eda

September 16, 2019

[ ]:
```
import gc
gc.collect()
```

[1]:
```
# Load libraries

%matplotlib inline
import matplotlib.pyplot as plt

import numpy as np

import pandas as pd

from scipy import stats
```

[2]:
```
def quick_overview_df( dataset_df ):
    display( 'shape:', dataset_df.shape )
    display( 'sample:', dataset_df.sample() )
    display( 'NaN values:', dataset_df.isnull().sum() )
    display( 'duplicates:', dataset_df.duplicated().sum() )
    dataset_df.info()
```

[3]:
```
# Overview 'Application' table (train and test)

APPLICATION_TRAIN_FILEPATH = 'data/application_train.csv'
application_train = pd.read_csv( APPLICATION_TRAIN_FILEPATH, header=0 )

APPLICATION_TEST_FILEPATH = 'data/application_test.csv'
application_test = pd.read_csv( APPLICATION_TEST_FILEPATH, header=0 )
```

[4]:
```
# quick_overview_df( application_train )
```

[5]:
```
# quick_overview_df( application_test )
```

[6]:
```
def display_freq_plot( dataset_df, col_name, ax, \
                      title_add='', sort_class=False, **kwargs):
    data_to_plot = dataset_df[col_name].value_counts()
    if sort_class:
        data_to_plot = data_to_plot.sort_index()
    ax.bar(
        data_to_plot.index.values, data_to_plot.values, **kwargs
```

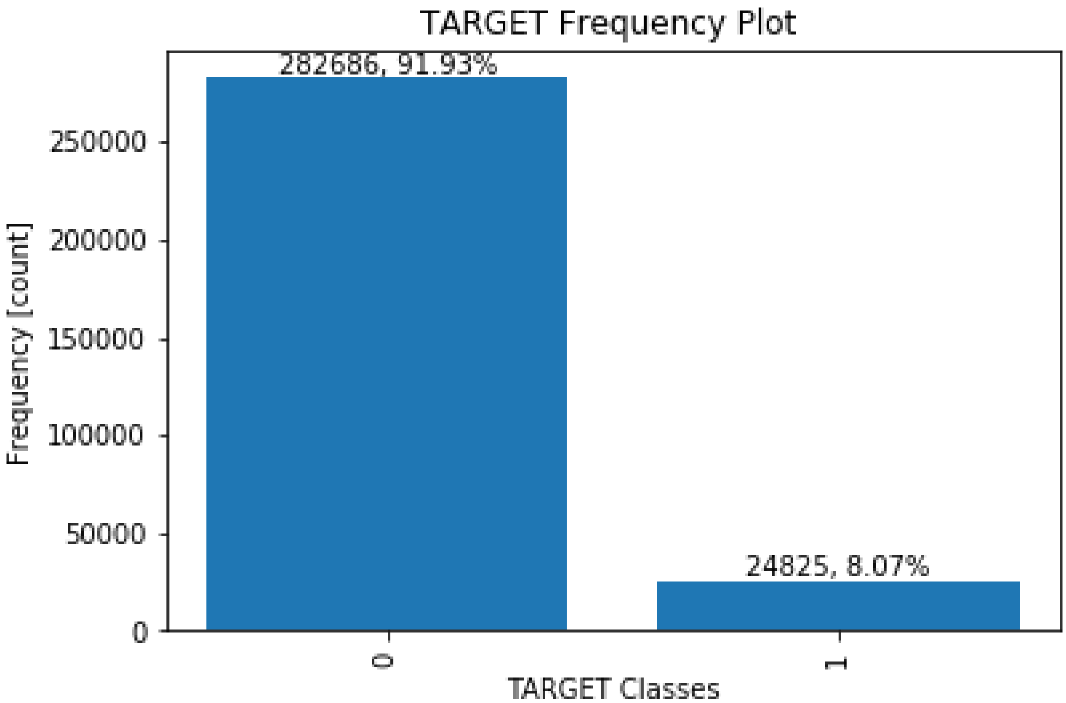
```
    )
    col_name_ncount = len( dataset_df[col_name] )
    for patch in ax.patches:
        x = patch.get_x()
        y = patch.get_height()
        y_pct = y * 100.0 / col_name_ncount
        ax.annotate(
            '{0}, {1:.2f}%'.format( y, y_pct ),
            (x + 0.4, y),
            ha='center', va='bottom'
        )
    for tick in ax.get_xticklabels():
        tick.set_rotation(90)
    ax.set_xticks( data_to_plot.index.values )
    ax.set_title( '{0} Frequency Plot {1}'.format(col_name, title_add) )
    ax.set_xlabel( '{0} Classes'.format(col_name) )
    ax.set_ylabel( 'Frequency [count]' )


def display_stacked_freq_plot_by_target( target_0_df, target_1_df, col_name, ax␣
 ↪):
    target_0_toplot_data = target_0_df[col_name].value_counts()
    target_1_toplot_data = target_1_df[col_name].value_counts()
    ax.bar(
        target_0_toplot_data.index.values, target_0_toplot_data.values,
        label='target=0'
    )
    ax.bar(
        target_1_toplot_data.index.values, target_1_toplot_data.values,
        label='target=1'
    )
    zipped_target0_target1_values = list( zip(target_0_toplot_data,␣
 ↪target_1_toplot_data) )
    for idx, patch in enumerate(ax.patches):
        if idx >= len(zipped_target0_target1_values):
            idx -= len(zipped_target0_target1_values)
        x = patch.get_x()
        y = patch.get_height()
        y_pct = y * 100.0 / sum(zipped_target0_target1_values[idx])
        ax.annotate(
            '{0:.2f}%'.format( y_pct ),
            (x + 0.4, y + 50),
            ha='center', va='bottom'
        )
    for tick in ax.get_xticklabels():
        tick.set_rotation(90)
    ax.set_title( '' )
```

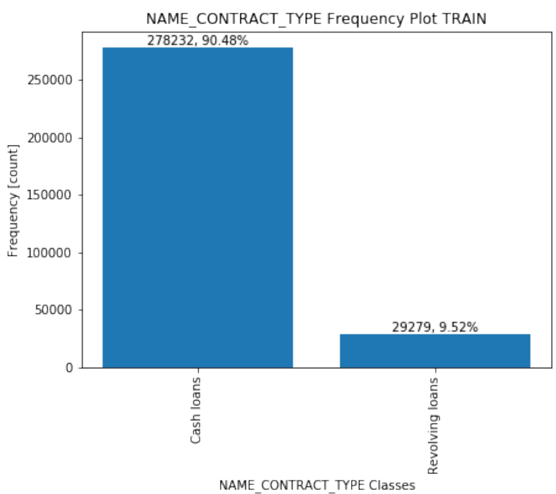
```
    ax.legend()

def display_freq_plot_by_target( target_0_df, target_1_df, col_name ):
    fig, [ax_0, ax_1, ax_2] = plt.subplots( 1, 3, figsize=(17, 5) )
    # target={0,1} - stacked bar chart
    display_stacked_freq_plot_by_target( target_0_df, target_1_df, col_name,␣
 ↪ax=ax_0 )
    ax_0.set_title('{0} (TARGET=[0;1])'.format(col_name))
    # target=0
    display_freq_plot( target_0_df, col_name, ax=ax_1 )
    ax_1.set_title('{0} (TARGET=0)'.format(col_name))
    # target=1
    display_freq_plot( target_1_df, col_name, ax=ax_2 )
    ax_2.set_title('{0} (TARGET=1)'.format(col_name))


def display_freq_plot_traintest( train_df, test_df, col_name ):
    fig, [ax_0, ax_1] = plt.subplots( 1, 2, figsize=(15, 5) )
    display_freq_plot( train_df, col_name, ax=ax_0, title_add='TRAIN' )
    display_freq_plot( test_df, col_name, ax=ax_1, title_add='TEST' )
```

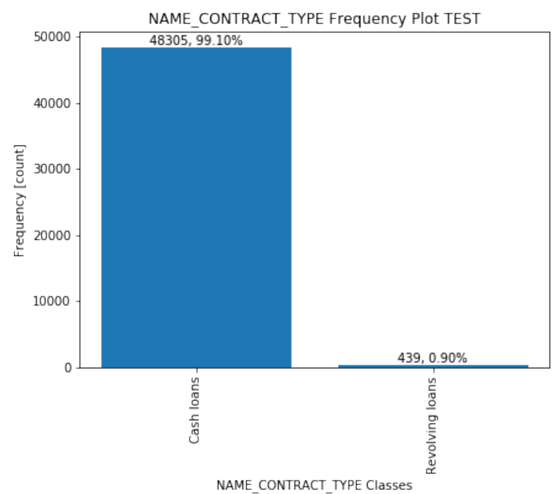
[7]:
```
# Type 1 overview: basic frequency overview

fig, ax_0 = plt.subplots()
display_freq_plot( application_train, 'TARGET', ax=ax_0 )
plt.show()

cols_to_overview = [
    'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'NAME_FAMILY_STATUS',
    'FLAG_OWN_CAR', 'FLAG_OWN_REALTY',
    'CNT_CHILDREN', 'CNT_FAM_MEMBERS',
    'NAME_INCOME_TYPE', 'OCCUPATION_TYPE', 'NAME_EDUCATION_TYPE',␣
 ↪'NAME_HOUSING_TYPE']

for col_name in cols_to_overview:
    display_freq_plot_traintest( application_train, application_test, col_name)

# Overall: Train and Test have almost the same proportion of people in all␣
 ↪classes

# TARGET:
# Unbalanced feature: 92%=0, 8%=1.
# Most of borrowers didn't have problems with repaying their loans

# NAME_CONTRACT_TYPE : Identification if loan is cash or revolving
# Cash loans are 10x more popular than revolving loans
# Extremely unbalanced in test: 99%/1% classes proportion in test set.
```

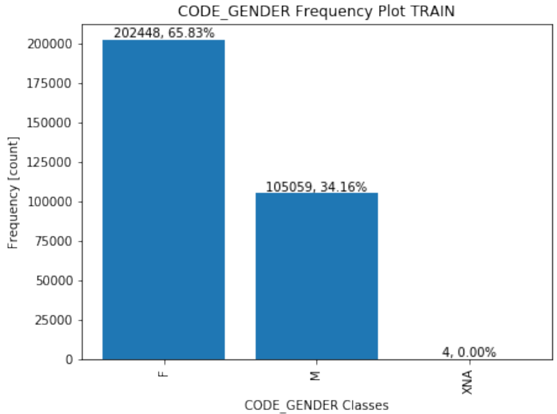
```
# CODE_GENDER : Gender of the client
# women applied twice as often as men

# NAME_FAMILY_STATUS : Family status of the client
# Percentage proportion in train / in test - almost the same
# Overwhelming category - married
# Main category: marries (train - 63%, test - 66%)

# FLAG_OWN_CAR
# Most of borrowers don't own a car (2/3)

# FLAG_OWN_REALTY
# Most of borrowers own a property (2/3)

# CNT_CHILDREN
# Most of borrowers (70% train, 71% test) don't have any children
# 0 / 1 / 2 children = 3.5 / 2 / 1 proportion

# CNT_FAM_MEMBERS
# Most borrowers have 2 family members
# >=5 members - <1.5% of total borrowers
# Might have correlation with cnt_children - 1 and 2 fam members - no children
↪(22%+51% in train, 21%+53% in test )

# NAME_INCOME_TYPE
# 50% of total borrowers - Working
# Almost no unemployed, students or businessmen
# Working / Commmercial associate = 2.5 / 1
# Pesioners - almost 20% - interesting class

# OCCUPATION_TYPE
# Most of the borrowers are laborers ("others" feature?), work in sales, core
↪staff ("others feature?"), 'managers', 'drivers'
# 'laborers' and 'core staff' might mean any kind o f occupation
# IT staff - least popular class of borrowers
# Interesting - 'high skill tech staff' - does high skill means education?

# NAME_EDUCATION_TYPE
# Top class: secondary/secondary special () degree - 70%
# Higher education: 25%
# Others: sum < 5%

# NAME_HOUSING_TYPE
# This might NOT be a good feature because it represents average state of how
↪people live in Russia
# Top class: home/apartment
```

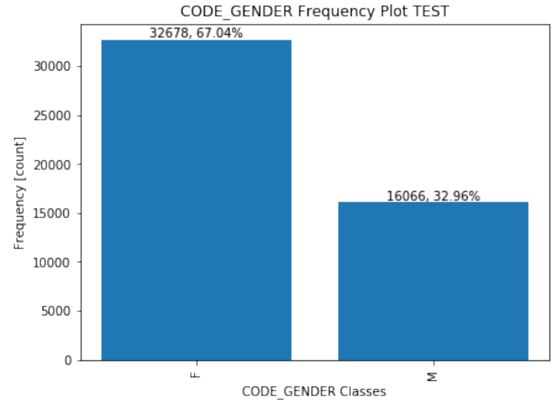
```
# Top class holds 90% of all borrowers

#
```

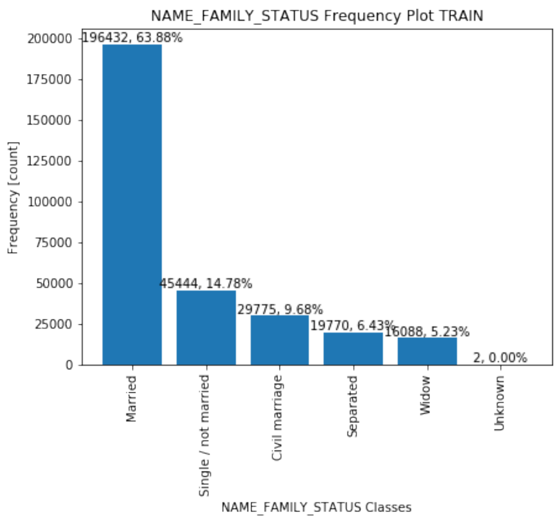


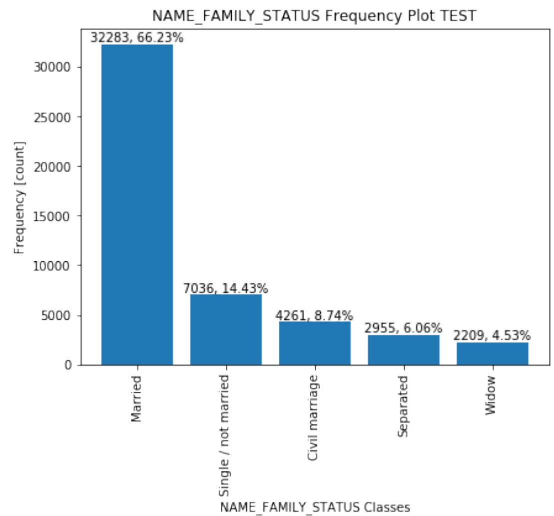


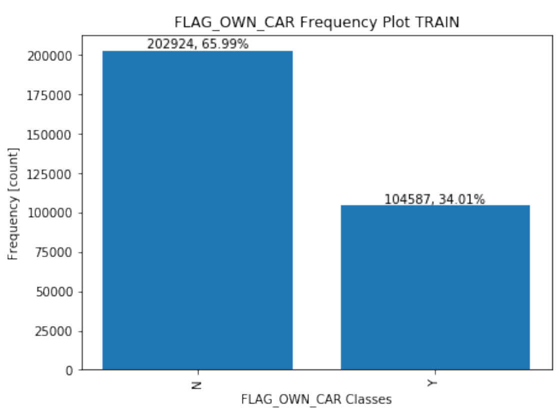


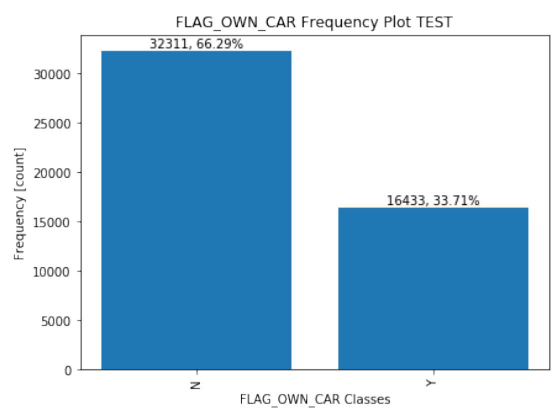

CODE_GENDER Frequency Plot TRAIN
Frequency [count]
CODE_GENDER Classes
F
M
XNA
202448, 65.83%
105059, 34.16%
4, 0.00%

