Predicting bank's customer response

Banks strive to increase the efficiency of their contacts with customers. One of the areas which require this is offering new products to existing clients (cross-selling). Instead of offering new products to all clients, it is a good idea to predict the probability of a positive response. Then the offers could be sent to those clients, for whom the probability of response is higher than some threshold value.

In this notebook I try to solve this problem. In 2011 OTP-Bank in Russia has organized a competition reflecting the aforementioned situation. The data is taken from that site. The competition's description and some data is in Russian, but I'll translate the necessary termins. Column names are already in English.

Dataset contains 15223 clients; 1812 of them had a positive response. I can't use test set, as competition is finished and quality of predictions on test data can't be verified. So I can only split data in train and test and check the accuracy this way.

The metric for the competition is AUC (area under curve). The winner achieved 0,6935, top-7 places have AUC higher than 0,67.

I don't aim to beat these values, my goal is to explore and visualize the data. Also I want to show how to process the data and make predictions so that model is stable and can be interpreted.

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.metrics import auc, roc_curve
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn import preprocessing
from sklearn import linear_model
pd.set_option("display.max_columns", 200)
pd.set_option("display.max_rows", 100)
#from IPython.core.interactiveshell import InteractiveShell
#InteractiveShell.ast_node_interactivity = "all"

import functions

%load_ext autoreload
%autoreload 2
```

Data loading and initial preprocessing

In [2]:
```
%%time
data = pd.read_excel('data set.xls', sheetname='данные')
```

```
Wall time: 6.37 s
```

I'll rename values for several columns first of all, and I'll drop some unnecessary columns.

In [3]:
```
data.loc[data['EDUCATION'] == 'Среднее специальное', 'EDUCATION'] = 'Profess
data.loc[data['EDUCATION'] == 'Среднее', 'EDUCATION'] = 'Some High School'
data.loc[data['EDUCATION'] == 'Неполное среднее', 'EDUCATION'] = 'Some Prima
data.loc[data['EDUCATION'] == 'Высшее', 'EDUCATION'] = 'Undergraduate Degree
data.loc[data['EDUCATION'] == 'Неоконченное высшее', 'EDUCATION'] = 'No Form
data.loc[data['EDUCATION'] == 'Два и более высших образования', 'EDUCATION']
data.loc[data['EDUCATION'] == 'Ученая степень', 'EDUCATION'] = 'Graduate Deg
```

In [4]:
```
data.loc[data['MARITAL_STATUS'] == 'Состою в браке', 'MARITAL_STATUS'] = 'Ma
data.loc[data['MARITAL_STATUS'] == 'Гражданский брак', 'MARITAL_STATUS'] = '
data.loc[data['MARITAL_STATUS'] == 'Разведен(а)', 'MARITAL_STATUS'] = 'Separ
data.loc[data['MARITAL_STATUS'] == 'Не состоял в браке', 'MARITAL_STATUS'] =
data.loc[data['MARITAL_STATUS'] == 'Вдовец/Вдова', 'MARITAL_STATUS'] = 'Wido
```

In [5]:
```
data.loc[data['GEN_INDUSTRY'] == 'Металлургия/Промышленность/Машиностроение'
data.loc[data['GEN_INDUSTRY'] == 'Строительство', 'GEN_INDUSTRY'] = 'Constru
data.loc[data['GEN_INDUSTRY'] == 'Нефтегазовая промышленность', 'GEN_INDUSTR
data.loc[data['GEN_INDUSTRY'] == 'Энергетика', 'GEN_INDUSTRY'] = 'Oil Well S
data.loc[data['GEN_INDUSTRY'] == 'Страхование', 'GEN_INDUSTRY'] = 'Insurance
data.loc[data['GEN_INDUSTRY'] == 'Банк/Финансы', 'GEN_INDUSTRY'] = 'Regional
data.loc[data['GEN_INDUSTRY'] == 'Здравоохранение', 'GEN_INDUSTRY'] = 'Healt
data.loc[data['GEN_INDUSTRY'] == 'Управляющая компания', 'GEN_INDUSTRY'] = '
data.loc[data['GEN_INDUSTRY'] == 'Туризм', 'GEN_INDUSTRY'] = 'Hotels & Motel
data.loc[data['GEN_INDUSTRY'] == 'Юридические услуги/нотариальные услуги', '
data.loc[data['GEN_INDUSTRY'] == 'Недвижимость', 'GEN_INDUSTRY'] = 'Real Est
data.loc[data['GEN_INDUSTRY'] == 'Развлечения/Искусство', 'GEN_INDUSTRY'] =
data.loc[data['GEN_INDUSTRY'] == 'Ресторанный бизнес /общественное питание',
data.loc[data['GEN_INDUSTRY'] == 'Образование', 'GEN_INDUSTRY'] = 'Schools'
data.loc[data['GEN_INDUSTRY'] == 'Наука', 'GEN_INDUSTRY'] = 'Scientific & Te
data.loc[data['GEN_INDUSTRY'] == 'Информационные технологии', 'GEN_INDUSTRY'
data.loc[data['GEN_INDUSTRY'] == 'Транспорт', 'GEN_INDUSTRY'] = 'Transportat
data.loc[data['GEN_INDUSTRY'] == 'Логистика', 'GEN_INDUSTRY'] = 'Trucking'
data.loc[data['GEN_INDUSTRY'] == 'Ресторанный бизнес/Общественное питание',
data.loc[data['GEN_INDUSTRY'] == 'Коммунальное хоз-во/Дорожные службы', 'GEN
data.loc[data['GEN_INDUSTRY'] == 'Салоны красоты и здоровья', 'GEN_INDUSTRY'
data.loc[data['GEN_INDUSTRY'] == 'Сборочные производства', 'GEN_INDUSTRY'] =
data.loc[data['GEN_INDUSTRY'] == 'Сельское хозяйство', 'GEN_INDUSTRY'] = 'Ag
data.loc[data['GEN_INDUSTRY'] == 'Химия/Парфюмерия/Фармацевтика', 'GEN_INDUS
data.loc[data['GEN_INDUSTRY'] == 'ЧОП/Детективная д-ть', 'GEN_INDUSTRY'] = '
data.loc[data['GEN_INDUSTRY'] == 'Другие сферы', 'GEN_INDUSTRY'] = 'Others f
data.loc[data['GEN_INDUSTRY'] == 'Государственная служба', 'GEN_INDUSTRY'] =
data.loc[data['GEN_INDUSTRY'] == 'Информационные услуги', 'GEN_INDUSTRY'] =
data.loc[data['GEN_INDUSTRY'] == 'Торговля', 'GEN_INDUSTRY'] = 'Market, real
data.loc[data['GEN_INDUSTRY'] == 'Маркетинг', 'GEN_INDUSTRY'] = 'Marketing'
```

```
data.loc[data['GEN_INDUSTRY'] == 'Подбор персонала', 'GEN_INDUSTRY'] = 'Staf
data.loc[data['GEN_INDUSTRY'] == 'СМИ/Реклама/PR-агенства', 'GEN_INDUSTRY']
```

In [6]:
```
data.loc[data['FAMILY_INCOME'] == 'от 10000 до 20000 руб.', 'FAMILY_INCOME']
data.loc[data['FAMILY_INCOME'] == 'от 20000 до 50000 руб.', 'FAMILY_INCOME']
data.loc[data['FAMILY_INCOME'] == 'от 5000 до 10000 руб.', 'FAMILY_INCOME']
data.loc[data['FAMILY_INCOME'] == 'свыше 50000 руб.', 'FAMILY_INCOME'] = '50
data.loc[data['FAMILY_INCOME'] == 'до 5000 руб.', 'FAMILY_INCOME'] = 'up to
```

In [7]:
```
data.drop(['GEN_TITLE', 'ORG_TP_STATE', 'ORG_TP_FCAPITAL', 'JOB_DIR', 'REG_A
           'FACT_ADDRESS_PROVINCE', 'POSTAL_ADDRESS_PROVINCE', 'TP_PROVINCE'
```

In [8]:
```
data.head()
```

Out[8]:

	AGREEMENT_RK	TARGET	AGE	SOCSTATUS_WORK_FL	SOCSTATUS_PENS_FL
0	59910150	0	49	1	0
1	59910230	0	32	1	0
2	59910525	0	52	1	0
3	59910803	0	39	1	0
4	59911781	0	30	1	0

In [9]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15223 entries, 0 to 15222
Data columns (total 43 columns):
AGREEMENT_RK                  15223 non-null int64
TARGET                        15223 non-null int64
AGE                           15223 non-null int64
SOCSTATUS_WORK_FL             15223 non-null int64
SOCSTATUS_PENS_FL             15223 non-null int64
GENDER                        15223 non-null int64
CHILD_TOTAL                   15223 non-null int64
DEPENDANTS                    15223 non-null int64
EDUCATION                     15223 non-null object
MARITAL_STATUS                15223 non-null object
GEN_INDUSTRY                  13856 non-null object
FAMILY_INCOME                 15223 non-null object
PERSONAL_INCOME               15223 non-null float64
REG_FACT_FL                   15223 non-null int64
FACT_POST_FL                  15223 non-null int64
REG_POST_FL                   15223 non-null int64
REG_FACT_POST_FL              15223 non-null int64
REG_FACT_POST_TP_FL           15223 non-null int64
FL_PRESENCE_FL                15223 non-null int64
OWN_AUTO                      15223 non-null int64
AUTO_RUS_FL                   15223 non-null int64
HS_PRESENCE_FL                15223 non-null int64
COT_PRESENCE_FL               15223 non-null int64
GAR_PRESENCE_FL               15223 non-null int64
LAND_PRESENCE_FL              15223 non-null int64
CREDIT                        15223 non-null float64
TERM                          15223 non-null int64
FST_PAYMENT                   15223 non-null float64
DL_DOCUMENT_FL                15223 non-null int64
GPF_DOCUMENT_FL               15223 non-null int64
FACT_LIVING_TERM              15223 non-null int64
WORK_TIME                     13855 non-null float64
FACT_PHONE_FL                 15223 non-null int64
REG_PHONE_FL                  15223 non-null int64
GEN_PHONE_FL                  15223 non-null int64
LOAN_NUM_TOTAL                15223 non-null int64
LOAN_NUM_CLOSED               15223 non-null int64
LOAN_NUM_PAYM                 15223 non-null int64
LOAN_DLQ_NUM                  15223 non-null int64
LOAN_MAX_DLQ                  15223 non-null int64
LOAN_AVG_DLQ_AMT              15223 non-null float64
LOAN_MAX_DLQ_AMT              15223 non-null float64
PREVIOUS_CARD_NUM_UTILIZED    288 non-null float64
dtypes: float64(7), int64(32), object(4)
memory usage: 5.0+ MB
```

This is how the data looks like. 43 columns and several of them have missing values. I'll do the following things:

- drop several columns, where one of the values is too prevalent (has 95% or more). This is an arbitrary value and can be changed. The reason to do this is that if other categories in the variable have less that 5% in total and the

target has ~11% positive response, than the variable will be hardly useful. Of course, maybe one of less common classes always has positive response (this needs to be checkes), in this case the feature should be used;
- process continuous variables;
- process categorical variables;
- select variables and build the model;

In [10]:
```
for col in data.columns:
    if data[col].value_counts(dropna=False, normalize=True).values[0] > 0.95
        if col == 'TARGET':
            pass
        else:
            print(col)
            data.drop([col], axis=1, inplace=True)
```

```
FACT_POST_FL
COT_PRESENCE_FL
GAR_PRESENCE_FL
LAND_PRESENCE_FL
DL_DOCUMENT_FL
PREVIOUS_CARD_NUM_UTILIZED
```

Continuous

It is worth noticing that often it makes sense to create new variables from the ones already existing. While separate variables can have some impact on the model performance, their interaction may bring much more value. As an example I create a new variable as the value of income divided by the credit amount. If credit amount is much higher than income, there could be problems in paying it, if credit is many times lower, it could be of little interest to the customer. Of course, the dependences are more difficults, but you get the gist.

In [11]:
```
data['Income_to_limit'] = data['PERSONAL_INCOME'] / data['CREDIT']
```

And now there is a question about what to do with continuous variables. Usually I use them as they are, or use some kind of transformation (for example log) if necessary or normalize the values. But if the model needs to be interpretable, this won't do. The model should show how certain values impact the probability of positive response. So I'll split continuous variables into bins, so that each variable will have a separate coefficient in the model. I have written the function **split_best_iv** for this in this file. It splits the continuous variable into bins to maximize IV (Information Value).

What is IV? In fact it was and still is widely used in bank analysis. In simple terms it shows how useful is the variable for predicting the target. It is calculated in the following way (you can see an example below for "GENDER"):

- For each category % of responders is calculated - how many people in the category have positive class;
- The same is calculated for negative class;
- WOE (Weight of Evidence) is calculated as logarithm of responders rate divided by non-resonders rate. WOE shows how good is the category in separating positive and negative outcomes. Also negative WOE shows that there are more non-responders, positive implies more responders;
- Difference between distributions of positive and negative incomes is calculated;
- IV for each category is a multiplication of the aforementioned difference and WOE;
- IV for the variable is the sum of IV for each category;

Rule of thumb for IV is the following:

- < 0.02 - feature isn't useful for prediction;
- 0.02 - 0.1 - weak impact on prediction quality;
- 0.1 - 0.3 - medium impact;
- 0.3 - 0.5 - strong impact;
- 0.5+ - may cause overfitting;

These aren't definite thesholds, but we should pay attention to them.

