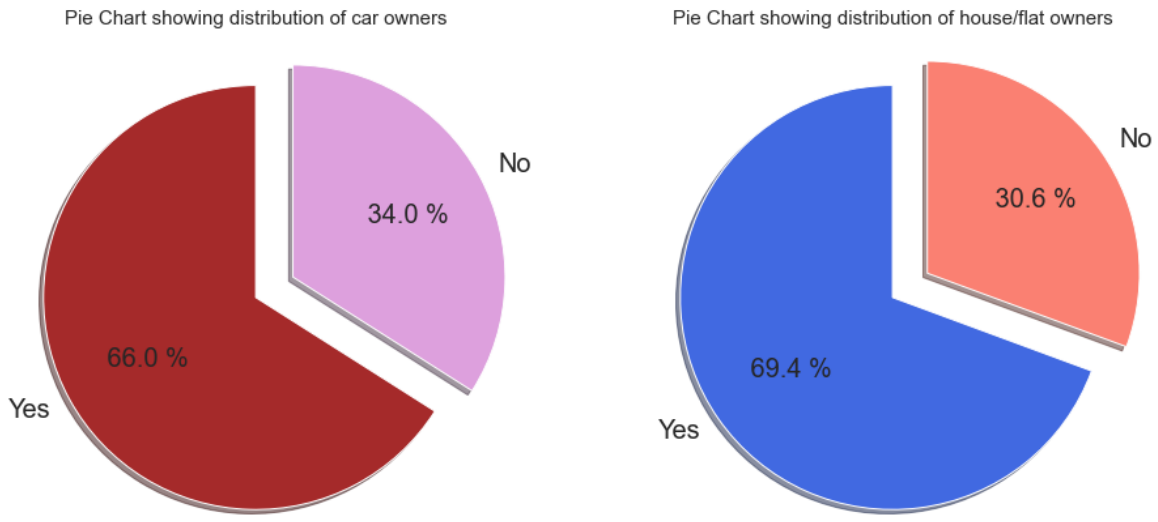


```
Wall time: 245 ms
```

Observations: The above pie chart tells us that number of Males in applying for loans are greater than number of females that apply for loans. The number of male is approximatly double the female

In [8]:

```
%%time
# set figuresize
plt.figure(figsize=(16,8))

# create subplot
plt.subplot(121)
# plot pie diagram
plt.pie(df_credit['FLAG_OWN_CAR'].value_counts(),autopct ='% 1.1f %%',shadow = True, explod
plt.title("Pie Chart showing distribution of car owners", fontdict={'fontsize':15})

# create subplot
plt.subplot(122)
# plot pie diagram
plt.pie(df_credit['FLAG_OWN_REALTY'].value_counts(),autopct ='% 1.1f %%',shadow = True, exp
plt.title("Pie Chart showing distribution of house/flat owners", fontdict={'fontsize':15})
plt.show()
```

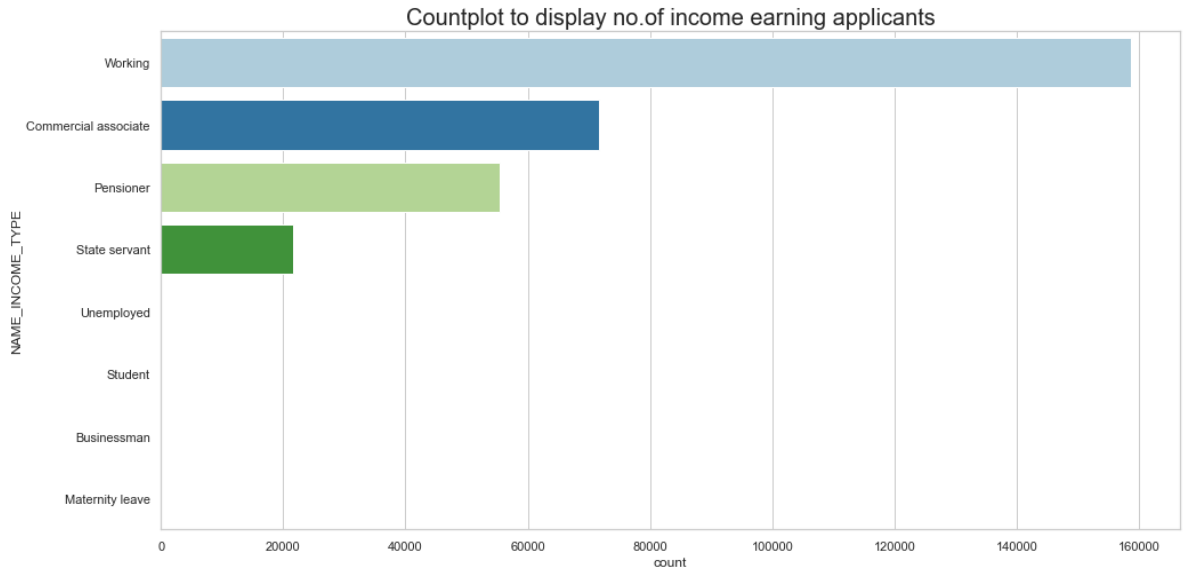



```
Wall time: 249 ms
```

Observations: 66% of clients are car owners. 69% of the clients are house/flat owners.

In [9]:

```
%%time
# create countplot
plt.figure(figsize=(16,8))
sns.set_theme(style="whitegrid")
sns.countplot(y=df_credit["NAME_INCOME_TYPE"],palette='Paired',order=df_credit["NAME_INCOME
plt.title("Countplot to display no.of income earning applicants", fontdict={'fontsize':20})
plt.show()
```

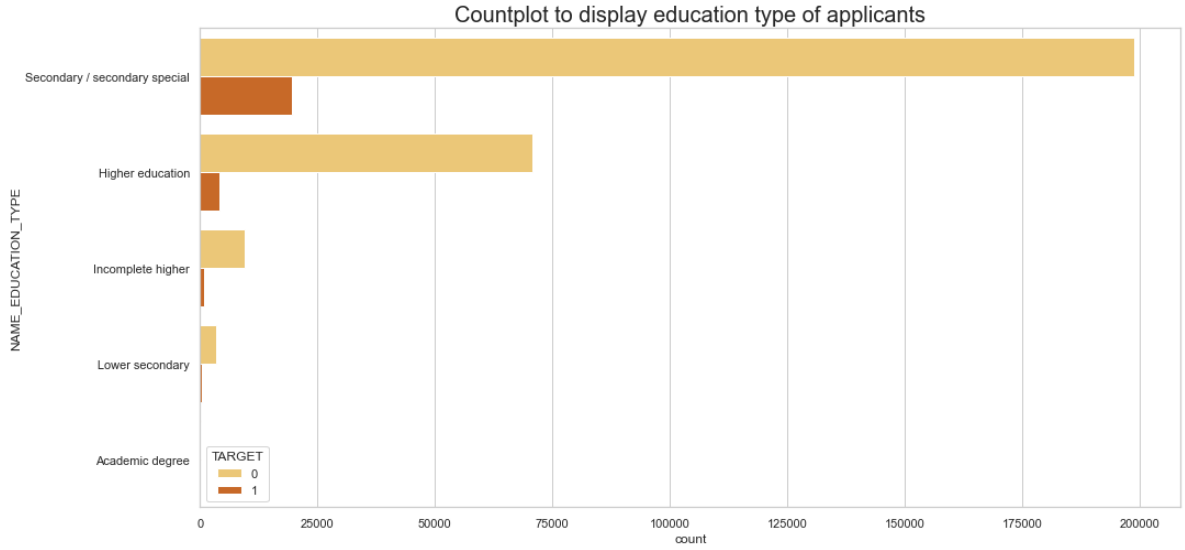



```
Wall time: 403 ms
```

Observations: Working clients have most income as comapred to Commercial associate , Pensioners and State servents.

In [10]:

```
%%time
# create countplot
plt.figure(figsize=(16,8))
sns.set_theme(style="whitegrid")
sns.countplot(y=df_credit["NAME_EDUCATION_TYPE"], hue= df_credit.TARGET, palette = 'YlOrBr'
plt.title("Countplot to display education type of applicants", fontdict={'fontsize':20})
plt.show()
```

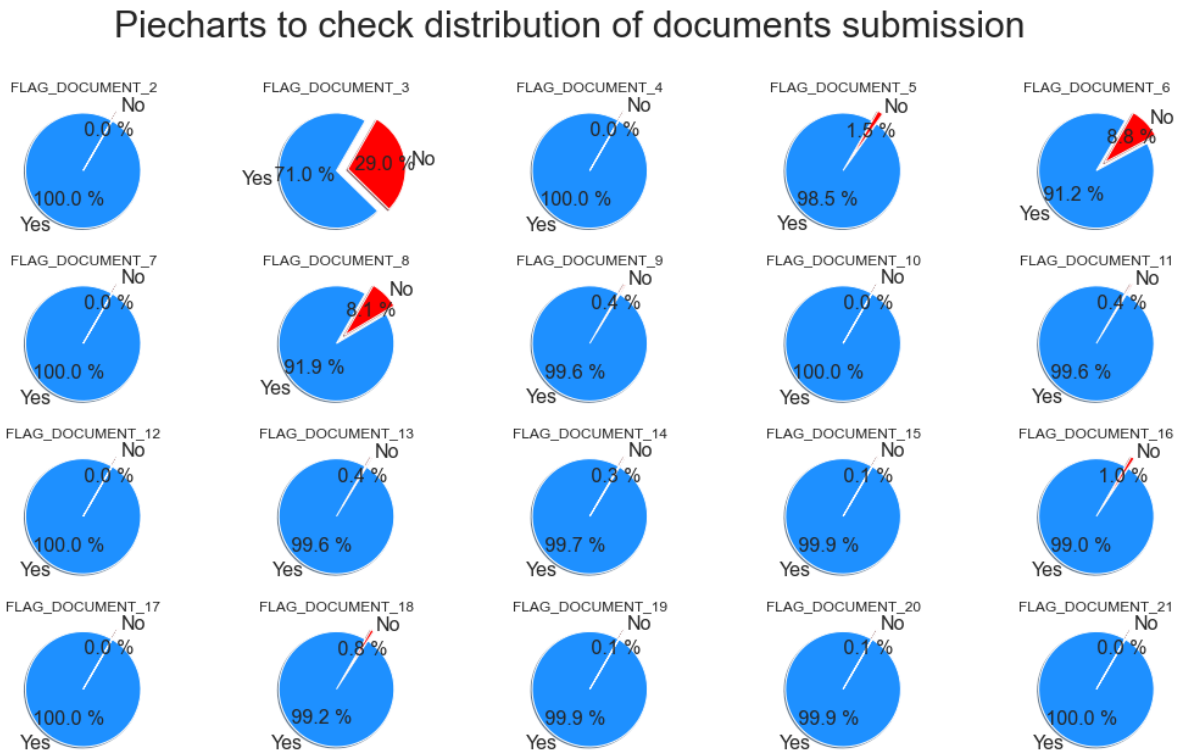


Wall time: 450 ms

Observations: People with Secondary education are more likely to default the loan and Academic degree holders are least

In [11]:

```
%%time

# create subplots
fig, axs = plt.subplots(4, 5,figsize=(18,10))

# create pie charts for each flag document feature
for index,ax in zip(range(23),axs.ravel()):
    sns.set_theme(style="whitegrid")
    ax.pie(df_credit[document_features].iloc[:,index].value_counts(),autopct ='% 1.1f %%',l
    ax.set_title(document_features[index])
plt.suptitle("Piecharts to check distribution of documents submission",fontsize=30)
plt.show()
```




```
Wall time: 2.55 s
```

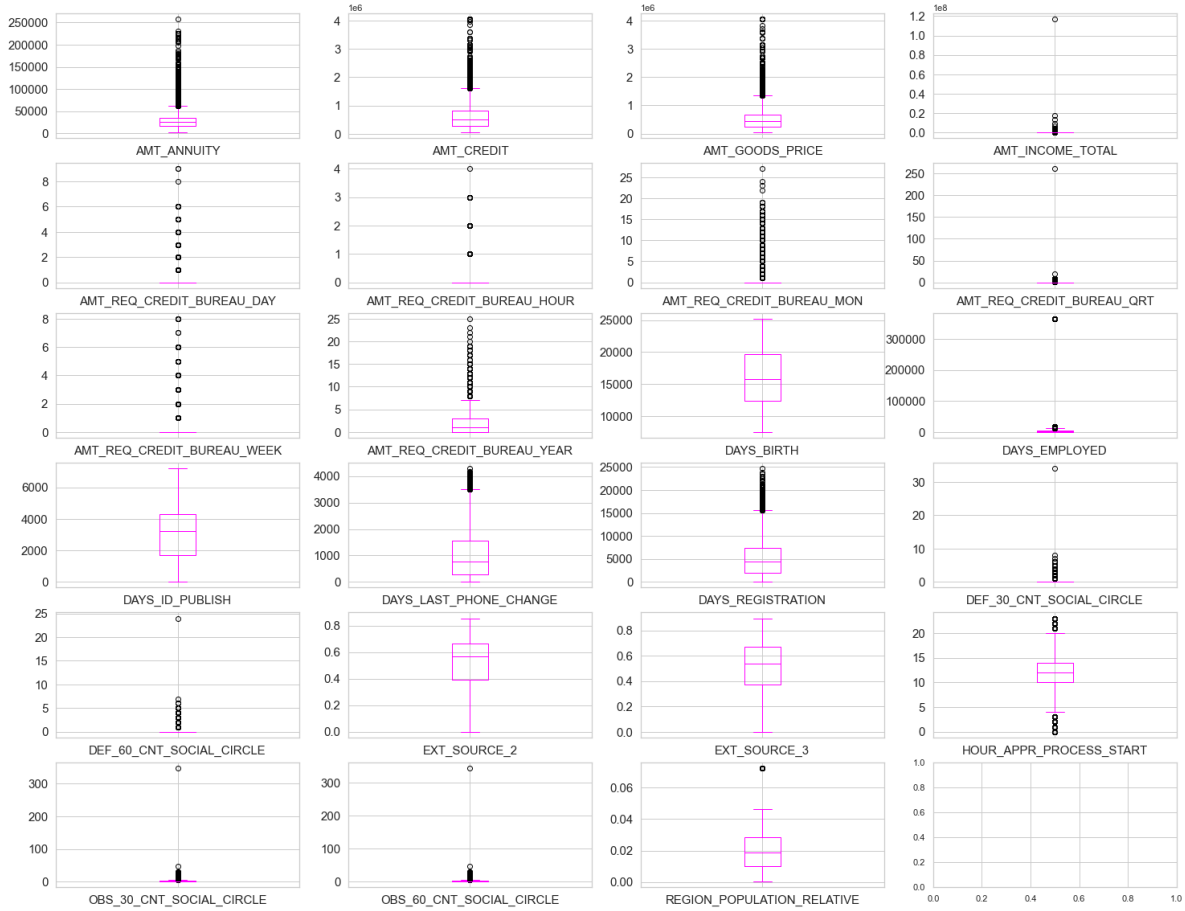
Observations: Clients tend to provide most of the documents asked from them. Document 3 seems to have low priority / not important/ optional while providing the document as around 29% of clients are not able to provide that document.

Outliers Detection

In [12]:

```
%%time
# check outliers presence using boxplot
fig, axs = plt.subplots(nrows=6, ncols=4, figsize=(25,20))
# create boxplot for each numerical column
for feature, ax in zip(numerical_columns, axs.flatten()):
    df_credit[feature].plot(kind='box',ax =ax, color='magenta',grid=True,fontsize=15)
plt.suptitle("Box plots to identify outliers in numerical features",fontsize=30)
plt.show()
```

Box plots to identify outliers in numerical features



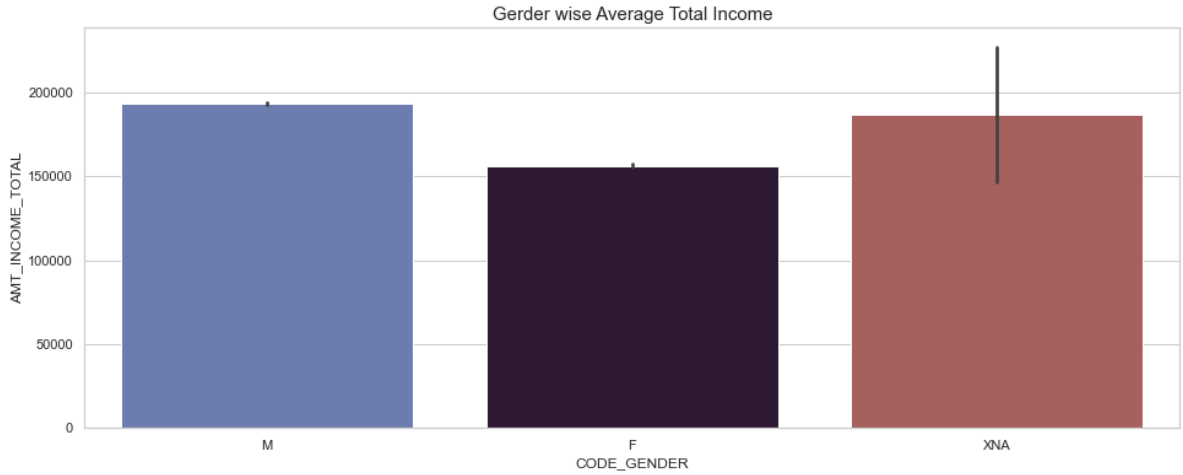

```
Wall time: 4.82 s
```

Observations: The above boxplots shows the presence of outliers except the REGION_POPULATION_RELATIVE, DAYS_BIRTH, DAYS_ID_PUBLISH, EXT_SOURCE_2 and EXT_SOURCE_3 feature.

Bivariate Analysis

In [13]:

```
%%time
# create barplot
plt.figure(figsize=(16,6))
sns.set_theme(style="whitegrid")
sns.barplot(data=df_credit, x='CODE_GENDER',y='AMT_INCOME_TOTAL',palette='twilight')
plt.title("Gerder wise Average Total Income",fontdict={'fontsize':15})
plt.show()
```

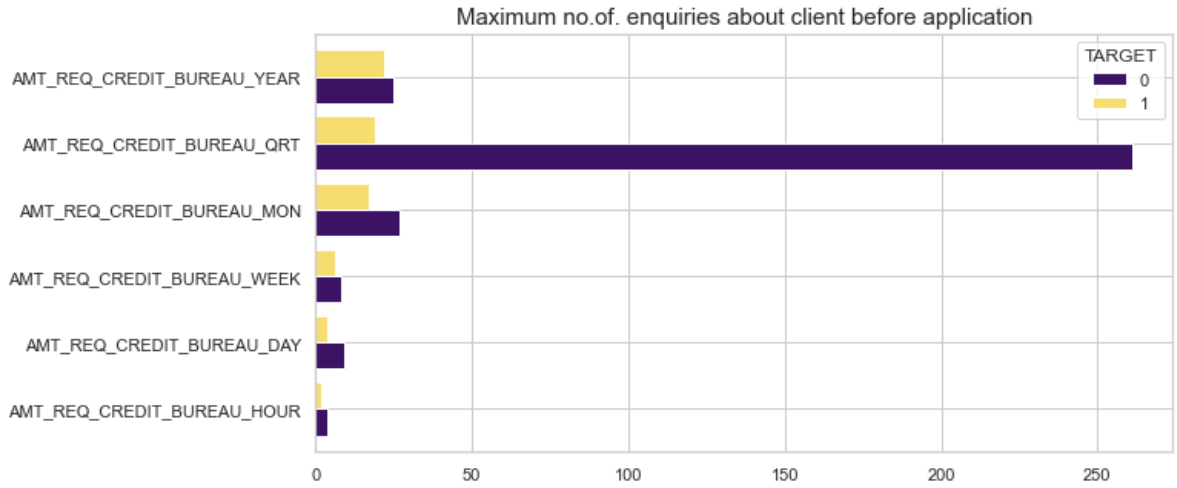



```
Wall time: 3.58 s
```

Observations: Males tend to earn more than the females.

In [14]:

```
%%time
# select credit bureau related features
amt_columns = ['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']
# create horizontal barplot
sns.set_theme(style="whitegrid")
df_credit.groupby("TARGET")[amt_columns].max().transpose().plot(kind="barh",figsize=(10,5),
plt.title("Maximum no.of. enquiries about client before application",fontdict={'fontsize':1
plt.show()
```

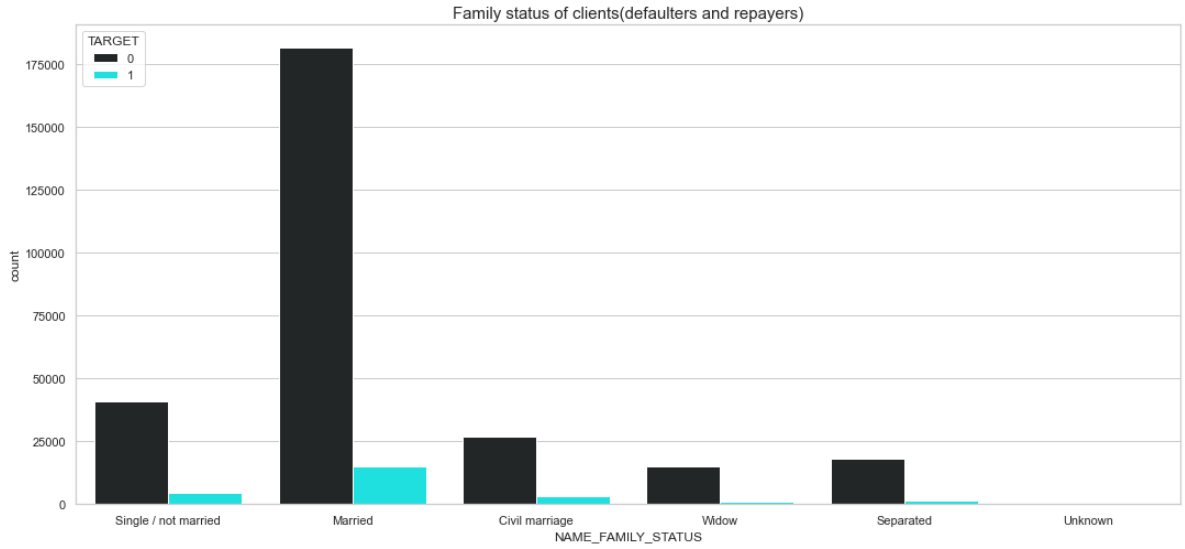



```
Wall time: 239 ms
```

Observations: Most number of enquiries to Credit Bureau about the client is done 3 month before application (excluding one month before application). The ratio of Defaulters and non Defaulters are maximum when the enquiries to Credit Bureau about the client one day year (excluding last 3 months before application).