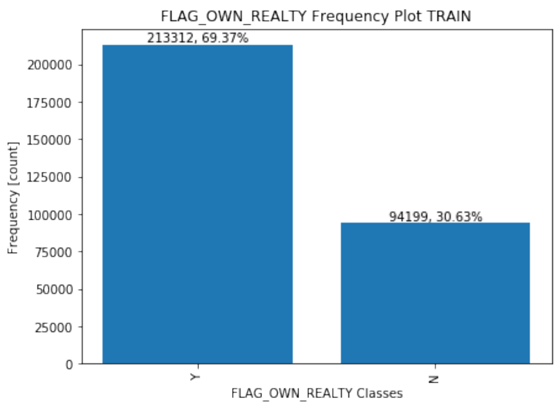

CODE_GENDER Frequency Plot TEST
Frequency [count]
CODE_GENDER Classes
F
M
32678, 67.04%
16066, 32.96%

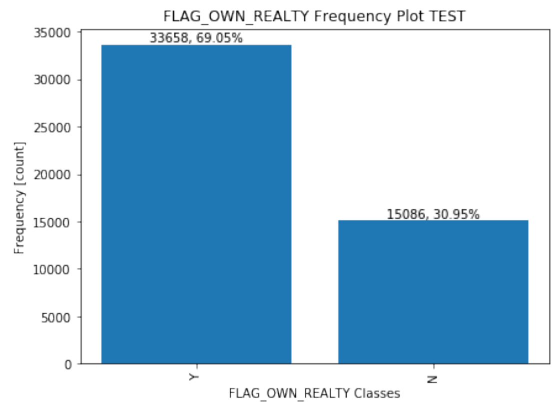

NAME_FAMILY_STATUS Frequency Plot TRAIN
Frequency [count]
NAME_FAMILY_STATUS Classes
Married
Single / not married
Civil marriage
Separated
Widow
Unknown
196432, 63.88%
45444, 14.78%
29775, 9.68%
19770, 6.43%
16088, 5.23%
2, 0.00%

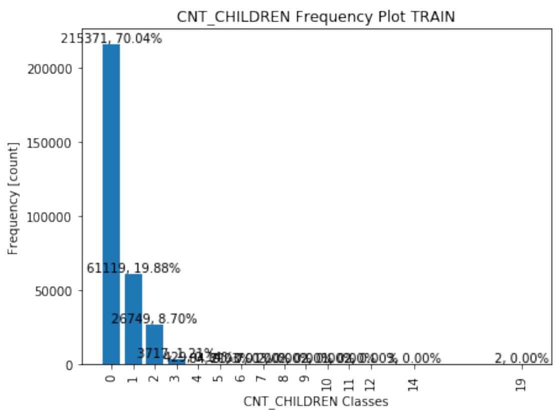

NAME_FAMILY_STATUS Frequency Plot TEST
Frequency [count]
NAME_FAMILY_STATUS Classes
Married
Single / not married
Civil marriage
Separated
Widow
32283, 66.23%
7036, 14.43%
4261, 8.74%
2955, 6.06%
2209, 4.53%

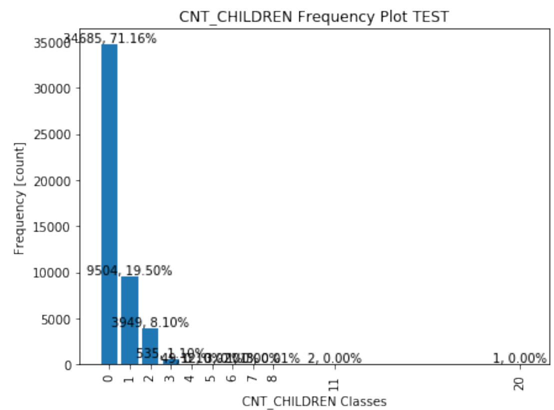

FLAG_OWN_CAR Frequency Plot TRAIN
Frequency [count]
FLAG_OWN_CAR Classes
N
Y
202924, 65.99%
104587, 34.01%

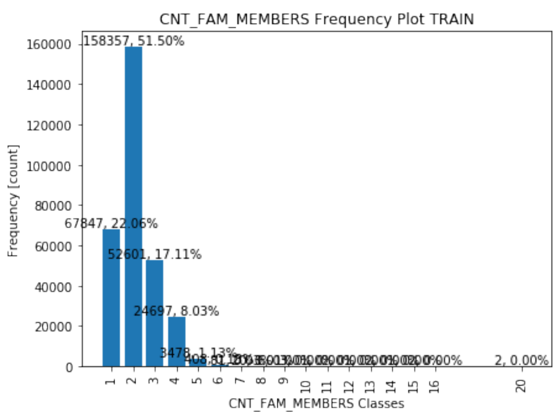

FLAG_OWN_CAR Frequency Plot TEST
Frequency [count]
FLAG_OWN_CAR Classes
N
Y
32311, 66.29%
16433, 33.71%

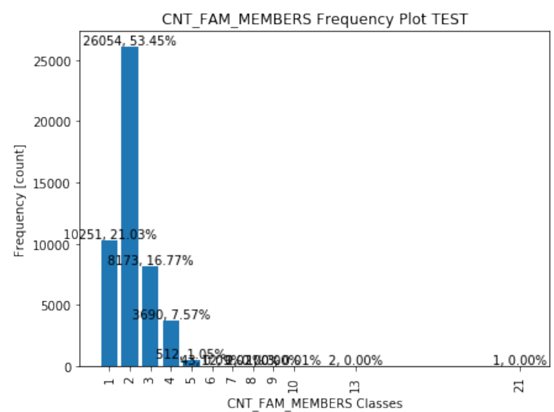

FLAG_OWN_REALTY Frequency Plot TRAIN
213312, 69.37%
94199, 30.63%
Frequency [count]
Y
N
FLAG_OWN_REALTY Classes

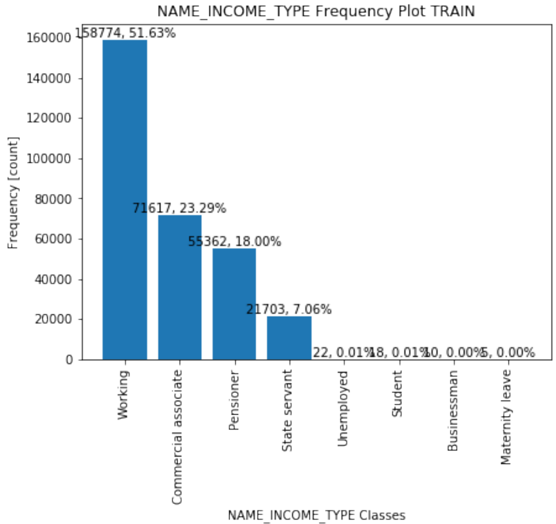

FLAG_OWN_REALTY Frequency Plot TEST
33658, 69.05%
15086, 30.95%
Frequency [count]
Y
N
FLAG_OWN_REALTY Classes

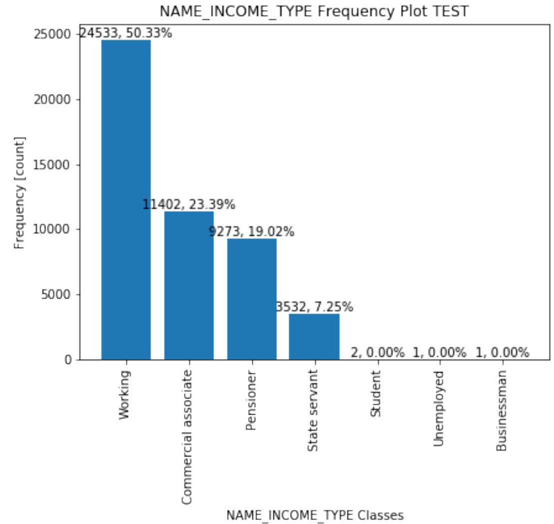

CNT_CHILDREN Frequency Plot TRAIN
215371, 70.04%
61119, 19.88%
26749, 8.70%
2, 0.00%
Frequency [count]
CNT_CHILDREN Classes

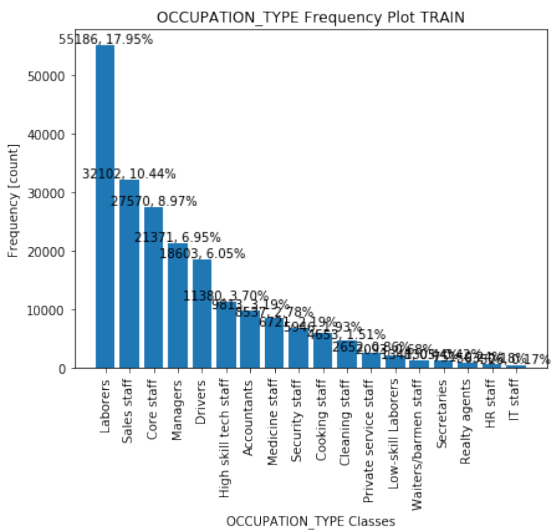

CNT_CHILDREN Frequency Plot TEST
34685, 71.16%
9504, 19.50%
3949, 8.10%
2, 0.00%
1, 0.00%
Frequency [count]
CNT_CHILDREN Classes

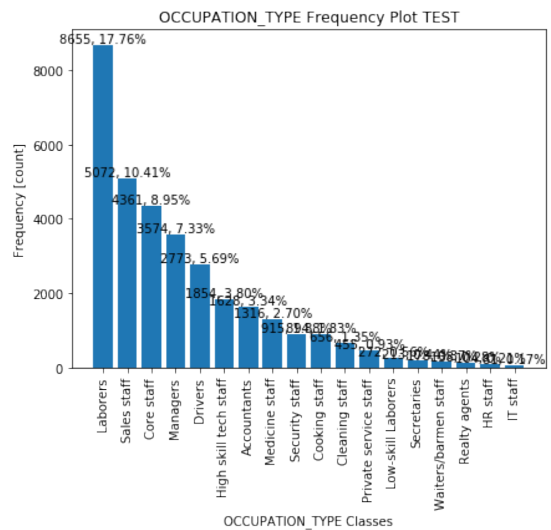

CNT_FAM_MEMBERS Frequency Plot TRAIN
158357, 51.50%
67847, 22.06%
52601, 17.11%
24697, 8.03%
2, 0.00%
Frequency [count]
CNT_FAM_MEMBERS Classes

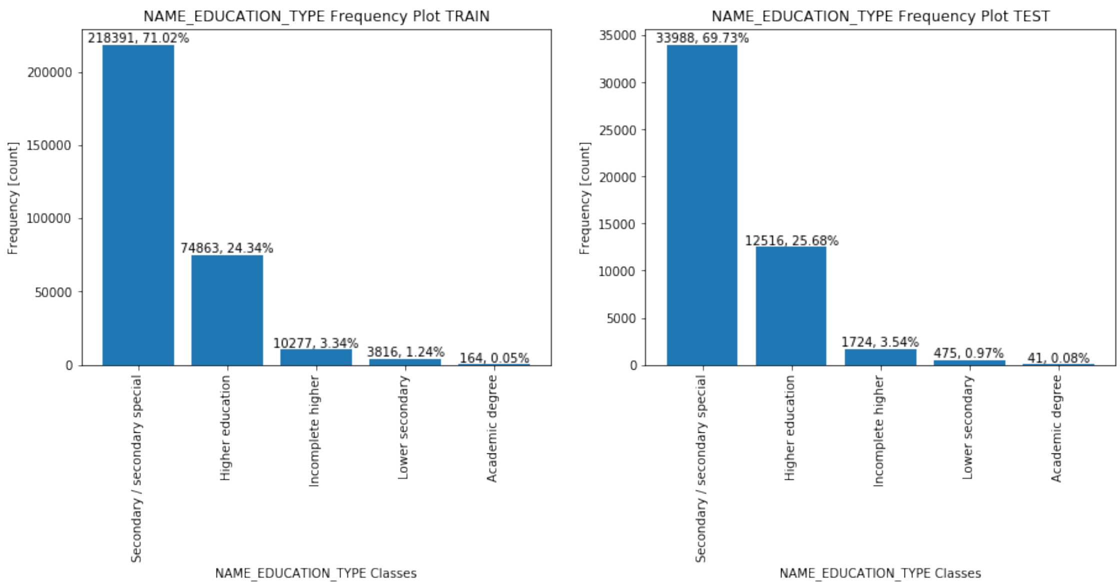

CNT_FAM_MEMBERS Frequency Plot TEST
26054, 53.45%
10251, 21.03%
8173, 16.77%
3690, 7.57%
2, 0.00%
1, 0.00%
Frequency [count]
CNT_FAM_MEMBERS Classes

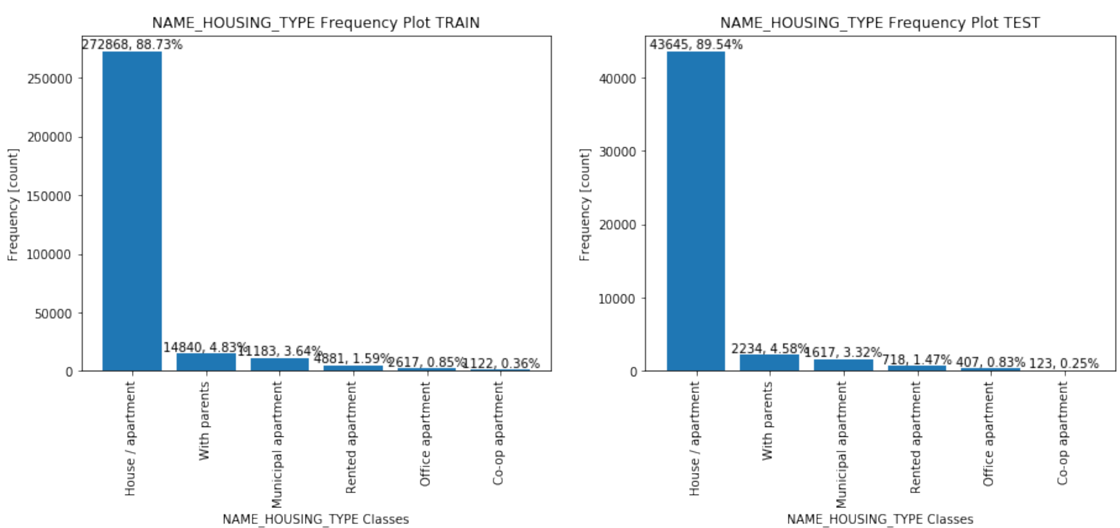

NAME_INCOME_TYPE Frequency Plot TRAIN
Frequency [count]
NAME_INCOME_TYPE Classes
Working
Commercial associate
Pensioner
State servant
Unemployed
Student
Businessman
Maternity leave


NAME_INCOME_TYPE Frequency Plot TEST
Frequency [count]
NAME_INCOME_TYPE Classes
24533, 50.33%
11402, 23.39%
9273, 19.02%
3532, 7.25%
2, 0.00%
1, 0.00%
1, 0.00%
Working
Commercial associate
Pensioner
State servant
Student
Unemployed
Businessman


OCCUPATION_TYPE Frequency Plot TRAIN
Frequency [count]
OCCUPATION_TYPE Classes
55186, 17.95%
Laborers
Sales staff
Core staff
Managers
Drivers
High skill tech staff
Accountants
Medicine staff
Security staff
Cooking staff
Cleaning staff
Private service staff
Low-skill Laborers
Waiters/barmen staff
Secretaries
Realty agents
HR staff
IT staff