In [12]:
```
df = pd.DataFrame(index = data['GENDER'].unique(),
                         data={'% responders': data.groupby('GENDER')['TARGET']
df['% non-responders'] = (data.groupby('GENDER')['TARGET'].count() - data.gr
                         / (len(data['TARGET']) - np.sum(data['TARGET']))
df['WOE'] = np.log(df['% responders'] / df['% non-responders'])
df['DG-DB'] = df['% responders'] - df['% non-responders']
df['IV'] = df['WOE'] * df['DG-DB']
df
print('IV is {:.2f}.'.format(np.sum(df['IV'])))
```

```
IV is 0.01.
```

Back to the function. Function **split_best_iv** calls function **cont_split**, which tries to split the variable into bins. I use DecisionTreeClassifier for this, which is really great for the purpose. Interesting parameters:

- criterion='entropy': to maximize information gain while branching trees;
- min_samples_split=0.05, min_samples_leaf=0.05: so that there are at least 5% values in each category. The reasons for choosing this value were mentioned higher;
- class_weight='balanced': great option for working with unbalanced classes;
- max_leaf_nodes=leafs: how many categories will be created, more about this lower;

After this I use **tree_to_thresholds** function to walk the tree and gather the thresholds for the decision rules. The code was adopted from this stackoverflow question. I round values, as having fractional age for example makes little sense. Then I calculate and save IV value. At the beginning there are 2 leafs. Then **split_best_iv** function increases number of leafs until IV stops increasing. This will be the optimal number of leafs and optimal split into the bins. The examples will be lower.

Outliers

It is very important to deal with outliers. Some of the usual ways are:

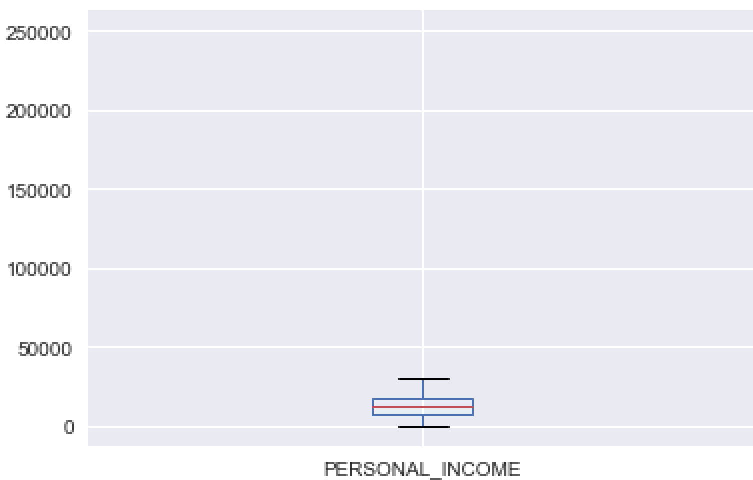
- Dropping rows with these values;
- Replacing these values with more reasonable figures;
- Building a separate model for them;

I'll go with the first choice.

To identify outliers I use either boxplots or simply look at the top values.

In [13]:
```
data['PERSONAL_INCOME'].plot(kind='box')
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1f177772208>



Boxplot shows that while median value is reasonable, max values are very high. In fact it is necessary to investigate whether these values are normal. Maybe they are VIP clients, maybe there is an error in the data, maybe this is completely normal or there could be some other reason. I have no additional data, so I'll just get rid of top-1% and low-1%.

In [14]:
```
data = data[(data.PERSONAL_INCOME < np.percentile(data.PERSONAL_INCOME, 99))
            & (data.PERSONAL_INCOME > np.percentile(data.PERSONAL_INCOME, 1))]
```

In [15]:
```
data['WORK_TIME'].nlargest(20)
```

Out[15]:
```
8984     2867959.0
4296       10000.0
2532        4320.0
5375        3500.0
9852        1500.0
1092        1312.0
11720       1254.0
13928       1120.0
9983         976.0
10677        864.0
10171        860.0
676          780.0
7711         730.0
3323         612.0
2983         600.0
8864         540.0
4122         528.0
9536         528.0
4571         519.0
1068         516.0
Name: WORK_TIME, dtype: float64
```

I may believe that people work at the current place for 10, 30, maybe even 50 years. More is quite unlikely. I'll drop these values. There is a possibility to replace these figures with more adequate values, but there is enough data, so dropping is okay.

In [16]:
```
data.drop([8984, 4296, 2532, 5375, 9852, 1092, 11720, 13928, 9983, 10677, 10
```

In [17]:
```
data['FST_PAYMENT'].nlargest()
```

Out[17]:
```
4124     140000.0
14367     75606.0
4874      75570.0
4162      75500.0
11300     70940.0
Name: FST_PAYMENT, dtype: float64
```

In [18]:
```
data.loc[data['FST_PAYMENT'] > data['CREDIT']][['CREDIT', 'FST_PAYMENT']][:1
len(data.loc[data['FST_PAYMENT'] > data['CREDIT']][['CREDIT', 'FST_PAYMENT']]
```

Out[18]:
```
485
```

We see that there are 485 rows where initial payment is higher than the credit amount. This definitely isn't normal.

In [19]:
```
data = data.loc[data['FST_PAYMENT'] < data['CREDIT']]
```

In [20]:
```
#Living in the place, months.
data['FACT_LIVING_TERM'].nlargest(20)
```

Out[20]:
```
6186     28101997
12261    16091983
8562        23916
14739        7200
988          6534
12869        6336
7650         3612
12134        3228
5681         3168
11004        2520
14707        1278
12232        1000
5369          980
1420          890
3789          720
5888          720
1937          708
4463          700
4705          696
1013          684
Name: FACT_LIVING_TERM, dtype: int64
```

While it is possible that people can live in the same place all their life, I don't think that there are many people living for 100+ years :)

In [21]:
```
data.drop([6186, 12261, 8562, 14739, 988, 12869, 7650, 12134, 5681, 11004, 1
```

In [22]:
```
data.shape, np.sum(data['TARGET'])
```

Out[22]:
```
((14276, 38), 1720)
```

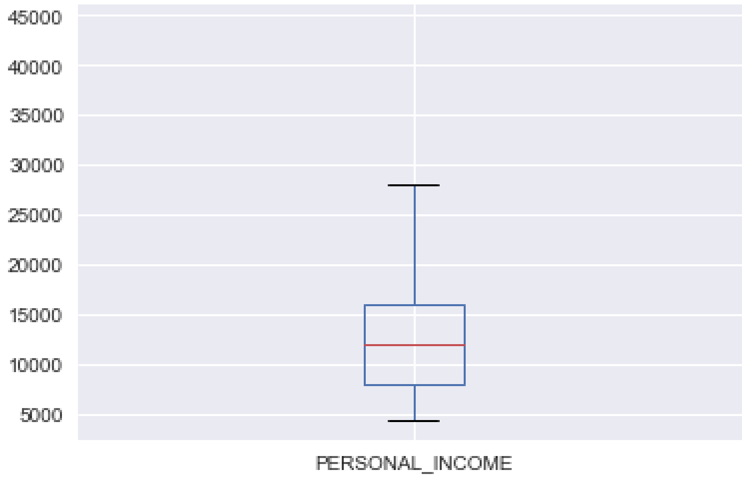
In [23]:
```
#This will be used lated.
initial_data = data.copy()
```

947 values were dropped, but only 92 of them had positive response.

PERSONAL_INCOME

In [24]:
```
data['PERSONAL_INCOME'].plot(kind='box')
```

Out[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f177757b38>
```



It is time to try splitting the variable.

In [25]:
```
data['PERSONAL_INCOME'] = functions.split_best_iv(data, 'PERSONAL_INCOME', '
```

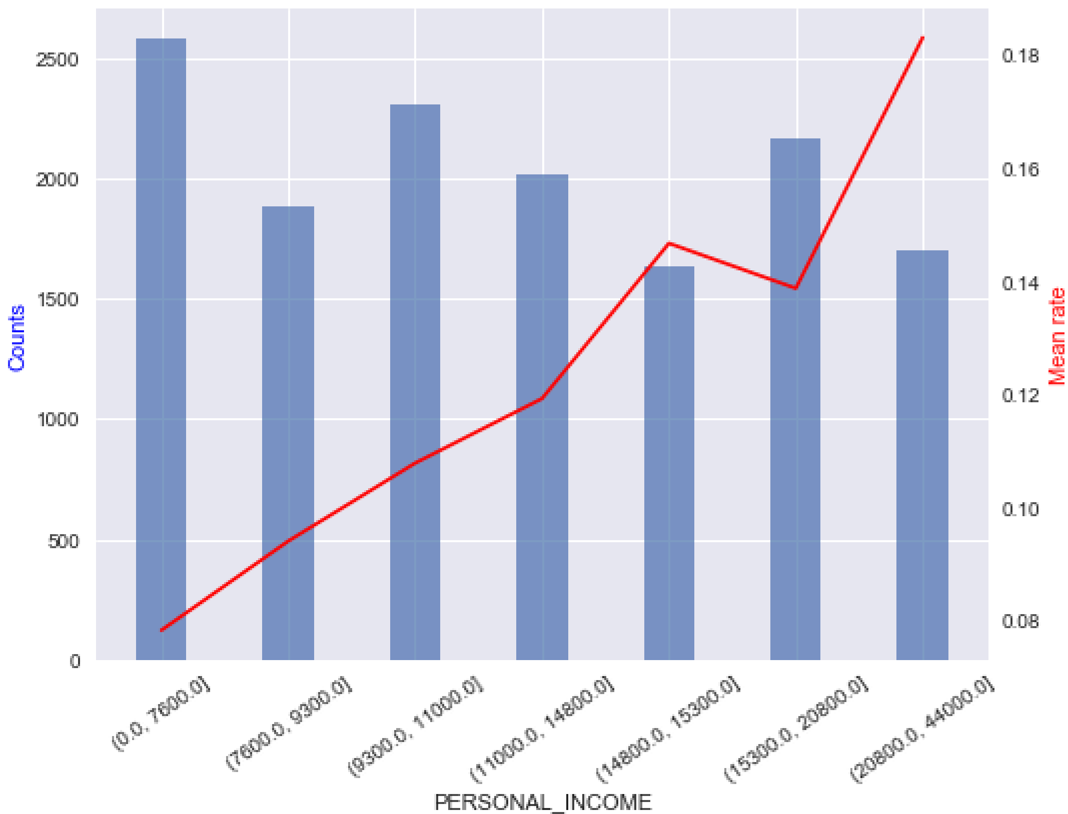
```
(0.0, 7600.0]         0.180513
(9300.0, 11000.0]     0.161600
(15300.0, 20800.0]    0.151863
(11000.0, 14800.0]    0.140866
(7600.0, 9300.0]      0.131690
(20800.0, 44000.0]    0.118941
(14800.0, 15300.0]    0.114528
Name: PERSONAL_INCOME, dtype: float64
IV:  0.0910365540526
```

Done, and there are two more functions. Second one was already used, it caculates IV. The first one shows the following things:

- Counts of each category;
- Normalized counts including missing values;
- Graph with blue bars for counts and red line for mean value of target (or what percent of values in category have positive income);

In [26]:
```
functions.feature_stat(data, 'PERSONAL_INCOME', 'TARGET')
functions.calc_iv(data, 'TARGET', 'PERSONAL_INCOME')[0]
```

```
Counts:
PERSONAL_INCOME
(0.0, 7600.0]         2577
(7600.0, 9300.0]      1880
(9300.0, 11000.0]     2307
(11000.0, 14800.0]    2011
(14800.0, 15300.0]    1635
(15300.0, 20800.0]    2168
(20800.0, 44000.0]    1698
Name: TARGET, dtype: int64
Frequencies:
(0.0, 7600.0]         0.180513
(9300.0, 11000.0]     0.161600
(15300.0, 20800.0]    0.151863
(11000.0, 14800.0]    0.140866
(7600.0, 9300.0]      0.131690
(20800.0, 44000.0]    0.118941
(14800.0, 15300.0]    0.114528
Name: PERSONAL_INCOME, dtype: float64
```




```
IV:  0.0910365540526
```

Out[26]:

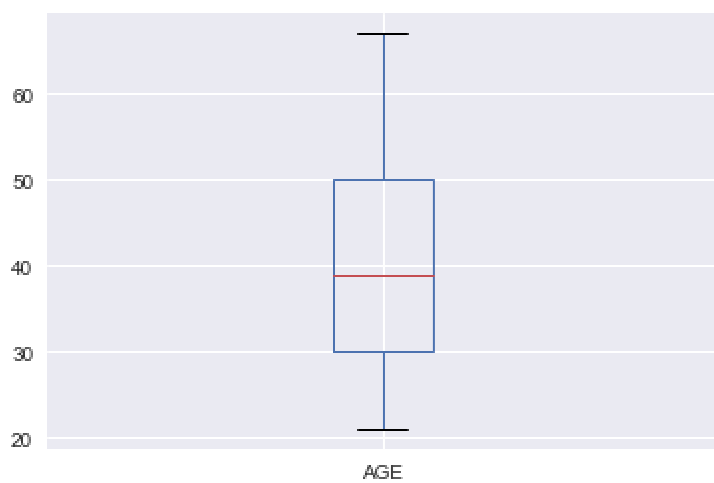
	% responders	% non-responders	WOE	DG-DB	IV
(11000.0, 14800.0]	0.139535	0.141048	-0.010786	-0.001513	0.000016
(7600.0, 9300.0]	0.102907	0.135632	-0.276123	-0.032725	0.009036
(20800.0, 44000.0]	0.180814	0.110465	0.492769	0.070349	0.034666
(0.0, 7600.0]	0.117442	0.189153	-0.476611	-0.071711	0.034178
(15300.0, 20800.0]	0.175000	0.148694	0.162896	0.026306	0.004285
(9300.0, 11000.0]	0.144767	0.163906	-0.124163	-0.019138	0.002376
(14800.0, 15300.0]	0.139535	0.111102	0.227864	0.028433	0.006479

People with higher income tend to have higher positive response rate.