In [15]:

```
%%time
# create countplot
plt.figure(figsize=(18,8))
sns.set_theme(style="whitegrid")
sns.countplot(data= df_credit,x='NAME_FAMILY_STATUS', hue='TARGET',palette='dark:cyan')
plt.title("Family status of clients(defaulters and repayers)",fontdict={'fontsize':15})
plt.show()
```



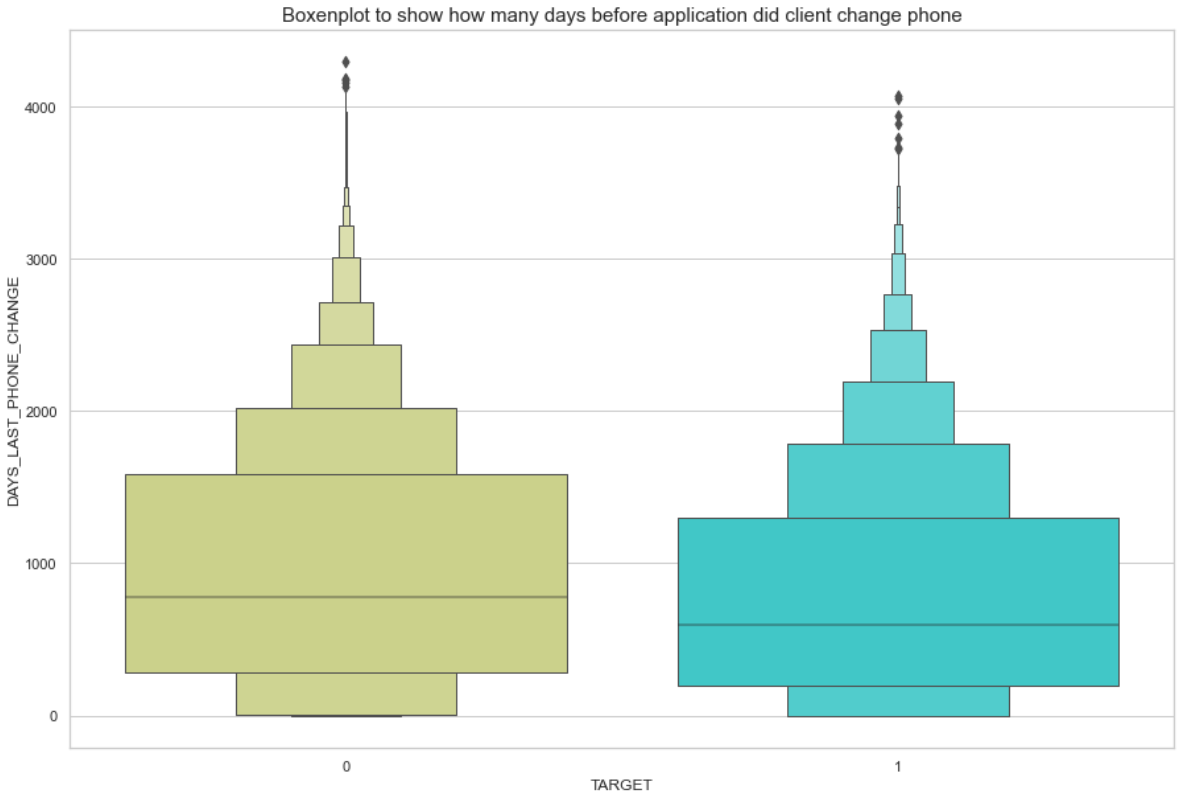

```
Wall time: 427 ms
```

Observations: According to the data the number of Married People tend to apply for the loan the maximum. Then Single/Unmarried people tend to apply for the loan. The least amount of loan are taken by Widows.

In [16]:

```
%%time
# create boxenplot
sns.set_theme(style="whitegrid")
ax= sns.boxenplot(df_credit["TARGET"],df_credit["DAYS_LAST_PHONE_CHANGE"],palette='rainbow_
ax.set_title("Boxenplot to show how many days before application did client change phone",f
plt.subplots_adjust(wspace = .2)
```

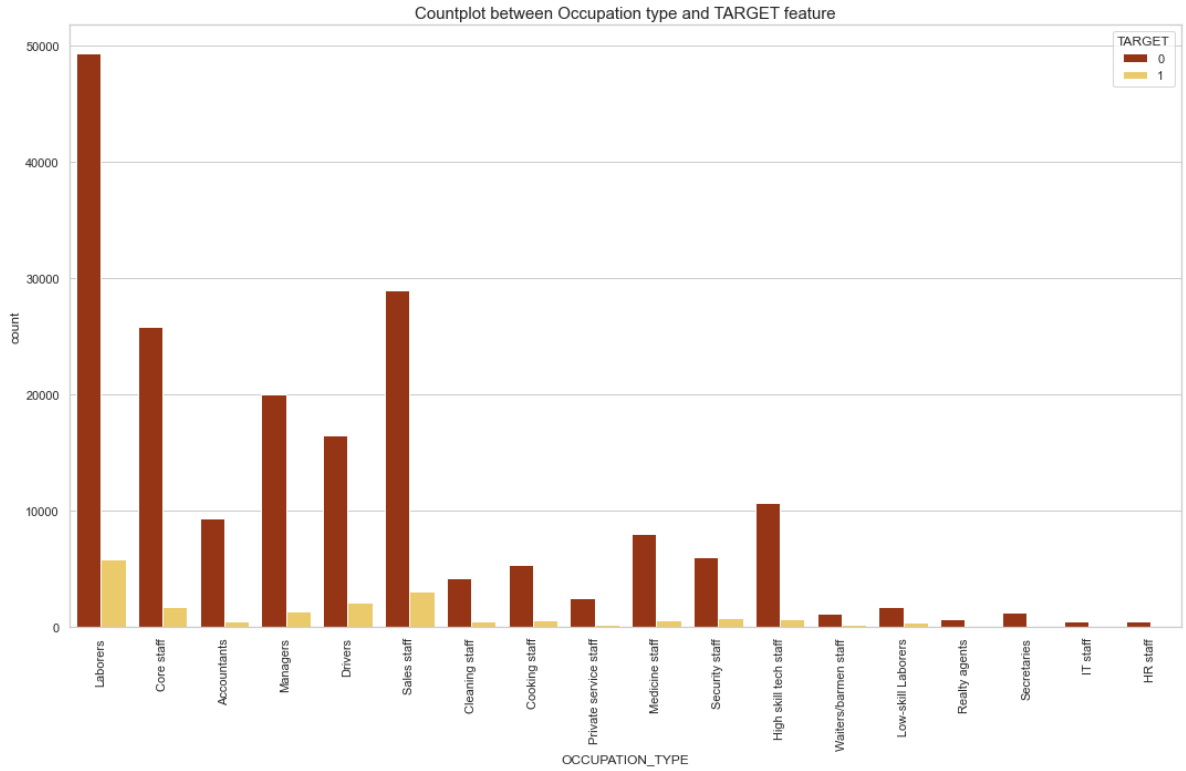
```
Wall time: 139 ms
```



Observations: The Average number of days the phone number was changed in case of a repayer is 800 days and for defaulters it is 500-600 days. There are prople who have not changed their number for a long time.

In [17]:

```
%%time
# create countplot
plt.figure(figsize=(18,10))
sns.set_theme(style="whitegrid")
sns.countplot(data=df_credit,x='OCCUPATION_TYPE',hue='TARGET',palette='afmhot')
plt.title("Countplot between Occupation type and TARGET feature",fontdict={'fontsize':15})
plt.xticks(rotation=90)
plt.show()
```



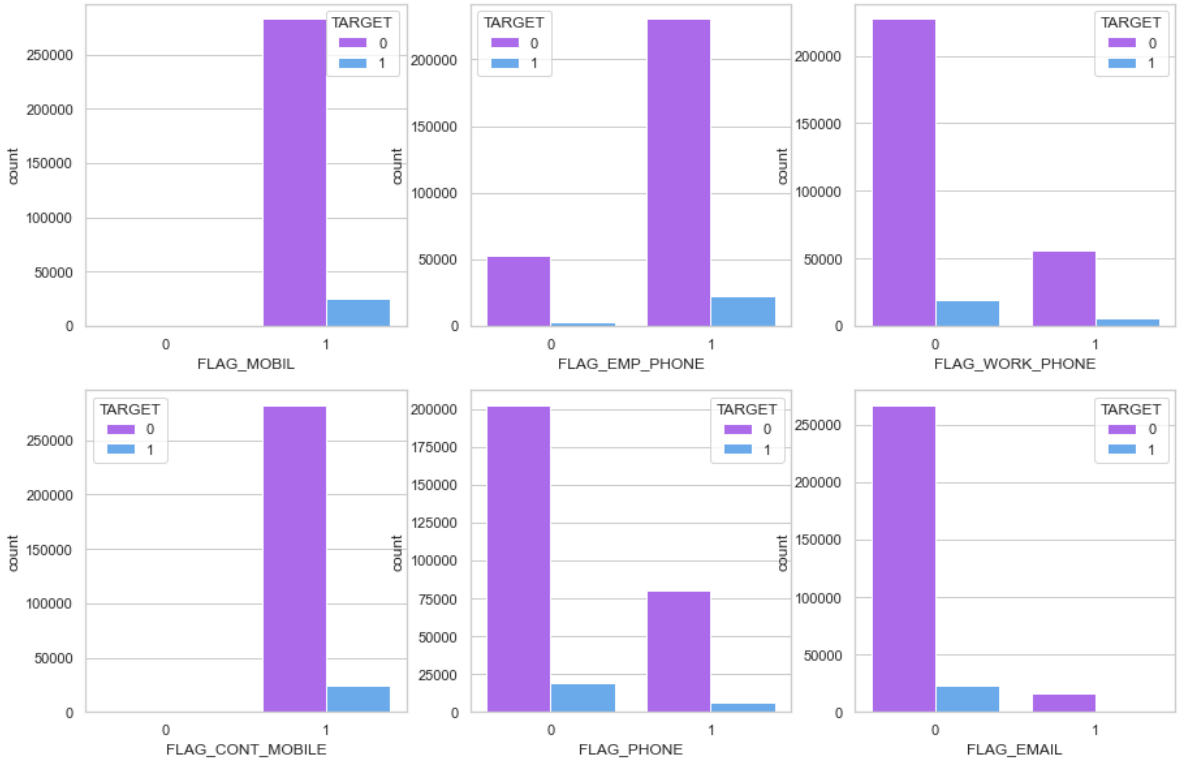
Wall time: 578 ms

Observations: The laborer occupation type has the most number of loans around 49K where as others are at an average of 20K. Sales Staff is the second occupation that take most number of loans. IT staff and Reality Agents tend to take less loan.

In [18]:

```
%%time
contact_columns= ['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE','FL
print(style.BOLD+style.RED+"Comparison of contact information using countplot"+style.END)
for feature,index in zip(contact_columns,range(6)):
    plt.subplot(2,3,index+1)
    sns.set_theme(style="whitegrid")
    sns.countplot(df_credit[feature],hue=df_credit["TARGET"],palette='cool_r')
plt.show()
```

Comparison of contact information using countplot

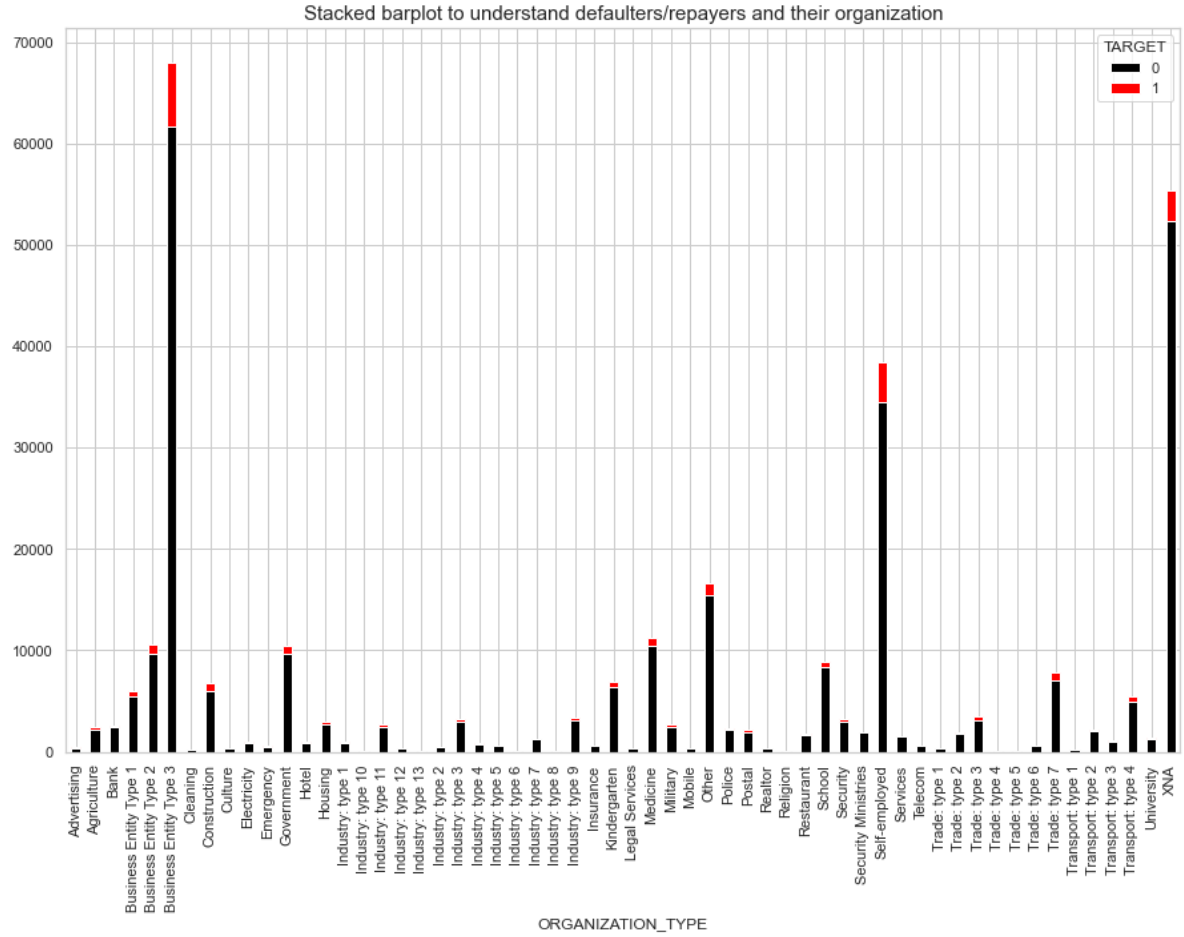


Wall time: 953 ms

Observations: Personal Mobile Number is provided by everyone where as email address is something which is not mostly provided by the loanee. Most of the mobile phones provided by people was in working and reachable condition. People did provide their work phone number. Most of the people tend to have mobile than a common home phone number.

In [19]:

```
%%time
# create stacked barplot using crosstab
sns.set_theme(style="whitegrid")
pd.crosstab(df_credit['ORGANIZATION_TYPE'],df_credit['TARGET']).plot(kind='bar',stacked=Tru
plt.title("Stacked barplot to understand defaulters/repayers and their organization",fontdi
plt.show()
```



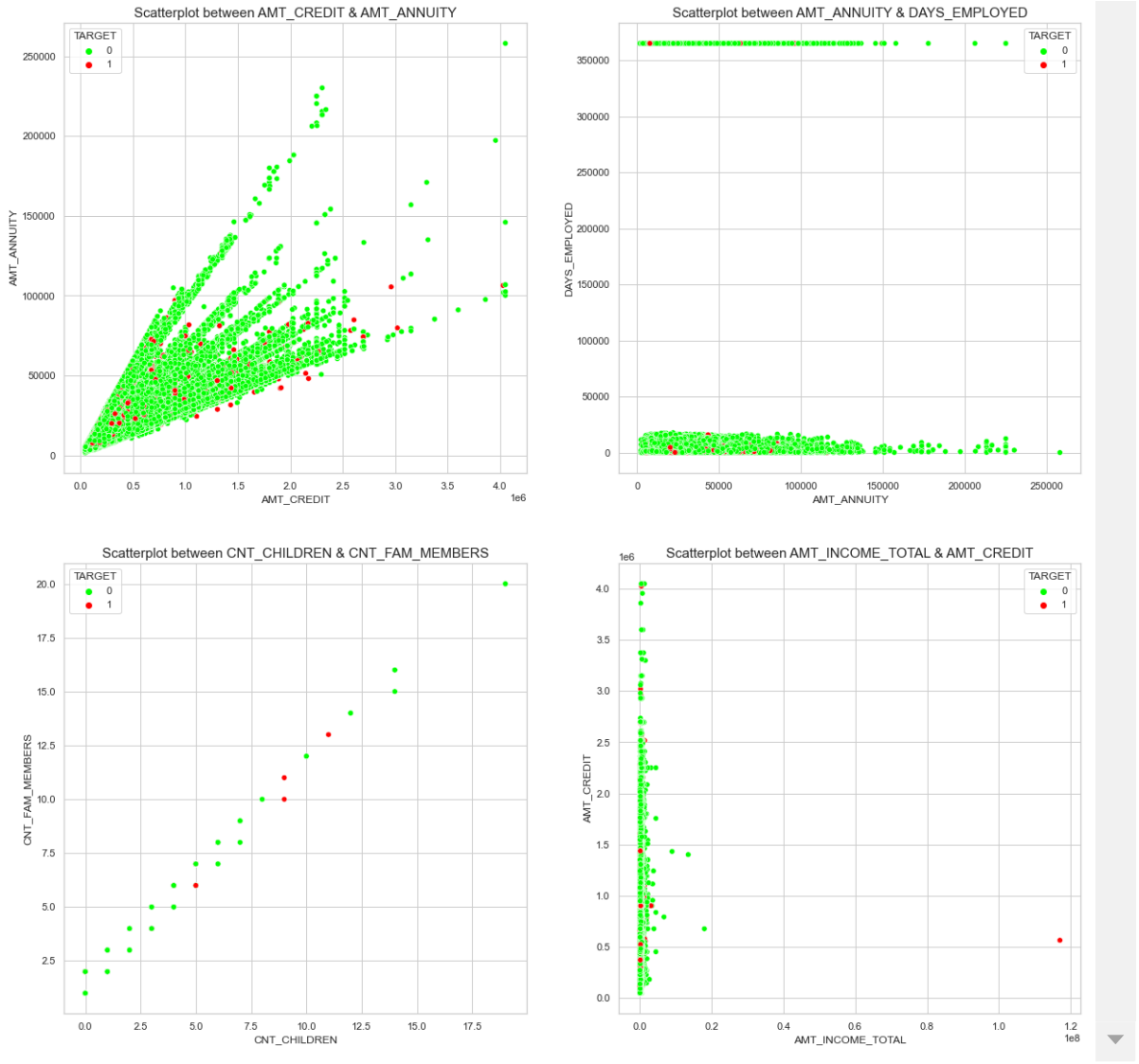

```
Wall time: 3.61 s
```

Observations: Business Entity Type 3 people is the Organization type took most number of loans. Around 53K people data about their Organization type is not available. Loan taken by Business Entity is more than the people working in Industry, Trade and Transport Sector

Multivariate Analysis

In [20]:

```
%%time
# create subplot
plt.figure(figsize=(20,20))
plt.subplot(2,2,1)
# create scatterplot
sns.set_theme(style="whitegrid")
sns.scatterplot(data=df_credit,x='AMT_CREDIT',y='AMT_ANNUITY',hue=df_credit['TARGET'],palet
plt.title("Scatterplot between AMT_CREDIT & AMT_ANNUITY",fontdict={'fontsize':15})

# create subplot
plt.subplot(2,2,2)
# create scatterplot
sns.set_theme(style="whitegrid")
sns.scatterplot(data=df_credit,x='AMT_ANNUITY',y='DAYS_EMPLOYED',hue=df_credit['TARGET'],pa
plt.title("Scatterplot between AMT_ANNUITY & DAYS_EMPLOYED",fontdict={'fontsize':15})

# create subplot
plt.subplot(2,2,3)
# create scatterplot
sns.set_theme(style="whitegrid")
sns.scatterplot(data=df_credit,x='CNT_CHILDREN',y='CNT_FAM_MEMBERS',hue=df_credit['TARGET']
plt.title("Scatterplot between CNT_CHILDREN & CNT_FAM_MEMBERS",fontdict={'fontsize':15})

# create subplot
plt.subplot(2,2,4)
# create scatterplot
sns.set_theme(style="whitegrid")
sns.scatterplot(data=df_credit,x='AMT_INCOME_TOTAL',y='AMT_CREDIT',hue=df_credit['TARGET'],
plt.title("Scatterplot between AMT_INCOME_TOTAL & AMT_CREDIT",fontdict={'fontsize':15})

plt.show()
```

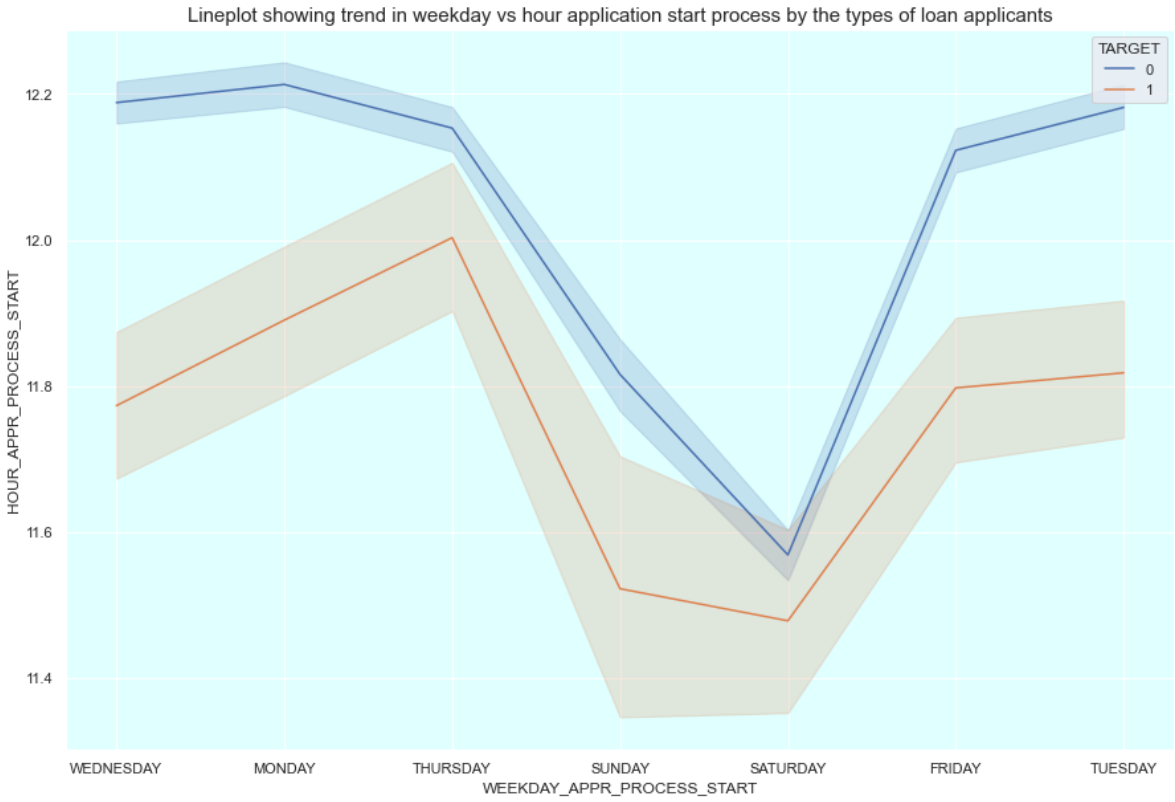



```
Wall time: 33.6 s
```

Observations: Family Count is directly proportional to the Count of children in a house. With increase in credit amount, annuity increases