OCCUPATION_TYPE Frequency Plot TEST
Frequency [count]
OCCUPATION_TYPE Classes
8655, 17.76%
5072, 10.41%
4361, 8.95%
3574, 7.33%
2773, 5.69%
Laborers
Sales staff
Core staff
Managers
Drivers
High skill tech staff
Accountants
Medicine staff
Security staff
Cooking staff
Cleaning staff
Private service staff
Low-skill Laborers
Secretaries
Waiters/barmen staff
Realty agents
HR staff
IT staff





[8]:
```
# ugly: Manually remove outliers
application_train = application_train[ application_train['NAME_FAMILY_STATUS'] !
 ↪= 'Unknown' ]
application_train = application_train[ application_train['CODE_GENDER'] !=␣
 ↪'XNA' ]
application_train = application_train[ application_train['CNT_CHILDREN'] < 4 ]
application_train = application_train[ application_train['NAME_INCOME_TYPE'] !=␣
 ↪'Businessman' ]
application_train = application_train[ application_train['NAME_INCOME_TYPE'] !=␣
 ↪'Student' ]
```

```
application_train = application_train[ application_train['NAME_INCOME_TYPE'] !=␣
↪'Unemployed' ]
```

[9]:
```
application_train['NAME_INCOME_TYPE'].value_counts()
```

[9]:
```
Working                 158390
Commercial associate     71514
Pensioner                55341
State servant            21650
Maternity leave              5
Name: NAME_INCOME_TYPE, dtype: int64
```

[10]:
```
application_test['NAME_INCOME_TYPE'].value_counts()
```

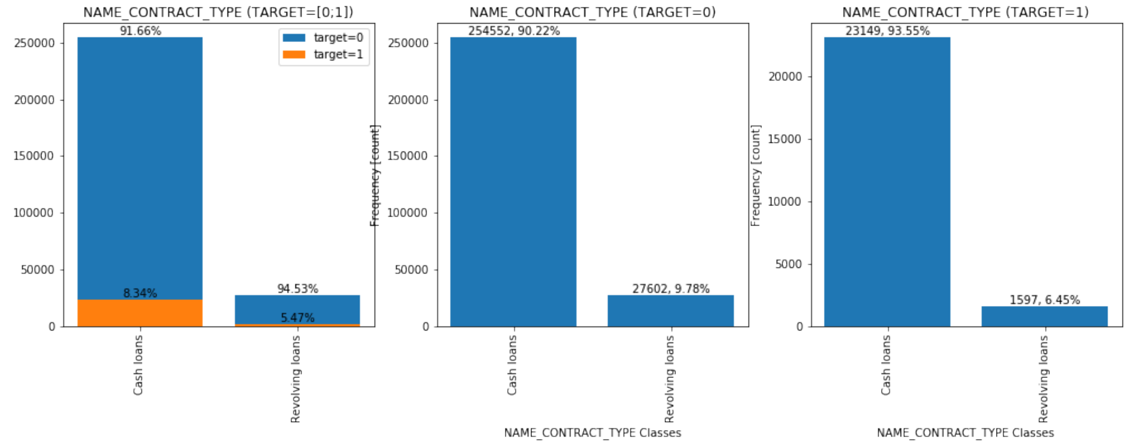
[10]:
```
Working                 24533
Commercial associate    11402
Pensioner                9273
State servant            3532
Student                     2
Unemployed                  1
Businessman                 1
Name: NAME_INCOME_TYPE, dtype: int64
```

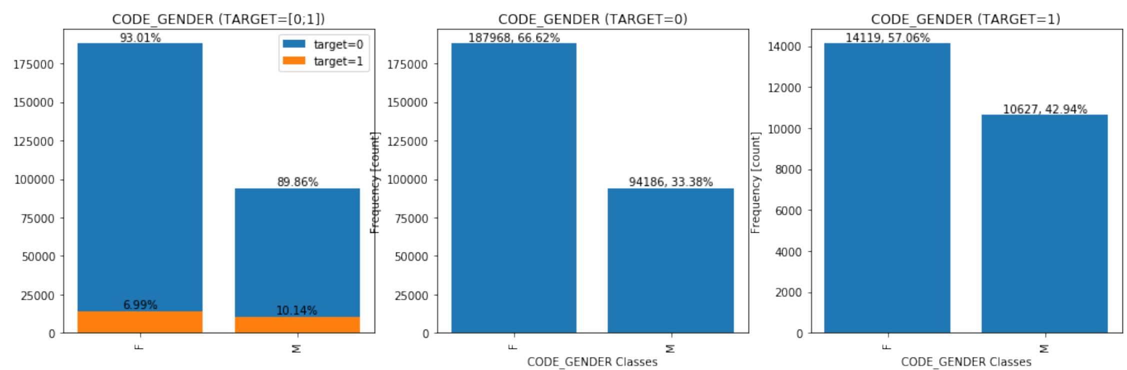
[11]:
```
# target=0 and target=1 DFs

train_target_0_rows = application_train[application_train['TARGET'] == 0]
train_target_1_rows = application_train[application_train['TARGET'] == 1]
```

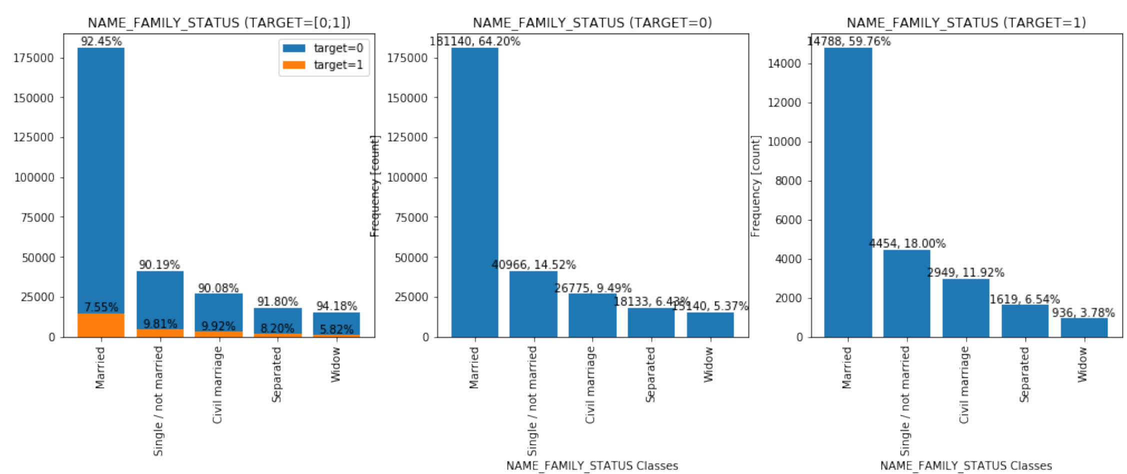
[12]:
```
# Type 2 overview: freq plot by target={0, 1}

cols_to_overview = [
    'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'NAME_FAMILY_STATUS',
    'FLAG_OWN_CAR', 'FLAG_OWN_REALTY',
    'CNT_CHILDREN', 'CNT_FAM_MEMBERS',
    'NAME_INCOME_TYPE', 'OCCUPATION_TYPE', 'NAME_EDUCATION_TYPE',␣
↪'NAME_HOUSING_TYPE',
    'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY'
]

for col_name in cols_to_overview:
    display_freq_plot_by_target( train_target_0_rows, train_target_1_rows,␣
↪col_name )

# NAME_CONTRACT_TYPE
# Cash loans are slightly more prone to become problematic (late payment)
# target=1 borrowers distributed almost equally between 2 classes: 8% in cash␣
↪loans, 5% in revolving loans.

# CODE_GENDER
```

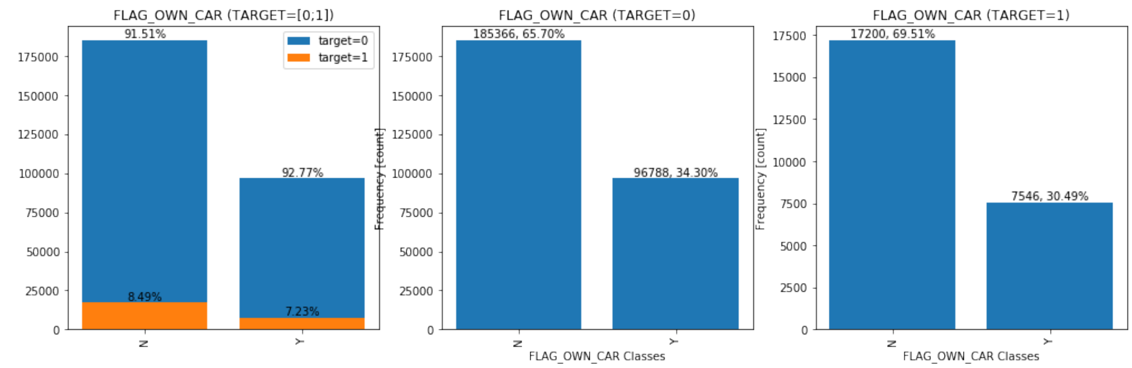
```
# Even though females borrow more often, MEN make more late payments (f:7%, m:
↪10%)

# NAME_FAMILY_STATUS
# All classes have almost equal percentage of bad borrowers: min=5.82%, max=9.
↪94%, mean=8.264%
# Top bad borrower class: civil marriage (9.94%), single/not married (9.81%)
# Top bad borrower classes are not the major borrowers: only 9.49% and 14.5%
# Top class by count - Married - are the second best class - only 7.56%
# Best class - widows; onlt 5.48 didn't repay their loans

# FLAG_OWN_CAR
# Equal distribution: those who don't have a car have slightly more chances (1.
↪25%) to not repay back

# FLAG_OWN_REALTY
# Equal distribution: borrowers without realty have slightly more chances (0.
↪4%) to not repay back

# CNT_CHILDREN
# 0, 1, 2 children - almost the same chance to NOT repay back
# 3 children - 3% - 1/3 of prev prob

# CNT_FAM_MEMBERS
# 5 members (3+ children) - highest probability to not repay back (9.5%)
# 1, 3, 4 members - higher prob to NOT repay back than 2 members

# OCCUPATION_TYPE
# Drivers - bad borrowers in test set
# Security staff - same as Drivers - bad in test set
# Top : laborers and sales staff = 10.5% and 9.6% didn't pay back their loans

# NAME_EDUCATION_TYPE
# Lower secondary - critical class - really bad borrowers: 18% didn't repay␣
↪back
# Higher education and academic degree - best ones
# Secondary and incomplete - same proportion of bad borrowers

# NAME_HOUSING_TYPE
# Rented apartment - worst category of borrowers - 12.3%
# With parents - second worst category of borrowers - 11.7%
# Others: 7-9%

# REG_CITY_NOT_LIVE_CITY, REG_CITY_NOT_WORK_CITY
# Clients permanent address NOT where one lives now - 12% (!) while 7.7% for␣
↪the opposite situation
```

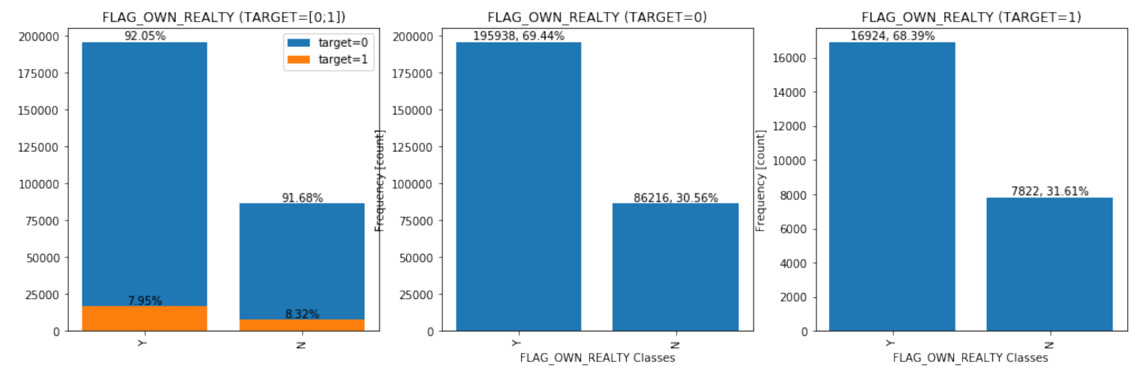
```
# Same for WORK - fake work = 10% that target will be a bad borrower
```