Age

In [27]:
```
data['AGE'].plot(kind='box')
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1776207b8>

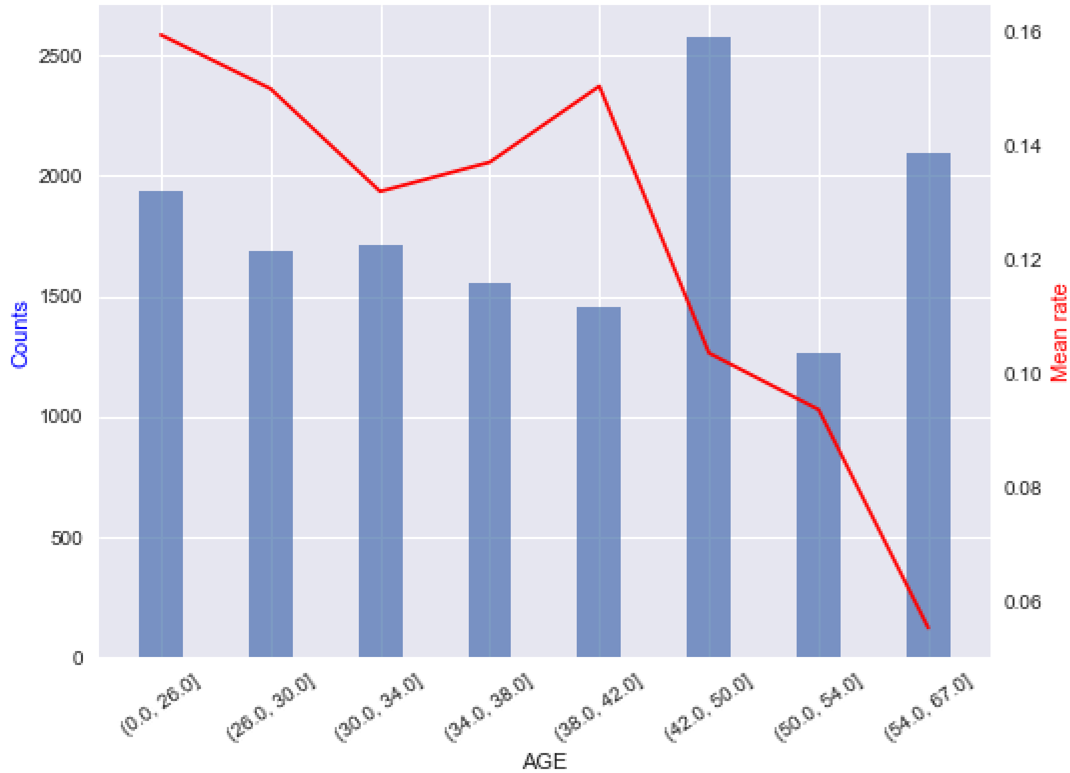


In [28]:
```
data['AGE'] = functions.split_best_iv(data, 'AGE', 'TARGET')
```

```
(42.0, 50.0]    0.180583
(54.0, 67.0]    0.146820
(0.0, 26.0]     0.135332
(30.0, 34.0]    0.119992
(26.0, 30.0]    0.118170
(34.0, 38.0]    0.108854
(38.0, 42.0]    0.101989
(50.0, 54.0]    0.088260
Name: AGE, dtype: float64
IV:  0.123625857889
```

In [29]:
```
functions.feature_stat(data, 'AGE', 'TARGET')
functions.calc_iv(data, 'TARGET', 'AGE')[0]
```

```
Counts:
AGE
(0.0, 26.0]     1932
(26.0, 30.0]    1687
(30.0, 34.0]    1713
(34.0, 38.0]    1554
(38.0, 42.0]    1456
(42.0, 50.0]    2578
(50.0, 54.0]    1260
(54.0, 67.0]    2096
Name: TARGET, dtype: int64
Frequencies:
(42.0, 50.0]    0.180583
(54.0, 67.0]    0.146820
(0.0, 26.0]     0.135332
(30.0, 34.0]    0.119992
(26.0, 30.0]    0.118170
(34.0, 38.0]    0.108854
(38.0, 42.0]    0.101989
(50.0, 54.0]    0.088260
Name: AGE, dtype: float64
```




```
IV:  0.123625857889
```

Out[29]:

	% responders	% non-responders	WOE	DG-DB	IV
(30.0, 34.0]	0.131395	0.118429	0.103893	0.012966	0.001347
(50.0, 54.0]	0.068605	0.090953	-0.281977	-0.022348	0.006302
(38.0, 42.0]	0.127326	0.098519	0.256502	0.028807	0.007389
(26.0, 30.0]	0.147093	0.114208	0.253041	0.032885	0.008321
(42.0, 50.0]	0.155233	0.184055	-0.170313	-0.028823	0.004909
(0.0, 26.0]	0.179070	0.129341	0.325327	0.049729	0.016178
(54.0, 67.0]	0.067442	0.157694	-0.849388	-0.090252	0.076659
(34.0, 38.0]	0.123837	0.106802	0.147996	0.017036	0.002521

Younger people take more credits, while only a fraction of elder people have positive response.

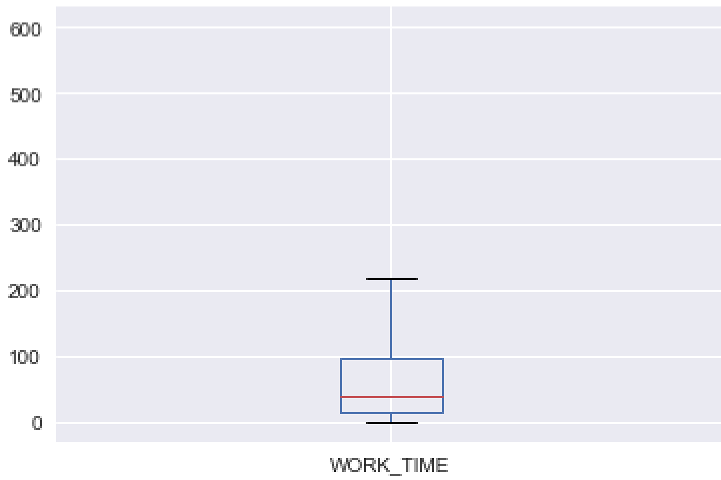
WORK_TIME

Time of work on the current workplace in months.

In [30]:
```
#I assume that missing values mean that the person didn't work at all.
data['WORK_TIME'].fillna(0, inplace=True)
```

In [31]:
```
data['WORK_TIME'].plot(kind='box')
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1781a8da0>



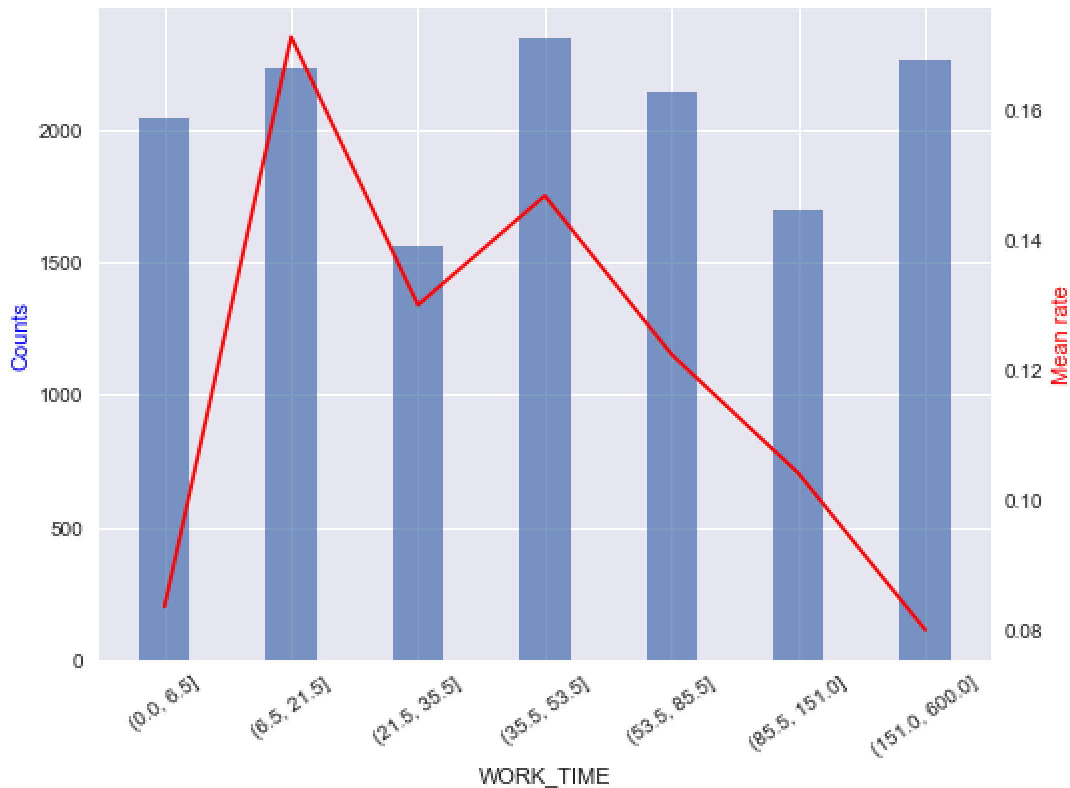
Here I add another line. If variable has zero values, DecisionTreeClassifier has problems with it. I combine zero values with the nearest interval.

In [32]:
```
data['WORK_TIME'] = functions.split_best_iv(data, 'WORK_TIME', 'TARGET')
data['WORK_TIME'].fillna(data['WORK_TIME'].cat.categories[0], inplace=True)
```

```
(35.5, 53.5]      0.164122
(151.0, 600.0]    0.158238
(6.5, 21.5]       0.156276
(53.5, 85.5]      0.149902
(85.5, 151.0]     0.119011
(21.5, 35.5]      0.109344
NaN               0.086579
(0.0, 6.5]        0.056528
Name: WORK_TIME, dtype: float64
IV:  0.075887395125
```

In [33]:
```
functions.feature_stat(data, 'WORK_TIME', 'TARGET')
functions.calc_iv(data, 'TARGET', 'WORK_TIME')[0]
```

```
Counts:
WORK_TIME
(0.0, 6.5]        2043
(6.5, 21.5]       2231
(21.5, 35.5]      1561
(35.5, 53.5]      2343
(53.5, 85.5]      2140
(85.5, 151.0]     1699
(151.0, 600.0]    2259
Name: TARGET, dtype: int64
Frequencies:
(35.5, 53.5]      0.164122
(151.0, 600.0]    0.158238
(6.5, 21.5]       0.156276
(53.5, 85.5]      0.149902
(0.0, 6.5]        0.143107
(85.5, 151.0]     0.119011
(21.5, 35.5]      0.109344
Name: WORK_TIME, dtype: float64
```




```
IV:  0.0913808898649
```

Out[33]:

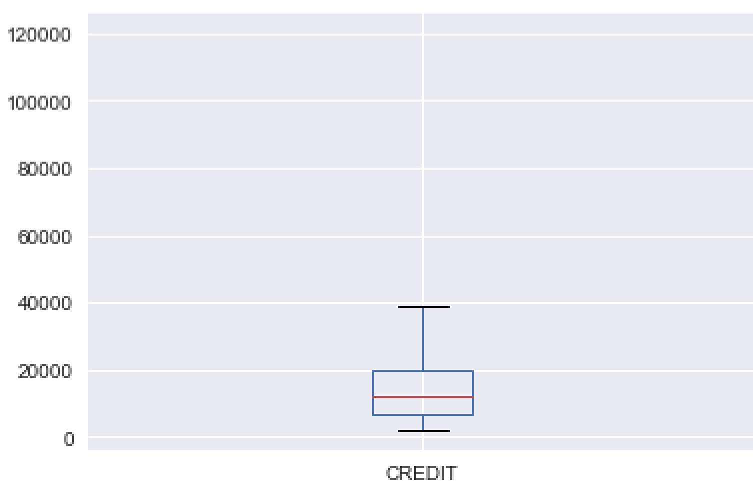
	% responders	% non-responders	WOE	DG-DB	IV
(85.5, 151.0]	0.102907	0.121217	-0.163756	-0.018310	0.002998
(53.5, 85.5]	0.152326	0.149570	0.018256	0.002756	0.000050
(151.0, 600.0]	0.105233	0.165499	-0.452790	-0.060266	0.027288
(35.5, 53.5]	0.200000	0.159207	0.228114	0.040793	0.009305
(0.0, 6.5]	0.099419	0.149092	-0.405225	-0.049673	0.020129
(21.5, 35.5]	0.118023	0.108155	0.087312	0.009868	0.000862
(6.5, 21.5]	0.222093	0.147260	0.410895	0.074833	0.030748

CREDIT

Credit amount in roubles.