In [21]:

```
%%time
# create lineplot
sns.set_theme(style="darkgrid")
ax = sns.lineplot(data=df_credit, x='WEEKDAY_APPR_PROCESS_START',y='HOUR_APPR_PROCESS_START
plt.title("Lineplot showing trend in weekday vs hour application start process by the types
ax.set_facecolor("LightCyan")
plt.show()
```




```
Wall time: 3.52 s
```

Observations: Clients applied for loan mostly on Thursday and weekdays overall and least on

Weekends

In [22]:

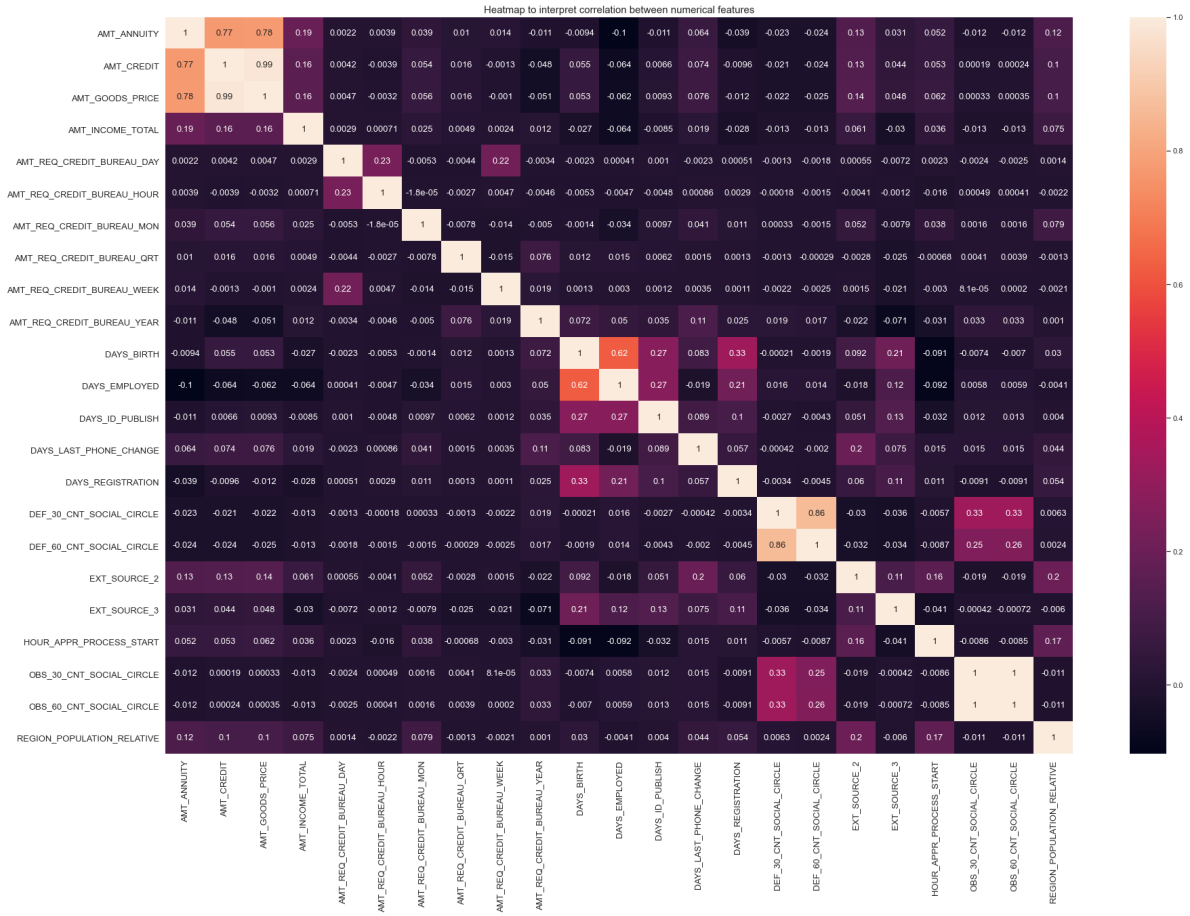
```
# check correlation among numerical features
df_credit[numerical_columns].corr()
```

Out[22]:

	AMT_ANNUITY	AMT_CREDIT	AMT_GOODS_PRICE	AMT_IN(
AMT_ANNUITY	1.000000	0.770138	0.775109	
AMT_CREDIT	0.770138	1.000000	0.986968	
AMT_GOODS_PRICE	0.775109	0.986968	1.000000	
AMT_INCOME_TOTAL	0.191657	0.156870	0.159610	
AMT_REQ_CREDIT_BUREAU_DAY	0.002185	0.004238	0.004677	
AMT_REQ_CREDIT_BUREAU_HOUR	0.003861	-0.003906	-0.003237	
AMT_REQ_CREDIT_BUREAU_MON	0.039148	0.054451	0.056422	
AMT_REQ_CREDIT_BUREAU_QRT	0.010124	0.015925	0.016432	
AMT_REQ_CREDIT_BUREAU_WEEK	0.013881	-0.001275	-0.001007	
AMT_REQ_CREDIT_BUREAU_YEAR	-0.011320	-0.048448	-0.050998	
DAYS_BIRTH	-0.009445	0.055436	0.053442	
DAYS_EMPLOYED	-0.102851	-0.064319	-0.062265	
DAYS_ID_PUBLISH	-0.011268	0.006575	0.009267	
DAYS_LAST_PHONE_CHANGE	0.063747	0.073701	0.076313	
DAYS_REGISTRATION	-0.038514	-0.009621	-0.011565	
DEF_30_CNT_SOCIAL_CIRCLE	-0.022833	-0.021229	-0.022244	
DEF_60_CNT_SOCIAL_CIRCLE	-0.024001	-0.023767	-0.024506	
EXT_SOURCE_2	0.125804	0.131228	0.139367	
EXT_SOURCE_3	0.030752	0.043516	0.047717	
HOUR_APPR_PROCESS_START	0.052269	0.052738	0.062320	
OBS_30_CNT_SOCIAL_CIRCLE	-0.011987	0.000190	0.000328	
OBS_60_CNT_SOCIAL_CIRCLE	-0.011731	0.000239	0.000347	
REGION_POPULATION_RELATIVE	0.118429	0.099738	0.103520	

In [23]:

```
%%time
plt.figure(figsize=(30, 20))
sns.heatmap(df_credit[numerical_columns].corr(), annot=True, annot_kws={"size": 13})
plt.title("Heatmap to interpret correlation between numerical features", fontdict={'fontsiz
plt.yticks(rotation='horizontal', fontsize=13)
plt.xticks(fontsize=13)
plt.show()
```




```
Wall time: 7.62 s
```

Observations: Following pair of features exhibit strong positive correlation

```
OBS_60_CNT_SOCIAL_CIRCLE      -    OBS_30_CNT_SOCIAL_CIRCLE
FLAG_EMP_PHONE                -    DAYS_EMPLOYED
AMT_GOODS_PRICE               -    AMT_CREDIT
REGION_RATING_CLIENT_W_CITY   -    REGION_RATING_CLIENT
CNT_FAM_MEMBERS               -    CNT_CHILDREN
DEF_60_CNT_SOCIAL_CIRCLE      -    DEF_30_CNT_SOCIAL_CIRCLE
LIVE_REGION_NOT_WORK_REGION   -    REG_REGION_NOT_WORK_REGION
LIVE_CITY_NOT_WORK_CITY       -    REG_CITY_NOT_WORK_CITY
AMT_ANNUITY                   -    AMT_CREDIT
AMT_GOODS_PRICE               -    AMT_ANNUITY

Following pair of features exhibit strong negative correlation: -
REGION_RATING_CLIENT_W_CITY    -    REGION_POPULATION_RELATIVE
REGION_RATING_CLIENT_CLIENT    -    REGION_POPULATION_RELATIVE
```

STATISTICAL TESTS

In [24]:

```
# select a copy of df_credit
df_statistics = df_credit.copy()

# select columns to impute with median ( skewed features )
cols_median = ['AMT_ANNUITY','AMT_GOODS_PRICE','DAYS_EMPLOYED','EXT_SOURCE_3','DAYS_LAST_PH
# select columns to impute with mode ( categorical features )
cols_mode = ['NAME_TYPE_SUITE','OCCUPATION_TYPE']

# fill null values in median_impute_cols with median
for feature in cols_median:
    df_statistics[feature].fillna(df_statistics[feature].median(), inplace=True)

# fill null values in mode_impute_cols with mode
for feature in cols_mode:
    df_statistics[feature].fillna(df_statistics[feature].mode()[0], inplace=True)
```

1.Run the test to check normality

In [25]:

```
# Defining Null and Alternative Hypotheses
#H0 = 'data is Normally distributed'
#H1 = 'data is not Normally distributed'
#alpha = 0.05
```

Shapiro-Wilk Test

In [26]:

```
# normality test for the columns
#AMT_CREDIT,AMT_INCOME_TOTAL,AMT_ANNUITY,'CNT_CHILDREN,REGION_RATING_CLIENT

from scipy.stats import shapiro
df1 = df_statistics['AMT_CREDIT']
df2 = df_statistics['AMT_INCOME_TOTAL']
df3 = df_statistics['AMT_ANNUITY']
df4 = df_statistics['CNT_CHILDREN']
df5 = df_statistics['REGION_RATING_CLIENT']


stat, p1 = shapiro(df1)
stat, p2 = shapiro(df2)
stat, p3 = shapiro(df3)
stat, p4 = shapiro(df4)
stat, p5 = shapiro(df5)
print('stat=%.3f, p1=%.3f, p2=%.3f,p3=%.3f,p4=%.3f,p5=%.3f' % (stat, p1,p2,p3,p4,p5))
if p1 > 0.05:
    print('we are accepting null hypothesis, hence AMT_CREDIT is normally distributed',)
else:
    print('we are rejecting null hypothesis,hence AMT_CREDIT is not normally distributed')
if p2 > 0.05:
    print('we are accepting null hypothesis, hence AMT_INCOME_TOTAL is normally distributed
else:
    print('we are rejecting null hypothesis,hence AMT_INCOME_TOTAL is not normally distribu
if p3 > 0.05:
    print('we are accepting null hypothesis, hence AMT_ANNUITY is normally distributed')
else:
    print('we are rejecting null hypothesis, hence AMT_ANNUITY is not normally distributed'
if p4 > 0.05:
    print('we are accepting null hypothesis, hence CNT_CHILDREN is  normally distributed')
else:
    print('we are rejecting null hypothesis,  hence CNT_CHILDREN is not normally distribute
if p5 > 0.05:
    print('we are accepting null hypothesis,  hence REGION_RATING_CLIENT is  normally distr
else:
    print('we are rejecting null hypothesis,  hence REGION_RATING_CLIENT is  normally distr
```

```
stat=0.685, p1=0.000, p2=0.000,p3=0.000,p4=0.000,p5=0.000
we are rejecting null hypothesis,hence AMT_CREDIT is not normally distribute
d
we are rejecting null hypothesis,hence AMT_INCOME_TOTAL is not normally dist
ributed
we are rejecting null hypothesis, hence AMT_ANNUITY is not normally distribu
ted
we are rejecting null hypothesis,  hence CNT_CHILDREN is not normally distri
buted
we are rejecting null hypothesis,  hence REGION_RATING_CLIENT is  normally d
istributed
```

D'Agostino's K^2 Normality Test

In [27]:

```
from scipy.stats import normaltest
df1 = df_statistics['AMT_CREDIT']
df2 = df_statistics['AMT_INCOME_TOTAL']
df3 = df_statistics['AMT_ANNUITY']
df4 = df_statistics['CNT_CHILDREN']
df5 = df_statistics['REGION_RATING_CLIENT']

stat, p1 = normaltest(df1)
stat, p2 = normaltest(df2)
stat, p3 = normaltest(df3)
stat, p4 = normaltest(df4)
stat, p5 = normaltest(df5)
print('stat=%.3f, p1=%.3f, p2=%.3f,p3=%.3f,p4=%.3f,p5=%.3f' % (stat, p1,p2,p3,p4,p5))
if p1 > 0.05:
    print('AMT_CREDIT-Probably Normally Distributed')
else:
    print('AMT_CREDIT-Probably not Normally Distributed')

if p2 > 0.05:
    print('AMT_INCOME_TOTAL-Probably Normally Distributed')
else:
    print('AMT_INCOME_TOTAL-Probably not Normally Distributed')
if p3 > 0.05:
    print('AMT_ANNUITY-Probably Normally Distributed')
else:
    print('AMT_ANNUITY-Probably not Normally Distributed')
if p4 > 0.05:
    print('CNT_CHILDREN-Probably Normally Distributed')
else:
    print('CNT_CHILDREN-Probably not Normally Distributed')
if p5 > 0.05:
    print('REGION_RATING_CLIENT-Probably Normally Distributed')
else:
    print('REGION_RATING_CLIENT-Probably not Normally Distributed')
```

```
stat=4706.031, p1=0.000, p2=0.000,p3=0.000,p4=0.000,p5=0.000
AMT_CREDIT-Probably not Normally Distributed
AMT_INCOME_TOTAL-Probably not Normally Distributed
AMT_ANNUITY-Probably not Normally Distributed
CNT_CHILDREN-Probably not Normally Distributed
REGION_RATING_CLIENT-Probably not Normally Distributed
```

2.Correlation Tests

Pearson's Correlation Coefficient

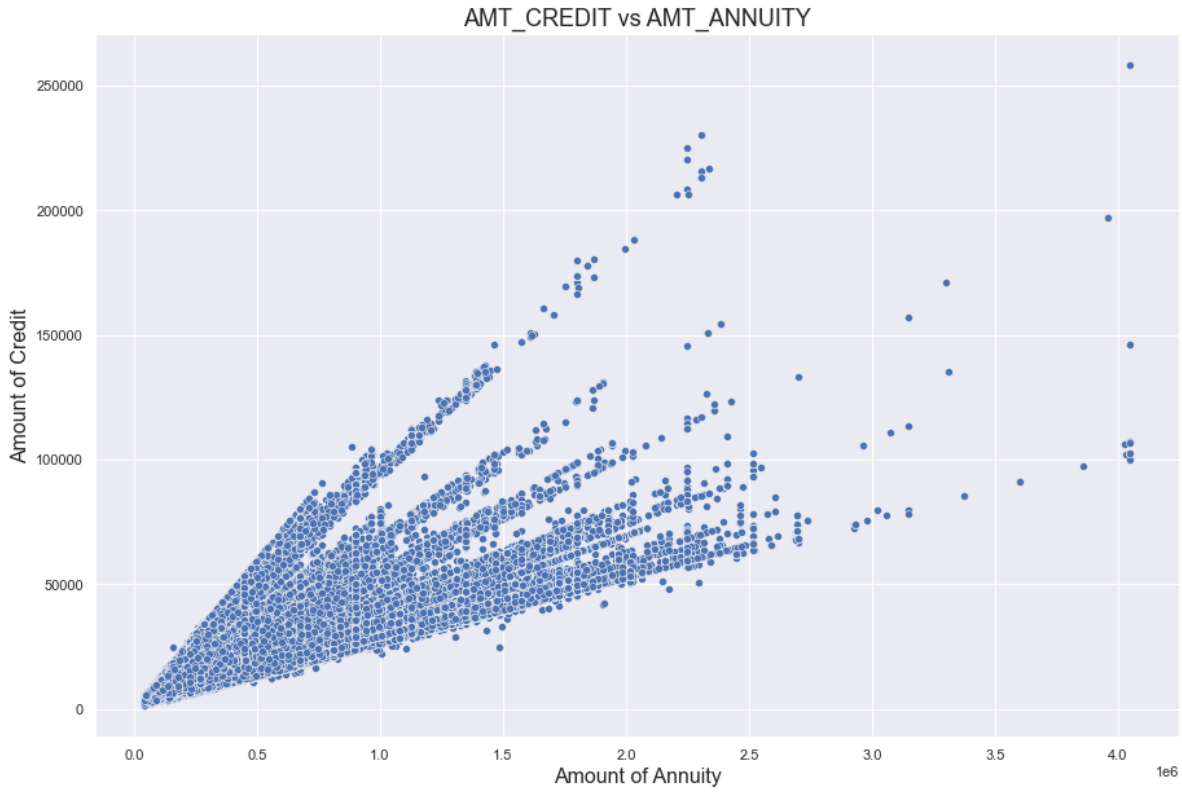
In [28]:

```
# Defining Null and Alternative Hypotheses
#H0 =correlation coefficient IS NOT significantly different from 0.There is not a significa
#H1 = correlation coefficient IS significantly different from 0.There is a significant rela
#alpha = 0.05
```

In [29]:

```
#Pearson's Correlation Coefficient

df = df_statistics[['AMT_CREDIT', 'AMT_ANNUITY']]
print(df.head())

from scipy import stats
data1=df_statistics.AMT_CREDIT.values
data2=df_statistics.AMT_ANNUITY.values

correlation, p_value = stats.pearsonr(data1,data2)

print(correlation)
import matplotlib.pyplot as plt
sns.scatterplot('AMT_CREDIT','AMT_ANNUITY',data=df_statistics)
plt.title('AMT_CREDIT vs AMT_ANNUITY', fontsize=18)
plt.ylabel('Amount of Credit', fontsize=16)
plt.xlabel('Amount of Annuity', fontsize=16)
plt.show()
```

```
   AMT_CREDIT  AMT_ANNUITY
0    406597.5      24700.5
1   1293502.5      35698.5
2    135000.0       6750.0
3    312682.5      29686.5
4    513000.0      21865.5
0.7701267228930904
```



Observation:

we can see that the relationship is not linear between the two columns.

Chi Square Test

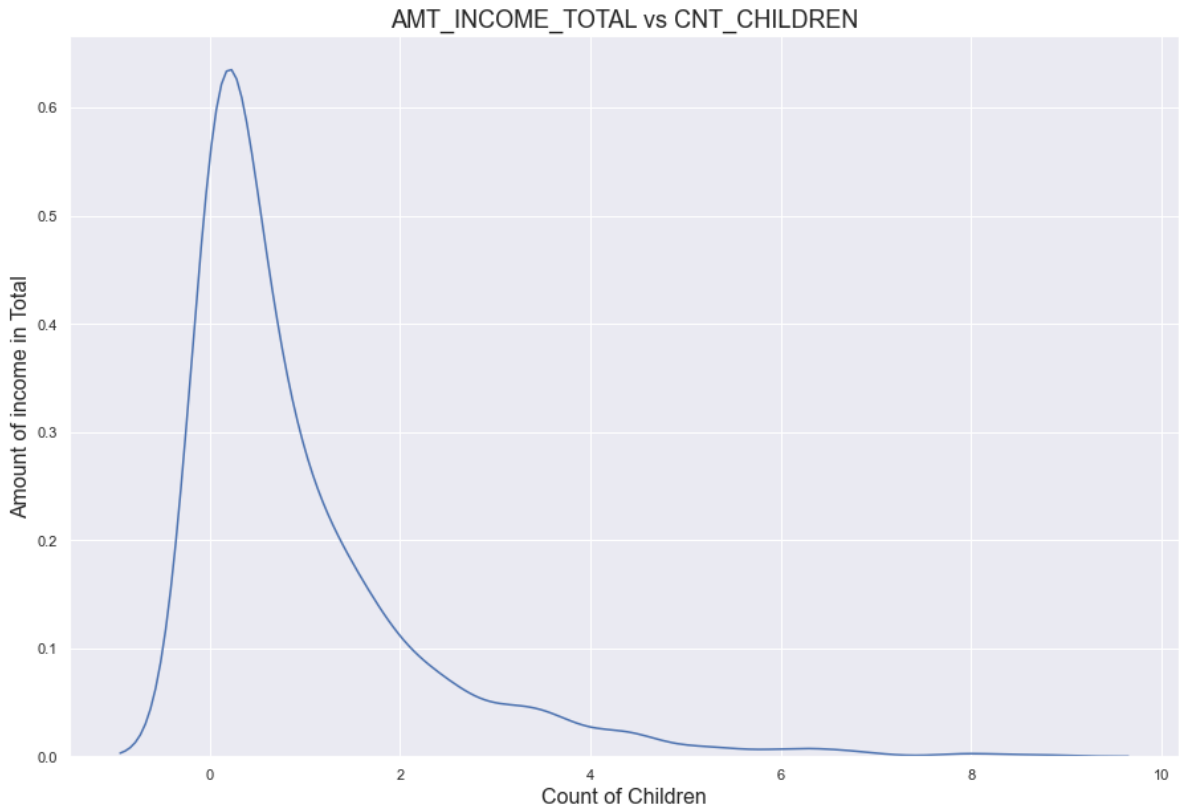
In [30]:

```
#Null and alternate hypothesis
#H0:-there is not a significant relationship between the columns
#H1:-there is a significant relationship between the columns
```

In [31]:

```
# the Chi-Squared Test of independence for columns-AMT_INCOME_TOTAL vs CNT_CHILDREN
import matplotlib.pyplot as plt
from numpy import random
from scipy.stats import chi2_contingency
df3 = df_statistics['AMT_INCOME_TOTAL']
df4 = df_statistics['CNT_CHILDREN']
table = [[df3],[df4]]
stat, p, dof, expected = chi2_contingency(table)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably independent')
else:
    print('Probably dependent')

sns.distplot(random.chisquare(df=1, size=1000), hist=False)


plt.title('AMT_INCOME_TOTAL vs CNT_CHILDREN',fontsize=18)
plt.ylabel('Amount of income in Total',fontsize=16)
plt.xlabel('Count of Children',fontsize=16)
plt.show()
```

```
stat=514939.431, p=0.000
Probably dependent
```



Observation:

The p value obtained from chi-square test for independence is significant (p < 0.05), and therefore, we conclude that there is a significant association between Columns CNT_CHILDREN and AMT_INCOME_TOTAL

In [32]:

```
#the Chi-Squared Test of independence for columns-NAME_INCOME_TYPE and OCCUPATION_TYPE
from scipy.stats import chi2_contingency
contingency_data=pd.crosstab(df_statistics["NAME_INCOME_TYPE"], df_statistics["OCCUPATION_T

stats, pvalue, dof, expected = chi2_contingency(contingency_data)

print("Stats :", stats, "Pvalue :", pvalue)

if pvalue> 0.05:
    print(" Both the categorical attributes are independent ( Fail to reject H0).")
else:
    print("Both the categorical attributes are dependent (Reject H0).")
```

```
Stats : 98842.68043941665 Pvalue : 0.0
Both the categorical attributes are dependent (Reject H0).
```

In [33]:

```
#independence test for columns-NAME_CONTRACT_TYPE  and WEEKDAY_APPR_PROCESS_START#
contingency_data2=pd.crosstab(df_statistics["NAME_CONTRACT_TYPE"],df_statistics["WEEKDAY_AP
stats, pvalue, dof, expected = chi2_contingency(contingency_data2)

print("Stats :", stats, "Pvalue :", pvalue)

if pvalue> 0.05:
    print(" Both the categorical attributes are independent ( Fail to reject H0).")
else:
    print("Both the categorical attributes are dependent (Reject H0).")
```

```
Stats : 67.99048638705025 Pvalue : 1.0553487110442855e-12
Both the categorical attributes are dependent (Reject H0).
```

3.Parametric Statistical Hypothesis Tests

Analysis of Variance Test (ANOVA)

In [34]:

```
# Example of the Analysis of Variance Test
from scipy.stats import f_oneway
df1 = df_statistics['AMT_CREDIT']
df2 = df_statistics['AMT_INCOME_TOTAL']
df3 = df_statistics['AMT_ANNUITY']
df4 = df_statistics['CNT_CHILDREN']
df5 = df_statistics['REGION_RATING_CLIENT']

stat, p = f_oneway(df1, df2, df3,df4,df5)

print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same distribution')
else:
    print('Probably different distributions')
```

```
stat=460478.031, p=0.000
Probably different distributions
```

Observation: The p value obtained from ANOVA analysis is significant (p < 0.05), and therefore, we conclude that there are significant differences among treatments.