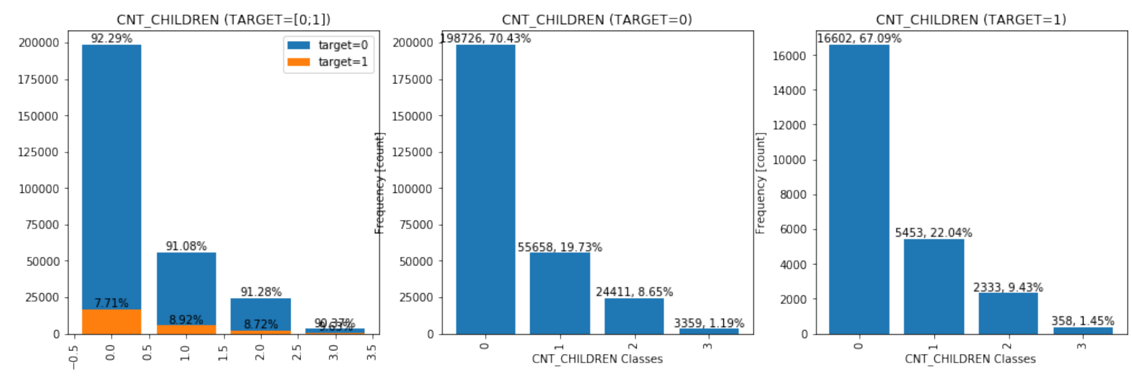


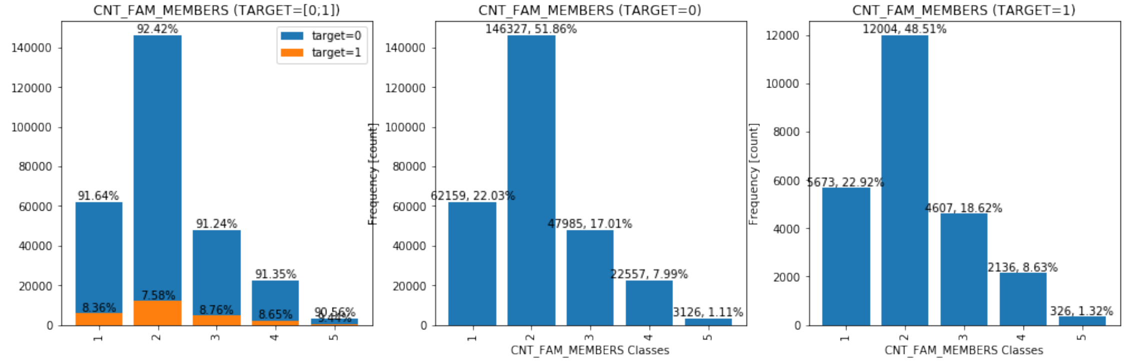


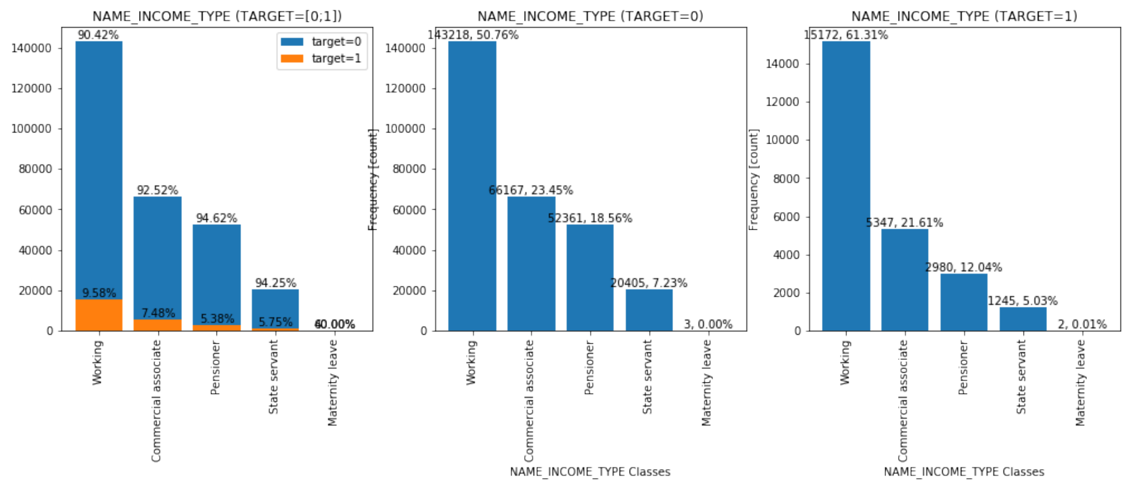


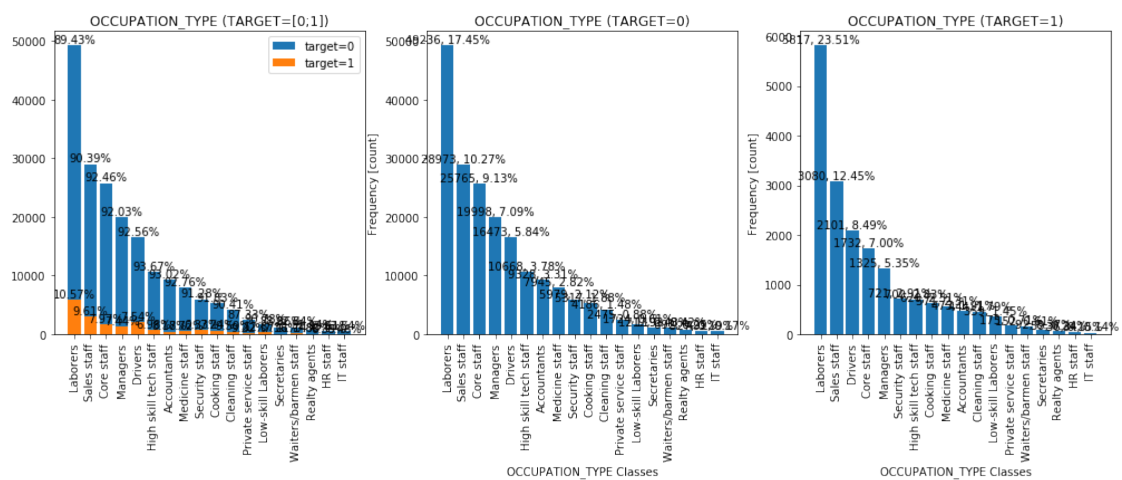

FLAG_OWN_CAR (TARGET=[0;1])
target=0
target=1
91.51%
92.77%
8.49%
7.23%
N
Y
FLAG_OWN_CAR (TARGET=0)
185366, 65.70%
96788, 34.30%
Frequency [count]
FLAG_OWN_CAR Classes
FLAG_OWN_CAR (TARGET=1)
17200, 69.51%
7546, 30.49%
Frequency [count]
FLAG_OWN_CAR Classes

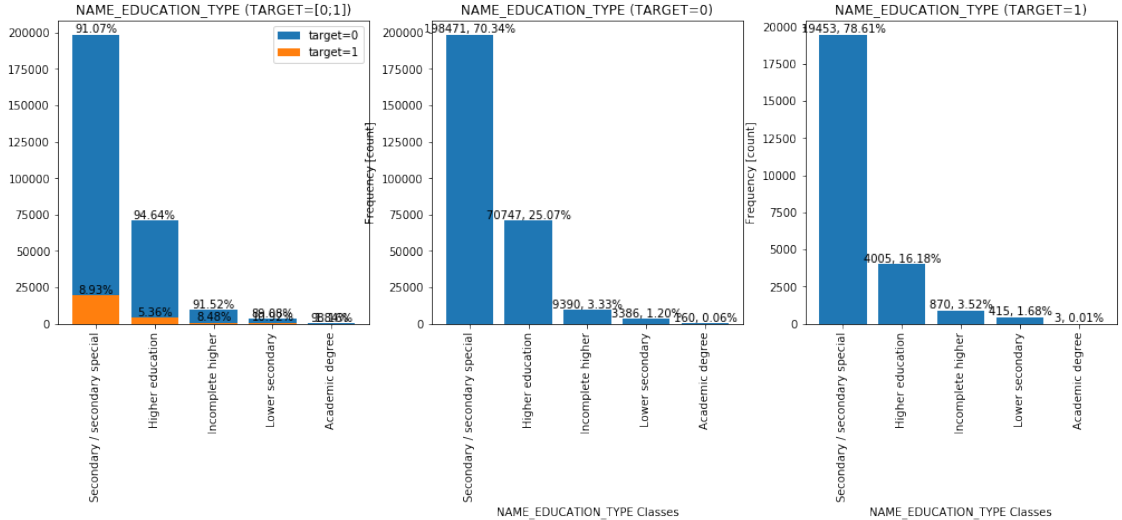

FLAG_OWN_REALTY (TARGET=[0;1])
target=0
target=1
92.05%
91.68%
7.95%
8.32%
Y
N
FLAG_OWN_REALTY (TARGET=0)
195938, 69.44%
86216, 30.56%
Frequency [count]
FLAG_OWN_REALTY Classes
FLAG_OWN_REALTY (TARGET=1)
16924, 68.39%
7822, 31.61%
Frequency [count]
FLAG_OWN_REALTY Classes

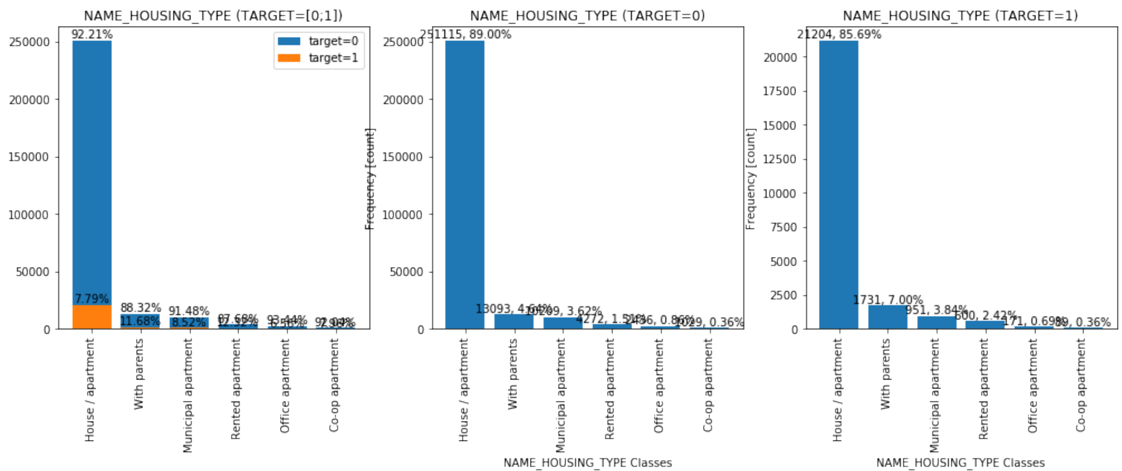

CNT_CHILDREN (TARGET=[0;1])
target=0
target=1
92.29%
91.08%
91.28%
7.71%
8.92%
8.72%
CNT_CHILDREN (TARGET=0)
198726, 70.43%
55658, 19.73%
24411, 8.65%
3359, 1.19%
Frequency [count]
CNT_CHILDREN Classes
CNT_CHILDREN (TARGET=1)
16602, 67.09%
5453, 22.04%
2333, 9.43%
358, 1.45%
Frequency [count]
CNT_CHILDREN Classes

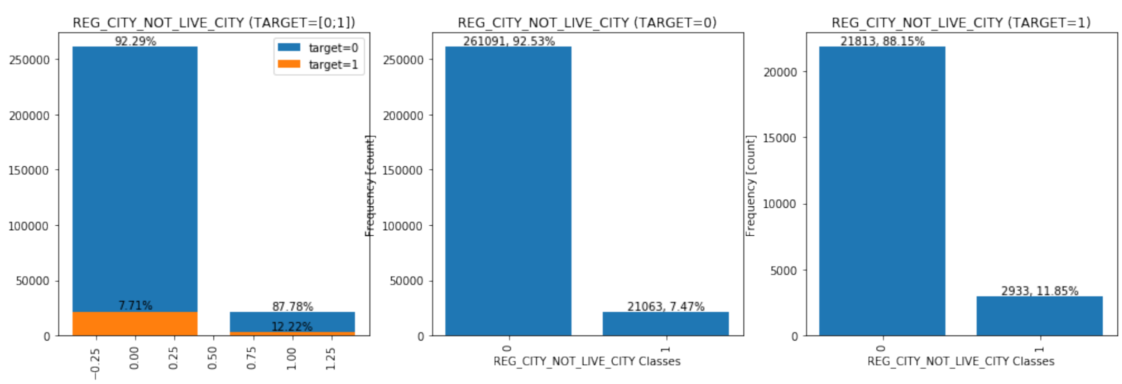

CNT_FAM_MEMBERS (TARGET=[0;1])
target=0
target=1
CNT_FAM_MEMBERS (TARGET=0)
CNT_FAM_MEMBERS (TARGET=1)
Frequency [count]
CNT_FAM_MEMBERS Classes
146327, 51.86%
62159, 22.03%
47985, 17.01%
22557, 7.99%
3126, 1.11%
12004, 48.51%
5673, 22.92%
4607, 18.62%
2136, 8.63%
326, 1.32%

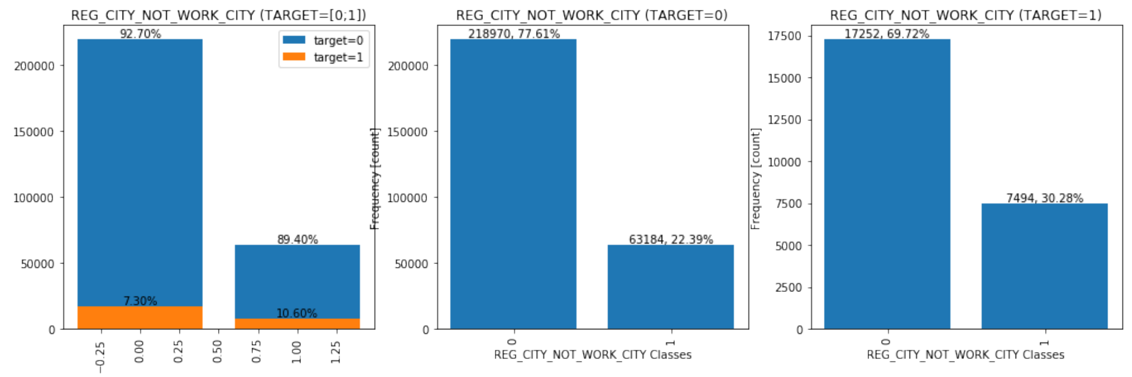

NAME_INCOME_TYPE (TARGET=[0;1])
target=0
target=1
NAME_INCOME_TYPE (TARGET=0)
NAME_INCOME_TYPE (TARGET=1)
Frequency [count]
NAME_INCOME_TYPE Classes
Working
Commercial associate
Pensioner
State servant
Maternity leave
143218, 50.76%
66167, 23.45%
52361, 18.56%
20405, 7.23%
3, 0.00%
15172, 61.31%
5347, 21.61%
2980, 12.04%
1245, 5.03%
2, 0.01%


OCCUPATION_TYPE (TARGET=[0;1])
target=0
target=1
OCCUPATION_TYPE (TARGET=0)
OCCUPATION_TYPE (TARGET=1)
Frequency [count]
OCCUPATION_TYPE Classes
Laborers
Sales staff
Core staff
Managers
Drivers
High skill tech staff
Accountants
Medicine staff
Security staff
Cooking staff
Cleaning staff
Private service staff
Low-skill Laborers
Secretaries
Waiters/barmen staff
Realty agents
HR staff
IT staff


NAME_EDUCATION_TYPE (TARGET=[0;1])
target=0
target=1
91.07%
8.93%
94.64%
5.36%
91.52%
8.48%
Secondary / secondary special
Higher education
Incomplete higher
Lower secondary
Academic degree
NAME_EDUCATION_TYPE (TARGET=0)
198471, 70.34%
70747, 25.07%
9390, 3.33%
3386, 1.20%
160, 0.06%
Frequency [count]
NAME_EDUCATION_TYPE Classes
NAME_EDUCATION_TYPE (TARGET=1)
19453, 78.61%
4005, 16.18%
870, 3.52%
415, 1.68%
3, 0.01%


NAME_HOUSING_TYPE (TARGET=[0;1])
target=0
target=1
92.21%
7.79%
88.32%
11.68%
91.48%
8.52%
House / apartment
With parents
Municipal apartment
Rented apartment
Office apartment
Co-op apartment
NAME_HOUSING_TYPE (TARGET=0)
251115, 89.00%
Frequency [count]
NAME_HOUSING_TYPE Classes
NAME_HOUSING_TYPE (TARGET=1)
21204, 85.69%
1731, 7.00%
951, 3.84%
171, 0.69%


REG_CITY_NOT_LIVE_CITY (TARGET=[0;1])
target=0
target=1
92.29%
7.71%
87.78%
12.22%
REG_CITY_NOT_LIVE_CITY (TARGET=0)
261091, 92.53%
21063, 7.47%
Frequency [count]
REG_CITY_NOT_LIVE_CITY Classes
REG_CITY_NOT_LIVE_CITY (TARGET=1)
21813, 88.15%
2933, 11.85%



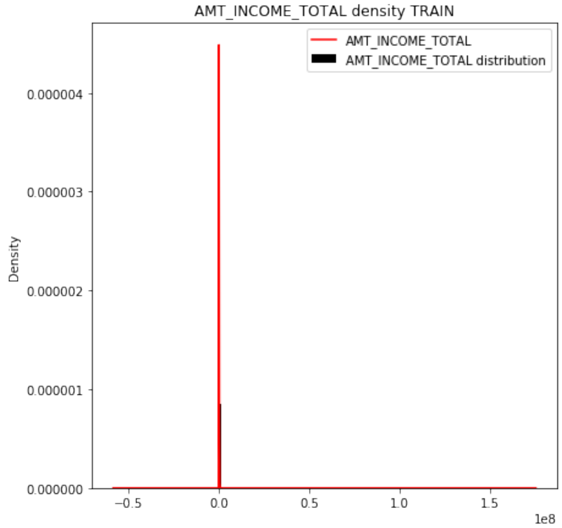
[13]:

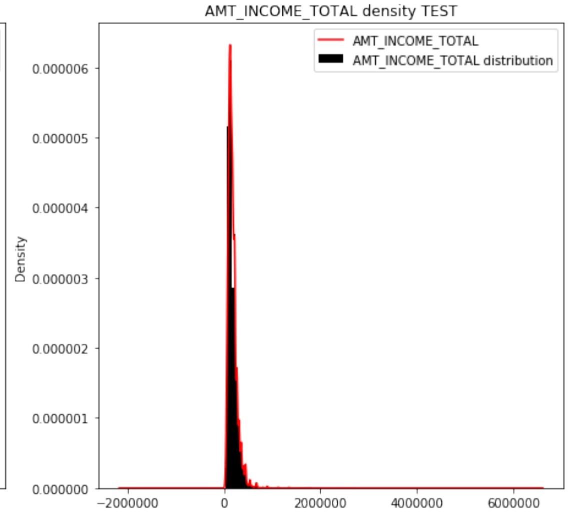
```
def display_distr( dataset_df, col_name, ax, \
                  n_bins=100, display_kde=True, title_add_text='',␣
↪log_transform=False, hist_color='black'):
    data_to_display = dataset_df[col_name]
    if log_transform:
        data_to_display = np.log( data_to_display )
    ax.hist(
        data_to_display,
        bins=n_bins,
        density=True,
        label='{0} distribution'.format(col_name),
        color=hist_color
    )
    if display_kde:
        data_to_display.plot(kind='density', color='red', ax=ax)
    ax.set_title('{0} density {1}'.format(col_name, title_add_text))
    ax.legend()


def display_distr_traintest( train_df, test_df, col_name, display_kde=False,␣
↪log_transform=False ):
    fig, [ax_0, ax_1] = plt.subplots( 1, 2, figsize=(15, 7) )
    display_distr( train_df, col_name, ax=ax_0,
                  title_add_text='TRAIN', display_kde=display_kde,␣
↪log_transform=log_transform )
    display_distr( test_df, col_name, ax=ax_1,
                  title_add_text='TEST', display_kde=display_kde,␣
↪log_transform=log_transform )

def display_full_distr_overview( train_df, test_df, col_name ):
    display( train_df[col_name].describe(include='all') )
    display( test_df[col_name].describe(include='all') )
    display_distr_traintest( train_df, test_df, col_name, display_kde=True )
    display_distr_traintest(
```