In [34]:
```
data['CREDIT'].plot(kind='box')
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1f177dd8198>



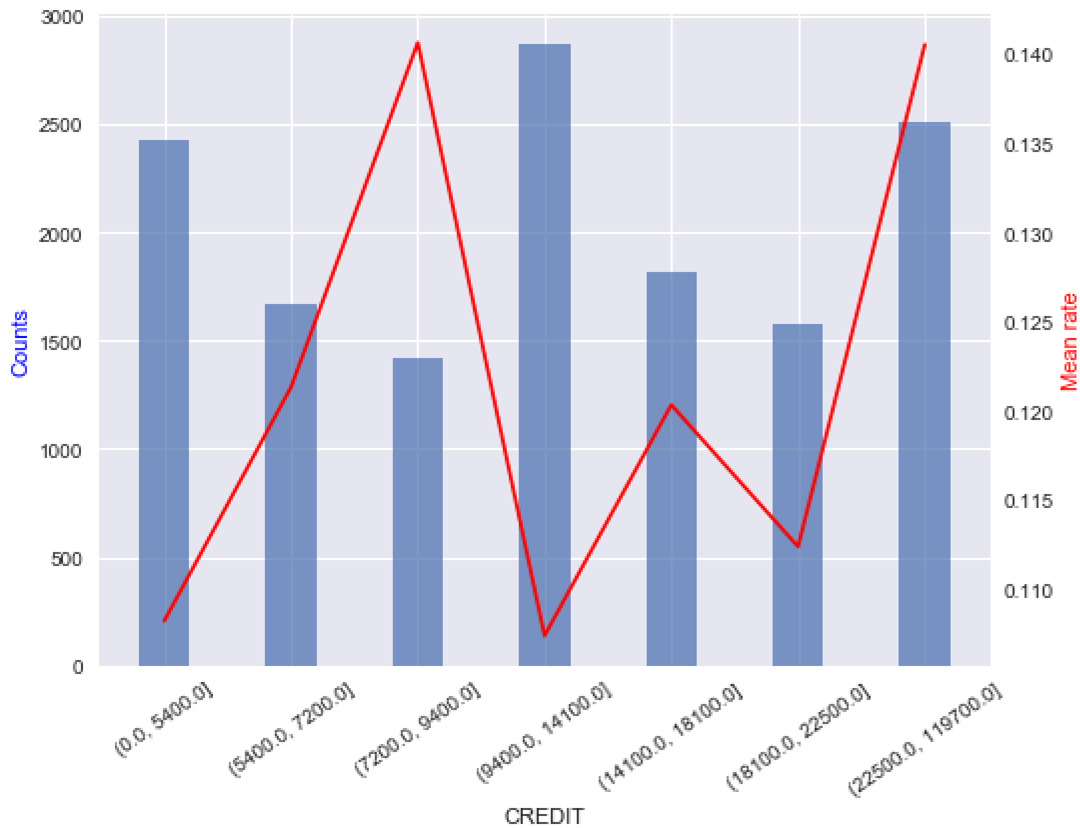
Some of credits have much higher values than median, but maybe these are special kinds of credit, how which these amounts are normal.

In [35]:
```
data['CREDIT'] = functions.split_best_iv(data, 'CREDIT', 'TARGET')
```

```
(9400.0, 14100.0]      0.200897
(22500.0, 119700.0]    0.175960
(0.0, 5400.0]          0.169585
(14100.0, 18100.0]     0.127487
(5400.0, 7200.0]       0.116629
(18100.0, 22500.0]     0.110325
(7200.0, 9400.0]       0.099117
Name: CREDIT, dtype: float64
IV:  0.0155129903385
```

In [36]:
```
functions.feature_stat(data, 'CREDIT', 'TARGET')
functions.calc_iv(data, 'TARGET', 'CREDIT')[0]
```

```
Counts:
CREDIT
(0.0, 5400.0]          2421
(5400.0, 7200.0]       1665
(7200.0, 9400.0]       1415
(9400.0, 14100.0]      2868
(14100.0, 18100.0]     1820
(18100.0, 22500.0]     1575
(22500.0, 119700.0]    2512
Name: TARGET, dtype: int64
Frequencies:
(9400.0, 14100.0]      0.200897
(22500.0, 119700.0]    0.175960
(0.0, 5400.0]          0.169585
(14100.0, 18100.0]     0.127487
(5400.0, 7200.0]       0.116629
(18100.0, 22500.0]     0.110325
(7200.0, 9400.0]       0.099117
Name: CREDIT, dtype: float64
```




```
IV:  0.0155129903385
```

Out[36]:

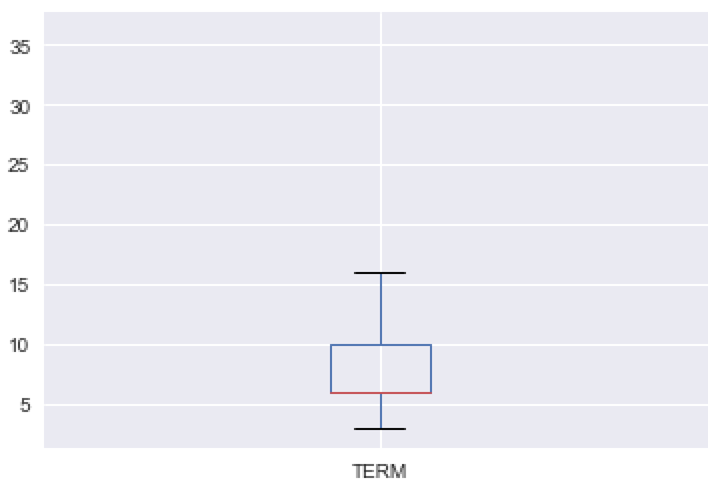
	% responders	% non-responders	WOE	DG-DB	IV
(18100.0, 22500.0]	0.102907	0.111341	-0.078774	-0.008434	6.643955e-04
(22500.0, 119700.0]	0.205233	0.171950	0.176942	0.033283	5.889141e-03
(7200.0, 9400.0]	0.115698	0.096846	0.177857	0.018852	3.352881e-03
(14100.0, 18100.0]	0.127326	0.127509	-0.001438	-0.000183	2.633451e-07
(0.0, 5400.0]	0.152326	0.171950	-0.121182	-0.019624	2.378077e-03
(9400.0, 14100.0]	0.179070	0.203887	-0.129788	-0.024817	3.220936e-03
(5400.0, 7200.0]	0.117442	0.116518	0.007898	0.000924	7.296327e-06

TERM

Credit length. I think in months.

In [37]:
```
data['TERM'].plot(kind='box')
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1f178188390>

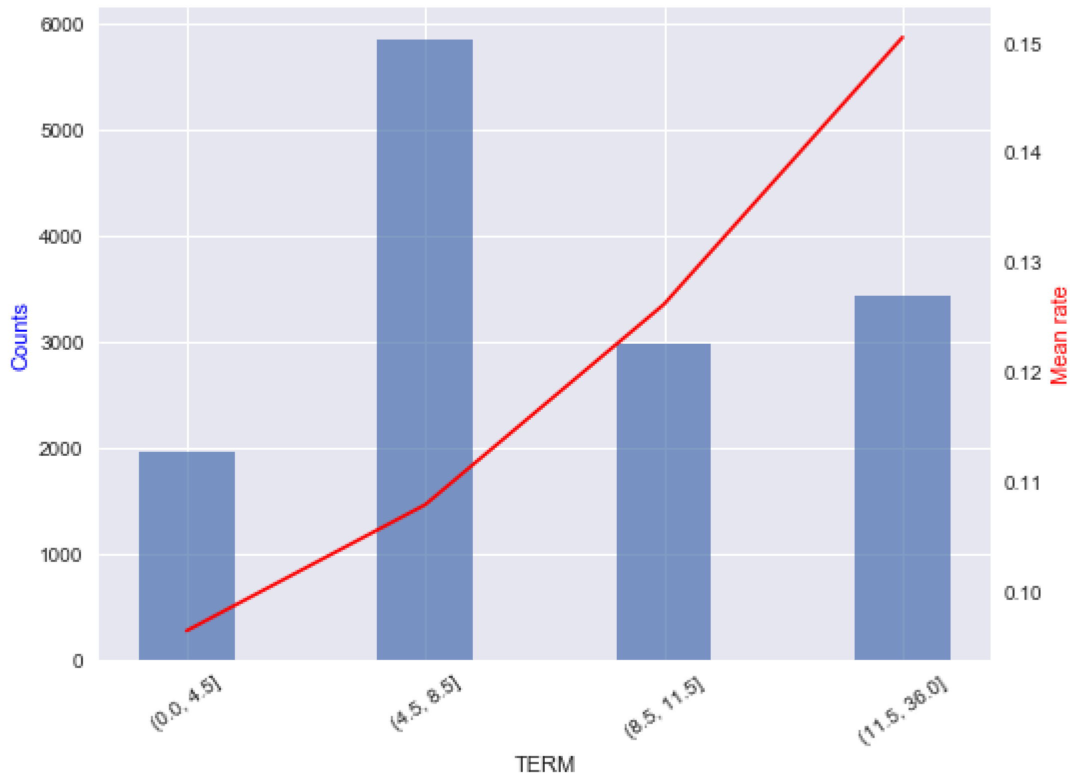


In [38]:
```
data['TERM'] = functions.split_best_iv(data, 'TERM', 'TARGET')
```

```
(4.5, 8.5]      0.410759
(11.5, 36.0]    0.241454
(8.5, 11.5]     0.209793
(0.0, 4.5]      0.137994
Name: TERM, dtype: float64
IV:  0.032100382616
```

In [39]:
```
functions.feature_stat(data, 'TERM', 'TARGET')
functions.calc_iv(data, 'TARGET', 'TERM')[0]
```

```
Counts:
TERM
(0.0, 4.5]      1970
(4.5, 8.5]      5864
(8.5, 11.5]     2995
(11.5, 36.0]    3447
Name: TARGET, dtype: int64
Frequencies:
(4.5, 8.5]      0.410759
(11.5, 36.0]    0.241454
(8.5, 11.5]     0.209793
(0.0, 4.5]      0.137994
Name: TERM, dtype: float64
```




```
IV:  0.032100382616
```

Out[39]:

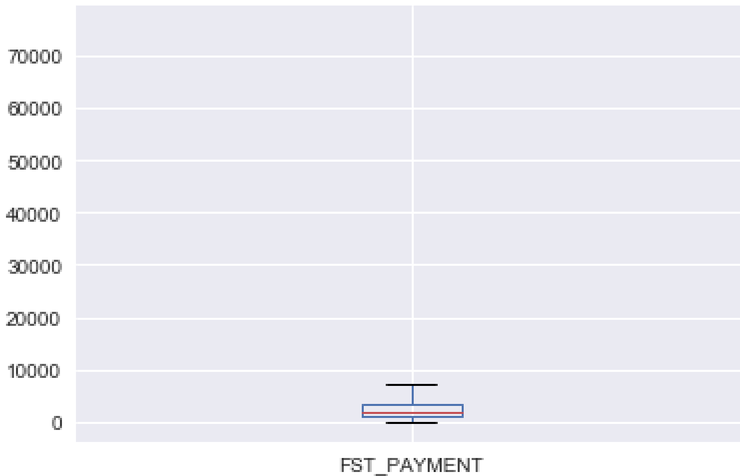
	% responders	% non-responders	WOE	DG-DB	IV
(4.5, 8.5]	0.368023	0.416614	-0.124013	-0.048590	0.006026
(11.5, 36.0]	0.301744	0.233195	0.257703	0.068549	0.017665
(8.5, 11.5]	0.219767	0.208426	0.052985	0.011341	0.000601
(0.0, 4.5]	0.110465	0.141765	-0.249470	-0.031300	0.007808

FST_PAYMENT

Initial fee amount in roubles

In [40]:
```
data['FST_PAYMENT'].plot(kind='box')
```

Out[40]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f178068320>
```

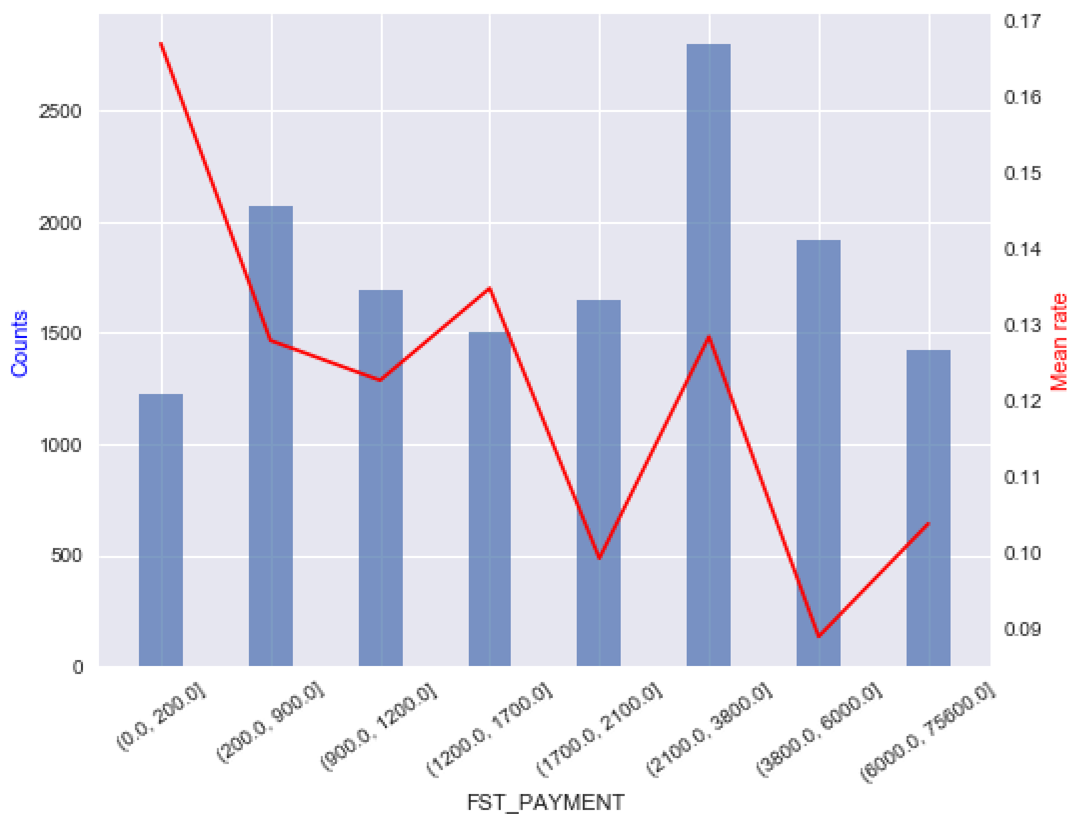


In [41]:
```
data['FST_PAYMENT'] = functions.split_best_iv(data, 'FST_PAYMENT', 'TARGET')
data['FST_PAYMENT'].fillna(data['FST_PAYMENT'].cat.categories[0], inplace=Tr
```

```
(2100.0, 3800.0]     0.195853
(200.0, 900.0]       0.145139
(3800.0, 6000.0]     0.134071
(900.0, 1200.0]      0.118801
(1700.0, 2100.0]     0.115158
(1200.0, 1700.0]     0.105492
(6000.0, 75600.0]    0.099958
NaN                  0.082726
(0.0, 200.0]         0.002802
Name: FST_PAYMENT, dtype: float64
IV:  0.025642074029
```

In [42]:
```
functions.feature_stat(data, 'FST_PAYMENT', 'TARGET')
functions.calc_iv(data, 'TARGET', 'FST_PAYMENT')[0]
```