One sample T Test

In [35]:

```
import matplotlib.pyplot as plt
from scipy.stats import ttest_1samp
df3 = df_statistics['AMT_ANNUITY']
tscore, pvalue = ttest_1samp(df3, popmean=20)
print("t Statistic: ", tscore)
print("P Value: ", pvalue)
plt.show()
```

```
t Statistic:  1036.4371745647163
P Value:  0.0
```

4.Nonparametric Statistical Hypothesis Tests

Mann-Whitney U Test

Checking whether the distributons of two or more independemt samples are equal or not.

In [36]:

```
#Null and alternate hypothesis
#H0: Same distribution (The two populations are equal).
#H1: Different distribution (The two populations are not equal).
```

In [37]:

```
# CNT_CHILDREN and REGION_RATING_CLIENT
from scipy.stats import mannwhitneyu
df4 = df_statistics['CNT_CHILDREN']
df5 = df_statistics['REGION_RATING_CLIENT']
stat, p = mannwhitneyu(df4, df5)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same distribution')
else:
    print('Probably different distributions')
```

```
stat=6104824969.500, p=0.000
Probably different distributions
```

Observation: The p-value strongly suggests that the sample distributions are different, as is expected.

In [38]:

```
# AMT_INCOME_TOTAL and DAYS_EMPLOYED
sample5=df_statistics[1:30]["AMT_INCOME_TOTAL"]
sample6=df_statistics[1:30]["DAYS_EMPLOYED"]

tstats, pvalue = st.mannwhitneyu(sample5, sample6)

print("stats: ", tstats, "Pvalue: ", pvalue)

if pvalue>0.05:
    print("Two populations are equal (Fail to reject H0)")
else:
    print("Two populations are not equal (Reject H0)")
```

```
stats:  84.0 Pvalue:  8.546693138064218e-08
Two populations are not equal (Reject H0)
```

Kruskal-Wallis H Test

Checking whether the distributons of two or more independemt samples are equal or not.

In [39]:

```
#alternate and null hypothesis
#H0: Same distribution (The two populations are equal).
#H1: Different distribution (The two populations are not equal).
```

In [40]:

```
#AMT_INCOME_TOTAL - CNT_CHILDREN
from scipy.stats import kruskal
df2 = df_statistics['AMT_INCOME_TOTAL']
df4 = df_statistics['CNT_CHILDREN']
stat, p = kruskal(df2, df5)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same distribution')
else:
    print('Probably different distributions')
```

```
stat=486306.354, p=0.000
Probably different distributions
```

Observation:

The p-value is interpreted, correctly rejecting the null hypothesis that all sampl es have the same distribution<b>

2) FEATURE ENGINEERING (FE)

In [20]:

```
%%time
''' ## CUSTOM FUNCTIONS '''

# define function to rectify the features
def rectify_features(df):
    print(style.BOLD+style.RED+"Logs during feature rectification process:"+style.END)
    ## Club classes into relevant organization type for the feature ORGANIZATION_TYPE
    print("No.of.classes in ORGANIZATION_TYPE before clubbing levels:",len(df.ORGANIZATION_
    display(pd.DataFrame(df.ORGANIZATION_TYPE.value_counts()).T)
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].str.contains("Business Entit
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].str.contains("Industry"), "I
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].str.contains("Trade"),"Trade
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].str.contains("Transport"),"T
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].isin(["School", "Kindergarte
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].isin(["Emergency","Police",
                                       "Military", "Security Ministries", "Legal Services"]
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].isin(["Bank", "Insurance"]),
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].isin(["Realtor", "Housing"])
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].isin(["Hotel", "Restaurant",
    df["ORGANIZATION_TYPE"] = np.where(df["ORGANIZATION_TYPE"].isin(["Cleaning","Electricit
                                       "Advertising","Religion", "Culture"]),"Other", df["
    print("No.of.classes in ORGANIZATION_TYPE after clubbing levels:",len(df.ORGANIZATION_T
    display(pd.DataFrame(df.ORGANIZATION_TYPE.value_counts()).T)
    ##-------------------------------------------------------------------------------------
    ## Club classes into relevant occupation type for the feature OCCUPATION_TYPE
    print("No.of.classes in OCCUPATION_TYPE before clubbing levels:",len(df.OCCUPATION_TYPE
    display(pd.DataFrame(df.OCCUPATION_TYPE.value_counts()).T)
    df["OCCUPATION_TYPE"] = np.where(df["OCCUPATION_TYPE"].isin(["Low-skill Laborers", "Coo
                                     "Private service staff", "Cleaning staff", "Waiters/ba
    df["OCCUPATION_TYPE"] = np.where(df["OCCUPATION_TYPE"].isin(["IT staff", "High skill te
    df["OCCUPATION_TYPE"] = np.where(df["OCCUPATION_TYPE"].isin(["Secretaries", "HR staff",
    print("No.of.classes in OCCUPATION_TYPE after clubbing levels:",len(df.OCCUPATION_TYPE.
    display(pd.DataFrame(df.OCCUPATION_TYPE.value_counts()).T)
    ##-------------------------------------------------------------------------------------
    ## Club classes into relevant income type for the feature NAME_INCOME_TYPE
    print("No.of.classes in NAME_INCOME_TYPE before clubbing levels:",len(df.NAME_INCOME_TY
    display(pd.DataFrame(df.NAME_INCOME_TYPE.value_counts()).T)
    df['NAME_INCOME_TYPE'].replace('Businessman','Commercial associate', inplace=True)
    df['NAME_INCOME_TYPE'].replace('Maternity leave','Pensioner', inplace=True)
    df['NAME_INCOME_TYPE'].replace('Student','State servant', inplace=True)
    df['NAME_INCOME_TYPE'].replace('Unemployed','Pensioner', inplace=True)
    print("No.of.classes in NAME_INCOME_TYPE after clubbing levels:",len(df.NAME_INCOME_TYP
    display(pd.DataFrame(df.NAME_INCOME_TYPE.value_counts()).T)
    ##-------------------------------------------------------------------------------------
    ## Club classes into relevant education type for the feature NAME_EDUCATION_TYPE
    df["NAME_EDUCATION_TYPE"] = np.where(df["NAME_EDUCATION_TYPE"] == "Academic degree",
                                         "Higher education", df["NAME_EDUCATION_TYPE"])
    ##-------------------------------------------------------------------------------------
    ## Club flag docuument features with some percentage into a single variable representin
    ## Select flag document features which show less submission percentage in piechart
    drop_flags = ['FLAG_DOCUMENT_12','FLAG_DOCUMENT_11','FLAG_DOCUMENT_19','FLAG_DOCUMENT_5
                  'FLAG_DOCUMENT_15','FLAG_DOCUMENT_7','FLAG_DOCUMENT_4','FLAG_DOCU
                  'FLAG_DOCUMENT_2','FLAG_DOCUMENT_21','FLAG_DOCUMENT_13','FLAG_DOC
                  'FLAG_DOCUMENT_9','FLAG_DOCUMENT_17']
    # drop columns in drop_flags
    for feature in drop_flags:
        if feature in df.columns:
            df.drop(feature, axis = 1, inplace = True)
    # select features which show some percentage to club them
```

```
sum_flags = ['FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_8']
df['SCORE_DOCUMENT_SUBMISSION'] = df[sum_flags].sum(axis=1)
df.drop(sum_flags, axis=1, inplace=True)
print("Correlation between the feature SCORE_DOCUMENT_SUBMISSION and TARGET",df.SCORE_D
##-------------------------------------------------------------------------------------
## Club classes into relevant category for the features DEF_30_CNT_SOCIAL_CIRCLE and DE
df.loc[(df['DEF_30_CNT_SOCIAL_CIRCLE'] > 0) & (df['DEF_60_CNT_SOCIAL_CIRCLE'] > 0),
       'CATEGORY_DEF_30_60_SOCIAL_CIRCLE'] = 'DEF_30_60'
df.loc[(df['DEF_30_CNT_SOCIAL_CIRCLE'] > 0) & (df['DEF_60_CNT_SOCIAL_CIRCLE'] == 0),
       'CATEGORY_DEF_30_60_SOCIAL_CIRCLE'] = 'DEF_30'
df.loc[(df['DEF_30_CNT_SOCIAL_CIRCLE'] == 0) & (df['DEF_60_CNT_SOCIAL_CIRCLE'] > 0),
       'CATEGORY_DEF_30_60_SOCIAL_CIRCLE'] = 'DEF_60'
df.loc[(df['DEF_30_CNT_SOCIAL_CIRCLE'] == 0) & (df['DEF_60_CNT_SOCIAL_CIRCLE'] == 0),
       'CATEGORY_DEF_30_60_SOCIAL_CIRCLE'] = 'None'
##-------------------------------------------------------------------------------------
## Club Region based columns into single feature to interpret their residential score
region_cols = ["REG_REGION_NOT_LIVE_REGION","REG_REGION_NOT_WORK_REGION", "LIVE_REGION_
       "REG_CITY_NOT_LIVE_CITY","REG_CITY_NOT_WORK_CITY","LIVE_CITY_NOT_WORK_CITY"]
df["SCORE_REGION"] = df[region_cols].sum(axis = 1)
df.drop(region_cols, axis = 1, inplace = True)
##-------------------------------------------------------------------------------------
## Club EXT_SOURCE related columns into single feature as their average score
ext_cols = ['EXT_SOURCE_2', 'EXT_SOURCE_3']
df["SCORE_EXT_SOURCE"] = df[ext_cols].mean(axis=1)
##-------------------------------------------------------------------------------------
## From histogram and boxplot, DAYS_EMPLOYED contains values > 300000 days (i.e. more t
## which doesn't hold true in real world. So, we consider them as NaNs
max_value = df['DAYS_EMPLOYED'].max()
print(f"{max_value} in DAYS_EMPLOYED replaced with NaNs")
df['DAYS_EMPLOYED'].replace(max_value, np.nan, inplace=True)
##-------------------------------------------------------------------------------------
## Gender distribution pie-chart shows that negligible no.of applicant's gender informa
## We can eliminate those observations
mask = df['CODE_GENDER'] == 'XNA'
print("No.of.observations having unavailable gender information", len(df[mask]))
df = df[~(mask)]
##-------------------------------------------------------------------------------------
## Barplot of NAME_FAMILY_STATUS shows 'Unknown' with count around 0. Let's exlude the
mask = df['NAME_FAMILY_STATUS'] == 'Unknown'
print("No.of.observations having unavailable family status", len(df[mask]))
df = df[~(mask)]
##-------------------------------------------------------------------------------------
## Dataset contains applicant's birth in no.of.days, we calculate their ages and create
df["DAYS_BIRTH_AS_AGE"] = round(df["DAYS_BIRTH"]/ 365)

df.loc[df["DAYS_BIRTH_AS_AGE"] <= 35 ,"CATEGORY_AGE"] = "Young"
df.loc[(df["DAYS_BIRTH_AS_AGE"] > 35)&(df["DAYS_BIRTH_AS_AGE"] <= 55) ,"CATEGORY_AGE"]
df.loc[(df["DAYS_BIRTH_AS_AGE"] > 55),"CATEGORY_AGE"] = "Old"
##-------------------------------------------------------------------------------------
## Create a categorical feature of income with the reference of histogram
df.loc[df["AMT_INCOME_TOTAL"] <= 100000 ,"CATEGORY_INCOME"] = "Low_Income"
df.loc[(df["AMT_INCOME_TOTAL"] > 100000)&(df["AMT_INCOME_TOTAL"] <= 200000) ,"CATEGORY_
df.loc[(df["AMT_INCOME_TOTAL"] > 200000),"CATEGORY_INCOME"] = "High_Income"
##-------------------------------------------------------------------------------------
## Let's create new features out of the independent variables that can be represented a
## (i.e., proportion(col1/col2) equivalent to proportion(marks_scored/total_marks)
## Proportion value between 0 to 1 indicates that denominator has more weight than nume
## Similarly, proportion value greater than 1 implies numerator has more weight than de
## Otheriwise, if proportion value = 1 both the numerator and denominator have equal we
df['RATIO_AMTCREDIT_AMTANNUITY'] = df['AMT_CREDIT'] / df['AMT_ANNUITY']
df['RATIO_AMTCREDIT_AMTINCOMETOTAL'] = df['AMT_CREDIT'] / df['AMT_INCOME_TOTAL']
```

```
    df['RATIO_DAYSEMPLOYED_DAYSBIRTH'] = df['DAYS_EMPLOYED'] / df['DAYS_BIRTH']
    df['RATIO_AMTCREDIT_AMTGOODSPRICE'] = df['AMT_CREDIT'] / df['AMT_GOODS_PRICE']
    df['RATIO_AMTINCOMETOTAL_DAYSEMPLOYED'] = df['AMT_INCOME_TOTAL'] / df['DAYS_EMPLOYED']
    # remove infinite values from RATIO_AMTINCOMETOTAL_DAYSEMPLOYED
    df['RATIO_AMTINCOMETOTAL_DAYSEMPLOYED'].replace([np.inf,-np.inf], np.nan, inplace=True)

    df['RATIO_AMTANNUITY_AMTINCOMETOTAL'] = df['AMT_ANNUITY'] / df['AMT_INCOME_TOTAL']
    df['RATIO_AMTINCOMETOTAL_DAYSBIRTH'] = df['AMT_INCOME_TOTAL'] / df['DAYS_BIRTH']
    df['RATIO_LASTPHONECHANGE_DAYSBIRTH'] = df['DAYS_LAST_PHONE_CHANGE'] / df['DAYS_BIRTH']
    df['RATIO_DAYSIDPUBLISH_DAYSBIRTH'] = df['DAYS_ID_PUBLISH'] / df['DAYS_BIRTH']
    #-----------------------------------------------------------------------------------------
    ## drop features with perfect correlation
    df.drop(['OBS_30_CNT_SOCIAL_CIRCLE','OBS_60_CNT_SOCIAL_CIRCLE'], axis = 1, inplace = Tr
    #-----------------------------------------------------------------------------------------
    # update numerical and categorical columns lists
    categorize_features(df)
    print("Shape of the data",df.shape)
    return df
##-----------------------------------------------------------------------------------------
# define function to treat missing values
def treat_null_values(df):
    print(style.BOLD+style.RED+"Null Value Imputation"+style.END)
    print("Columns with standard missing values:",df.columns[df.isna().any()].tolist())
    print("\nTotal number of missing values before treatment: ",df.isna().sum().sum())
    # Null value percentage from bargraph, shows that there are features with equal or almo
    # we shall impute them with zeroes
    zero_impute_cols =['AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_DAY','AMT_REQ_CR
                       'AMT_REQ_CREDIT_BUREAU_MON','AMT_REQ_CREDIT_BUREAU_QRT','AMT_REQ_CR
                       'DEF_30_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE','EXT_SOURCE_
                       'RATIO_AMTCREDIT_AMTANNUITY','RATIO_DAYSEMPLOYED_DAYSBIRTH','RATIO_
                       'RATIO_AMTINCOMETOTAL_DAYSEMPLOYED', 'RATIO_AMTANNUITY_AMTINCOMETOT
    # select columns to impute with mean ( normal distribution => None )
    mean_impute_cols = ['']
    # select columns to impute with median ( skewed distribution )
    median_impute_cols = ['AMT_ANNUITY','AMT_GOODS_PRICE','DAYS_EMPLOYED','EXT_SOURCE_3','D
    # select columns to impute with mode ( categorical features )
    mode_impute_cols = ['NAME_TYPE_SUITE','OCCUPATION_TYPE','CATEGORY_AGE','CATEGORY_INCOME

    # fill null values in median_impute_cols with median
    for feature in median_impute_cols:
        df[feature].fillna(df[feature].median(), inplace=True)

    # fill null values in zero_impute_cols with '0'
    for feature in zero_impute_cols:
        df[feature].fillna(0, inplace=True)

    # fill null values in mode_impute_cols with mode
    for feature in mode_impute_cols:
        df[feature].fillna(df[feature].mode()[0], inplace=True)
    print("Columns with standard missing values:",df.columns[df.isna().any()].tolist())
    print("Total number of missing values after treatment: ",df.isna().sum().sum(),'\n')
    print("Shape of the data",df.shape)
    return df
##-----------------------------------------------------------------------------------------
# define function to apply transformation
def transform_data(df, transform=False):
    # log_trans_features = ['AMT_INCOME_TOTAL','AMT_CREDIT']
    if(transform):
        print(style.BOLD+style.RED+"Transformaton:"+style.END)
        for feature in numerical_columns:
            display("Feature name is:",feature)
```

```
            transformer = PowerTransformer(method = 'yeo-johnson')
            skew_series = pd.Series(index=['original','log','exp','sqrt','cbrt','boxcox'])
            skew_series['original'] = df[feature].skew()
            df_trans = pd.DataFrame()
            if(len(df[df[feature]==0])):
                print("Feature contains zero(s)")
                skew_series['log'] = None
                skew_series['exp'] = st.skew(np.exp(df[feature]))
                skew_series['sqrt'] =  st.skew(np.sqrt(df[feature]))
                skew_series['cbrt'] = st.skew(np.cbrt(df[feature]))
                skew_series['boxcox'] = None
                x=transformer.fit_transform(df[[feature]])
                skew_series['yeo-johnson']=pd.DataFrame(x).skew()[0]
            elif(len(df[df[feature]<0])):
                print("Feature contains negative values")
                skew_series['log'] = None
                skew_series['exp'] = st.skew(np.exp(df[feature]))
                skew_series['sqrt'] =  st.skew(np.sqrt(df[feature]))
                skew_series['cbrt'] = st.skew(np.cbrt(df[feature]))
                skew_series['boxcox'] = None
                x=transformer.fit_transform(df[[feature]])
                skew_series['yeo-johnson']=pd.DataFrame(x).skew()[0]
            elif(len(df[df[feature]>0])):
                print("Feature contains all positive values")
                skew_series['log'] =  st.skew(np.log(df[feature]))
                skew_series['exp'] = st.skew(np.exp(df[feature]))
                skew_series['sqrt'] =  st.skew(np.sqrt(df[feature]))
                skew_series['cbrt'] = st.skew(np.cbrt(df[feature]))
                skew_series['boxcox'] = st.skew(st.boxcox(df[feature])[0])
                x=transformer.fit_transform(df[[feature]])
                skew_series['yeo-johnson']=pd.DataFrame(x).skew()[0]
            else:
                print("Invalid values found! check value counts")
            df_trans.insert(loc=0, column='Skewness', value=skew_series)
            display(df_trans.T)
            best_trans = df_trans[np.abs(df_trans['Skewness'])==np.abs(df_trans['Skewness']
            print('Skewness best reduced with:',best_trans)
            if(best_trans=='log'):
                df[feature]=np.log(df[feature])
            if(best_trans=='exp'):
                df[feature]=np.exp(df[feature])
            if(best_trans=='sqrt'):
                df[feature]=np.sqrt(df[feature])
            if(best_trans=='cbrt'):
                df[feature]=np.cbrt(df[feature])
            if(best_trans=='boxcox'):
                df[feature]=st.boxcox(df[feature])[0]
            if(best_trans=='yeo-johnson'):
                df[feature]=transformer.fit_transform(df[[feature]])

    # create histograms for each numerical feature
    fig, axs = plt.subplots(nrows=8, ncols=3, figsize=(15,30))
    for feature, ax in zip(numerical_columns, axs.flatten()):
        sns.set_theme(style="whitegrid")
        ax.hist(df[feature], bins=50, rwidth=0.8, color= random.choice(color_codes))
        ax.set_title(feature,fontsize=13)
        plt.suptitle("After transformation, distributions",fontsize=20)
    plt.show()
    return df
##-------------------------------------------------------------------------------------
# define function to treat outliers
```

```
def treat_outliers(df, plot=False):
    print(style.BOLD+style.RED+"Visualizing boxplots after outlier treatment"+style.END)

    # apply flooring and capping
    for feature in numerical_columns:
        lowerlimit = df[feature].quantile(0.05)
        upperlimit = df[feature].quantile(0.95)
        df[feature] = np.where(df[feature] < lowerlimit, lowerlimit,df[feature])
        df[feature] = np.where(df[feature] > upperlimit, upperlimit,df[feature])

    # check outliers presence using boxplot
    if(plot==True):
        fig, axs = plt.subplots(nrows=6, ncols=4, figsize=(25,20))
        # create boxplot for each numerical column
        for feature, ax in zip(numerical_columns, axs.flatten()):
            df[feature].plot(kind='box',ax =ax, color='magenta',grid=True,fontsize=15)
        plt.suptitle("Box plots to identify outliers in numerical features",fontsize=20)
        plt.show()
    return df

##-------------------------------------------------------------------------------------------
# define function to encode features
def encode_variables(df):
    # select label encode columns ( columns which have binary values )
    label_encode_columns = ['FLAG_OWN_CAR','FLAG_OWN_REALTY','NAME_CONTRACT_TYPE','CODE_GEN
    # select ordinal encode columns
    ordinal_encode_columns = ['NAME_EDUCATION_TYPE']
    # select dummy encode columns
    global dummy_encode_columns
    dummy_encode_columns = ['NAME_TYPE_SUITE','NAME_INCOME_TYPE','NAME_FAMILY_STATUS',
                            'NAME_HOUSING_TYPE','WEEKDAY_APPR_PROCESS_START','OCCUPATION_TYP
                             'ORGANIZATION_TYPE','CATEGORY_AGE','CATEGORY_INCOME','CATEGORY_
    ##-------------------------------------------------------------------------------------
    ''' LABEL ENCODING '''
    # create an instance of LabelEncoder
    le = LabelEncoder()
    # encode each feature
    for feature in label_encode_columns:
        df[feature] = le.fit_transform(df[feature])
    ##-------------------------------------------------------------------------------------
    ''' ORDINAL ENCODING '''
    # create education type dictionary for ordinal encoding
    education_dict = {'Lower secondary':1,'Secondary / secondary special':2,'Incomplete hig
                      'Higher education':4,"Academic degree":5}
    # perform ordinal encoding
    df['NAME_EDUCATION_TYPE'] = df['NAME_EDUCATION_TYPE'].map(education_dict)
    ##-------------------------------------------------------------------------------------
    ''' DUMMY ENCODING '''
    # apply get_dummies on features
    df_dummy= pd.get_dummies(df[dummy_encode_columns], drop_first=True, prefix_sep='_dummy_
    ##-------------------------------------------------------------------------------------
    # drop original columns which were dummy encoded
    df.drop(dummy_encode_columns, axis=1, inplace=True)

    # concat dummy encoded dataframe and df
    df = pd.concat([df,df_dummy], axis=1)
    print(style.BOLD+style.RED+"Encoding finished"+style.END)

    # update numerical and categorical columns lists
    categorize_features(df)
    print("Encoding Result")
```

```
    display(df.head())
    print("Shape after encoding:", df.shape)
    return df
##--------------------------------------------------------------------------------------------
# define function to perform SMOTE
def apply_SMOTE(df):
    print(style.BOLD+style.RED+"Applying Synthetic Minority Oversampling Technique"+style.E
    # set figuresize
    plt.figure(figsize=(10,6))
    # create pie chart
    plt.subplot(1, 2, 1)
    plt.pie(df['TARGET'].value_counts(),autopct ='% 1.1f %%',shadow = True, explode = [0,0.
    plt.title("Before SMOTE on TARGET", fontdict={'fontsize':20})

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

    # create instance of smote
    smot = SMOTE(sampling_strategy=0.65,random_state=10)

    # fit and resample
    X_smot, y_smot = smot.fit_resample(X,y)

    # concat independent and dependent variables from SMOTE results
    df = pd.concat([X_smot, y_smot], axis=1)

    # create pie chart
    plt.subplot(1, 2, 2)
    plt.pie(df['TARGET'].value_counts(),autopct ='% 1.1f %%',shadow = True, explode = [0,0.
    plt.title("After SMOTE on TARGET", fontdict={'fontsize':20})
    plt.show()

    # select target variable after smote for later use
    global target_after_smote
    target_after_smote = y_smot
    return df
##--------------------------------------------------------------------------------------------
# define function to scale data
''' Scale numerical data'''
def scale_data(df, scale_only_numeric_cols=False):
    # df => source dataframe to select features for scaling
    # scale_only_numeric_feats => boolean to apply scaling on numerical features or all ind

    # initialize the standard scalar
    scaler = StandardScaler()

    if(scale_only_numeric_cols):
        # create list to select binary columns to start with string
        binary_like_list = ['NAME_TYPE_SUITE','NAME_INCOME_TYPE','NAME_CONTRACT_TYPE','NAME
                            'NAME_HOUSING_TYPE','WEEKDAY_APPR_PROCESS_START','OCCUPATION_TYP
                             'ORGANIZATION_TYPE','CATEGORY_','TARGET','FLAG_','CODE_GENDER']
        # select columns with binary values
        binary_columns = [feature for feature in df.columns for string in binary_like_list

        # select columns with non-binary values
        non_binary_columns = set(df.columns)-set(binary_columns)

        # filter the numerical features in the dataset
        df_num = df[non_binary_columns]

        # check first five observations of non-binary columns
```

```
        print("Numerical Independent Features")
        display(df_num.head())

        # select dummy encoded data
        df_cat = df[binary_columns]

        # check first five observations of binary columns
        print("Categorical Independent Features")
        display(df_cat.head())

        # scale all the numerical columns
        num_scaled = scaler.fit_transform(df_num)

        # create a dataframe of scaled numerical variables
        global df_numerical_scaled
        df_numerical_scaled = pd.DataFrame(num_scaled, columns = df_num.columns)
        df_scale_result = pd.concat([df_numerical_scaled, df_cat], axis = 1)
        print("Scaling Result")
        display(df_scale_result.head())
        print('Shape after scaling:', df_scale_result.shape)
        return df_scale_result
    else:
        # select all independent features
        df_features  = df.drop('TARGET', axis=1)

        # scale all the numerical columns
        num_scaled = scaler.fit_transform(df_features)

        # create a dataframe of scaled numerical variables
        df_scaled = pd.DataFrame(num_scaled, columns = df_features.columns)

        # concat TARGET variable
        target = df['TARGET']
        df_scale_result = pd.concat([df_scaled, target], axis = 1)
        print("Scaling Result")
        display(df_scale_result.head())
        print('Shape after scaling:', df_scale_result.shape)
        return df_scale_result
##-------------------------------------------------------------------------------------------
# define function to perform feature engineering process
# df  : input dataframe to perform feature engineering
def do_feature_engineering(df):
    df = cleanse_dataset(df)
    df = rectify_features(df)
    df = treat_null_values(df)
    df = transform_data(df,transform=True)
    df = treat_outliers(df, plot=True)
    df = encode_variables(df)
    df = apply_SMOTE(df)
    df = scale_data(df,scale_only_numeric_cols=True)

    # update numerical and categorical columns lists
    categorize_features(df)
    print(style.BOLD+style.RED+"**** Feature engineering completed ****"+style.END)
    return df
##-------------------------------------------------------------------------------------------
# call the function to perform feature engineering
# initialize 'df_application' with raw data
df_application = fetch_raw_data()
df_application = do_feature_engineering(df_application)
# display first five observations
```

```
print("Result:")
display(df_application.head())
print('Shape of dataset:', df_application.shape)
```