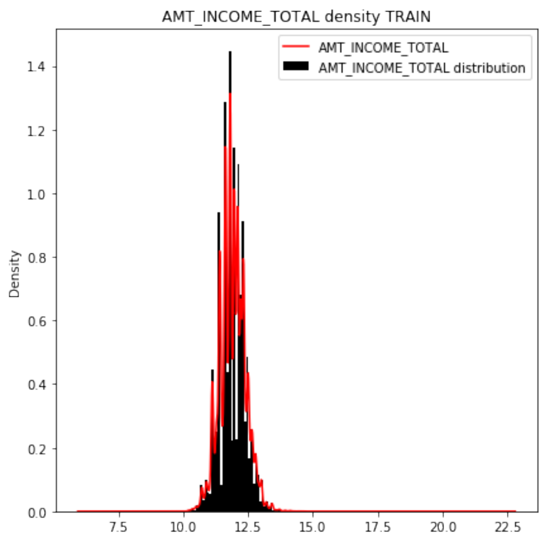
```
        train_df, test_df, col_name,
        log_transform=True, display_kde=True
    )
```

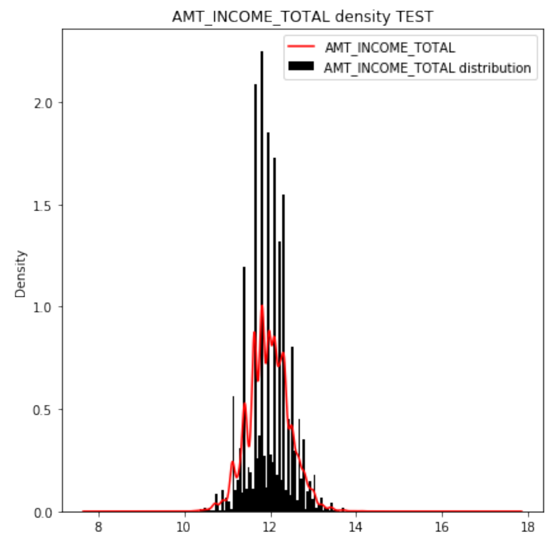
[14]:
```
# Type 3 overview: distribution of continuous features

# AMT_INCOME_TOTAL
# train: lots of outliers; range: [0.02565 mln; 117 mln]; mean = 0.0168 mln =␣
 ↪168k
# test: range: [0.0269415 mln; 4.41 mln]; mean = 0.0178 mln = 178k
display( 'AMT_INCOME_TOTAL' )
display_full_distr_overview( application_train, application_test,␣
 ↪'AMT_INCOME_TOTAL' )
display_distr_traintest(  # borrowers withh total income < 10 mln
    application_train[ application_train['AMT_INCOME_TOTAL'] < 10**6 ],
    application_test[ application_test['AMT_INCOME_TOTAL'] < 10**6 ],
    'AMT_INCOME_TOTAL',
    display_kde=True
)
```

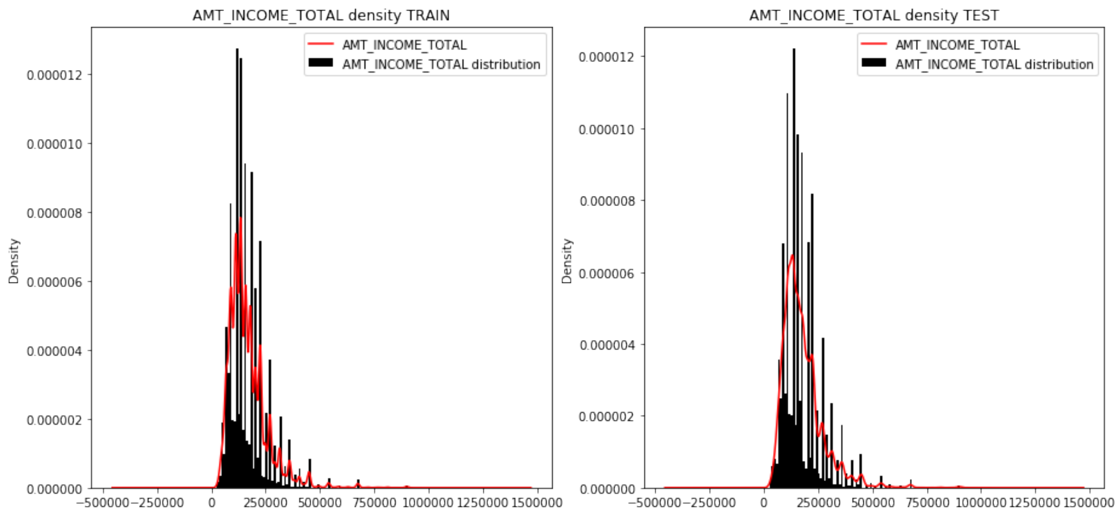
```
'AMT_INCOME_TOTAL'


count    3.069000e+05
mean     1.687837e+05
std      2.372756e+05
min      2.565000e+04
25%      1.125000e+05
50%      1.475235e+05
75%      2.025000e+05
max      1.170000e+08
Name: AMT_INCOME_TOTAL, dtype: float64


count    4.874400e+04
mean     1.784318e+05
std      1.015226e+05
min      2.694150e+04
25%      1.125000e+05
50%      1.575000e+05
75%      2.250000e+05
max      4.410000e+06
Name: AMT_INCOME_TOTAL, dtype: float64
```


AMT_INCOME_TOTAL density TRAIN
AMT_INCOME_TOTAL
AMT_INCOME_TOTAL distribution
Density
1e8


AMT_INCOME_TOTAL density TEST
AMT_INCOME_TOTAL
AMT_INCOME_TOTAL distribution
Density

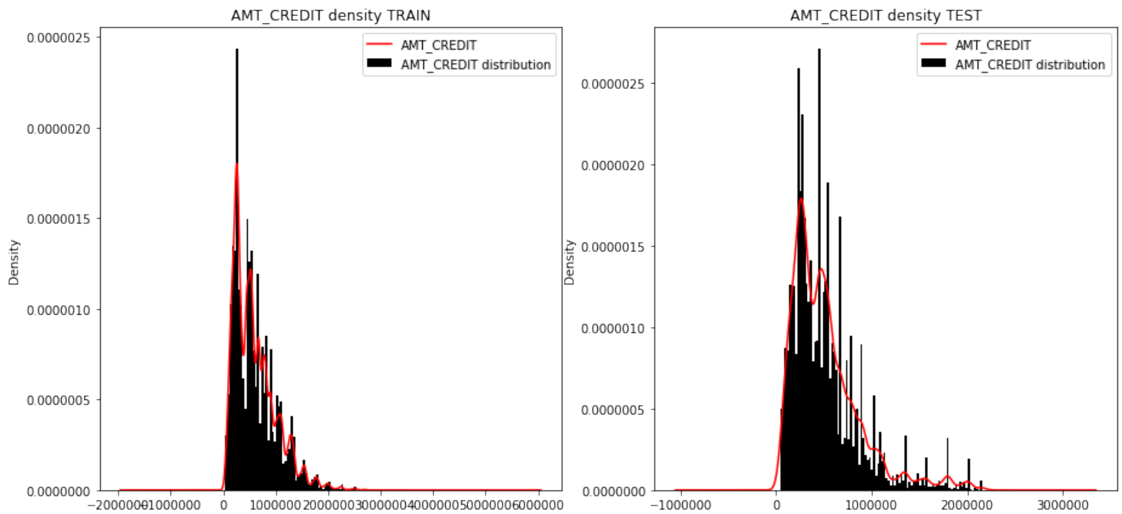

AMT_INCOME_TOTAL density TRAIN
AMT_INCOME_TOTAL
AMT_INCOME_TOTAL distribution
Density

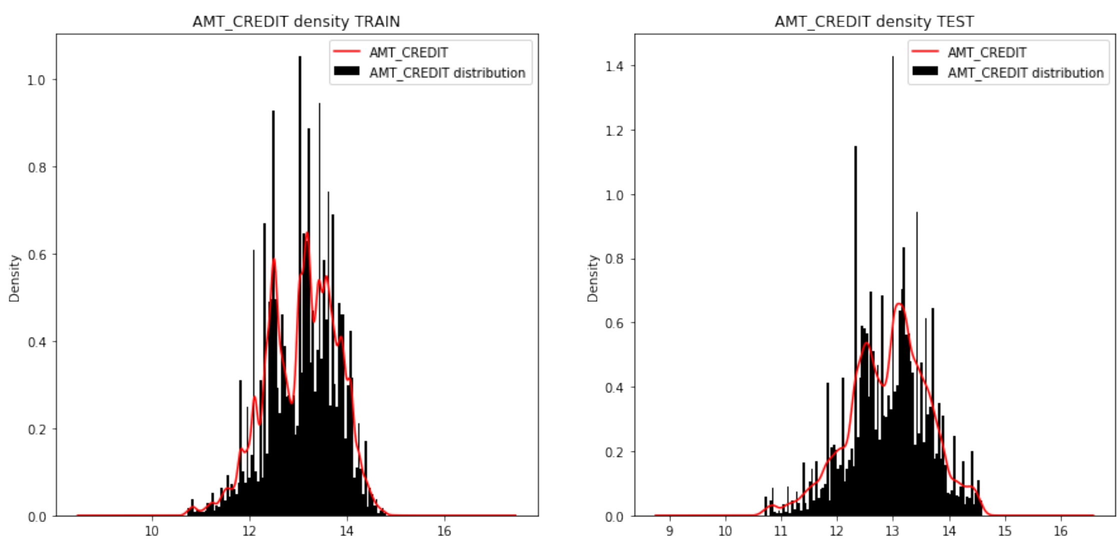

AMT_INCOME_TOTAL density TEST
AMT_INCOME_TOTAL
AMT_INCOME_TOTAL distribution
Density



[15]:
```
# AMT_CREDIT
display( 'AMT_CREDIT' )
display_full_distr_overview( application_train, application_test, 'AMT_CREDIT' )
```

```
'AMT_CREDIT'


count    3.069000e+05
mean     5.989941e+05
std      4.024483e+05
min      4.500000e+04
25%      2.700000e+05
50%      5.135310e+05
75%      8.086500e+05
max      4.050000e+06
Name: AMT_CREDIT, dtype: float64


count    4.874400e+04
mean     5.167404e+05
std      3.653970e+05
min      4.500000e+04
25%      2.606400e+05
50%      4.500000e+05
75%      6.750000e+05
max      2.245500e+06
Name: AMT_CREDIT, dtype: float64
```



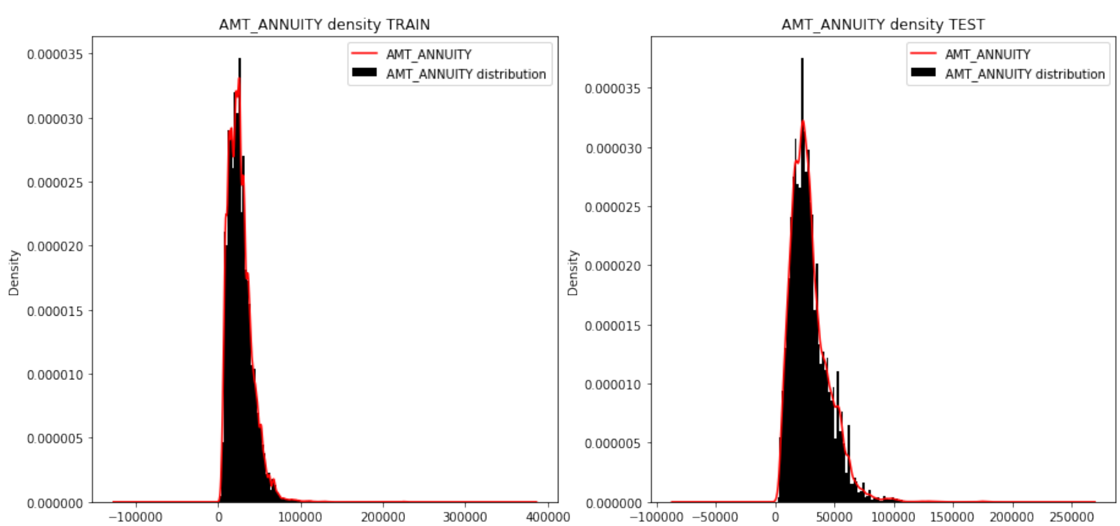


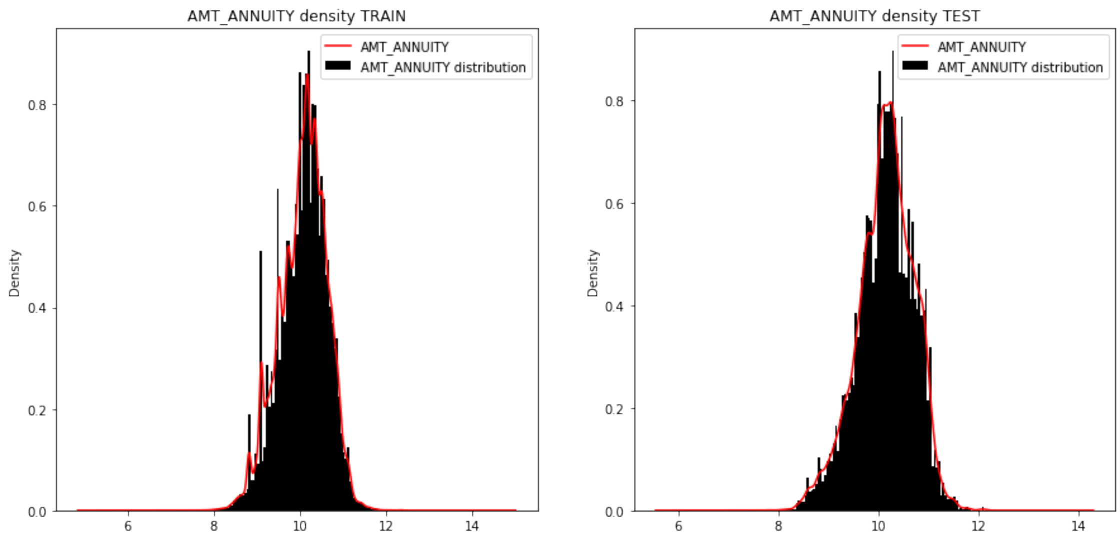
[16]:
```
# AMT_ANNUITY
# Most of borrowers should have pay <100k per year - weird why such a small␣
↪amount
display( 'AMT_ANNUITY' )
display_full_distr_overview( application_train, application_test, 'AMT_ANNUITY'␣
↪)
```

```
'AMT_ANNUITY'
```

```
count     306888.000000
```