```
Counts:
FST_PAYMENT
(0.0, 200.0]         1221
(200.0, 900.0]       2072
(900.0, 1200.0]      1696
(1200.0, 1700.0]     1506
(1700.0, 2100.0]     1644
(2100.0, 3800.0]     2796
(3800.0, 6000.0]     1914
(6000.0, 75600.0]    1427
Name: TARGET, dtype: int64
Frequencies:
(2100.0, 3800.0]     0.195853
(200.0, 900.0]       0.145139
(3800.0, 6000.0]     0.134071
(900.0, 1200.0]      0.118801
(1700.0, 2100.0]     0.115158
(1200.0, 1700.0]     0.105492
(6000.0, 75600.0]    0.099958
(0.0, 200.0]         0.085528
Name: FST_PAYMENT, dtype: float64
```




```
IV:  0.039354549526
```

Out[42]:

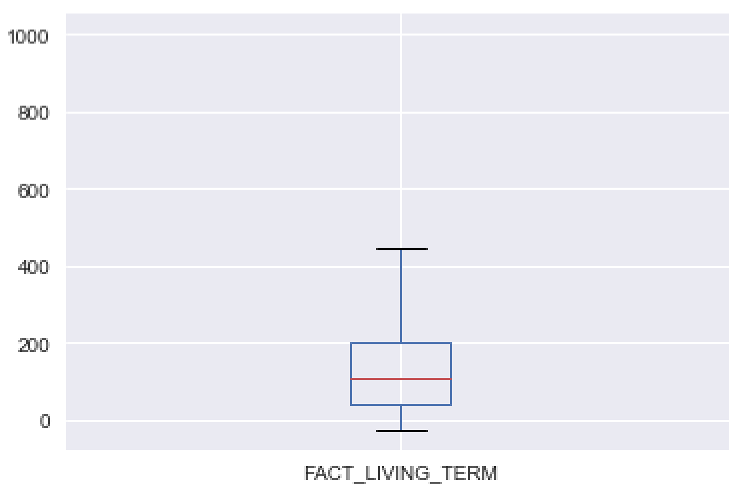
	% responders	% non-responders	WOE	DG-DB	IV
(3800.0, 6000.0]	0.098837	0.138898	-0.340264	-0.040061	0.013631
(2100.0, 3800.0]	0.208721	0.194090	0.072674	0.014630	0.001063
(200.0, 900.0]	0.154070	0.143915	0.068181	0.010155	0.000692
(6000.0, 75600.0]	0.086047	0.101864	-0.168747	-0.015817	0.002669
(900.0, 1200.0]	0.120930	0.118509	0.020224	0.002421	0.000049
(1200.0, 1700.0]	0.118023	0.103775	0.128656	0.014248	0.001833
(1700.0, 2100.0]	0.094767	0.117952	-0.218848	-0.023184	0.005074
(0.0, 200.0]	0.118605	0.080997	0.381382	0.037608	0.014343

FACT_LIVING_TERM

How long the person lives in the fact place, months.

In [43]:
```
data['FACT_LIVING_TERM'].plot(kind='box')
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1780060b8>

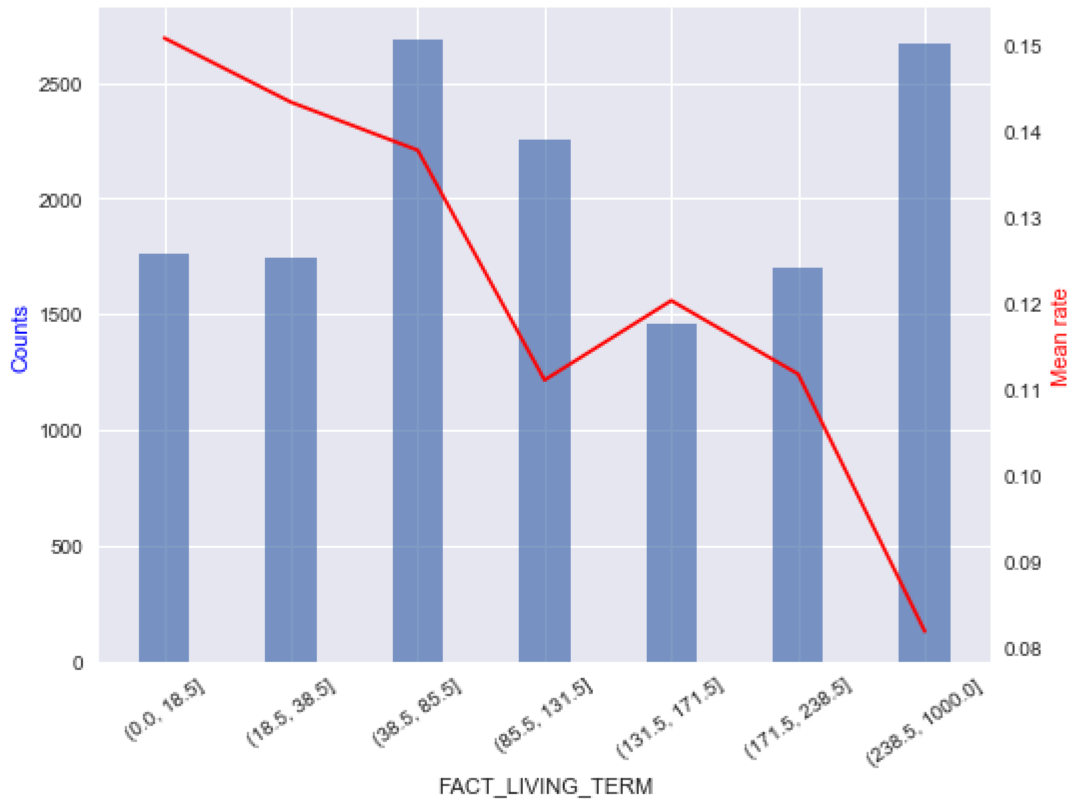


In [44]:
```
data['FACT_LIVING_TERM'] = functions.split_best_iv(data, 'FACT_LIVING_TERM',
data['FACT_LIVING_TERM'].fillna(data['FACT_LIVING_TERM'].cat.categories[0],
```

```
(38.5, 85.5]       0.188218
(238.5, 1000.0]    0.187237
(85.5, 131.5]      0.157677
(0.0, 18.5]        0.122373
(18.5, 38.5]       0.122233
(171.5, 238.5]     0.119081
(131.5, 171.5]     0.101919
NaN                0.001261
Name: FACT_LIVING_TERM, dtype: float64
IV:  0.0508487769524
```

In [45]:
```python
functions.feature_stat(data, 'FACT_LIVING_TERM', 'TARGET')
functions.calc_iv(data, 'TARGET', 'FACT_LIVING_TERM')[0]
```

```
Counts:
FACT_LIVING_TERM
(0.0, 18.5]        1765
(18.5, 38.5]       1745
(38.5, 85.5]       2687
(85.5, 131.5]      2251
(131.5, 171.5]     1455
(171.5, 238.5]     1700
(238.5, 1000.0]    2673
Name: TARGET, dtype: int64
Frequencies:
(38.5, 85.5]       0.188218
(238.5, 1000.0]    0.187237
(85.5, 131.5]      0.157677
(0.0, 18.5]        0.123634
(18.5, 38.5]       0.122233
(171.5, 238.5]     0.119081
(131.5, 171.5]     0.101919
Name: FACT_LIVING_TERM, dtype: float64
```




```
IV:  0.0503735245857
```

Out[45]:

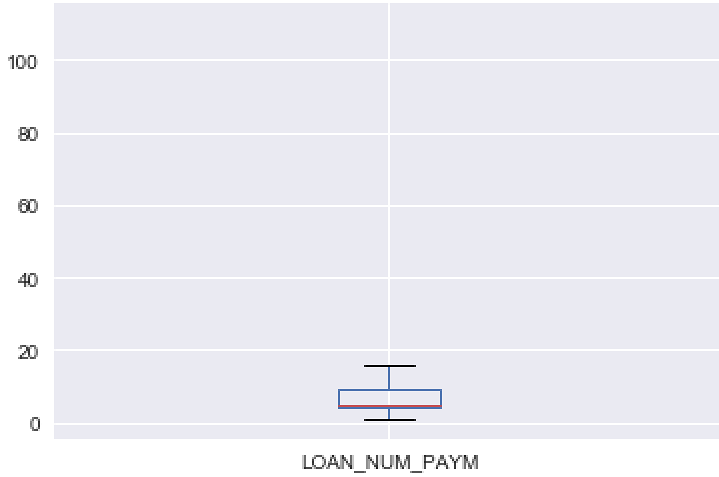
	% responders	% non-responders	WOE	DG-DB	IV
(131.5, 171.5]	0.101744	0.101943	-0.001955	-0.000199	3.892631e-07
(238.5, 1000.0]	0.127326	0.195444	-0.428529	-0.068119	2.919086e-02
(18.5, 38.5]	0.145349	0.119067	0.199454	0.026282	5.242095e-03
(38.5, 85.5]	0.215116	0.184533	0.153349	0.030583	4.689865e-03
(85.5, 131.5]	0.145349	0.159366	-0.092067	-0.014017	1.290523e-03
(171.5, 238.5]	0.110465	0.120261	-0.084967	-0.009796	8.323416e-04
(0.0, 18.5]	0.154651	0.119385	0.258817	0.035266	9.127448e-03

LOAN_NUM_PAYM

Number of payments by the client

In [46]:
```
data['LOAN_NUM_PAYM'].plot(kind='box')
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x1f177f492b0>

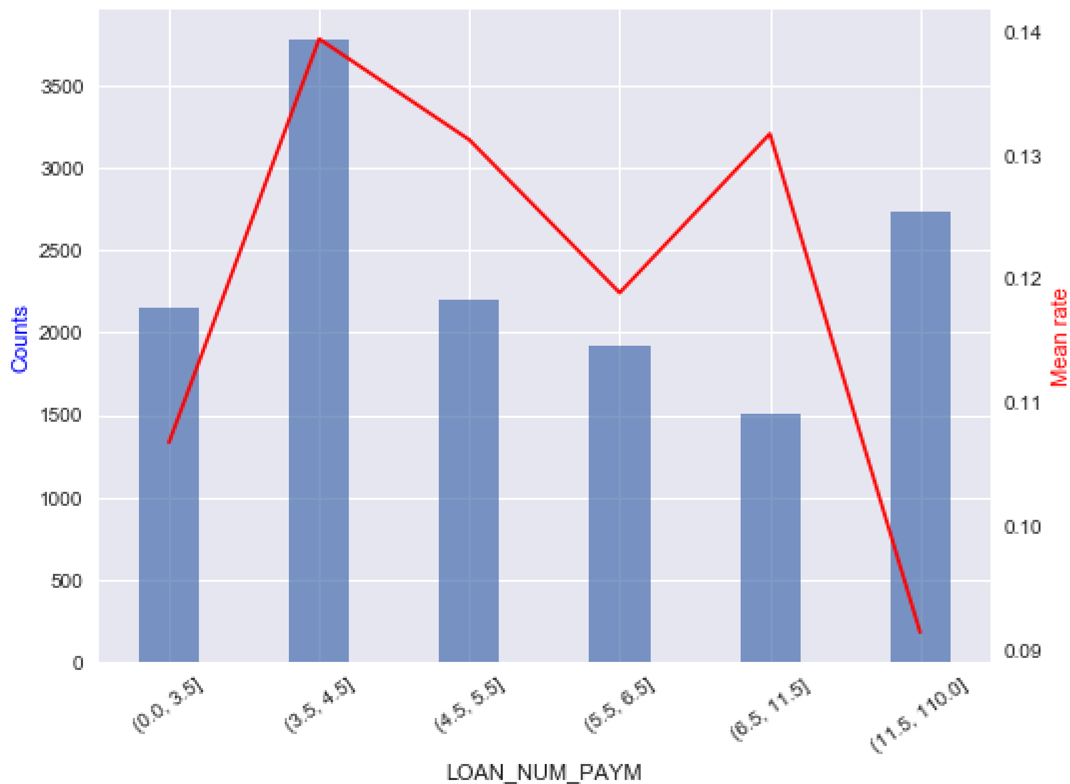


In [47]:
```
data['LOAN_NUM_PAYM'] = functions.split_best_iv(data, 'LOAN_NUM_PAYM', 'TARG
```

```
(3.5, 4.5]       0.264290
(11.5, 110.0]    0.191580
(4.5, 5.5]       0.154245
(0.0, 3.5]       0.150252
(5.5, 6.5]       0.134351
(6.5, 11.5]      0.105282
Name: LOAN_NUM_PAYM, dtype: float64
IV:  0.0295041530193
```

In [48]:
```
functions.feature_stat(data, 'LOAN_NUM_PAYM', 'TARGET')
functions.calc_iv(data, 'TARGET', 'LOAN_NUM_PAYM')[0]
```