Cleansing the dataset

```
Shape before dropping columns having more than 40% missing data: (307511, 12
1)
Missing value Percentage
```

	COMMONAREA_MEDI	COMMONAREA_AVG	COMMONAREA_MODE	NONLIVINGAPARTMENTS_
0	69.872297	69.872297	69.872297	69.4

```
No.of columns with more than 40% missing values: 49
Shape after dropping columns having more than 40% missing data: (307511, 72)
No.of duplicates in the data: 0
Total number of categorical features after cleansing the data:  49
Total number of numerical features after cleansing the data:  23
```

Logs during feature rectification process:

```
No.of.classes in ORGANIZATION_TYPE before clubbing levels: 58
```

	Business Entity Type 3	XNA	Self-employed	Other	Medicine	Business Entity Type 2	Government	S
ORGANIZATION_TYPE	67992	55374	38412	16683	11193	10553	10404	

```
No.of.classes in ORGANIZATION_TYPE after clubbing levels: 15
```

	Business_Entity	XNA	Self-employed	Official	Other	Education	Trade	In
ORGANIZATION_TYPE	84529	55374	38412	31568	19680	17100	14315	

```
No.of.classes in OCCUPATION_TYPE before clubbing levels: 19
```

	Laborers	Sales staff	Core staff	Managers	Drivers	High skill tech staff	Accountants	Medicine staff
OCCUPATION_TYPE	55186	32102	27570	21371	18603	11380	9813	8537

```
No.of.classes in OCCUPATION_TYPE after clubbing levels: 11
```

	Laborers	Sales staff	Core staff	Low_skill_staff	Managers	Drivers	High_skill_staf
OCCUPATION_TYPE	55186	32102	27570	23413	21371	18603	1190

```
No.of.classes in NAME_INCOME_TYPE before clubbing levels: 8
```

	Working	Commercial associate	Pensioner	State servant	Unemployed	Student	Busine
NAME_INCOME_TYPE	158774	71617	55362	21703	22	18	

No.of.classes in NAME_INCOME_TYPE after clubbing levels: 4

	Working	Commercial associate	Pensioner	State servant
NAME_INCOME_TYPE	158774	71627	55389	21721

```
Correlation between the feature SCORE_DOCUMENT_SUBMISSION and TARGET 0.03015
619952371004
365243 in DAYS_EMPLOYED replaced with NaNs
No.of.observations having unavailable gender information 4
No.of.observations having unavailable family status 2
Shape of the data (307505, 60)
```

Null Value Imputation

```
Columns with standard missing values: ['AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NA
ME_TYPE_SUITE', 'DAYS_EMPLOYED', 'OCCUPATION_TYPE', 'EXT_SOURCE_2', 'EXT_SOU
RCE_3', 'DEF_30_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_P
HONE_CHANGE', 'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AM
T_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BURE
AU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR', 'CATEGORY_DEF_30_60_SOCIAL_CIRCLE',
 'SCORE_EXT_SOURCE', 'RATIO_AMTCREDIT_AMTANNUITY', 'RATIO_DAYSEMPLOYED_DAYSB
IRTH', 'RATIO_AMTCREDIT_AMTGOODSPRICE', 'RATIO_AMTINCOMETOTAL_DAYSEMPLOYED',
'RATIO_AMTANNUITY_AMTINCOMETOTAL', 'RATIO_LASTPHONECHANGE_DAYSBIRTH']

Total number of missing values before treatment:  578418
Columns with standard missing values: []
Total number of missing values after treatment:  0

Shape of the data (307505, 60)
```

Transformaton:

```
'Feature name is:'

'AMT_ANNUITY'

Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.579811	-0.345763	NaN	0.452116	0.172701	-0.004292	-0.004292

```
Skewness best reduced with: boxcox

'Feature name is:'

'AMT_CREDIT'

Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.234759	-0.338822	NaN	0.447113	0.194653	-0.02407	-0.024069

```
Skewness best reduced with: yeo-johnson

'Feature name is:'
```

'AMT_GOODS_PRICE'

Feature contains all positive values

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.350132	-0.293304	NaN	0.520984	0.258207	-0.017775	-0.017774

Skewness best reduced with: yeo-johnson

'Feature name is:'

'AMT_INCOME_TOTAL'

Feature contains all positive values

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	391.558872	0.169974	NaN	4.907222	1.32023	-0.008006	0.0

Skewness best reduced with: yeo-johnson

'Feature name is:'

'AMT_REQ_CREDIT_BUREAU_DAY'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	29.081293	NaN	358.355509	15.977638	14.830648	NaN	14.266207

Skewness best reduced with: yeo-johnson

'Feature name is:'

'AMT_REQ_CREDIT_BUREAU_HOUR'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	15.641835	NaN	89.197971	13.883663	13.727442	NaN	13.642749

Skewness best reduced with: yeo-johnson

'Feature name is:'

'AMT_REQ_CREDIT_BUREAU_MON'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	8.371773	NaN	552.229806	2.999297	2.361103	NaN	2.047782

Skewness best reduced with: yeo-johnson

'Feature name is:'

'AMT_REQ_CREDIT_BUREAU_QRT'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	141.400595	NaN	NaN	2.178646	1.911079	NaN	1.810353

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'AMT_REQ_CREDIT_BUREAU_WEEK'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	10.007933	NaN	211.165556	6.041765	5.835547	NaN	5.749205

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'AMT_REQ_CREDIT_BUREAU_YEAR'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.371752	NaN	538.749169	0.162879	-0.195689	NaN	0.076716

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'DAYS_BIRTH'
Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.115655	-0.300812	NaN	-0.086192	-0.156278	-0.056069	-0.056064

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'DAYS_BIRTH_AS_AGE'
Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.115117	-0.303005	15.896779	-0.087428	-0.157799	-0.05621	-0.054303

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'DAYS_EMPLOYED'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'DAYS_ID_PUBLISH'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-0.349332	NaN	NaN	-0.883493	-1.182918	NaN	-0.408665

```
Skewness best reduced with: original
'Feature name is:'
'DAYS_LAST_PHONE_CHANGE'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.713598	NaN	NaN	-0.240435	-0.761982	NaN	-0.473804

```
Skewness best reduced with: sqrt
'Feature name is:'
'DAYS_REGISTRATION'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.590862	NaN	NaN	-0.179603	-0.530903	NaN	-0.184563

```
Skewness best reduced with: sqrt
'Feature name is:'
'DEF_30_CNT_SOCIAL_CIRCLE'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	5.192485	NaN	554.528629	2.673479	2.515746	NaN	2.423645

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'DEF_60_CNT_SOCIAL_CIRCLE'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	5.286445	NaN	554.528629	3.232681	3.087049	NaN	3.004265

```
Skewness best reduced with: yeo-johnson
```

'Feature name is:'

'EXT_SOURCE_2'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-0.800069	NaN	-0.493564	-1.475729	-1.963283	NaN	-0.207997

Skewness best reduced with: yeo-johnson

'Feature name is:'

'EXT_SOURCE_3'

Feature contains all positive values

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-0.537697	-5.295623	-0.109578	-1.280021	-1.778911	-0.221808	-0.053573

Skewness best reduced with: yeo-johnson

'Feature name is:'

'HOUR_APPR_PROCESS_START'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-0.028	NaN	43.927831	-0.5374	-0.824956	NaN	-0.013831

Skewness best reduced with: yeo-johnson

'Feature name is:'

'RATIO_AMTANNUITY_AMTINCOMETOTAL'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.511643	NaN	2.794954	0.491965	0.195737	NaN	0.044421

Skewness best reduced with: yeo-johnson

'Feature name is:'

'RATIO_AMTCREDIT_AMTANNUITY'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.304106	NaN	139.967821	-0.032569	-0.163054	NaN	-0.042841

Skewness best reduced with: sqrt

'Feature name is:'

'RATIO_AMTCREDIT_AMTGOODSPRICE'

Feature contains zero(s)

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.823508	NaN	275.635565	-3.207615	-8.455748	NaN	0.227691

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'RATIO_AMTCREDIT_AMTINCOMETOTAL'
Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.835933	-0.266964	554.528629	0.676129	0.363503	-0.003996	0.011136

```
Skewness best reduced with: boxcox
'Feature name is:'
'RATIO_AMTINCOMETOTAL_DAYSBIRTH'
Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	403.960601	-0.06123	NaN	4.048352	0.972815	0.002143	-0.002121

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'RATIO_AMTINCOMETOTAL_DAYSEMPLOYED'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	145.324626	NaN	NaN	3.358352	0.56321	NaN	-0.050127

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'RATIO_DAYSEMPLOYED_DAYSBIRTH'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.421286	NaN	1.82928	0.171131	-0.452858	NaN	0.227648

```
Skewness best reduced with: sqrt
'Feature name is:'
'RATIO_DAYSIDPUBLISH_DAYSBIRTH'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-0.016348	NaN	0.151507	-0.712114	-1.073681	NaN	-0.024306

```
Skewness best reduced with: original
'Feature name is:'
'RATIO_LASTPHONECHANGE_DAYSBIRTH'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	0.925543	NaN	1.065014	-0.170114	-0.723962	NaN	0.14766

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'REGION_POPULATION_RELATIVE'
Feature contains all positive values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.488036	-0.565093	1.551907	0.443715	0.114943	-0.010702	0.09617

```
Skewness best reduced with: boxcox
'Feature name is:'
'SCORE_DOCUMENT_SUBMISSION'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-2.331077	NaN	-2.331065	-2.331065	-2.331065	NaN	-2.331077

```
Skewness best reduced with: sqrt
'Feature name is:'
'SCORE_EXT_SOURCE'
Feature contains zero(s)
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	-0.634181	NaN	-0.278399	-1.381751	-1.934285	NaN	-0.087224

```
Skewness best reduced with: yeo-johnson
'Feature name is:'
'SCORE_EXT_SOURCE'
Feature contains negative values
```

	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson

```
Skewness best reduced with: yeo-johnson
```

```
'Feature name is:'
```

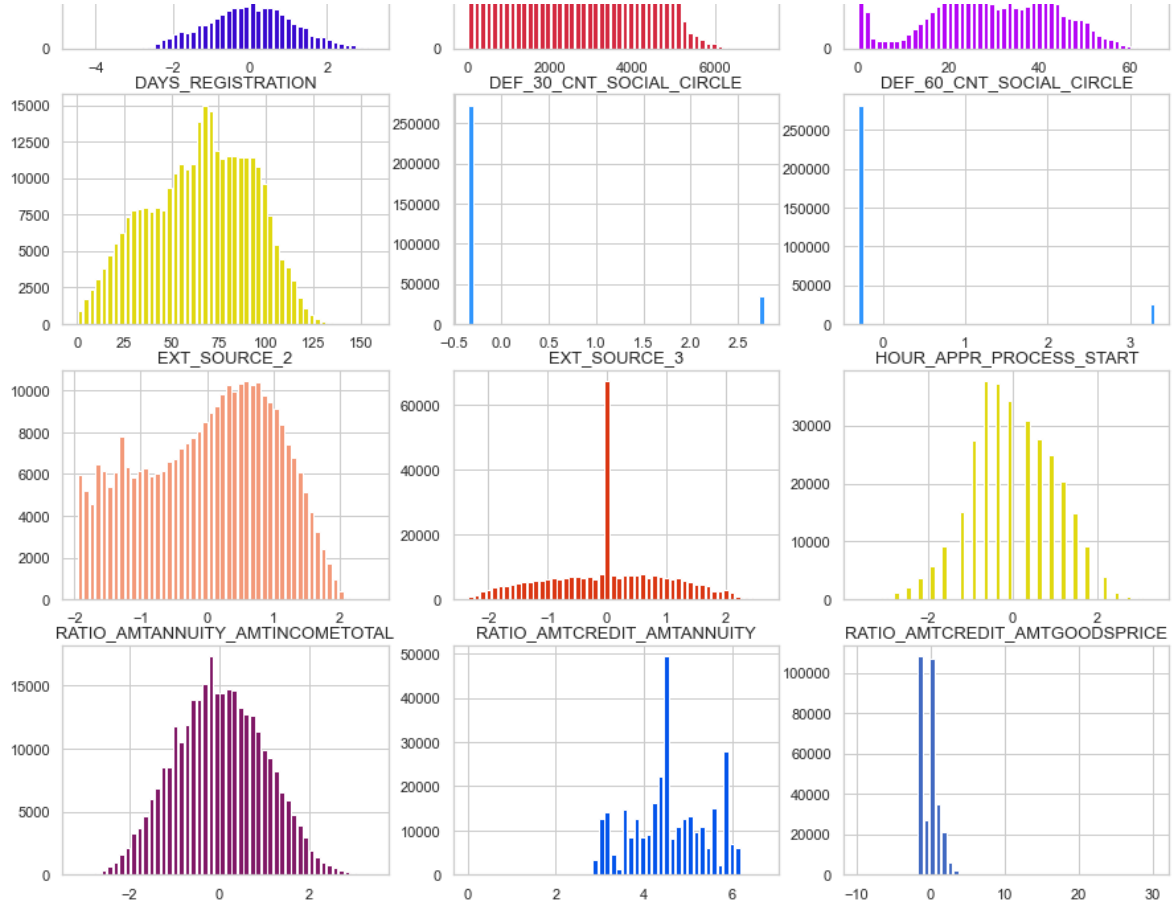
```
'SCORE_REGION'
```

```
Feature contains zero(s)
```

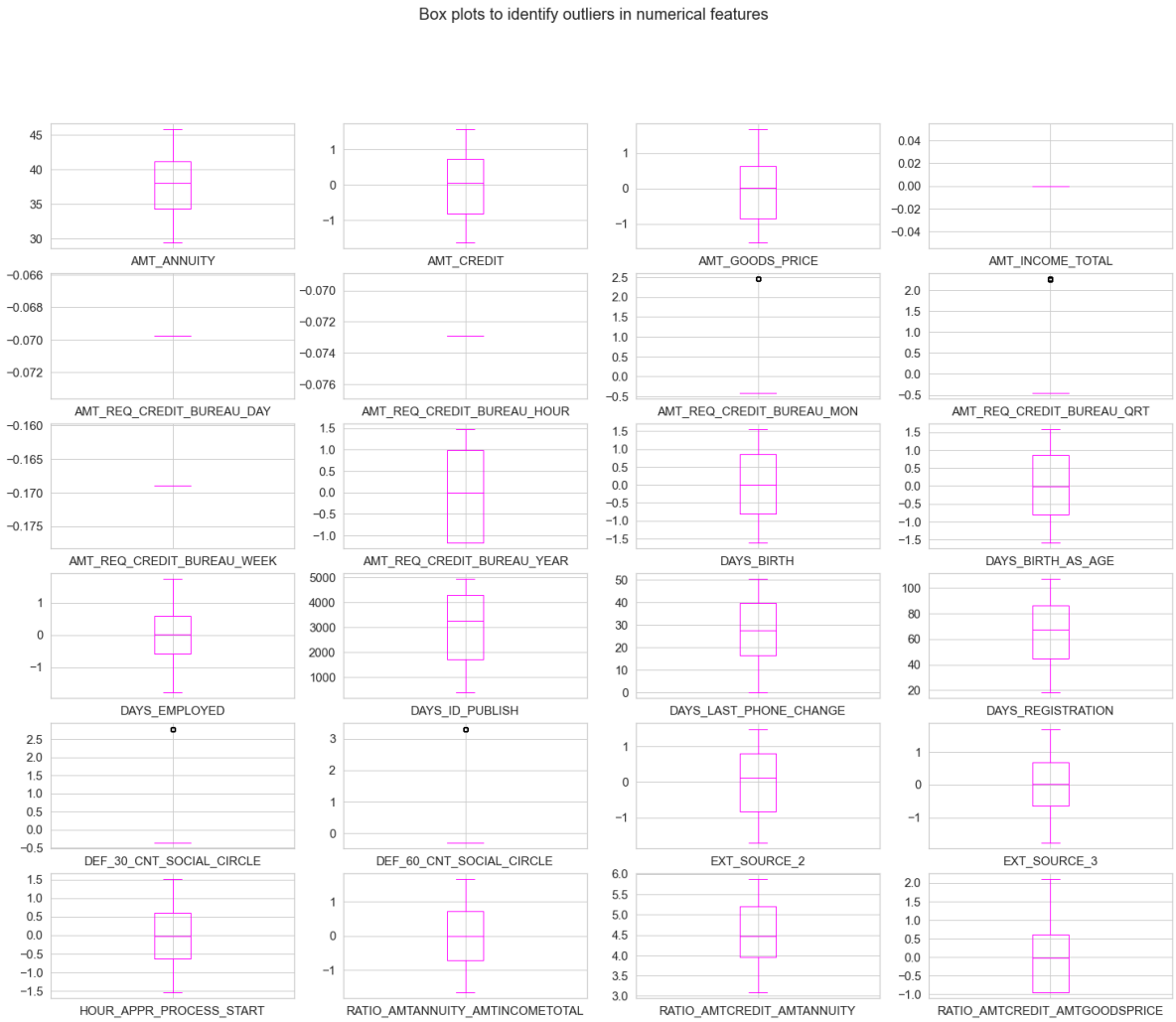
	original	log	exp	sqrt	cbrt	boxcox	yeo-johnson
Skewness	1.717836	NaN	13.958651	1.228885	1.157683	NaN	1.11117

```
Skewness best reduced with: yeo-johnson
```