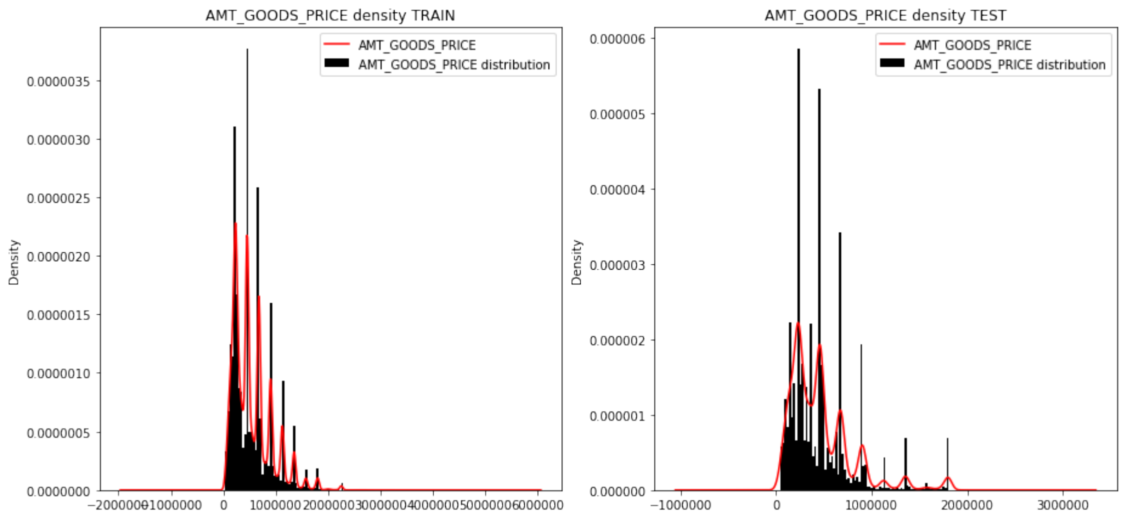
```
mean       27105.435486
std        14483.291752
min         1615.500000
25%        16524.000000
50%        24903.000000
75%        34596.000000
max       258025.500000
Name: AMT_ANNUITY, dtype: float64


count      48720.000000
mean       29426.240209
std        16016.368315
min         2295.000000
25%        17973.000000
50%        26199.000000
75%        37390.500000
max       180576.000000
Name: AMT_ANNUITY, dtype: float64


/home/max/.local/lib/python3.7/site-packages/numpy/lib/histograms.py:824:
RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/home/max/.local/lib/python3.7/site-packages/numpy/lib/histograms.py:825:
RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

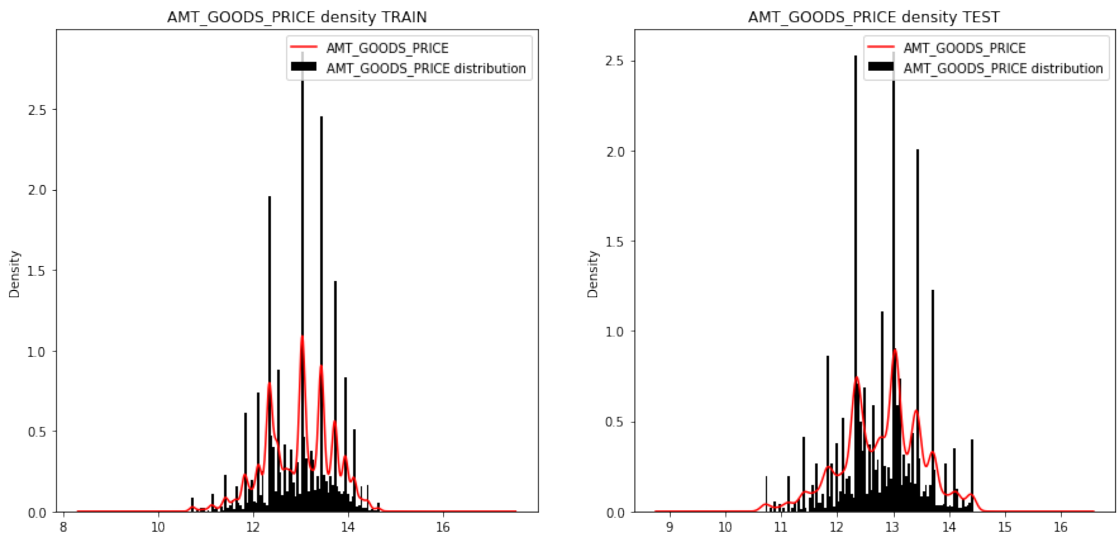




[17]:
```
# AMT_GOODS_PRICE
# Peaks mean '25k', '50k', '75k', '100k', '150k', '200k' - approximate costs␣
↪told by borrowers
display( 'AMT_GOODS_PRICE' )
display_full_distr_overview( application_train, application_test,␣
↪'AMT_GOODS_PRICE' )
```

```
'AMT_GOODS_PRICE'


count    3.066260e+05
mean     5.383678e+05
std      3.693848e+05
min      4.050000e+04
25%      2.385000e+05
50%      4.500000e+05
75%      6.795000e+05
max      4.050000e+06
Name: AMT_GOODS_PRICE, dtype: float64


count    4.874400e+04
mean     4.626188e+05
std      3.367102e+05
min      4.500000e+04
25%      2.250000e+05
50%      3.960000e+05
75%      6.300000e+05
max      2.245500e+06
Name: AMT_GOODS_PRICE, dtype: float64
```





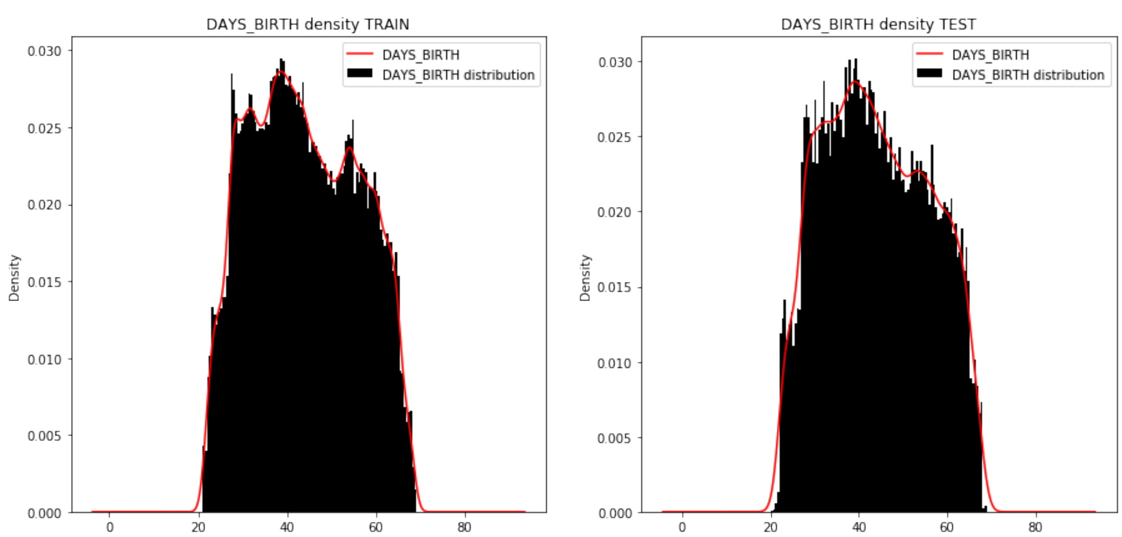
[18]:
```
# DAYS_BIRTH
# [20, 69] (so pensioners are not 80yo, but max=69y)
# mean: 43y train, 44y test
# 40->50 plunge - reason ?
# 50->55 rise - retirement?

display( 'DAYS_BIRTH transformed to YEARS_BIRTH' )

DAYS_IN_YEAR = 365
train_years_birth = pd.DataFrame( application_train['DAYS_BIRTH'] /␣
↪DAYS_IN_YEAR * -1.0 )
```

```
test_years_birth = pd.DataFrame( application_test['DAYS_BIRTH'] / DAYS_IN_YEAR␣
 ↪* -1.0 )

display( train_years_birth.describe(include='all').T )
display( test_years_birth.describe(include='all').T )

display_distr_traintest(  # borrowers withh total income < 10 mln
    train_years_birth, test_years_birth, 'DAYS_BIRTH',
    display_kde=True, log_transform=False
)
```

```
'DAYS_BIRTH transformed to YEARS_BIRTH'
```

```
                count       mean        std        min        25%        50%  \
DAYS_BIRTH   306900.0  43.946621  11.961693  20.517808  34.005479  43.171233

                  75%        max
DAYS_BIRTH  53.939726  69.120548
```

```
               count      mean        std       min        25%        50%  \
DAYS_BIRTH   48744.0  44.02215  11.851782  20.10411  34.235616  43.246575

              75%        max
DAYS_BIRTH   53.8  69.027397
```



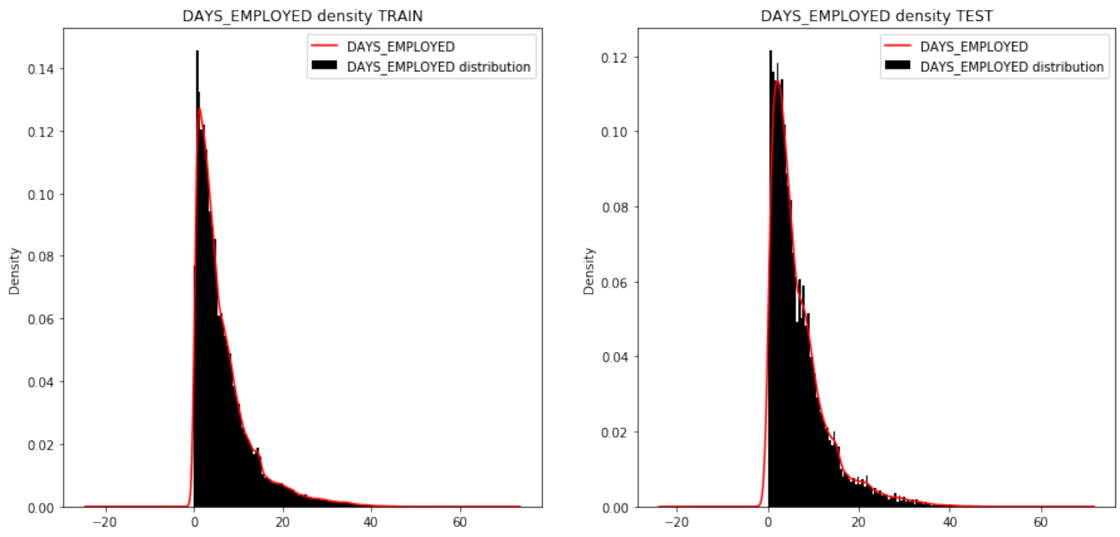
[19]:
```
# DAYS_EMPLOYED
# anomaly at years=-1000 - 'unemployed' ?
```

```
# note: because data source comes from Russia, many of borrowers could lie␣
↪about job OR job could not register them officially (gray/dark salary)
# 90s - did Home Credit count job experience from USSR ?

# Most of borrowers are 'young' (?!) professionals - 50pcntl is 4.5y in train,␣
↪4.8 in test
# Almost no borrowers with 40+ years job experience

display( 'DAYS_EMPLOYED transformed to YEARS_EMPLOYED' )

DAYS_IN_YEAR = 365
train_years_emp = pd.DataFrame( application_train['DAYS_EMPLOYED'] /␣
↪DAYS_IN_YEAR * -1.0 )
test_years_emp = pd.DataFrame( application_test['DAYS_EMPLOYED'] / DAYS_IN_YEAR␣
↪* -1.0 )

display( train_years_emp[train_years_emp['DAYS_EMPLOYED'] > 0].
↪describe(include='all').T )
display( test_years_emp[test_years_emp['DAYS_EMPLOYED'] > 0].
↪describe(include='all').T )

display_distr_traintest(  # borrowers withh total income < 10 mln
    train_years_emp[train_years_emp['DAYS_EMPLOYED'] > 0],
    test_years_emp[test_years_emp['DAYS_EMPLOYED'] > 0],
    'DAYS_EMPLOYED',
    display_kde=True, log_transform=False
)
```

```
'DAYS_EMPLOYED transformed to YEARS_EMPLOYED'
```

```
                  count      mean       std      min      25%       50%  \
DAYS_EMPLOYED  251567.0  6.532025  6.409002  0.00274  2.10137  4.512329

                   75%        max
DAYS_EMPLOYED  8.69863  49.073973
```

```
                 count      mean       std      min       25%       50%  \
DAYS_EMPLOYED  39470.0  6.785586  6.323189  0.00274  2.358904  4.835616

                    75%        max
DAYS_EMPLOYED  9.119863  47.843836
```

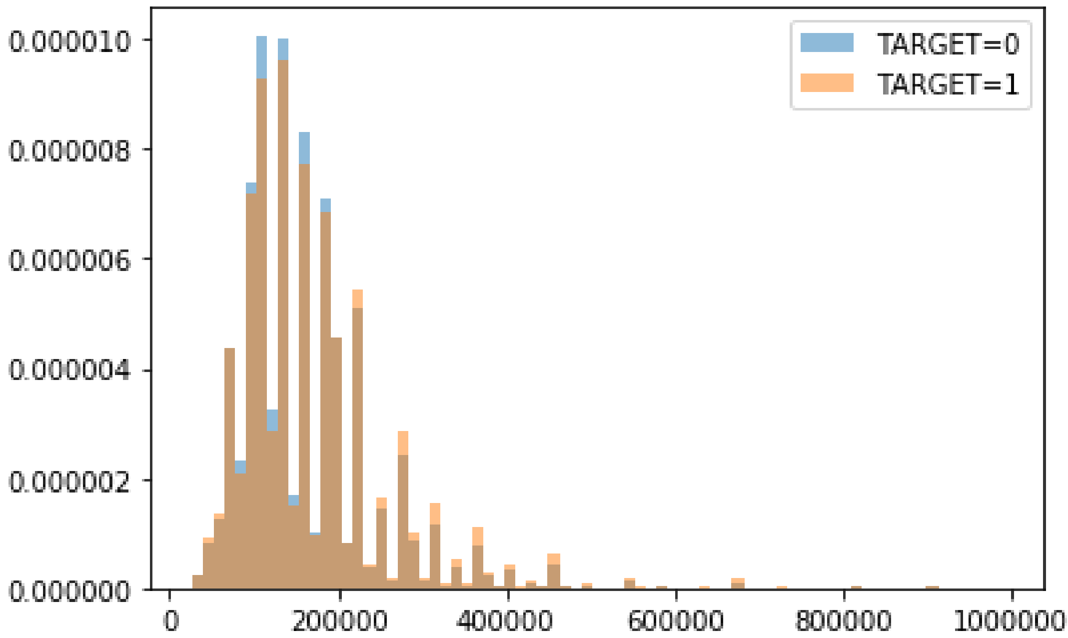


[20]:
```
def display_hist_density_target_0_1( target_1_df, target_0_df, col_name ):
    display(col_name)

    fig, ax = plt.subplots()
    ax.hist( target_0_df[col_name], bins=75, alpha=0.5, label='TARGET=0',␣
 ↪density=True )
    ax.hist( target_1_df[col_name], bins=75, alpha=0.5, label='TARGET=1',␣
 ↪density=True )
    ax.legend()
    plt.show()

    display(  # reject
        'KS test: for {0}: {1}'.format(
            col_name,
            stats.ks_2samp(
                target_0_df['AMT_INCOME_TOTAL'],
                target_1_df['AMT_INCOME_TOTAL']
            )
        )
    )
```

[21]:
```
# Type 4 overview: compare distributions of continuous features for␣
 ↪target={0,1}

train_0_less_mln = train_target_0_rows[train_target_0_rows['AMT_INCOME_TOTAL']␣
 ↪< 10**6]
train_1_less_mln = train_target_1_rows[train_target_1_rows['AMT_INCOME_TOTAL']␣
 ↪< 10**6]
```

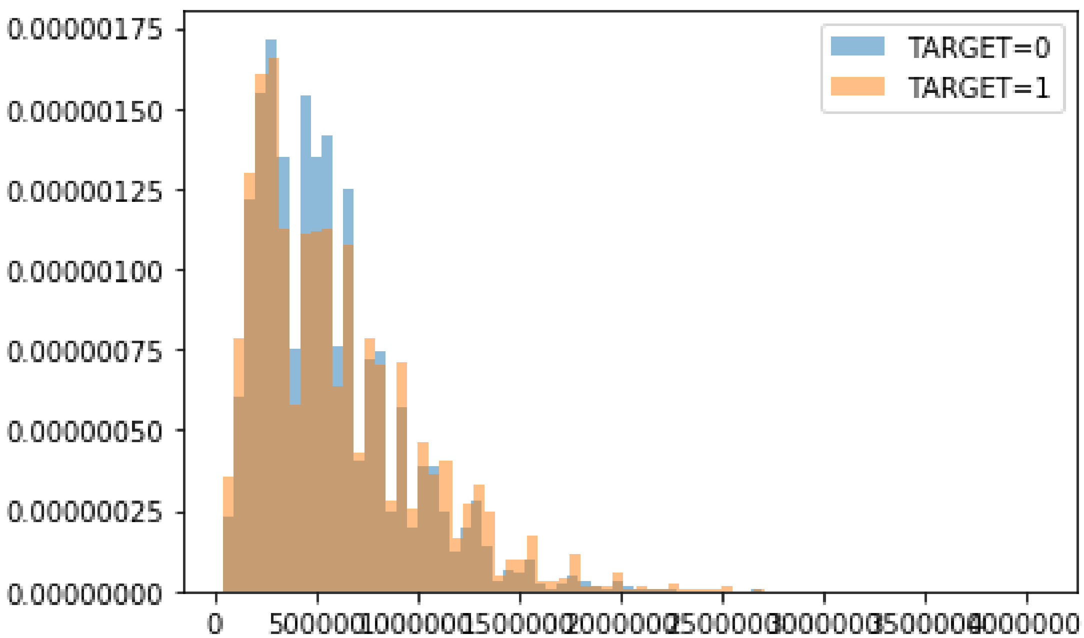
```python
display_hist_density_target_0_1( train_0_less_mln, train_1_less_mln,␣
 ↪'AMT_INCOME_TOTAL' )