```
Counts:
LOAN_NUM_PAYM
(0.0, 3.5]       2145
(3.5, 4.5]       3773
(4.5, 5.5]       2202
(5.5, 6.5]       1918
(6.5, 11.5]      1503
(11.5, 110.0]    2735
Name: TARGET, dtype: int64
Frequencies:
(3.5, 4.5]       0.264290
(11.5, 110.0]    0.191580
(4.5, 5.5]       0.154245
(0.0, 3.5]       0.150252
(5.5, 6.5]       0.134351
(6.5, 11.5]      0.105282
Name: LOAN_NUM_PAYM, dtype: float64
```



IV: 0.0295041530193

Out[48]:

	% responders	% non-responders	WOE	DG-DB	IV
(5.5, 6.5]	0.132558	0.134597	-0.015264	-0.002039	0.000031
(6.5, 11.5]	0.115116	0.103934	0.102183	0.011182	0.001143
(11.5, 110.0]	0.145349	0.197913	-0.308693	-0.052565	0.016226
(0.0, 3.5]	0.133140	0.152596	-0.136399	-0.019457	0.002654
(3.5, 4.5]	0.305814	0.258601	0.167689	0.047212	0.007917
(4.5, 5.5]	0.168023	0.152357	0.097873	0.015666	0.001533

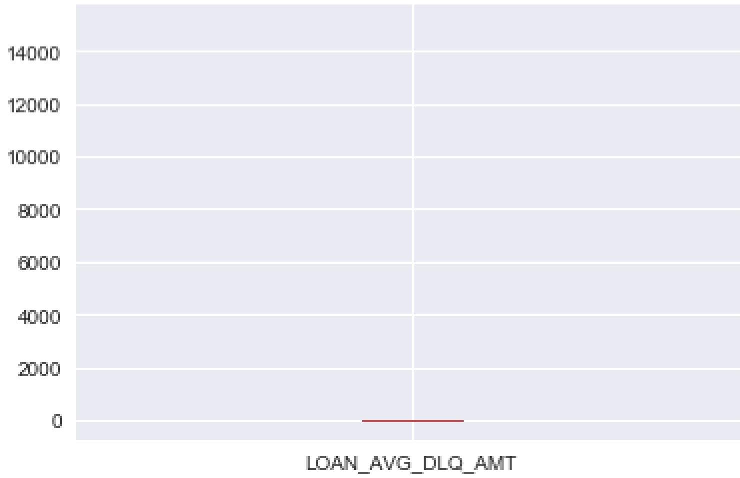
LOAN_AVG_DLQ_AMT

Average deliquency amount

In [49]:

```
data['LOAN_AVG_DLQ_AMT'].plot(kind='box')
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1781d8c50>

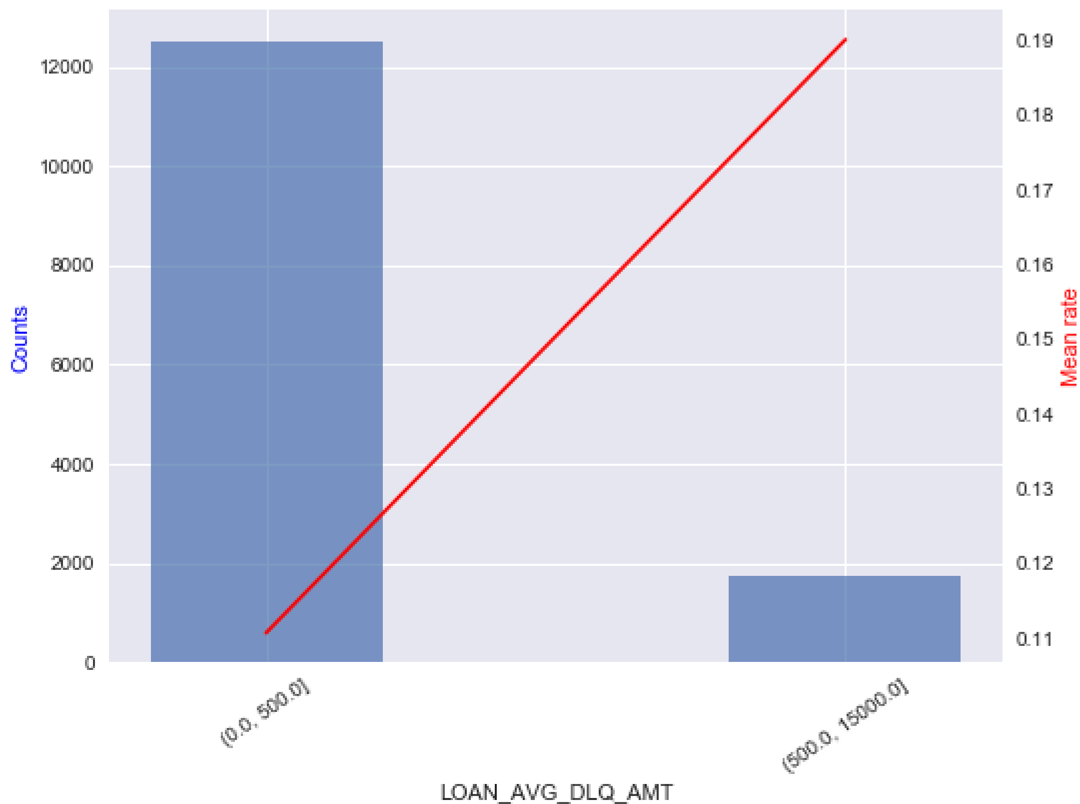


In [50]:
```
data['LOAN_AVG_DLQ_AMT'] = functions.split_best_iv(data, 'LOAN_AVG_DLQ_AMT',
data['LOAN_AVG_DLQ_AMT'].fillna(data['LOAN_AVG_DLQ_AMT'].cat.categories[0],
```

```
NaN                    0.871603
(500.0, 15000.0]       0.123074
(0.0, 500.0]           0.005324
Name: LOAN_AVG_DLQ_AMT, dtype: float64
IV:  0.0437967491802
```

In [51]:
```
functions.feature_stat(data, 'LOAN_AVG_DLQ_AMT', 'TARGET')
functions.calc_iv(data, 'TARGET', 'LOAN_AVG_DLQ_AMT')[0]
```

```
Counts:
LOAN_AVG_DLQ_AMT
(0.0, 500.0]           12519
(500.0, 15000.0]        1757
Name: TARGET, dtype: int64
Frequencies:
(0.0, 500.0]           0.876926
(500.0, 15000.0]       0.123074
Name: LOAN_AVG_DLQ_AMT, dtype: float64
```



IV: 0.0512702006508

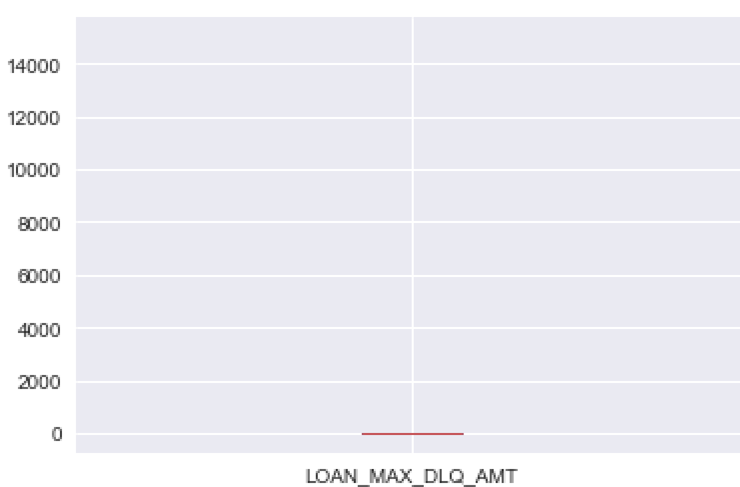
Out[51]:

	% responders	% non-responders	WOE	DG-DB	IV
(500.0, 15000.0]	0.194186	0.113332	0.538493	0.080854	0.043539
(0.0, 500.0]	0.805814	0.886668	-0.095617	-0.080854	0.007731

LOAN_MAX_DLQ_AMT

In [52]:
```
data['LOAN_MAX_DLQ_AMT'].plot(kind='box')
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1f17888a860>

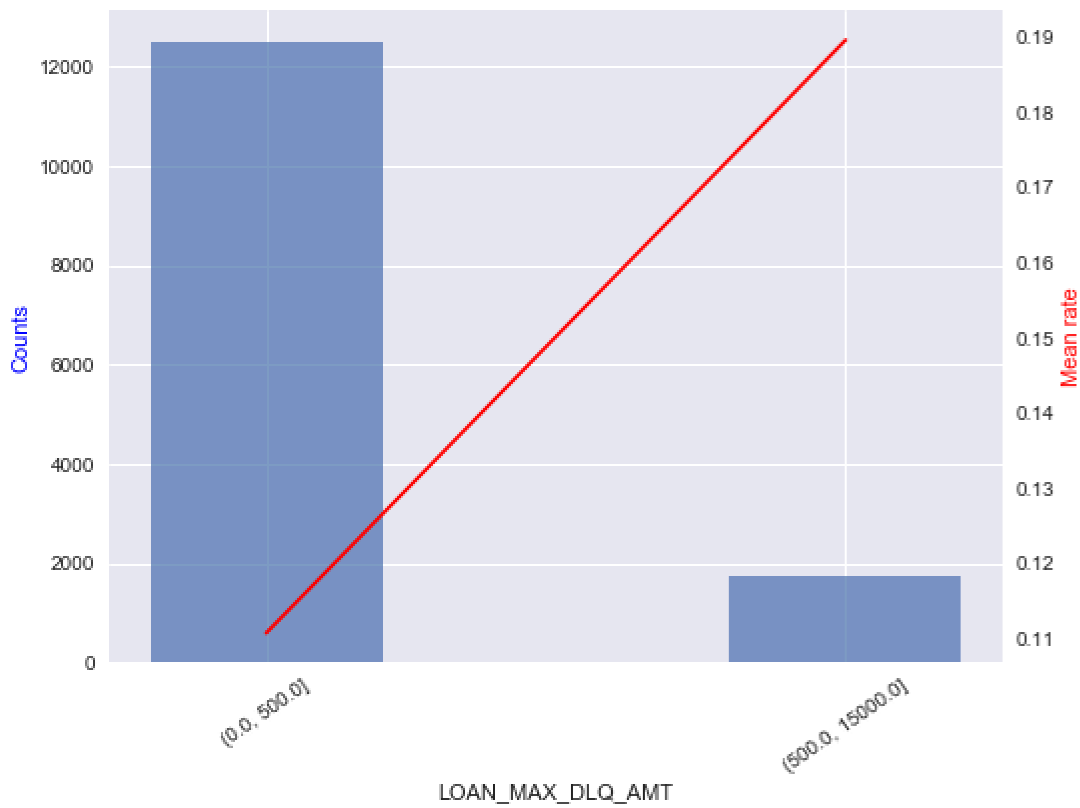


In [53]:
```
data['LOAN_MAX_DLQ_AMT'] = functions.split_best_iv(data, 'LOAN_MAX_DLQ_AMT',
data['LOAN_MAX_DLQ_AMT'].fillna(data['LOAN_MAX_DLQ_AMT'].cat.categories[0],
```

```
NaN                  0.871603
(500.0, 15000.0]     0.123354
(0.0, 500.0]         0.005043
Name: LOAN_MAX_DLQ_AMT, dtype: float64
IV:  0.0435641041626
```

In [54]:
```
functions.feature_stat(data, 'LOAN_MAX_DLQ_AMT', 'TARGET')
functions.calc_iv(data, 'TARGET', 'LOAN_MAX_DLQ_AMT')[0]
```

```
Counts:
LOAN_MAX_DLQ_AMT
(0.0, 500.0]         12515
(500.0, 15000.0]      1761
Name: TARGET, dtype: int64
Frequencies:
(0.0, 500.0]         0.876646
(500.0, 15000.0]     0.123354
Name: LOAN_MAX_DLQ_AMT, dtype: float64
```




```
IV:  0.0508131856608
```

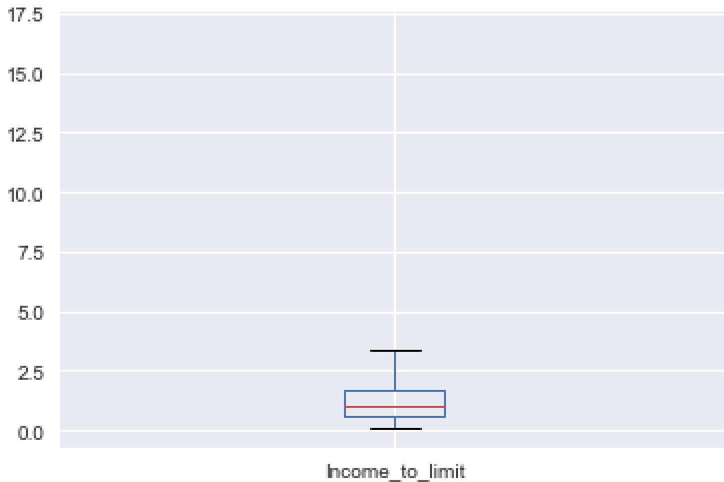
Out[54]:

	% responders	% non-responders	WOE	DG-DB	IV
(500.0, 15000.0]	0.194186	0.113651	0.535686	0.080535	0.043142
(0.0, 500.0]	0.805814	0.886349	-0.095258	-0.080535	0.007672

Income_to_limit