After transformation, distributions



Visualizing boxplots after outlier treatment



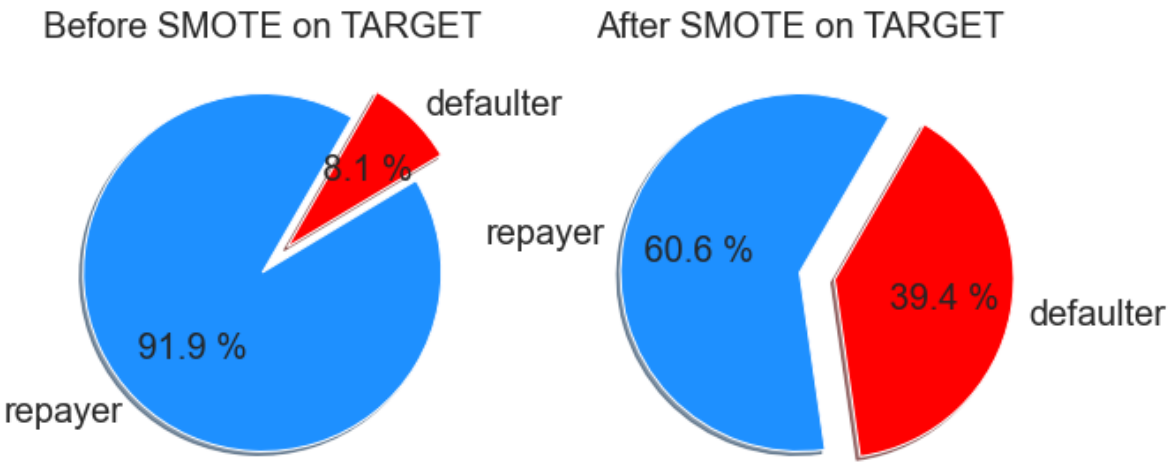
Encoding finished

Encoding Result

	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	1	0	1	0	1
1	0	0	0	0	0
2	0	1	1	1	1
3	0	0	0	0	1
4	0	0	1	0	1

Shape after encoding: (307505, 103)

Applying Synthetic Minority Oversampling Technique



Numerical Independent Features

	SCORE_EXT_SOURCE	AMT_GOODS_PRICE	DEF_30_CNT_SOCIAL_CIRCLE	RATIO_LASTPHON
0	-1.654763	-0.324484	2.782683	
1	0.683199	1.434248	-0.359329	
2	0.854598	-1.534465	-0.359329	
3	0.920578	-0.549760	-0.359329	
4	-1.206002	0.210496	-0.359329	

Categorical Independent Features

	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	FLAG_
0	0	1	0	1	
1	0	0	0	0	
2	1	1	1	1	
3	0	0	0	1	
4	0	1	0	1	

Scaling Result

	SCORE_EXT_SOURCE	AMT_GOODS_PRICE	DEF_30_CNT_SOCIAL_CIRCLE	RATIO_LASTPHON
0	-1.545038	-0.354936	2.857940	
1	0.966819	1.681382	-0.394927	
2	1.150966	-1.755892	-0.394927	
3	1.221854	-0.615768	-0.394927	
4	-1.062898	0.264481	-0.394927	

Shape after scaling: (466422, 103)
**** Feature engineering completed ****
Result:

	SCORE_EXT_SOURCE	AMT_GOODS_PRICE	DEF_30_CNT_SOCIAL_CIRCLE	RATIO_LASTPHON
0	-1.545038	-0.354936	2.857940	
1	0.966819	1.681382	-0.394927	
2	1.150966	-1.755892	-0.394927	
3	1.221854	-0.615768	-0.394927	
4	-1.062898	0.264481	-0.394927	

Shape of dataset: (466422, 103)
Wall time: 1min 12s

3) FEATURE SELECTION

In [4]:

```
%%time
''' Low Variance Removal => Remove low variance columns'''
def perform_VaianceThreshold(df_VT, df_VT_fit):
    ## df_VT => dataframe from which low variance columns to be dropped
    ## df_VT_fit => dataframe to fit into VarianceThreshold() object
    var_thres=VarianceThreshold(threshold=0.1)
    var_thres.fit(df_VT_fit)

    global VT_dropped_cols
    VT_dropped_cols = []
    for col in df_VT_fit.columns:
        if col not in df_VT_fit.columns[var_thres.get_support()]:
            VT_dropped_cols.append(col)

    df_VT.drop(VT_dropped_cols, axis=1, inplace=True)
    print("Columns dropped with Low Variance:",VT_dropped_cols)
    return df_VT

# call the function perform_VaianceThreshold()
df_application_VT_scaled = perform_VaianceThreshold(df_application, df_numerical_scaled)
print('Shape of dataset:', df_application_VT_scaled.shape)
```

```
Columns dropped with Low Variance: ['AMT_INCOME_TOTAL', 'AMT_REQ_CREDIT_BURE
AU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK']
Shape of dataset: (466422, 99)
Wall time: 301 ms
```

In [6]:

```
%%time
''' VIF => Remove features with muticollinearity'''
def perform_VIF(df):
    # df => source dataframe to apply VIF on
    print('Shape of the dataset before VIF:',df.shape)
    global df_numeric_features_vif
    df_numeric_features_vif = df.drop("TARGET", axis=1)

    # for each numeric variable, calculate VIF and save it in a dataframe 'vif'

    # use for loop to iterate the VIF function
    for ind in range(len(df_numeric_features_vif.columns)):

        # create an empty dataframe
        vif = pd.DataFrame()

        # calculate VIF using list comprehension
        vif["VIF_Factor"] = [variance_inflation_factor(df_numeric_features_vif.values, i) f

        # create a column of variable names
        vif["Features"] = df_numeric_features_vif.columns

        # filter the variables with VIF greater than 2.5 and store it in a dataframe 'multi
        multi = vif[vif['VIF_Factor'] > 2.5]

        # if dataframe 'multi' is not empty, then sort the dataframe by VIF values
        if(multi.empty == False):
            df_sorted = multi.sort_values(by = 'VIF_Factor', ascending = False)
        else:
            print(vif)
            break

        # use if-else to drop the variable with the highest VIF
        if (df_sorted.empty == False):
            df_numeric_features_vif = df_numeric_features_vif.drop(df_sorted.Features.iloc[
        else:
            print(vif)

    # select TAEGET variable
    target = df['TARGET']
    # create vif result dataframe
    df_VIF_result = pd.concat([df_numeric_features_vif,target], axis=1)
    # export to CSV
    df_VIF_result.to_csv('df_VIF_num_scaled.csv',index = False)
    return df_VIF_result

# boolean to perform VIF only when the VIF dataset is not available
# set the vaue to True to execute perform_VIF()
dataset_notavailable = False
if(dataset_notavailable):
    # pass doVIF=True as parameter only if VIF has to be performed
    df_application_VIF = perform_VIF(df_application_VT_scaled)
else:
    df_application_VIF = pd.read_csv('df_VIF_num_scaled.csv')

print("Shape of dataset after VIF:",df_application_VIF.shape)

# display first five observations
display(df_application_VIF.head())
```

```
Shape of dataset after VIF: (466422, 73)
```

	SCORE_REGION	NAME_EDUCATION_TYPE	HOUR_APPR_PROCESS_START	RATIO_DAYSIDPU
0	-0.664832	-0.497960	-0.718030	
1	-0.664832	2.051877	-0.359337	
2	-0.664832	-0.497960	-1.076105	
3	-0.664832	-0.497960	1.803420	
4	1.704853	-0.497960	-0.359337	

```
Wall time: 4.43 s
```

4) MODELLING

LOGISTIC REGRESSION

In [2]:

```
# read the dataset
df_application_VIF = pd.read_csv('df_VIF_num_scaled.csv')
```

Obtain top 30 significant features

In [3]:

```
%%time
''' RFE '''
# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# initiate logistic regression model to use in feature selection
rfe_logreg = LogisticRegression()

# build the RFE model
rfe_model = RFE(estimator = rfe_logreg, n_features_to_select=30)

# fit the RFE model on the training dataset using fit()
rfe_model = rfe_model.fit(X_train, y_train)

# create a series containing feature and its corresponding rank obtained from RFE
feat_index = pd.Series(data = rfe_model.ranking_, index = X_train.columns)

# select the features with rank = 1
best_features_LR = list(feat_index[feat_index==1].index)

# print the significant features obtained from RFE
print("Top features selected by LogisticRegression:", best_features_LR, sep='\n')
```

```
Top features selected by LogisticRegression:
['FLAG_EMAIL', 'NAME_TYPE_SUITE_dummy_Family', 'NAME_TYPE_SUITE_dummy_Other_
A', 'NAME_TYPE_SUITE_dummy_Spouse, partner', 'NAME_FAMILY_STATUS_dummy_Separ
ated', 'NAME_FAMILY_STATUS_dummy_Widow', 'NAME_HOUSING_TYPE_dummy_Municipal
apartment', 'NAME_HOUSING_TYPE_dummy_Office apartment', 'WEEKDAY_APPR_PROCES
S_START_dummy_MONDAY', 'WEEKDAY_APPR_PROCESS_START_dummy_SATURDAY', 'WEEKDAY
_APPR_PROCESS_START_dummy_SUNDAY', 'WEEKDAY_APPR_PROCESS_START_dummy_THURSDA
Y', 'WEEKDAY_APPR_PROCESS_START_dummy_TUESDAY', 'WEEKDAY_APPR_PROCESS_START_
dummy_WEDNESDAY', 'OCCUPATION_TYPE_dummy_High_skill_staff', 'OCCUPATION_TYPE
_dummy_Managers', 'OCCUPATION_TYPE_dummy_Others', 'ORGANIZATION_TYPE_dummy_C
onstruction', 'ORGANIZATION_TYPE_dummy_Education', 'ORGANIZATION_TYPE_dummy_
Finance', 'ORGANIZATION_TYPE_dummy_Industry', 'ORGANIZATION_TYPE_dummy_Offic
ial', 'ORGANIZATION_TYPE_dummy_Other', 'ORGANIZATION_TYPE_dummy_Realty', 'OR
GANIZATION_TYPE_dummy_Security', 'ORGANIZATION_TYPE_dummy_Self-employed', 'O
RGANIZATION_TYPE_dummy_TourismFoodSector', 'ORGANIZATION_TYPE_dummy_Trade',
'ORGANIZATION_TYPE_dummy_Transport', 'CATEGORY_AGE_dummy_Old']
Wall time: 3min 8s
```

Build logit model using the variables obtained from RFE.

In [4]:

```
%%time
# select best independent features
X = df_application_VIF.drop('TARGET', axis = 1)[best_features_LR]

# add a constant column to the dataframe
X = sm.add_constant(X)

# select target variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# build the model on train data (X_train and y_train)
logreg = sm.Logit(y_train, X_train).fit()

# print the summary of the model
print(logreg.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.375987
         Iterations 7
                           Logit Regression Results
==============================================================================
==
Dep. Variable:                 TARGET   No. Observations:               3731
37
Model:                          Logit   Df Residuals:                   3731
06
Method:                           MLE   Df Model:
30
Date:                Thu, 04 Nov 2021   Pseudo R-squ.:                   0.43
91
Time:                        22:55:50   Log-Likelihood:            -1.4029e+
05
converged:                       True   LL-Null:                   -2.5013e+
05
Covariance Type:            nonrobust   LLR p-value:                     0.0
00
==============================================================================
==================================
                                                 coef    std err          z
P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
----------------------------------
const                                          2.0846      0.008    248.216
0.000       2.068       2.101
FLAG_EMAIL                                    -1.3060      0.033    -40.053
0.000      -1.370      -1.242
NAME_TYPE_SUITE_dummy_Family                  -1.1815      0.020    -58.808
0.000      -1.221      -1.142
NAME_TYPE_SUITE_dummy_Other_A                 -1.3311      0.146     -9.137
0.000      -1.617      -1.046
NAME_TYPE_SUITE_dummy_Spouse, partner         -1.4729      0.041    -36.285
0.000      -1.552      -1.393
NAME_FAMILY_STATUS_dummy_Separated             -1.1784      0.029    -40.291
0.000      -1.236      -1.121
NAME_FAMILY_STATUS_dummy_Widow                -1.2282      0.036    -33.715
0.000      -1.300      -1.157
```

```
NAME_HOUSING_TYPE_dummy_Municipal apartment    -1.1356      0.040    -28.299
0.000      -1.214      -1.057
NAME_HOUSING_TYPE_dummy_Office apartment       -1.4496      0.098    -14.836
0.000      -1.641      -1.258
WEEKDAY_APPR_PROCESS_START_dummy_MONDAY        -2.4442      0.017   -147.809
0.000      -2.477      -2.412
WEEKDAY_APPR_PROCESS_START_dummy_SATURDAY      -2.5386      0.020   -125.058
0.000      -2.578      -2.499
WEEKDAY_APPR_PROCESS_START_dummy_SUNDAY        -2.8115      0.031    -89.725
0.000      -2.873      -2.750
WEEKDAY_APPR_PROCESS_START_dummy_THURSDAY      -2.3657      0.016   -146.474
0.000      -2.397      -2.334
WEEKDAY_APPR_PROCESS_START_dummy_TUESDAY       -2.3213      0.016   -149.727
0.000      -2.352      -2.291
WEEKDAY_APPR_PROCESS_START_dummy_WEDNESDAY     -2.3279      0.016   -147.589
0.000      -2.359      -2.297
OCCUPATION_TYPE_dummy_High_skill_staff         -1.8594      0.044    -41.802
0.000      -1.947      -1.772
OCCUPATION_TYPE_dummy_Managers                 -1.7029      0.031    -54.222
0.000      -1.764      -1.641
OCCUPATION_TYPE_dummy_Others                   -1.4923      0.094    -15.851
0.000      -1.677      -1.308
ORGANIZATION_TYPE_dummy_Construction           -1.7359      0.046    -37.919
0.000      -1.826      -1.646
ORGANIZATION_TYPE_dummy_Education              -2.4687      0.035    -70.301
0.000      -2.538      -2.400
ORGANIZATION_TYPE_dummy_Finance                -2.8854      0.096    -30.183
0.000      -3.073      -2.698
ORGANIZATION_TYPE_dummy_Industry               -2.0304      0.034    -60.599
0.000      -2.096      -1.965
ORGANIZATION_TYPE_dummy_Official               -2.2338      0.024    -92.592
0.000      -2.281      -2.187
ORGANIZATION_TYPE_dummy_Other                  -2.0970      0.029    -72.014
0.000      -2.154      -2.040
ORGANIZATION_TYPE_dummy_Realty                 -2.1104      0.076    -27.867
0.000      -2.259      -1.962
ORGANIZATION_TYPE_dummy_Security               -2.0883      0.070    -29.638
0.000      -2.226      -1.950
ORGANIZATION_TYPE_dummy_Self-employed          -1.5784      0.017    -91.167
0.000      -1.612      -1.544
ORGANIZATION_TYPE_dummy_TourismFoodSector      -2.2907      0.065    -35.178
0.000      -2.418      -2.163
ORGANIZATION_TYPE_dummy_Trade                  -1.9856      0.032    -61.792
0.000      -2.049      -1.923
ORGANIZATION_TYPE_dummy_Transport              -1.9745      0.041    -48.425
0.000      -2.054      -1.895
CATEGORY_AGE_dummy_Old                         -1.7815      0.015   -118.764
0.000      -1.811      -1.752
================================================================================
==================================
Wall time: 6.32 s
```

In [5]:

```
%%time
# 'aic' retuns the AIC value for the model
print('AIC:', logreg.aic)
```

```
AIC: 280651.1209686509
Wall time: 1.99 ms
```

Find out the best cut-off value

In [8]:

```
%%time
# create an empty dataframe to store the scores for various algorithms
score_card = pd.DataFrame(columns=['Probability Cutoff', 'AUC Score', 'Precision Score', 'R
                                   'Accuracy Score', 'Kappa Score', 'f1-score'])

# append the result table for all performance scores
def update_score_card(model, cutoff):

    # let 'y_pred_prob' be the predicted values of y
    y_pred_prob = logreg.predict(X_test[['const']+best_features_LR])

    # convert probabilities to 0 and 1 using 'if_else'
    y_pred = [ 0 if x < cutoff else 1 for x in y_pred_prob]

    # assign 'score_card' as global variable
    global score_card

    # append the results to the dataframe 'score_card'
    # 'ignore_index = True' do not consider the index labels
    score_card = score_card.append({'Probability Cutoff': cutoff,
                                    'AUC Score' : metrics.roc_auc_score(y_test, y_pred),
                                    'Precision Score': metrics.precision_score(y_test, y_pr
                                    'Recall Score': metrics.recall_score(y_test, y_pred),
                                    'Accuracy Score': metrics.accuracy_score(y_test, y_pred
                                    'Kappa Score':metrics.cohen_kappa_score(y_test, y_pred)
                                    'f1-score': metrics.f1_score(y_test, y_pred)},
                                    ignore_index = True)
```

```
Wall time: 1.99 ms
```

In [9]:

```
# consider a list of values for cut-off
cutoff = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]

# use the for loop to compute performance measures for each value of the cut-off
for value in cutoff:
    update_score_card(logreg, value)
```

In [13]:

```
%%time
# print the score card
print('Score Card for Logistic regression:')

# sort the dataframe based on the probability cut-off values ascending order
score_card = score_card.sort_values('Probability Cutoff').reset_index(drop = True)

# color the cell in the columns 'AUC Score','Precision Score', 'Accuracy Score','Recall Sco
score_card.style.highlight_max(color = 'lightblue', subset = ['AUC Score','Precision Score'
```

```
Score Card for Logistic regression:
Wall time: 999 µs
```

Out[13]:

	Probability Cutoff	AUC Score	Precision Score	Recall Score	Accuracy Score	Kappa Score	f1-score
0	0.100000	0.715557	0.548152	0.934917	0.669625	0.384182	0.691103
1	0.200000	0.806215	0.676012	0.891854	0.788283	0.580348	0.769076
2	0.300000	0.816673	0.696946	0.884884	0.802391	0.605096	0.779751
3	0.400000	0.824403	0.722270	0.866661	0.815554	0.627100	0.787905
4	0.500000	0.831586	0.852357	0.747858	0.849118	0.677555	0.796695
5	0.600000	0.825132	0.902336	0.699778	0.851380	0.676560	0.788252
6	0.700000	0.820298	0.928089	0.674775	0.850769	0.672370	0.781415
7	0.800000	0.816071	0.942508	0.658396	0.849086	0.666950	0.775241
8	0.900000	0.500000	0.000000	0.000000	0.604695	0.000000	0.000000

Do predictions on the test set.

In [17]:

```
%%time
# let 'y_pred_prob' be the predicted values of y
y_pred_prob = logreg.predict(X_test[['const']+best_features_LR])

# print the y_pred_prob
y_pred_prob.head()
```

```
Wall time: 32.9 ms
```

Out[17]:

```
419907    0.889392
162210    0.125866
147737    0.012431
207924    0.037456
26261     0.051040
dtype: float64
```

In [18]:

```
%%time
# convert probabilities to 0 and 1 using 'if_else'
y_pred = [ 0 if x < 0.5 else 1 for x in y_pred_prob]
```

```
Wall time: 20.9 ms
```

In [19]:

```
%%time
# print the first five observations of y_pred
y_pred[0:5]
```

```
Wall time: 0 ns
```

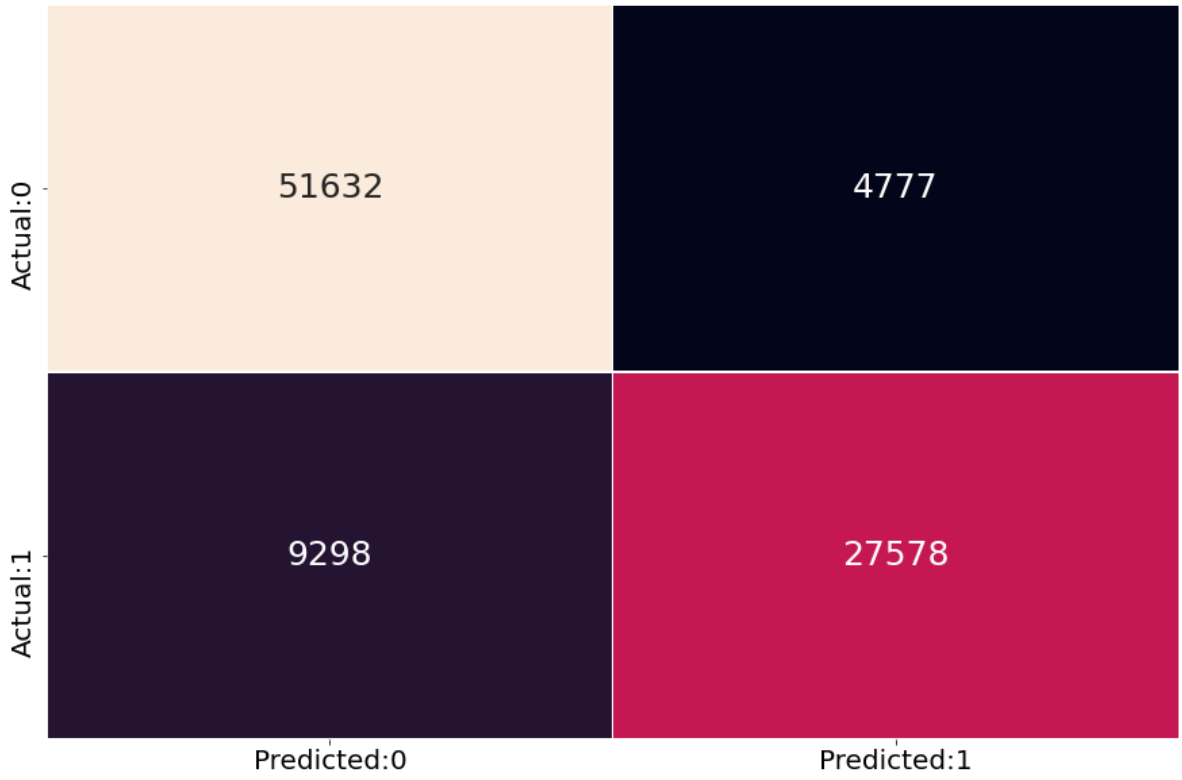
Out[19]:

```
[1, 0, 0, 0, 0]
```

Plot the confusion matrix.

In [20]:

```
%%time
# create a confusion matrix
cm = confusion_matrix(y_test, y_pred)

# label the confusion matrix
conf_matrix = pd.DataFrame(data = cm,columns = ['Predicted:0','Predicted:1'], index = ['Act

# plot a heatmap to visualize the confusion matrix
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})

# set the font size of x-axis ticks using 'fontsize'
plt.xticks(fontsize = 20)

# set the font size of y-axis ticks using 'fontsize'
plt.yticks(fontsize = 20)

# display the plot
plt.show()
```




```
Wall time: 282 ms
```

Compute the performance measures.