# 'AMT_INCOME_TOTAL'
# density is almost the same - why?

cols_to_overview = [
    'AMT_CREDIT', 'AMT_ANNUITY', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH'
]

for col_name in cols_to_overview:
    display_hist_density_target_0_1( train_0_less_mln, train_1_less_mln,␣
 ↪col_name )

# 'AMT_CREDIT'
# 30k-60k - most borrowers didn't repay back
# 0-25k - same density; 100+k - same density

# 'AMT_ANNUITY'
# Low annuity 25k-40k - sign for borrower to become target=1

# 'DAYS_REGISTRATION'
# Days -6000+ - clear sign for target=1; for <-6000 - sign for target=0

# 'DAYS_ID_PUBLISH'
# Days -3000+ - clear sign for target=1; for <-4000 - sign for target=0
# -3000 - -4000 - 50/50
```

```
'AMT_INCOME_TOTAL'
```



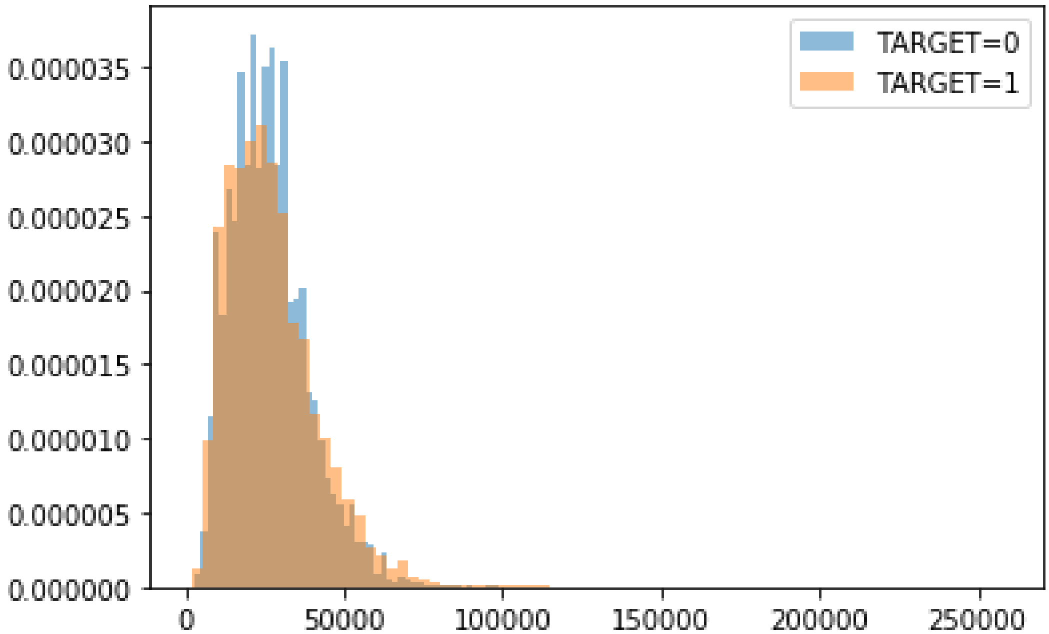

```
'KS test: for AMT_INCOME_TOTAL: Ks_2sampResult(statistic=0.03685621333822653, pvalue=2.9707498
```

```
'AMT_CREDIT'
```



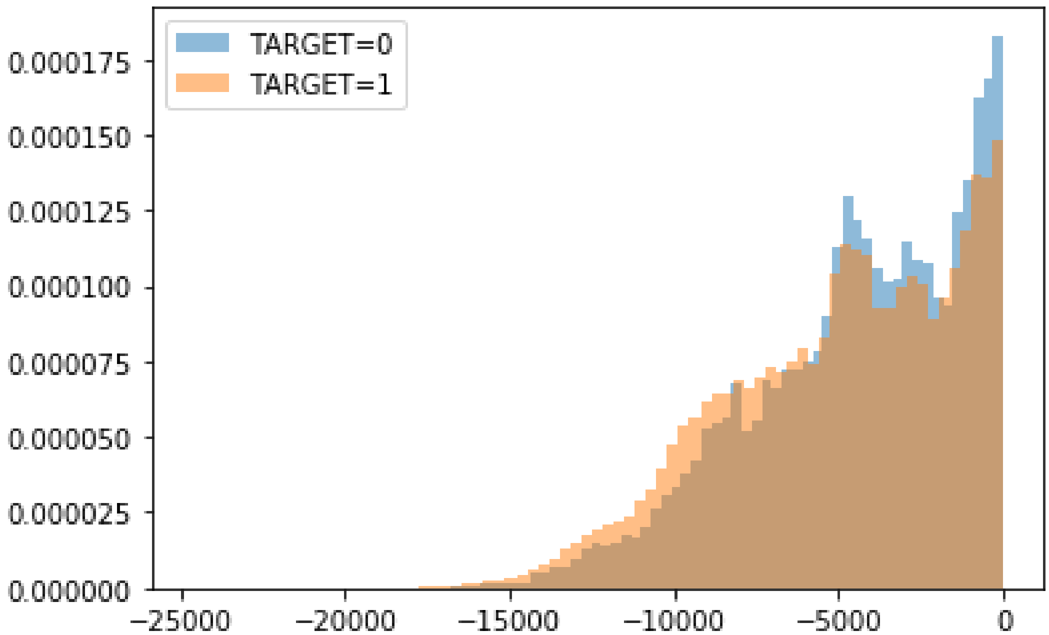
```
'KS test: for AMT_CREDIT: Ks_2sampResult(statistic=0.03685621333822653, pvalue=2.9707498148311
```

```
'AMT_ANNUITY'
```



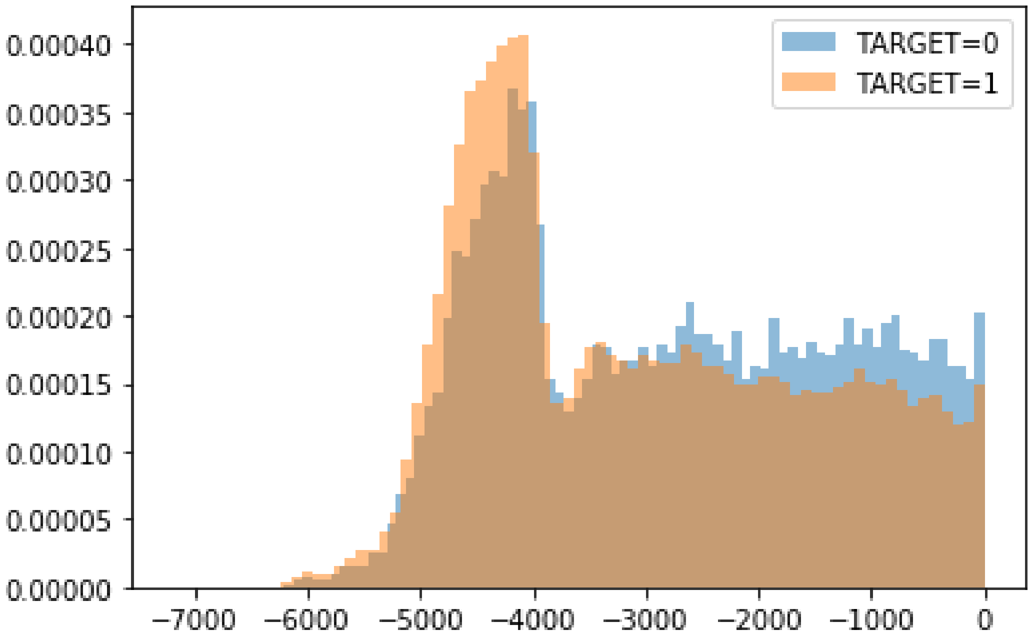

```
'KS test: for AMT_ANNUITY: Ks_2sampResult(statistic=0.03685621333822653, pvalue=2.970749814831
```

```
'DAYS_REGISTRATION'
```




```
'KS test: for DAYS_REGISTRATION: Ks_2sampResult(statistic=0.03685621333822653, pvalue=2.9707498
```

```
'DAYS_ID_PUBLISH'
```



```
'KS test: for DAYS_ID_PUBLISH: Ks_2sampResult(statistic=0.03685621333822653, pvalue=2.97074981
```

[22]:
```
# Overview 'Bureau' table

# SK_ID_CURR - FK for application_X table

BUREAU_FILEPATH = 'data/bureau.csv'
bureau = pd.read_csv( BUREAU_FILEPATH, header=0 )
```

[24]:
```
# quick_overview_df( bureau )
```

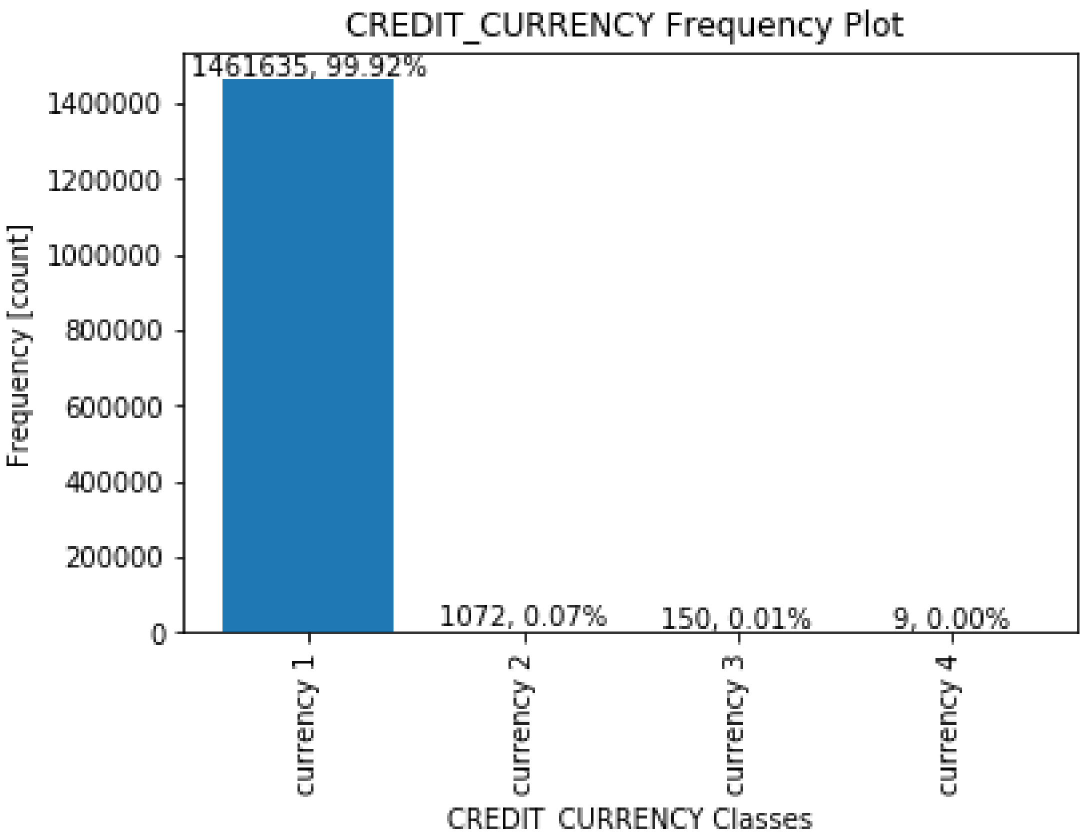
[25]:
```
merged_applicationtrain_bureau = pd.merge(
    left=application_train, right=bureau,
    on='SK_ID_CURR',
    how='inner'
)
```

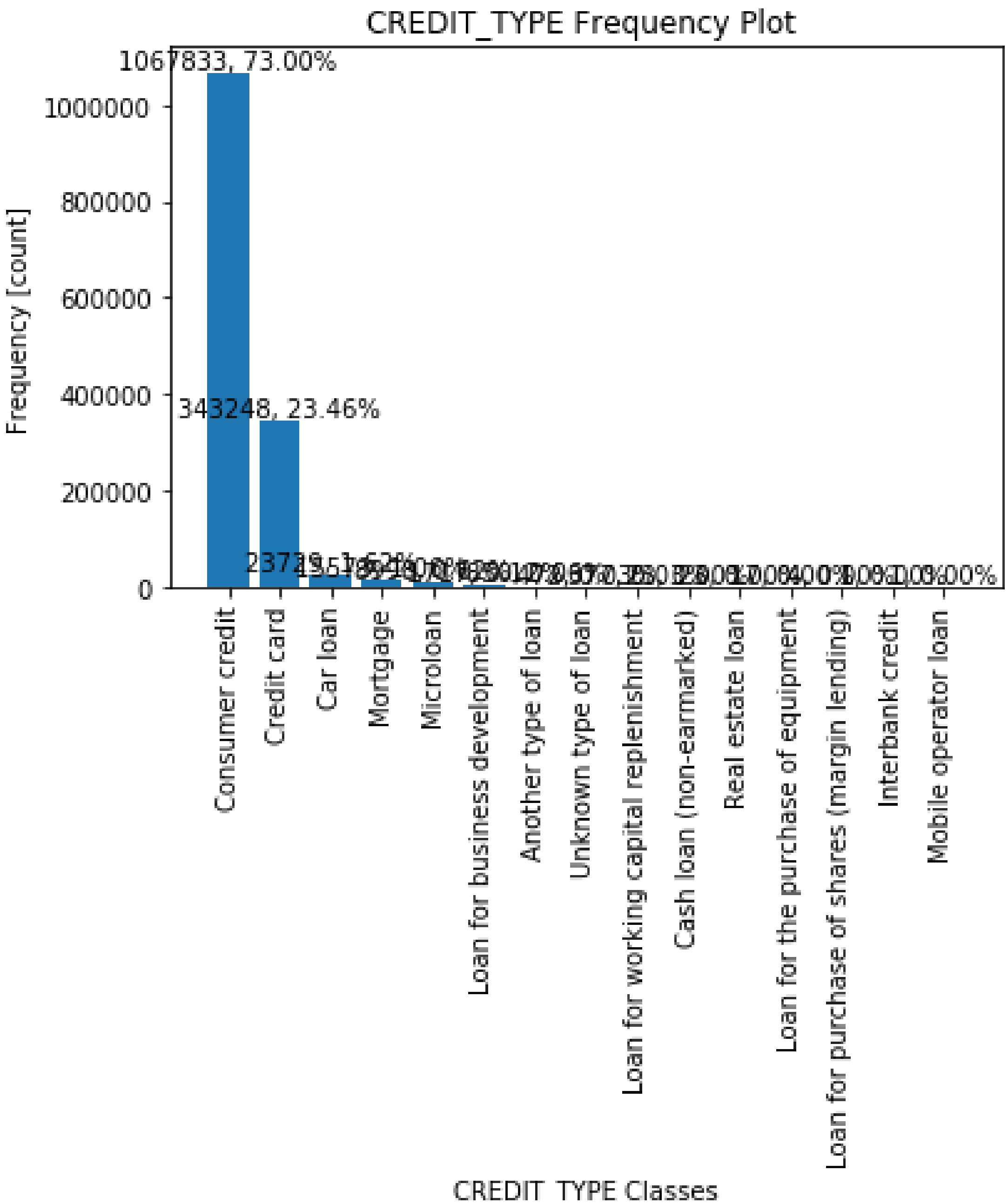
[28]:
```
# quick_overview_df( merged_applicationtrain_bureau )
```

[29]:
```
merged_apptrain_bur_target_0 =␣
↪merged_applicationtrain_bureau[merged_applicationtrain_bureau['TARGET'] == 0]
merged_apptrain_bur_target_1 =␣
↪merged_applicationtrain_bureau[merged_applicationtrain_bureau['TARGET'] == 1]
```

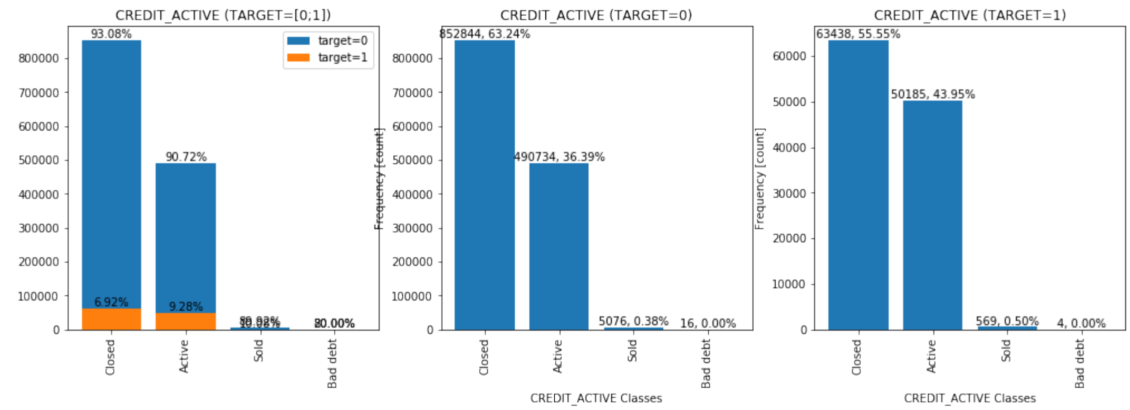
[36]:
```
cols_to_overview_distr_t0_t1 = [
    'CREDIT_CURRENCY', 'CREDIT_TYPE'
]
cols_to_overview_prop = [
    'CREDIT_ACTIVE',
]