```
In [55]: data['Income_to_limit'].plot(kind='box')
```

Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1789b3128>

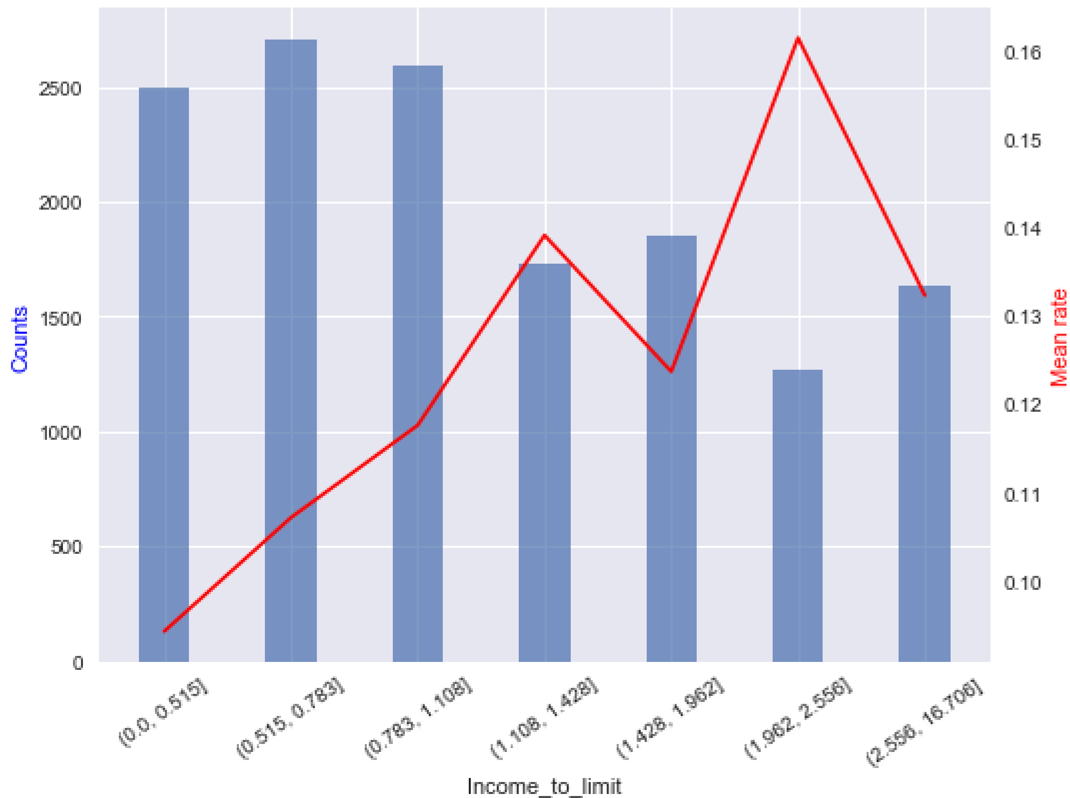



```
In [56]: data['Income_to_limit'] = functions.split_best_iv(data, 'Income_to_limit', '
```

```
(0.515, 0.783]     0.189619
(0.783, 1.108]     0.181704
(0.0, 0.515]       0.174629
(1.428, 1.962]     0.129728
(1.108, 1.428]     0.121393
(2.556, 16.706]    0.114388
(1.962, 2.556]     0.088540
Name: Income_to_limit, dtype: float64
IV:  0.0317804169333
```

```
In [57]: functions.feature_stat(data, 'Income_to_limit', 'TARGET')
         functions.calc_iv(data, 'TARGET', 'Income_to_limit')[0]
```

```
Counts:
Income_to_limit
(0.0, 0.515]       2493
(0.515, 0.783]     2707
(0.783, 1.108]     2594
(1.108, 1.428]     1733
(1.428, 1.962]     1852
(1.962, 2.556]     1264
(2.556, 16.706]    1633
Name: TARGET, dtype: int64
Frequencies:
(0.515, 0.783]     0.189619
(0.783, 1.108]     0.181704
(0.0, 0.515]       0.174629
(1.428, 1.962]     0.129728
(1.108, 1.428]     0.121393
(2.556, 16.706]    0.114388
(1.962, 2.556]     0.088540
Name: Income_to_limit, dtype: float64
```




```
IV:  0.0317804169333
```

Out[57]:

	% responders	% non-responders	WOE	DG-DB	IV
(0.515, 0.783]	0.168605	0.192498	-0.132527	-0.023893	0.003166
(0.0, 0.515]	0.136628	0.179834	-0.274775	-0.043206	0.011872
(2.556, 16.706]	0.125581	0.112854	0.106856	0.012727	0.001360
(1.428, 1.962]	0.133140	0.129261	0.029565	0.003879	0.000115
(1.962, 2.556]	0.118605	0.084422	0.339970	0.034183	0.011621
(1.108, 1.428]	0.140116	0.118828	0.164799	0.021289	0.003508
(0.783, 1.108]	0.177326	0.182303	-0.027684	-0.004978	0.000138

Categorical

Now categorical variables are different. Usually the main problem is that some categories have too little values. Again I'll try to do so that there are no categories with less than 5%. Most of the time it is necessary to combine categories based on the common or business case. I convert variables into type "category" for easier processing. Missing values are treated as a separate category.

```
In [58]: for col in ['GENDER', 'CHILD_TOTAL', 'DEPENDANTS', 'EDUCATION', 'MARITAL_STA
                     'FAMILY_INCOME', 'LOAN_NUM_TOTAL', 'LOAN_NUM_CLOSED', 'LOAN_DLQ_
             data[col] = data[col].astype('category')
             if (data[col].isnull() == True).any():
                 data[col].cat.add_categories(['Unknown'], inplace=True)
                 data[col].fillna('Unknown', inplace=True)
```

OWN_AUTO

Number of cars owned.

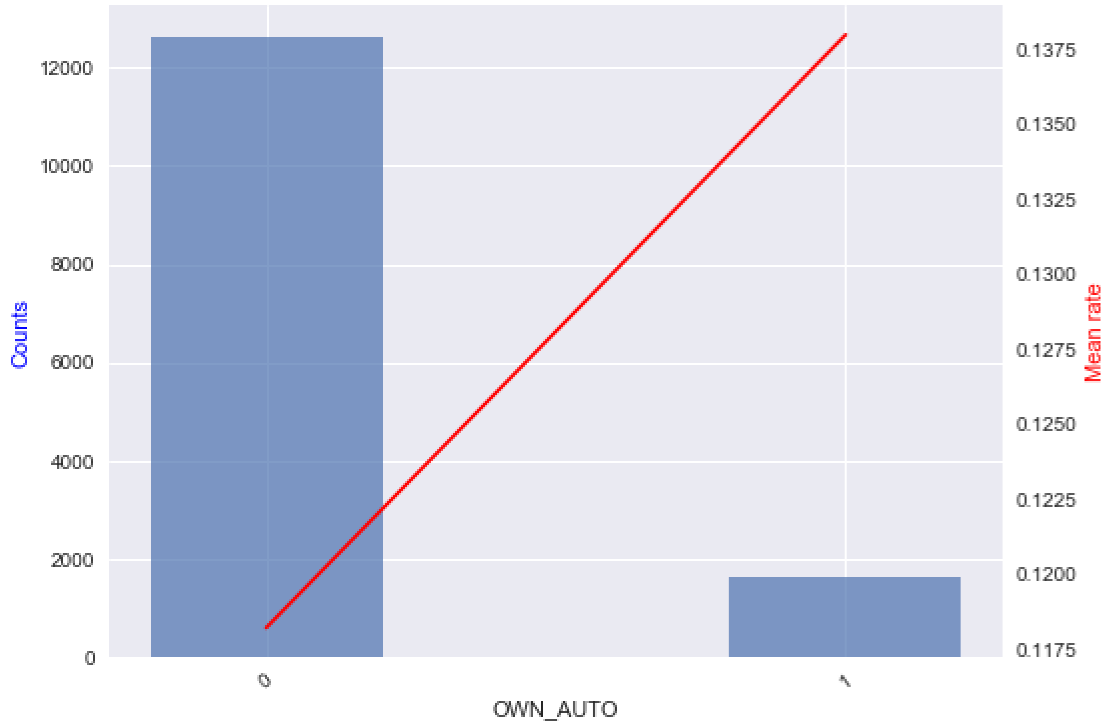
```
In [59]: data['OWN_AUTO'].value_counts(dropna=False, normalize=True)
```

```
Out[59]: 0    0.885262
         1    0.114668
         2    0.000070
         Name: OWN_AUTO, dtype: float64
```

```
In [60]: data.loc[data['OWN_AUTO'] == 2, 'OWN_AUTO'] = 1
         data['OWN_AUTO'] = data['OWN_AUTO'].cat.remove_unused_categories()
```

```
In [61]: functions.feature_stat(data, 'OWN_AUTO', 'TARGET')
         functions.calc_iv(data, 'TARGET', 'OWN_AUTO')[0]
```

```
Counts:
OWN_AUTO
0    12638
1     1638
Name: TARGET, dtype: int64
Frequencies:
0    0.885262
1    0.114738
Name: OWN_AUTO, dtype: float64
```




```
IV:  0.00335633471077
```

Out[61]:

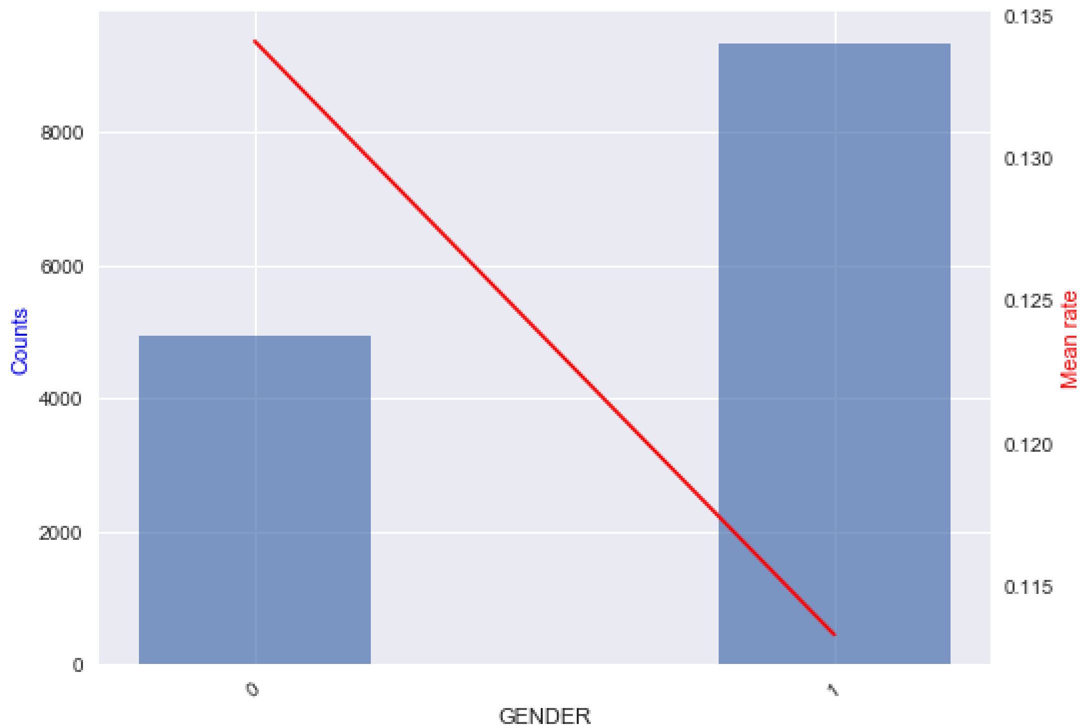
	% responders	% non-responders	WOE	DG-DB	IV
0	0.868605	0.887544	-0.021570	-0.018939	0.000409
1	0.131395	0.112456	0.155647	0.018939	0.002948

GENDER

In [62]:

```
functions.feature_stat(data, 'GENDER', 'TARGET')
functions.calc_iv(data, 'TARGET', 'GENDER')[0]
```

```
Counts:
GENDER
0    4936
1    9340
Name: TARGET, dtype: int64
Frequencies:
1    0.654245
0    0.345755
Name: GENDER, dtype: float64
```




```
IV:  0.00857138118803
```

Out[62]:

	% responders	% non-responders	WOE	DG-DB	IV
1	0.615116	0.659605	-0.069830	-0.044489	0.003107
0	0.384884	0.340395	0.122834	0.044489	0.005465

CHILD_TOTAL

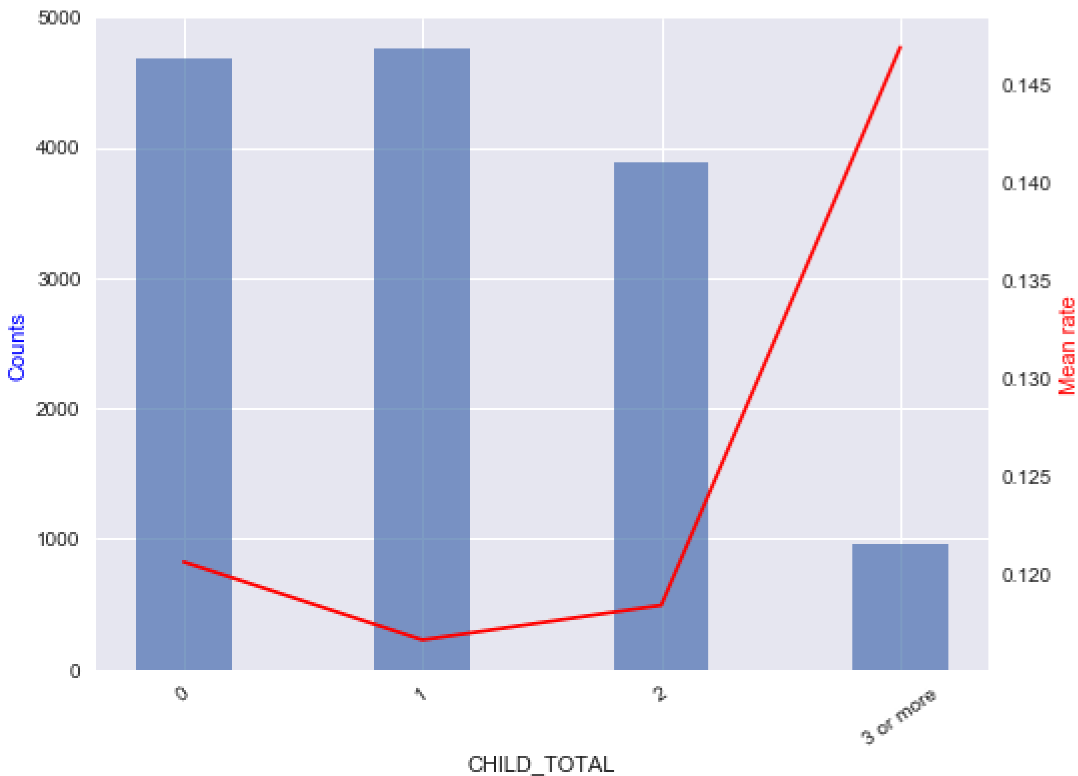
In [63]:
```
data['CHILD_TOTAL'].value_counts(dropna=False, normalize=True)
```

Out[63]:
```
1     0.333217
0     0.327473
2     0.272065
3     0.053026
4     0.008826
5     0.003993
6     0.000841
7     0.000350
10    0.000140
8     0.000070
Name: CHILD_TOTAL, dtype: float64
```

In [64]:
```
data['CHILD_TOTAL'].cat.add_categories(['3 or more'], inplace=True)
data.loc[data['CHILD_TOTAL'].isin([1.0, 0.0, 2.0]) == False, 'CHILD_TOTAL']
data['CHILD_TOTAL'] = data['CHILD_TOTAL'].cat.remove_unused_categories()
```

In [65]:
```
functions.feature_stat(data, 'CHILD_TOTAL', 'TARGET')
functions.calc_iv(data, 'TARGET', 'CHILD_TOTAL')[0]
```