In [21]:

```
%%time
# True Negatives are denoted by 'TN'
# Actual 'O' values which are classified correctly
TN = cm[0,0]

# True Positives are denoted by 'TP'
# Actual '1' values which are classified correctly
TP = cm[1,1]

# False Positives are denoted by 'FP'
# it is the type 1 error
# Actual 'O' values which are classified wrongly as '1'
FP = cm[0,1]

# False Negatives are denoted by 'FN'
# it is the type 2 error
# Actual '1' values which are classified wrongly as '0'
FN = cm[1,0]


# calculate the precision value
precision = TP / (TP+FP)
print('precision:',precision)

# calculate the recall value
recall = TP / (TP+FN)
# print the value
print('recall:',recall)

# calculate the specificity value
specificity = TN / (TN+FP)
# print the value
print('specificity:',specificity)

# calculate the FPR value (1-Specificity)
FPR = FP / (FP+TN)
# print the value
print('False positive rate:',FPR)
```

```
precision: 0.8523566682120228
recall: 0.7478576852153161
specificity: 0.9153149320143948
False positive rate: 0.08468506798560513
```

In [22]:

```
%%time
# performance measures obtained by classification_report()
result = classification_report(y_test, y_pred)

# print the result
print(result)
```

```
              precision    recall  f1-score   support

           0       0.85      0.92      0.88     56409
           1       0.85      0.75      0.80     36876

    accuracy                           0.85     93285
   macro avg       0.85      0.83      0.84     93285
weighted avg       0.85      0.85      0.85     93285

Wall time: 176 ms
```

In [23]:

```
%%time
# compute the kappa value
kappa = cohen_kappa_score(y_test, y_pred)

# print the kappa value
print('kappa value:',kappa)
```

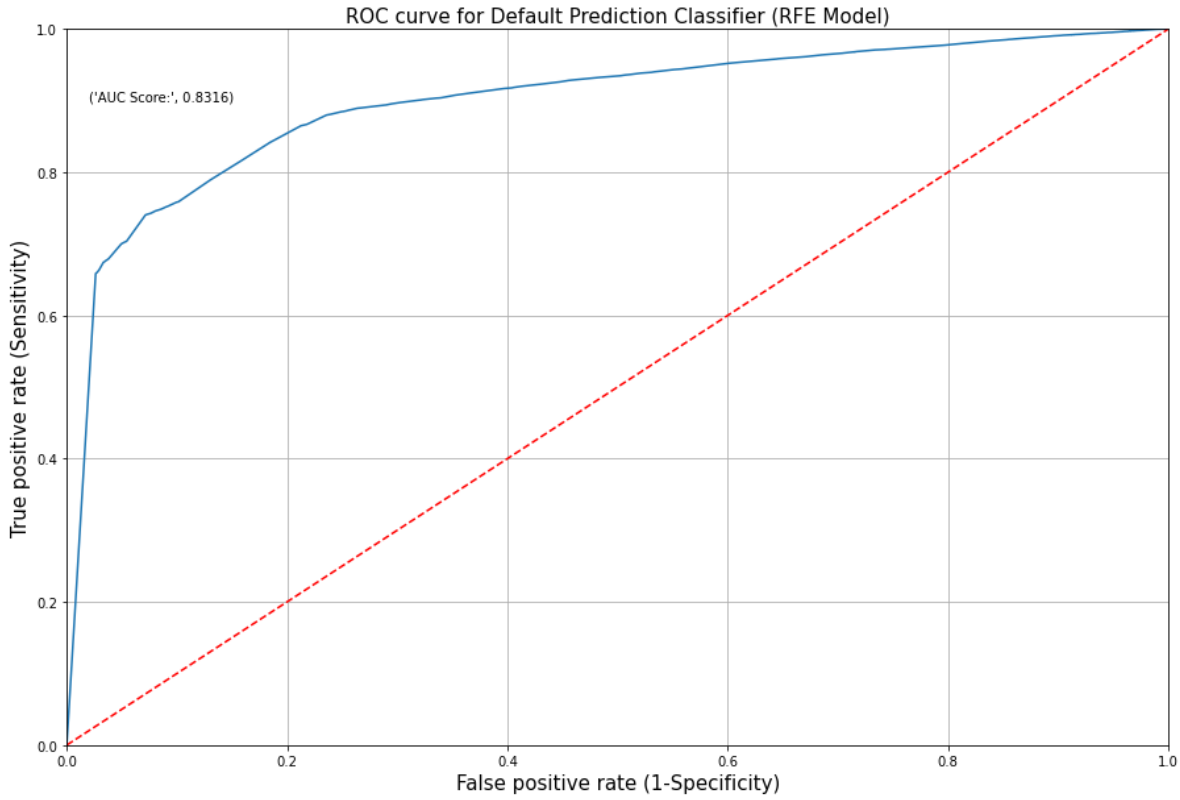
```
kappa value: 0.6775548296780214
Wall time: 127 ms
```

Plot the ROC curve.

In [32]:

```
%%time
# the roc_curve() returns the values for false positive rate, true positive rate and thresh
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

# plot the ROC curve
plt.plot(fpr, tpr)

# set limits for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])

# plot the straight line showing worst prediction for the model
plt.plot([0, 1], [0, 1],'r--')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('ROC curve for Default Prediction Classifier (RFE Model)', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)

# add the AUC score to the plot
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.roc_auc_score(y_test, y_pred),

# plot the grid
plt.grid(True)
```

```
Wall time: 135 ms
```



Build the model using significant features obtained from RFE

In [25]:

```
%%time
# instantiate the 'LogisticRegression'
model_LR = LogisticRegression(random_state=10)

# fit the model using fit() on train data
model_LR = model_LR.fit(X_train[best_features_LR] , y_train)
```

```
Wall time: 2.48 s
```

Tune the Hyperparameters using GridSearchCV (Logistic Regression)

In [18]:

```
%%time
# create a dictionary with hyperparameters and its values
tuned_paramaters = [{'penalty': ['l1', 'l2'],
                     'C': np.logspace(0, 4, 10)}]

# use GridSearchCV() to find the optimal value of the hyperparameters
grid_logreg = GridSearchCV(estimator = model_LR,
                           param_grid = tuned_paramaters,
                           cv = 5,
                           verbose=0,
                           n_jobs=-1)

# fit the model on X_train and y_train using fit()
grid_model_logreg = grid_logreg.fit(X_train[best_features_LR], y_train)

# get the best parameters
print('Best parameters for decision tree classifier: ', grid_model_logreg.best_params_, '\n
```

```
Best parameters for decision tree classifier:  {'C': 1.0, 'penalty': 'l2'}

Wall time: 1min 1s
```

Build the model using the tuned hyperparameters.

In [19]:

```
%%time
# instantiate the 'LogisticRegression'
model_LR = LogisticRegression( penalty = grid_model_logreg.best_params_.get('penalty'),
                               C = grid_model_logreg.best_params_.get('C'))

# fit the model using fit() on train data
model_LR = model_LR.fit(X_train[best_features_LR],y_train)
```

```
Wall time: 3.24 s
```

Model Performance

In [20]:

```
%%time
print('Training set score: ' + str(model_LR.score(X_train[best_features_LR], y_train)))
print('Test set score: ' + str(model_LR.score(X_test[best_features_LR], y_test)))
```

```
Training set score: 0.8499157146034835
Test set score: 0.8487430991048937
Wall time: 205 ms
```

Model Evaluation

In [21]:

```
%%time
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model_LR, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)
print("Mean ROC AUC:", np.mean(scores))
```

```
Mean ROC AUC: 0.8993102845577502
Wall time: 1min 4s
```

DECISION TREE

In [30]:

```
# read the dataset
df_application_VIF = pd.read_csv('df_VIF_num_scaled.csv')
```

Obtain top 30 significant features

In [31]:

```
%%time
''' RFE '''
# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# initiate DecisionTreeClassifier model to use in feature selection
rfe_DT = DecisionTreeClassifier()

# build the RFE model
rfe_model = RFE(estimator = rfe_DT, n_features_to_select=30)

# fit the RFE model on the training dataset using fit()
rfe_model = rfe_model.fit(X_train, y_train)

# create a series containing feature and its corresponding rank obtained from RFE
feat_index = pd.Series(data = rfe_model.ranking_, index = X_train.columns)

# select the features with rank = 1
best_features_DT = feat_index[feat_index==1].index

# print the significant features obtained from RFE
print("Top features selected by DecisionTreeClassifier:", best_features_DT, sep='\n')
```

```
Top features selected by DecisionTreeClassifier:
Index(['SCORE_REGION', 'NAME_EDUCATION_TYPE', 'HOUR_APPR_PROCESS_START',
       'RATIO_DAYSIDPUBLISH_DAYSBIRTH', 'DAYS_REGISTRATION',
       'RATIO_AMTANNUITY_AMTINCOMETOTAL', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'REGION_POPULATION_RELATIVE', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'RATIO_DAYSEMPLOYED_DAYSBIRTH', 'AMT_REQ_CREDIT_BUREAU_MON',
       'RATIO_AMTCREDIT_AMTGOODSPRICE', 'DEF_30_CNT_SOCIAL_CIRCLE',
       'RATIO_AMTINCOMETOTAL_DAYSEMPLOYED', 'RATIO_AMTCREDIT_AMTANNUITY',
       'AMT_REQ_CREDIT_BUREAU_YEAR', 'SCORE_DOCUMENT_SUBMISSION',
       'DAYS_LAST_PHONE_CHANGE', 'FLAG_OWN_CAR',
       'WEEKDAY_APPR_PROCESS_START_dummy_SATURDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_THURSDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_TUESDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_WEDNESDAY',
       'OCCUPATION_TYPE_dummy_Low_skill_staff',
       'OCCUPATION_TYPE_dummy_Sales staff', 'ORGANIZATION_TYPE_dummy_Officia
l',
       'CATEGORY_AGE_dummy_Old', 'CATEGORY_INCOME_dummy_Low_Income',
       'CATEGORY_INCOME_dummy_Middle_Income'],
      dtype='object')
Wall time: 10min 10s
```

Build the model using significant features obtained from RFE

In [32]:

```
%%time
# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# instantiate the 'DecisionTreeClassifier'
model_DT = DecisionTreeClassifier(random_state=10)

# fit the model using fit() on train data
model_DT = model_DT.fit(X_train[best_features_DT] , y_train)
```

```
Wall time: 11.5 s
```

Tune the Hyperparameters using GridSearchCV (Decision Tree)

In [33]:

```
%%time
# create a dictionary with hyperparameters and its values
tuned_paramaters = [{'criterion': ['entropy', 'gini'],
                     'max_depth': range(2, 10),
                     'max_features': ["sqrt", "log2"]}]

# use GridSearchCV() to find the optimal value of the hyperparameters
grid_tree = GridSearchCV(estimator = model_DT,
                         param_grid = tuned_paramaters,
                         cv = 5,
                         verbose=0,
                         n_jobs=-1)

# fit the model on X_train and y_train using fit()
grid_model_tree = grid_tree.fit(X_train[best_features_DT], y_train)

# get the best parameters
print('Best parameters for decision tree classifier: ', grid_model_tree.best_params_, '\n')
```

```
Best parameters for decision tree classifier:  {'criterion': 'gini', 'max_de
pth': 9, 'max_features': 'sqrt'}

Wall time: 48.9 s
```

Build the model using the tuned hyperparameters.

In [34]:

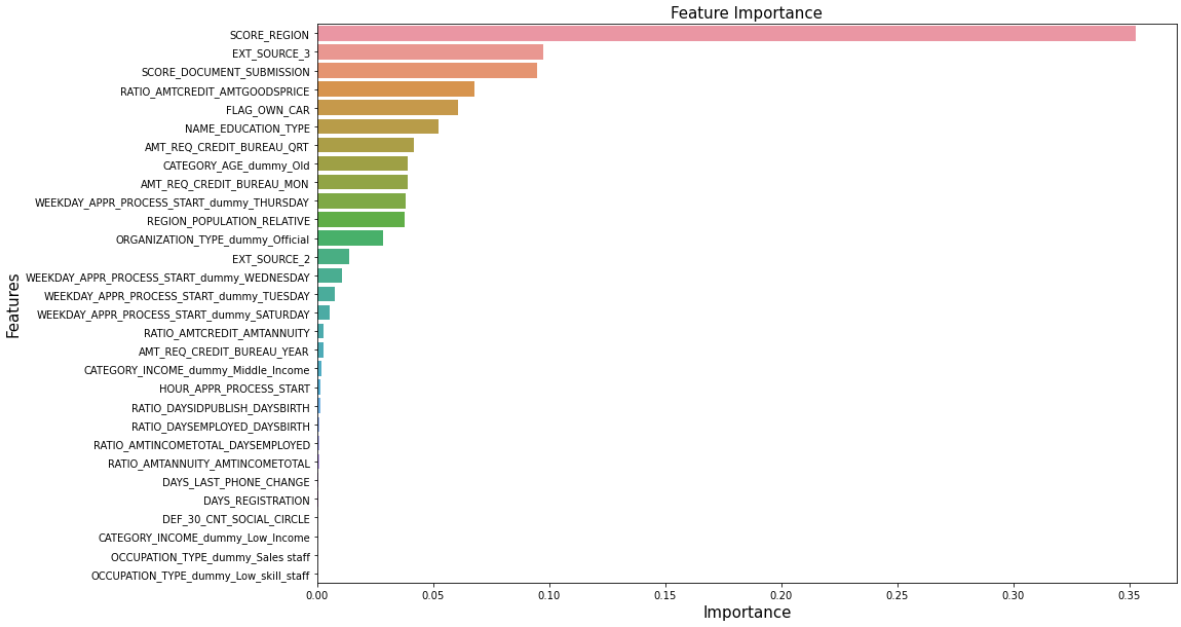
```
%%time
# instantiate the 'DecisionTreeClassifier'
model_DT = DecisionTreeClassifier(criterion = grid_model_tree.best_params_.get('criterion')
                                  max_depth = grid_model_tree.best_params_.get('max_depth')
                                  max_features = grid_model_tree.best_params_.get('max_feat

# fit the model using fit() on train data
model_DT = model_DT.fit(X_train[best_features_DT],y_train)
```

```
Wall time: 1.11 s
```

Visualize top 30 Important Features

In [35]:

```
%%time
# create a dataframe that stores the feature names and their importance
# 'feature_importances_' returns the features based on the gini importance
important_features = pd.DataFrame({'Features': X_train[best_features_DT].columns,
                                   'Importance': model_DT.feature_importances_})

# sort the dataframe in the descending order according to the feature importance
important_features = important_features.sort_values('Importance', ascending = False)

# create a barplot to visualize the features based on their importance
sns.barplot(x = 'Importance', y = 'Features', data = important_features)

# add plot and axes labels
# set text size using 'fontsize'
plt.title('Feature Importance', fontsize = 15)
plt.xlabel('Importance', fontsize = 15)
plt.ylabel('Features', fontsize = 15)

# display the plot
plt.show()
```




```
Wall time: 527 ms
```

Plot the decision tree

In [36]:

```
%%time
# save the column names in 'labels'
labels = X_train[best_features_DT].columns

# export a decision tree in DOT format
dot_data = tree.export_graphviz(model_DT, feature_names = labels, class_names = ["0","1"])

# plot the decision tree using DOT format in 'dot_data'
graph = pydotplus.graph_from_dot_data(dot_data)

# display the decision tree
Image(graph.create_png())

# double-click on the image below to get an expanded view
```

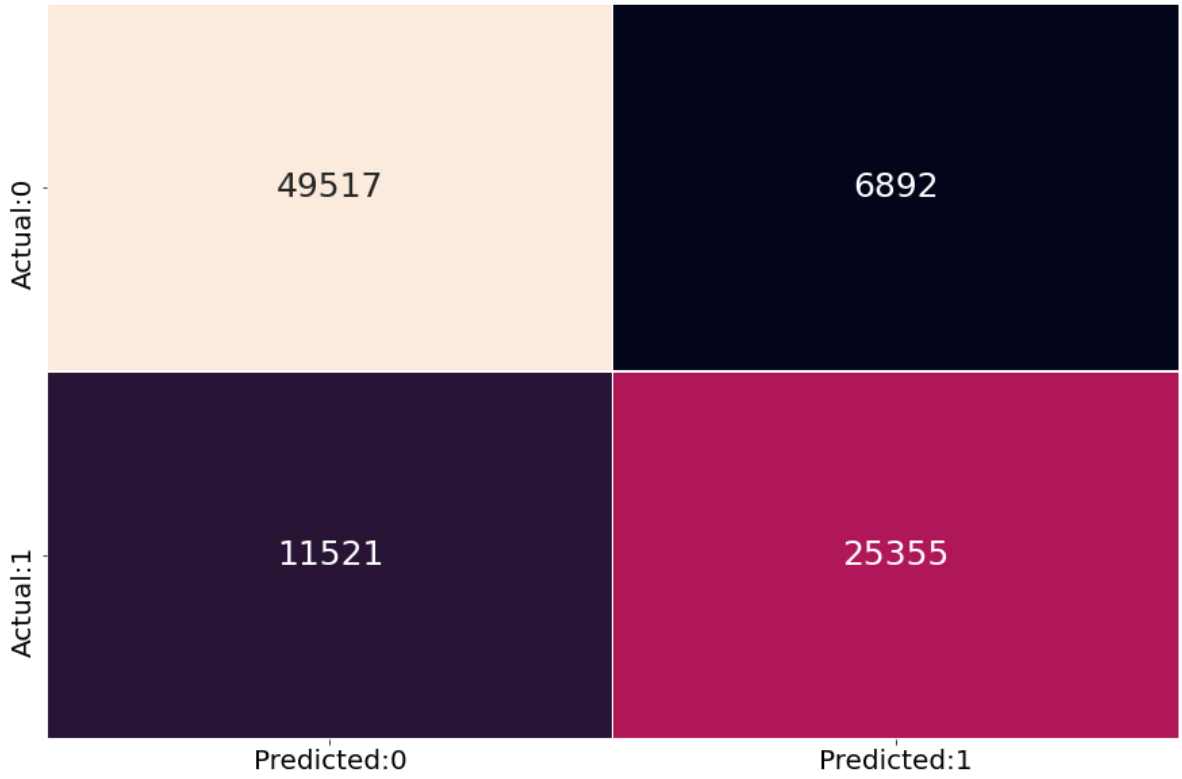
```
dot: graph is too large for cairo-renderer bitmaps. Scaling by 0.483503 to f
it

Wall time: 6.42 s
```

Out[36]:

Model Performance

In [37]:

```
%%time
y_pred = model_DT.predict(X_test[best_features_DT])
cm = confusion_matrix(y_test,y_pred)
conf_matrix = pd.DataFrame(data = cm,columns = ['Predicted:0','Predicted:1'], index = ['Act
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
Wall time: 219 ms
```

In [38]:

```
%%time
# performance measures obtained by classification_report()
result = classification_report(y_test, y_pred)
print(result)
```

```
              precision    recall  f1-score   support

           0       0.81      0.88      0.84     56409
           1       0.79      0.69      0.73     36876

    accuracy                           0.80     93285
   macro avg       0.80      0.78      0.79     93285
weighted avg       0.80      0.80      0.80     93285

Wall time: 135 ms
```

In [39]:

```
%%time
# compute the kappa value
kappa = cohen_kappa_score(y_test, y_pred)

# print the kappa value
print('kappa value:',kappa)
```

```
kappa value: 0.5779566329477557
Wall time: 76.8 ms
```

In [40]:

```
%%time
print('Training set score: ' + str(model_DT.score(X_train[best_features_DT],y_train)))
print('Test set score: ' + str(model_DT.score(X_test[best_features_DT],y_test)))
```

```
Training set score: 0.8048652371649019
Test set score: 0.8026156402422683
Wall time: 205 ms
```

Model Evaluation

In [41]:

```
%%time
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model_DT, X_train[best_features_DT], y_train, scoring='roc_auc', c
print("Mean ROC AUC:", np.mean(scores))
```

```
Mean ROC AUC: 0.8681984902061501
Wall time: 14.8 s
```

RANDOM FOREST

In [4]:

```
# read the dataset
df_application_VIF = pd.read_csv('df_VIF_num_scaled.csv')
```

Obtain top 30 significant features

In [5]:

```
%%time
''' RFE '''
# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# initiate RandomForestClassifier model to use in feature selection
rfe_RF = RandomForestClassifier()

# build the RFE model
rfe_model = RFE(estimator = rfe_RF, n_features_to_select=30)

# fit the RFE model on the training dataset using fit()
rfe_model = rfe_model.fit(X_train, y_train)

# create a series containing feature and its corresponding rank obtained from RFE
feat_index = pd.Series(data = rfe_model.ranking_, index = X_train.columns)

# select the features with rank = 1
best_features_RF = feat_index[feat_index==1].index

# print the significant features obtained from RFE
print("Top features selected by RandomForestClassifier:", best_features_RF, sep='\n')
```

```
Top features selected by RandomForestClassifier:
Index(['SCORE_REGION', 'NAME_EDUCATION_TYPE', 'HOUR_APPR_PROCESS_START',
       'RATIO_DAYSIDPUBLISH_DAYSBIRTH', 'DAYS_REGISTRATION',
       'RATIO_AMTANNUITY_AMTINCOMETOTAL', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'REGION_POPULATION_RELATIVE', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'RATIO_DAYSEMPLOYED_DAYSBIRTH', 'AMT_REQ_CREDIT_BUREAU_MON',
       'RATIO_AMTCREDIT_AMTGOODSPRICE', 'DEF_30_CNT_SOCIAL_CIRCLE',
       'RATIO_AMTINCOMETOTAL_DAYSEMPLOYED', 'RATIO_AMTCREDIT_AMTANNUITY',
       'AMT_REQ_CREDIT_BUREAU_YEAR', 'SCORE_DOCUMENT_SUBMISSION',
       'DAYS_LAST_PHONE_CHANGE', 'FLAG_OWN_CAR', 'FLAG_PHONE',
       'WEEKDAY_APPR_PROCESS_START_dummy_MONDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_SATURDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_THURSDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_TUESDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_WEDNESDAY',
       'ORGANIZATION_TYPE_dummy_Official', 'CATEGORY_AGE_dummy_Old',
       'CATEGORY_INCOME_dummy_Low_Income',
       'CATEGORY_INCOME_dummy_Middle_Income'],
      dtype='object')
Wall time: 1h 53min 43s
```

Build the model using significant features obtained from RFE

In [6]:

```
%%time
# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# instantiate the 'RandomForestClassifier'
model_RF = RandomForestClassifier(random_state=10)

# fit the model using fit() on train data
model_RF = model_RF.fit(X_train[best_features_RF] , y_train)
```

```
Wall time: 2min 20s
```

Tune the Hyperparameters using GridSearchCV (Random Forest)

In [7]:

```
%%time
# create a dictionary with hyperparameters and its values
tuned_paramaters = [{'criterion': ['gini'],
                     'n_estimators': [10, 30, 50, 70, 90],
                     'max_depth': range(2, 10),
                     'max_features': ["sqrt", "log2"]}]

# use GridSearchCV() to find the optimal value of the hyperparameters
grid_forest = GridSearchCV(estimator = model_RF,
                           param_grid = tuned_paramaters,
                           cv = 5,
                           verbose=0,
                           n_jobs=-1)

# fit the model on X_train and y_train using fit()
grid_model_forest = grid_forest.fit(X_train[best_features_RF], y_train)

# get the best parameters
print('Best parameters for random forest classifier: ', grid_model_forest.best_params_, '\n
```

```
Best parameters for random forest classifier:  {'criterion': 'gini', 'max_de
pth': 9, 'max_features': 'log2', 'n_estimators': 70}

Wall time: 58min 51s
```

Build the model using the tuned hyperparameters.