for col_name in cols_to_overview_distr_t0_t1:
    fig, ax_0 = plt.subplots()
    display_freq_plot( merged_applicationtrain_bureau, col_name, ax=ax_0 )
    plt.show()

for col_name in cols_to_overview_prop:
    display_freq_plot_by_target( merged_apptrain_bur_target_0,␣
↪merged_apptrain_bur_target_1, col_name )

# 'CREDIT_CURRENCY'
# Mostly credits are in 'currency_1' (RUB?)
# Proportion of clients with TARGET=1 is different: currency_3 (12%) ->␣
↪currency_1 (9%) -> currency_2 (5%) -> currency_4 (0%)
# This might NOT be a good feature

# 'CREDIT_TYPE'
# Consumer dept - 73% of total contracts; 23.46% - credit card; <5% - all␣
↪others
```

```
# However, when looking at credit_type with target=1:
# loan for the purchase of equipment - 25% (!) becoming target=1
# microloan - 20% (!)
# credit card - 13%
# consumer credit - 8%

# 'CREDIT_ACTIVE'
# Most of the contracts are already closed (2/3); 1/3 is active
# Sold debts and Bad debt are <1% of grand total
# People with TARGET=0 share same proportion as general distribution: 2/3␣
↪closed 1/3 active
# Whereas people with TARGET=1 are more prone to have 'active' status: 44%
# PCT of grand total for TARGET=1: bad dept (20%) -> sold (10%) -> active (9.
↪3%) -> closed (7%)
```





CREDIT_TYPE Frequency Plot
1067833, 73.00%
343248, 23.46%
Frequency [count]
0
200000
400000
600000
800000
1000000
Consumer credit
Credit card
Car loan
Mortgage
Microloan
Loan for business development
Another type of loan
Unknown type of loan
Loan for working capital replenishment
Cash loan (non-earmarked)
Real estate loan
Loan for the purchase of equipment
Loan for purchase of shares (margin lending)
Interbank credit
Mobile operator loan
CREDIT_TYPE Classes



[37]:
```
# Overview 'Prev applications' table

# SK_ID_CURR - FK for application_X table

PREVAPPLICATIONS_FILEPATH = 'data/previous_application.csv'
prevapplications = pd.read_csv( PREVAPPLICATIONS_FILEPATH, header=0 )
```

[39]:
```
# quick_overview_df( prevapplications )
```

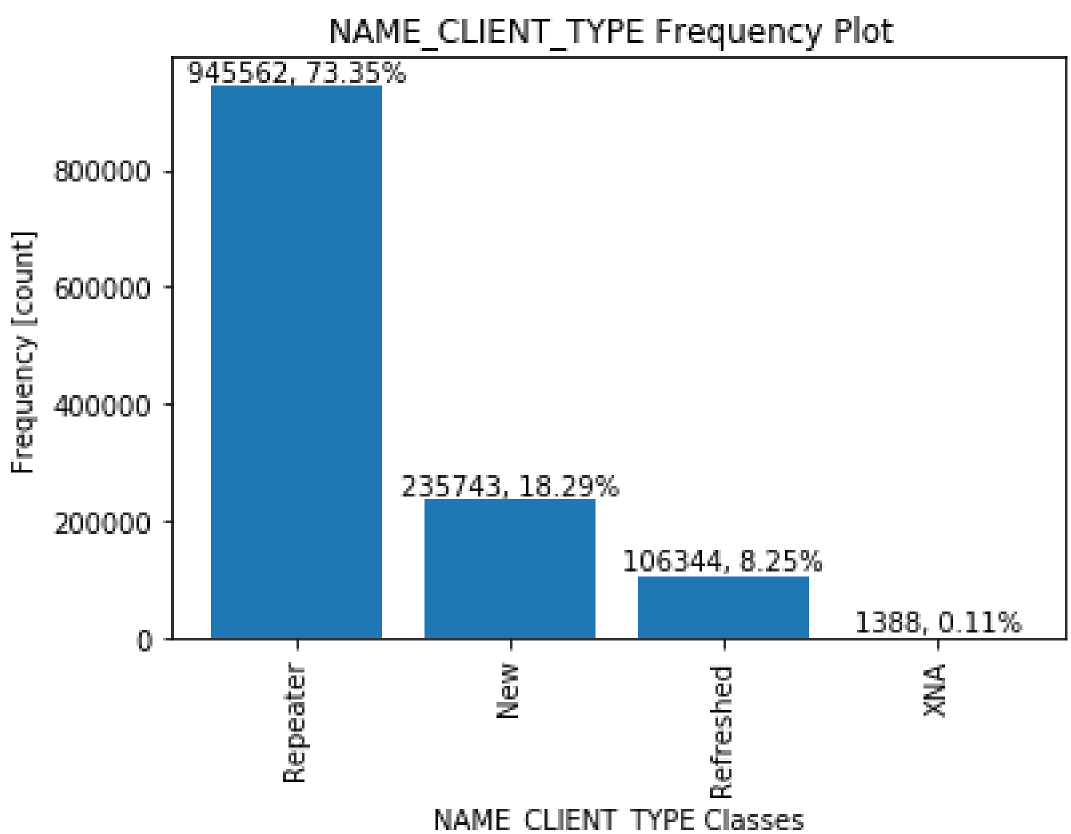
[40]:
```
merged_apptrain_prevapps = pd.merge(
    left=application_train, right=prevapplications,
    on='SK_ID_CURR',
    how='inner'
)
```

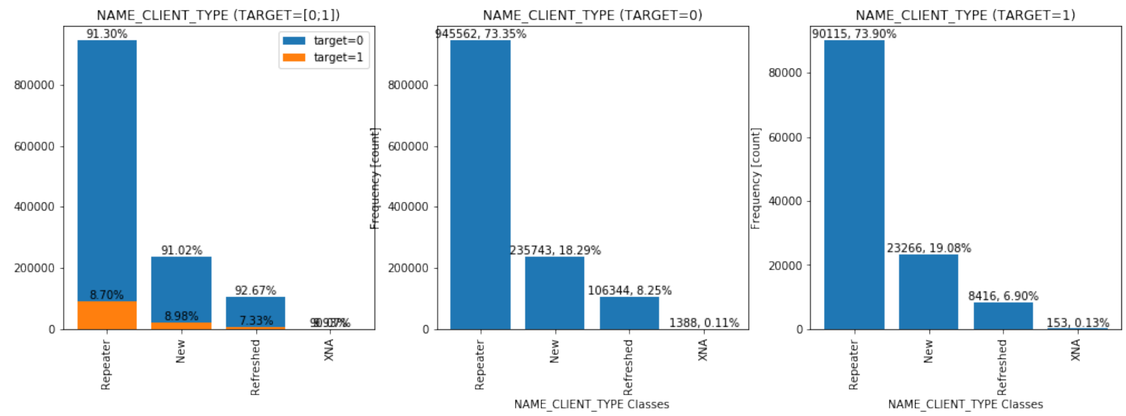
[42]:
```
# quick_overview_df( merged_apptrain_prevapps )
```

[43]:
```
merged_apptrain_prevapp_target_0 =␣
 ↪merged_apptrain_prevapps[merged_apptrain_prevapps['TARGET'] == 0]
merged_apptrain_prevapp_target_1 =␣
 ↪merged_apptrain_prevapps[merged_apptrain_prevapps['TARGET'] == 1]
```

[47]:
```
# 'NAME_CLIENT_TYPE'
# Either you are repeater, new - prob of getting TARGET=1 is the same - 9%
# Most of clients are 'repeater'-s (73%)

# 'NAME_CONTRACT_TYPE_y'
# 2 main contract made earlier: Cash loans, Consumer loans (44%, 44%). 3rd type␣
 ↪- Revolving loans, 11%
# Most problematic was 'Revolving loans' category - 10.5% of borrowers didn't␣
 ↪pay back in time
# 2nd problematic - consumer loans (9%), 3rd problematic - cash loans (7.8%)

# 'NAME_PAYMENT_TYPE'
# Most of borrowers received their cash from the bank.
```

```
# 'XNA' on 2nd place of popularity - weird. Does it mean through the post? Or␣
↪from e-bank (Qiwi?)
# Chance of getting TARGET=1 status is almost equal in all classes - +-8%

# 'NAME_CONTRACT_STATUS'
# Cancelled vs Refused - ?!
# Note: only 1% of offers are UNUSED
# Clients with previous contracts have target=1 mostly when their status were␣
↪'Refused' (11%) or Cancelled (10%)
# Clients that were earlier 'Approved' have 8% chance to become TARGET=1

fig, ax_0 = plt.subplots()
display_freq_plot( merged_apptrain_prevapp_target_0, 'NAME_CLIENT_TYPE',␣
↪ax=ax_0 )
plt.show()

display_freq_plot_by_target( merged_apptrain_prevapp_target_0,␣
↪merged_apptrain_prevapp_target_1, 'NAME_CLIENT_TYPE' )
```

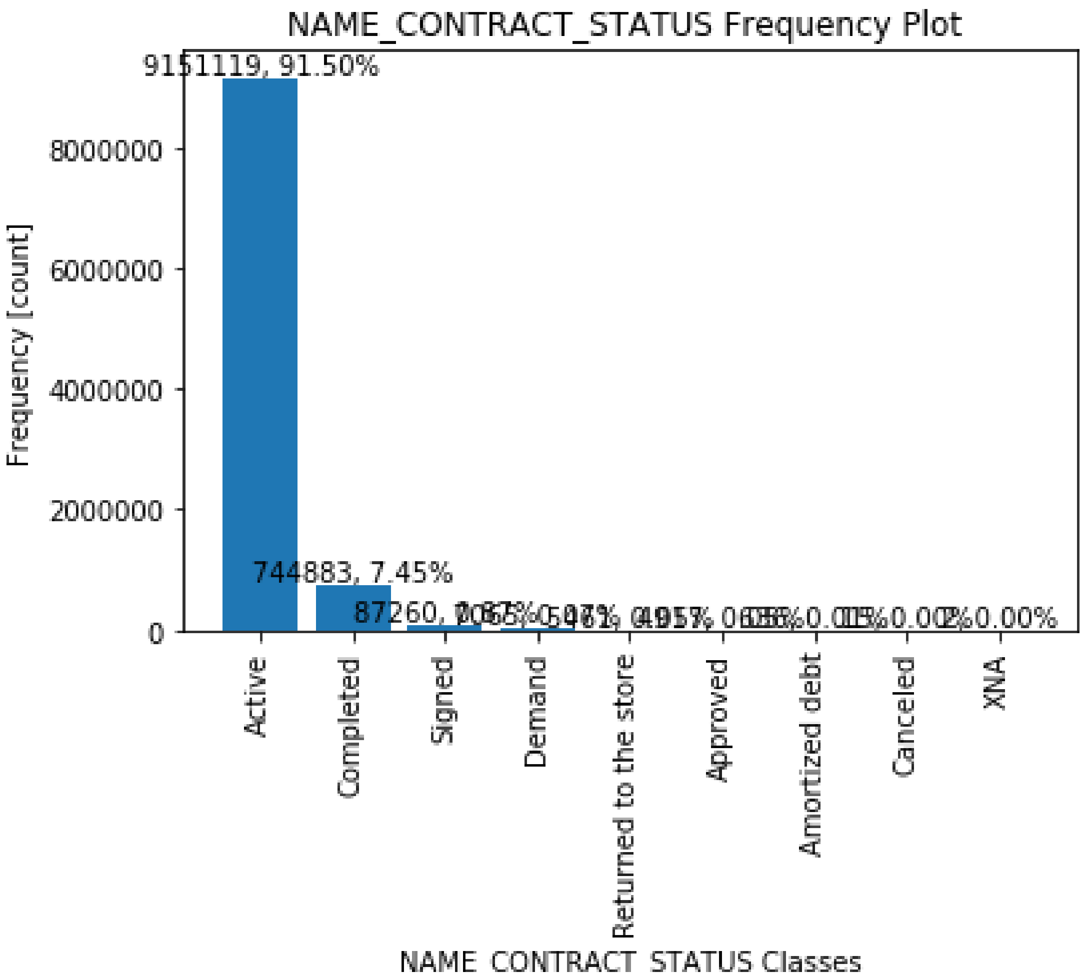




[49]:
```
# Overview 'POS_CASH_balance' table

POSCASHBALANCE_FILEPATH = 'data/POS_CASH_balance.csv'
poscashbalance = pd.read_csv( POSCASHBALANCE_FILEPATH, header=0 )
```

[51]:
```
# quick_overview_df( poscashbalance )
```

[56]:
```
# Max contract lifetime - 9 months

# poscashbalance.groupby(['SK_ID_CURR', 'MONTHS_BALANCE']).size().max()  # 9

# 'NAME_CONTRACT_STATUS'
# Most (99%) are either Active or completed - nothing special there
fig, ax_0 = plt.subplots()
display_freq_plot( poscashbalance, 'NAME_CONTRACT_STATUS', ax=ax_0 )
plt.show()
```


NAME_CONTRACT_STATUS Frequency Plot
9151119, 91.50%
744883, 7.45%
8000000
6000000
4000000
2000000
0
Frequency [count]
Active
Completed
Signed
Demand
Returned to the store
Approved
Amortized debt
Canceled
XNA
NAME_CONTRACT_STATUS Classes