In [8]:

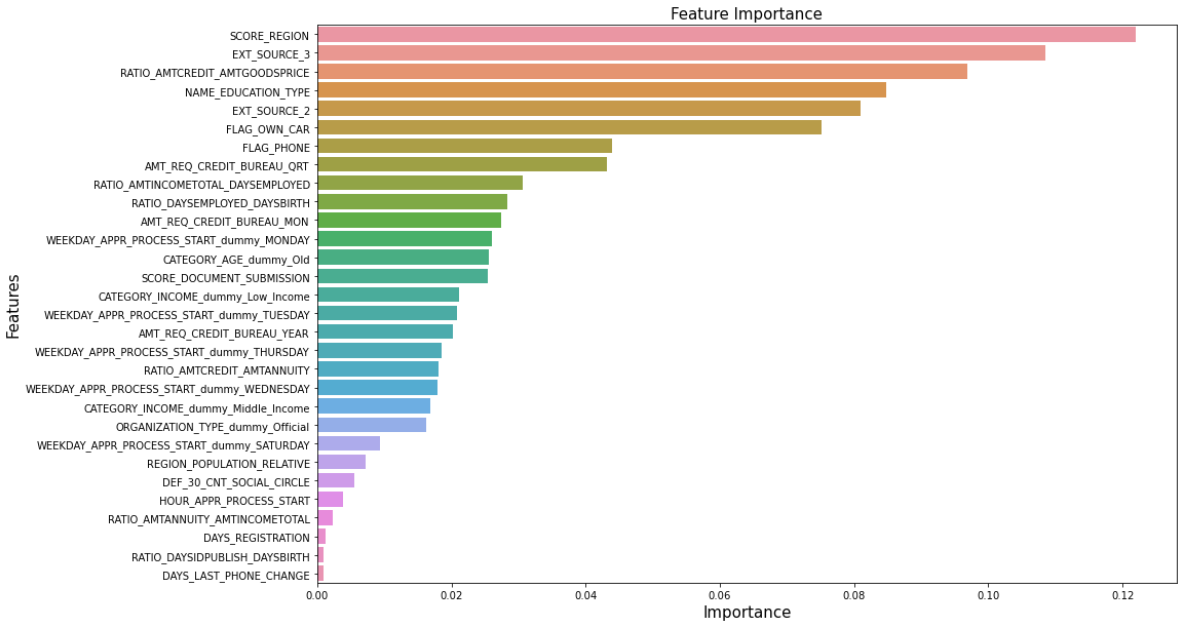
```
%%time
# instantiate the 'RandomForestClassifier'
model_RF = RandomForestClassifier(criterion = grid_model_forest.best_params_.get('criterion
                                  n_estimators = grid_model_forest.best_params_.get('n_esti
                                  max_depth = grid_model_forest.best_params_.get('max_depth
                                  max_features = grid_model_forest.best_params_.get('max_fe

# fit the model using fit() on train data
model_RF = model_RF.fit(X_train[best_features_RF],y_train)
```

```
Wall time: 41.9 s
```

Visualize top 30 Important Features

In [9]:

```
%%time
# create a dataframe that stores the feature names and their importance
# 'feature_importances_' returns the features based on the gini importance
important_features = pd.DataFrame({'Features': X_train[best_features_RF].columns,
                                   'Importance': model_RF.feature_importances_})

# sort the dataframe in the descending order according to the feature importance
important_features = important_features.sort_values('Importance', ascending = False)

# create a barplot to visualize the features based on their importance
sns.barplot(x = 'Importance', y = 'Features', data = important_features)

# add plot and axes labels
# set text size using 'fontsize'
plt.title('Feature Importance', fontsize = 15)
plt.xlabel('Importance', fontsize = 15)
plt.ylabel('Features', fontsize = 15)

# display the plot
plt.show()
```

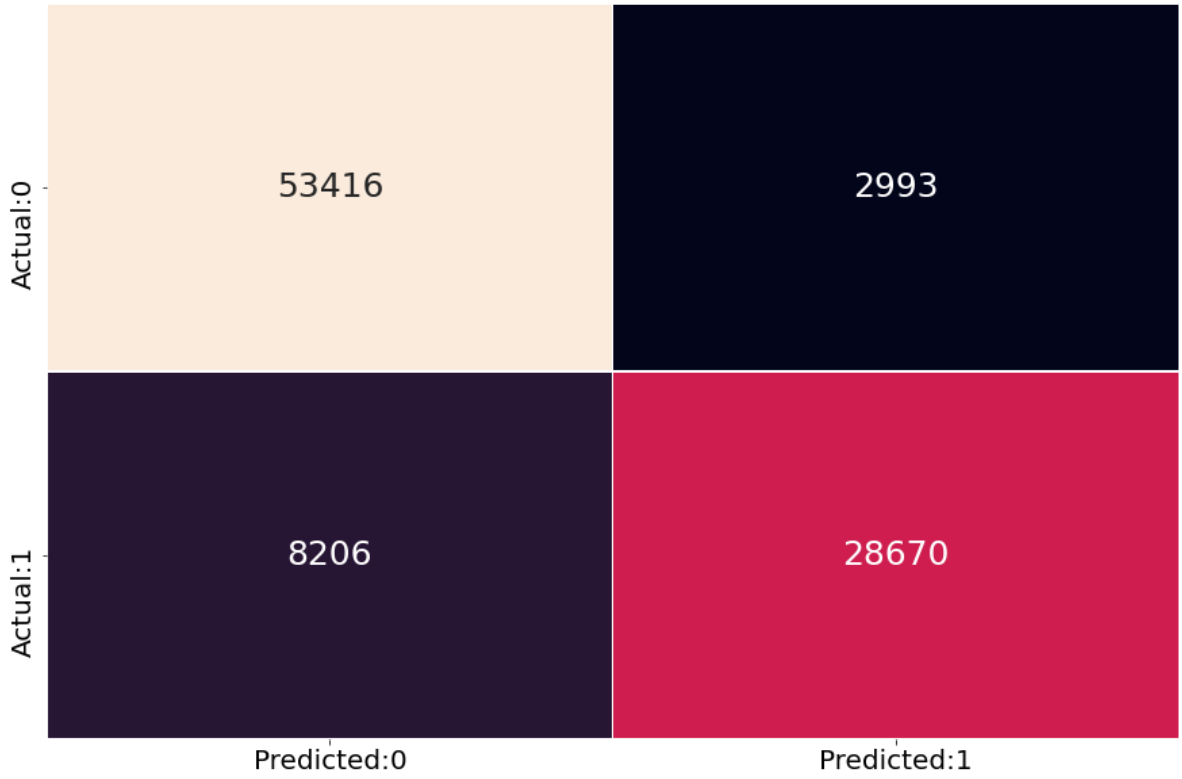



```
Wall time: 607 ms
```

Model Performance

In [27]:

```
%%time
y_pred = model_RF.predict(X_test[best_features_RF])
cm = confusion_matrix(y_test,y_pred)
conf_matrix = pd.DataFrame(data = cm,columns = ['Predicted:0','Predicted:1'], index = ['Act
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
Wall time: 928 ms
```

In [28]:

```
%%time
# performance measures obtained by classification_report()
result = classification_report(y_test, y_pred)
print(result)
```

```
              precision    recall  f1-score   support

           0       0.87      0.95      0.91     56409
           1       0.91      0.78      0.84     36876

    accuracy                           0.88     93285
   macro avg       0.89      0.86      0.87     93285
weighted avg       0.88      0.88      0.88     93285

Wall time: 133 ms
```

In [29]:

```
%%time
# compute the kappa value
kappa = cohen_kappa_score(y_test, y_pred)

# print the kappa value
print('kappa value:',kappa)
```

```
kappa value: 0.7425868379436178
Wall time: 87.8 ms
```

In [10]:

```
%%time
print('Training set score: ' + str(model_RF.score(X_train[best_features_RF],y_train)))
print('Test set score: ' + str(model_RF.score(X_test[best_features_RF],y_test)))
```

```
Training set score: 0.880405856294069
Test set score: 0.8799485447821193
Wall time: 3.73 s
```

Model Evaluation

In [11]:

```
%%time
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model_RF, X_train[best_features_RF], y_train, scoring='roc_auc', c
print("Mean ROC AUC:", np.mean(scores))
```

```
Mean ROC AUC: 0.9352877807742559
Wall time: 8min 37s
```

XGBOOST

In [12]:

```
# read the dataset
df_application_VIF = pd.read_csv('df_VIF_num_scaled.csv')
```

In [13]:

```
%%time
''' RFE '''

# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

# initiate XGBClassifier model to use in feature selection
rfe_xgb = XGBClassifier(verbosity = 0)

# build the RFE model
rfe_model = RFE(estimator = rfe_xgb, n_features_to_select=30)

# fit the RFE model on the training dataset using fit()
rfe_model = rfe_model.fit(X_train, y_train)

# create a series containing feature and its corresponding rank obtained from RFE
feat_index = pd.Series(data = rfe_model.ranking_, index = X_train.columns)

# select the features with rank = 1
best_features_XGB = feat_index[feat_index==1].index

# print the significant features obtained from RFE
print("Top features selected by XGBoost Classifiaction:", best_features_XGB, sep='\n')
```

```
Top features selected by XGBoost Classifiaction:
Index(['SCORE_REGION', 'NAME_EDUCATION_TYPE', 'HOUR_APPR_PROCESS_START',
       'AMT_REQ_CREDIT_BUREAU_QRT', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'AMT_REQ_CREDIT_BUREAU_MON', 'RATIO_AMTCREDIT_AMTGOODSPRICE',
       'DEF_30_CNT_SOCIAL_CIRCLE', 'AMT_REQ_CREDIT_BUREAU_YEAR',
       'SCORE_DOCUMENT_SUBMISSION', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY',
       'FLAG_PHONE', 'NAME_TYPE_SUITE_dummy_Family',
       'NAME_INCOME_TYPE_dummy_State servant',
       'WEEKDAY_APPR_PROCESS_START_dummy_MONDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_SATURDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_SUNDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_THURSDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_TUESDAY',
       'WEEKDAY_APPR_PROCESS_START_dummy_WEDNESDAY',
       'OCCUPATION_TYPE_dummy_Core staff',
       'OCCUPATION_TYPE_dummy_Low_skill_staff',
       'OCCUPATION_TYPE_dummy_Sales staff',
       'ORGANIZATION_TYPE_dummy_Education', 'ORGANIZATION_TYPE_dummy_Officia
l',
       'CATEGORY_AGE_dummy_Old', 'CATEGORY_INCOME_dummy_Low_Income',
       'CATEGORY_INCOME_dummy_Middle_Income'],
      dtype='object')
Wall time: 41min 9s
```

Build the model using significant features obtained from RFE

In [14]:

```
%%time
# select independent variables
X = df_application_VIF.drop('TARGET', axis = 1)

# select dependent variable
y = df_application_VIF['TARGET']

# split data into train subset and test subset
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 10, test_size = 0.

model_xgb = XGBClassifier(max_depth = 10, gamma = 1, verbosity = 0)

# fit the model using fit() on train data
model_xgb= model_xgb.fit(X_train, y_train)

# fit the model using fit() on train data
model_xgb = model_xgb.fit(X_train[best_features_XGB] , y_train)
```

```
Wall time: 3min 16s
```

Tune the Hyperparameters using GridSearchCV (XG Boost)

In [15]:

```
%%time
tuning_parameters = {'learning_rate': [0.1, 0.01, 0.05],
                     'max_depth': range(3,10,2),
                     'gamma': [0, 1, 2, 3, 4]}
model_xgb = XGBClassifier(verbosity = 0)
xgb_grid = GridSearchCV(estimator = model_xgb, param_grid = tuning_parameters, cv = 3, scor
xgb_grid.fit(X_train[best_features_XGB], y_train)

# get the best parameters
print('Best parameters for XGBoost classifier: ', xgb_grid.best_params_, '\n')
```

```
Best parameters for XGBoost classifier:  {'gamma': 4, 'learning_rate': 0.1,
'max_depth': 9}

Wall time: 1h 12min 21s
```

Build the model using the tuned hyperparameters.

In [16]:

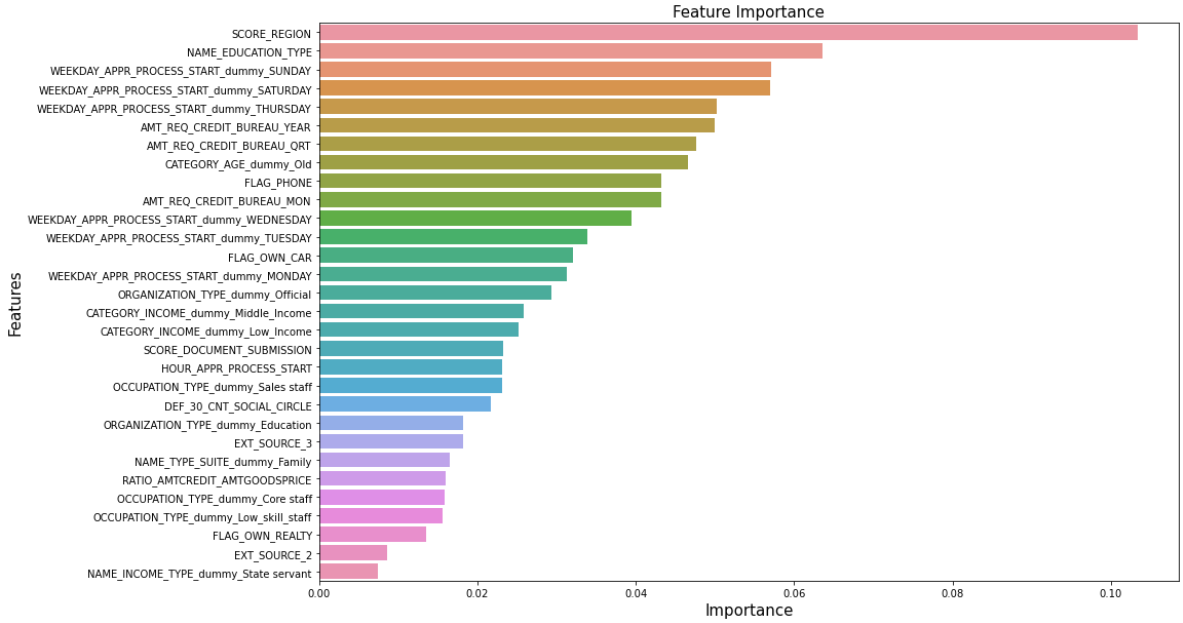
```
%%time
# instantiate the 'XGBClassifier'
model_xgb =  XGBClassifier(gamma = xgb_grid.best_params_.get('gamma'),
                           learning_rate = xgb_grid.best_params_.get('learning_rate'
                           max_depth = xgb_grid.best_params_.get('max_depth'))

# fit the model using fit() on train data
model_xgb = model_xgb.fit(X_train[best_features_XGB],y_train)
```

```
Wall time: 54.6 s
```

Visualize top 30 Important Features

In [17]:

```
%%time
# create a dataframe that stores the feature names and their importance
# 'feature_importances_' returns the features based on the gini importance
important_features = pd.DataFrame({'Features': X_train[best_features_XGB].columns,
                                   'Importance': model_xgb.feature_importances_})

# sort the dataframe in the descending order according to the feature importance
important_features = important_features.sort_values('Importance', ascending = False)

# create a barplot to visualize the features based on their importance
sns.barplot(x = 'Importance', y = 'Features', data = important_features)

# add plot and axes labels
# set text size using 'fontsize'
plt.title('Feature Importance', fontsize = 15)
plt.xlabel('Importance', fontsize = 15)
plt.ylabel('Features', fontsize = 15)

# display the plot
plt.show()
```

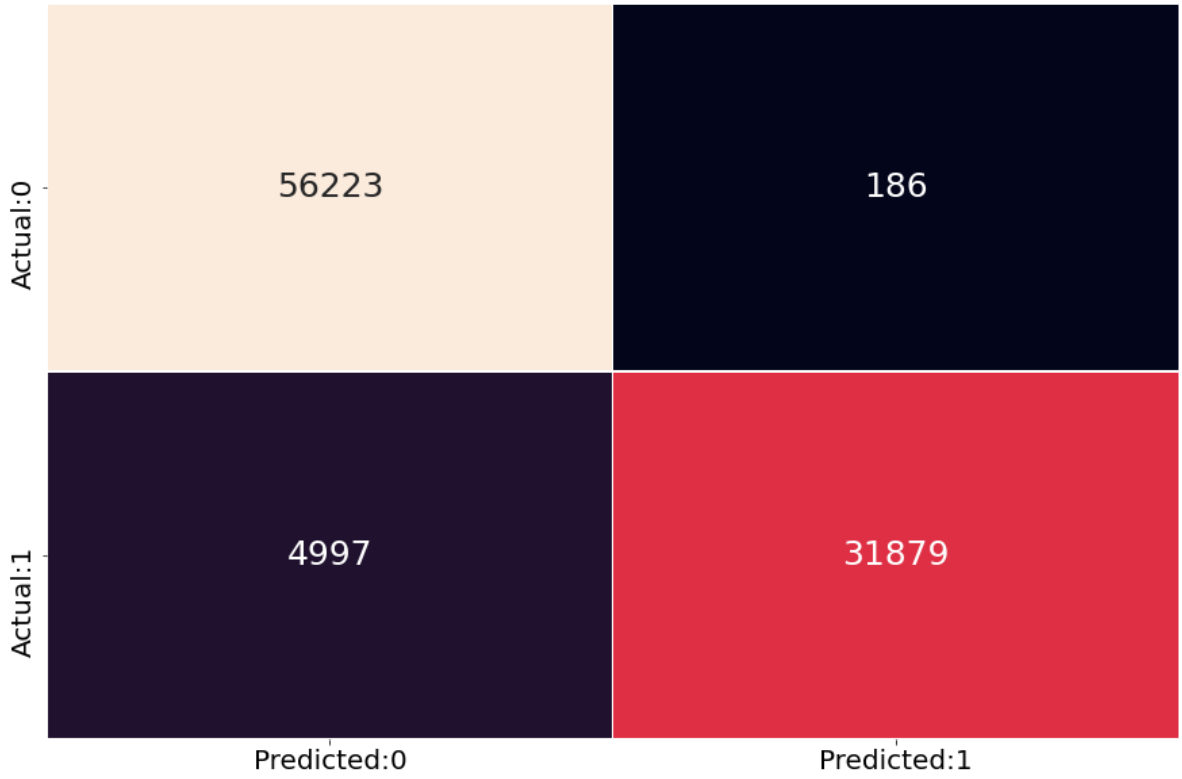



```
Wall time: 747 ms
```

Model Performance

In [18]:

```
%%time
y_pred = model_xgb.predict(X_test[best_features_XGB])
cm = confusion_matrix(y_test,y_pred)
conf_matrix = pd.DataFrame(data = cm,columns = ['Predicted:0','Predicted:1'], index = ['Act
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cbar = False,
            linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```




```
Wall time: 485 ms
```

In [19]:

```
%%time
# performance measures obtained by classification_report()
result = classification_report(y_test, y_pred)
print(result)
```

```
              precision    recall  f1-score   support

           0       0.92      1.00      0.96     56409
           1       0.99      0.86      0.92     36876

    accuracy                           0.94     93285
   macro avg       0.96      0.93      0.94     93285
weighted avg       0.95      0.94      0.94     93285

Wall time: 121 ms
```

In [20]:

```
%%time
# compute the kappa value
kappa = cohen_kappa_score(y_test, y_pred)

# print the kappa value
print('kappa value:',kappa)
```

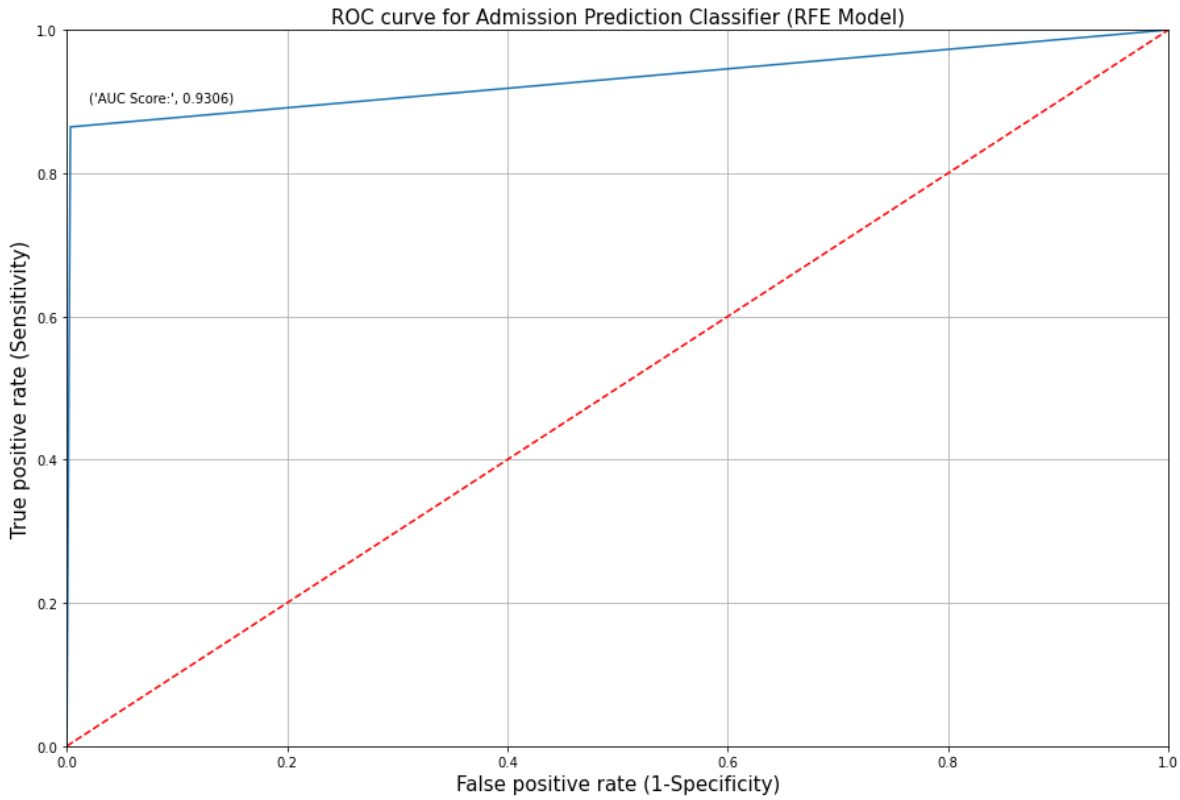
```
kappa value: 0.8810968787287745
Wall time: 66.9 ms
```

Plot the ROC curve

In [21]:

```
%%time
# the roc_curve() returns the values for false positive rate, true positive rate and thresh
fpr, tpr, thresholds = roc_curve(y_test, y_pred)

# plot the ROC curve
plt.plot(fpr, tpr)

# set limits for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])

# plot the straight line showing worst prediction for the model
plt.plot([0, 1], [0, 1],'r--')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('ROC curve for Admission Prediction Classifier (RFE Model)', fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)

# add the AUC score to the plot
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.roc_auc_score(y_test, y_pred),

# plot the grid
plt.grid(True)
```

```
Wall time: 51.9 ms
```



In [22]:

```
print('Training set score: ' + str(model_xgb.score(X_train[best_features_XGB],y_train)))
print('Test set score: ' + str(model_xgb.score(X_test[best_features_XGB],y_test)))
```

```
Training set score: 0.9462690647134967
Test set score: 0.9444390845259152
```

Model Evaluation

In [23]:

```
%%time
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_score(model_xgb, X_train[best_features_XGB], y_train, scoring='roc_auc',
print("Mean ROC AUC:", np.mean(scores))
```

```
Mean ROC AUC: 0.9616813220603285
Wall time: 23min 34s
```