```
Counts:
CHILD_TOTAL
0             4675
1             4757
2             3884
3 or more      960
Name: TARGET, dtype: int64
Frequencies:
1             0.333217
0             0.327473
2             0.272065
3 or more     0.067246
Name: CHILD_TOTAL, dtype: float64
```




```
IV:  0.00436821503813
```

Out[65]:

	% responders	% non-responders	WOE	DG-DB	IV
3 or more	0.081977	0.065228	0.228550	0.016749	3.827978e-03
1	0.322674	0.334661	-0.036473	-0.011986	4.371814e-04
0	0.327907	0.327413	0.001507	0.000494	7.441446e-07
2	0.267442	0.272698	-0.019464	-0.005256	1.023110e-04

DEPENDANTS

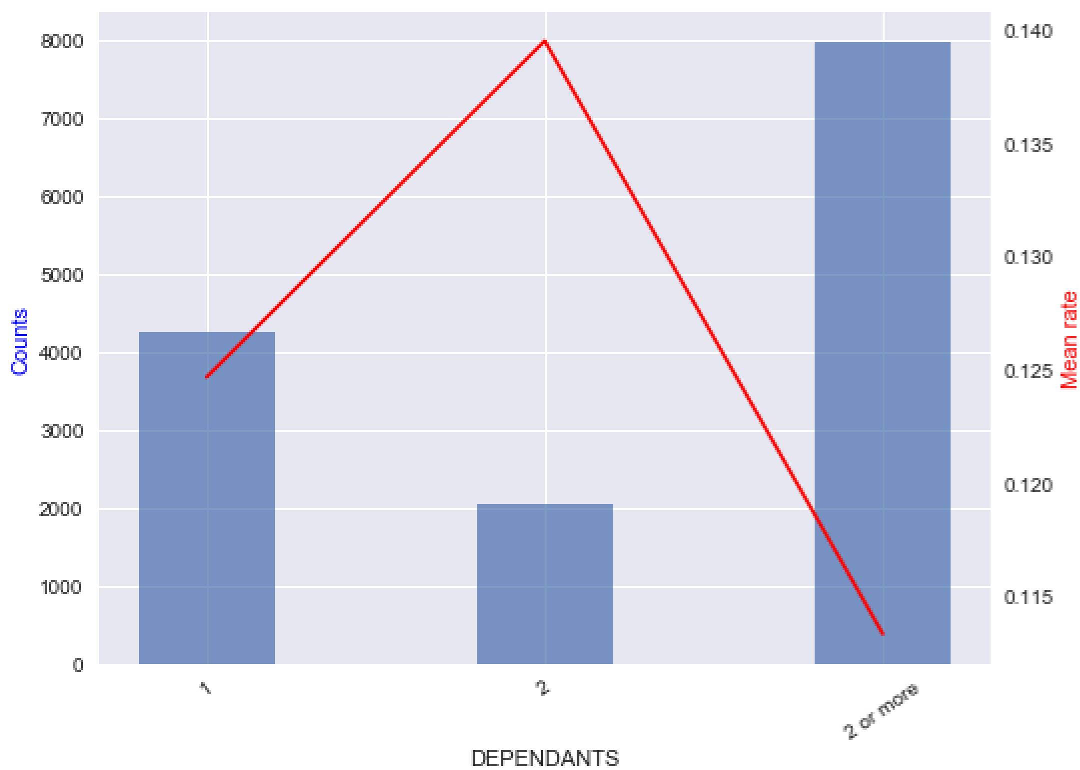
In [66]:
```
data['DEPENDANTS'].value_counts(dropna=False, normalize=True)
```

Out[66]:
```
0    0.538386
1    0.297772
2    0.144088
3    0.016251
4    0.002802
5    0.000350
6    0.000280
7    0.000070
Name: DEPENDANTS, dtype: float64
```

In [67]:
```
data['DEPENDANTS'].cat.add_categories(['2 or more'], inplace=True)
data.loc[data['DEPENDANTS'].isin([1.0, 2.0]) == False, 'DEPENDANTS'] = '2 or
data['DEPENDANTS'] = data['DEPENDANTS'].cat.remove_unused_categories()
```

In [68]:
```
functions.feature_stat(data, 'DEPENDANTS', 'TARGET')
functions.calc_iv(data, 'TARGET', 'DEPENDANTS')[0]
```

```
Counts:
DEPENDANTS
1            4251
2            2057
2 or more    7968
Name: TARGET, dtype: int64
Frequencies:
2 or more    0.558140
1            0.297772
2            0.144088
Name: DEPENDANTS, dtype: float64
```




```
IV:  0.00743729564542
```

Out[68]:

	% responders	% non-responders	WOE	DG-DB	IV
2 or more	0.52500	0.562679	-0.069311	-0.037679	0.002612
1	0.30814	0.296352	0.039004	0.011787	0.000460
2	0.16686	0.140968	0.168622	0.025892	0.004366

EDUCATION

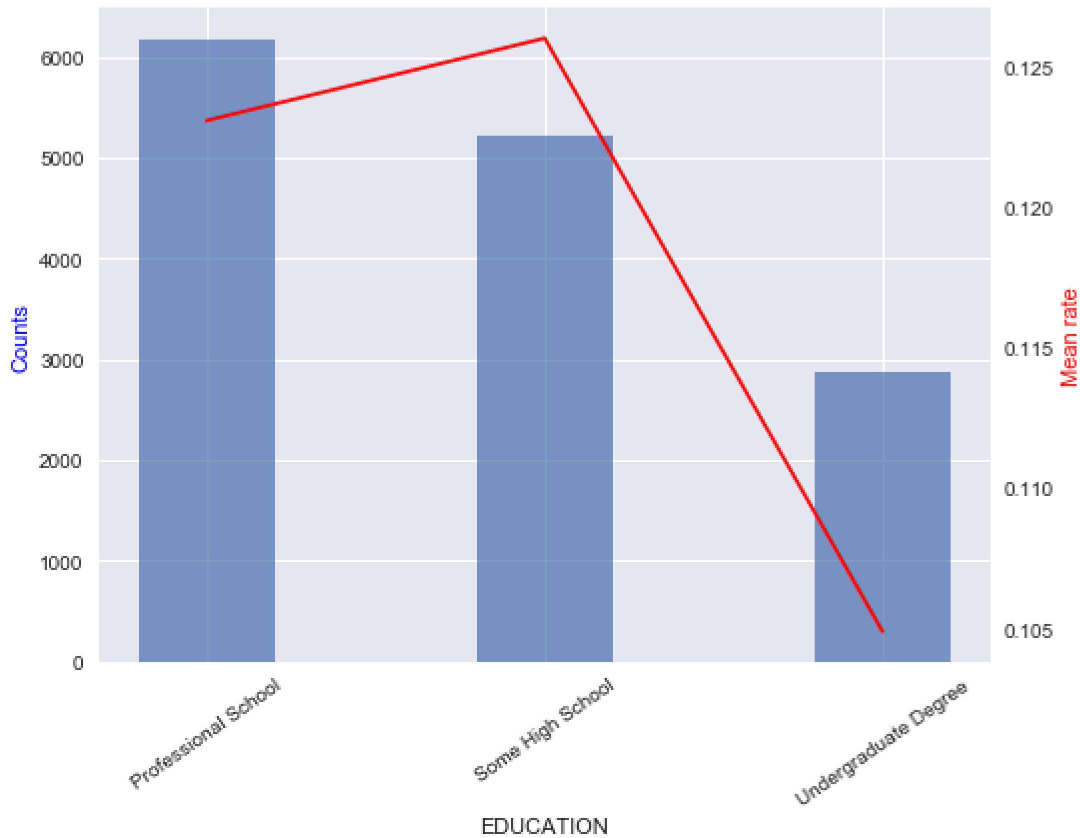
In [69]:
```
data['EDUCATION'].value_counts(dropna=False, normalize=True)
```

Out[69]:
```
Professional School     0.432544
Some High School        0.308700
Undergraduate Degree    0.200406
No Formal Education     0.034744
Some Primary School     0.022345
Post-Graduate Work      0.001191
Graduate Degree         0.000070
Name: EDUCATION, dtype: float64
```

In [70]:
```
data.loc[data['EDUCATION'].isin(['Undergraduate Degree', 'Post-Graduate Work
         'EDUCATION'] = 'Undergraduate Degree'
data.loc[data['EDUCATION'].isin(['Some High School', 'No Formal Education',
         'EDUCATION'] = 'Some High School'
data['EDUCATION'] = data['EDUCATION'].cat.remove_unused_categories()
```

In [71]:
```
functions.feature_stat(data, 'EDUCATION', 'TARGET')
functions.calc_iv(data, 'TARGET', 'EDUCATION')[0]
```

```
Counts:
EDUCATION
Professional School     6175
Some High School        5222
Undergraduate Degree    2879
Name: TARGET, dtype: int64
Frequencies:
Professional School     0.432544
Some High School        0.365789
Undergraduate Degree    0.201667
Name: EDUCATION, dtype: float64
```




```
IV:  0.00586098683881
```

Out[71]:

	% responders	% non-responders	WOE	DG-DB	IV
Some High School	0.382558	0.363492	0.051125	0.019067	0.000975
Undergraduate Degree	0.175581	0.205241	-0.156080	-0.029659	0.004629
Professional School	0.441860	0.431268	0.024265	0.010593	0.000257

MARITAL_STATUS

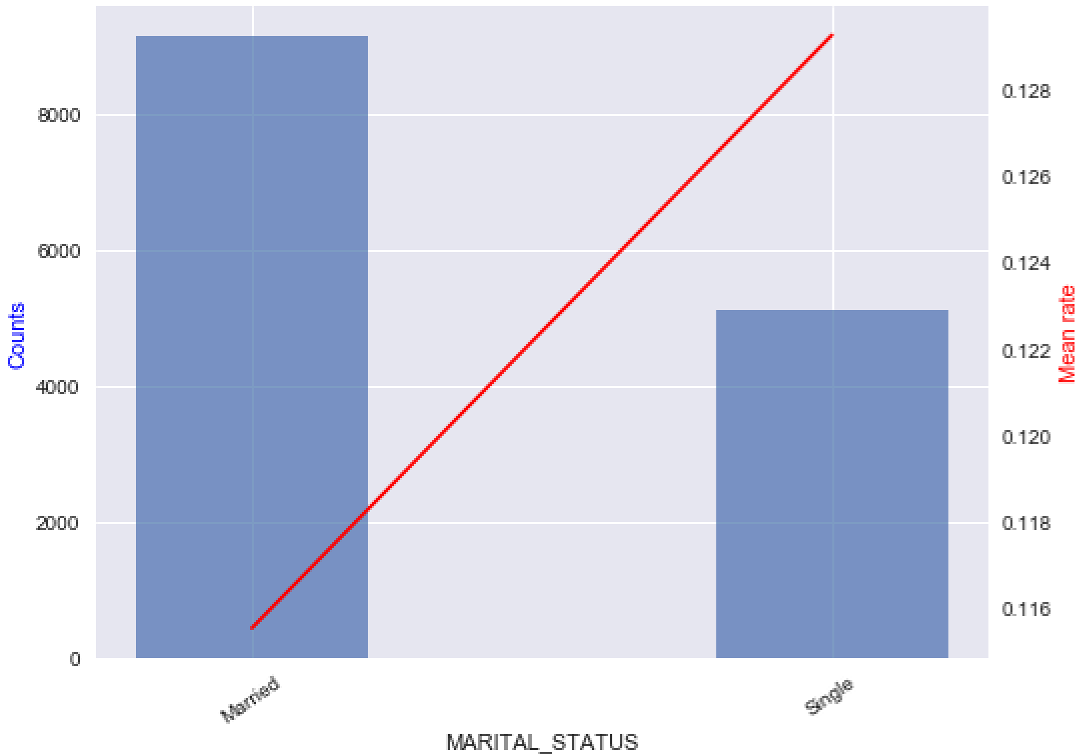
In [72]:
```
data['MARITAL_STATUS'].value_counts(dropna=False, normalize=True)
```

Out[72]:
```
Married      0.617750
Single       0.238652
Separated    0.081816
Widowed      0.038806
Partner      0.022976
Name: MARITAL_STATUS, dtype: float64
```

In [73]:
```
data.loc[data['MARITAL_STATUS'].isin(['Married', 'Partner']), 'MARITAL_STATU
data.loc[data['MARITAL_STATUS'].isin(['Single', 'Separated', 'Widowed']), 'M
data['MARITAL_STATUS'] = data['MARITAL_STATUS'].cat.remove_unused_categories
```

In [74]:
```
functions.feature_stat(data, 'MARITAL_STATUS', 'TARGET')
functions.calc_iv(data, 'TARGET', 'MARITAL_STATUS')[0]
```

```
Counts:
MARITAL_STATUS
Married    9147
Single     5129
Name: TARGET, dtype: int64
Frequencies:
Married    0.640726
Single     0.359274
Name: MARITAL_STATUS, dtype: float64
```




```
IV:  0.00380333908871
```

Out[74]:

	% responders	% non-responders	WOE	DG-DB	IV
Married	0.614535	0.644313	-0.047320	-0.029779	0.001409
Single	0.385465	0.355687	0.080401	0.029779	0.002394

GEN_INDUSTRY

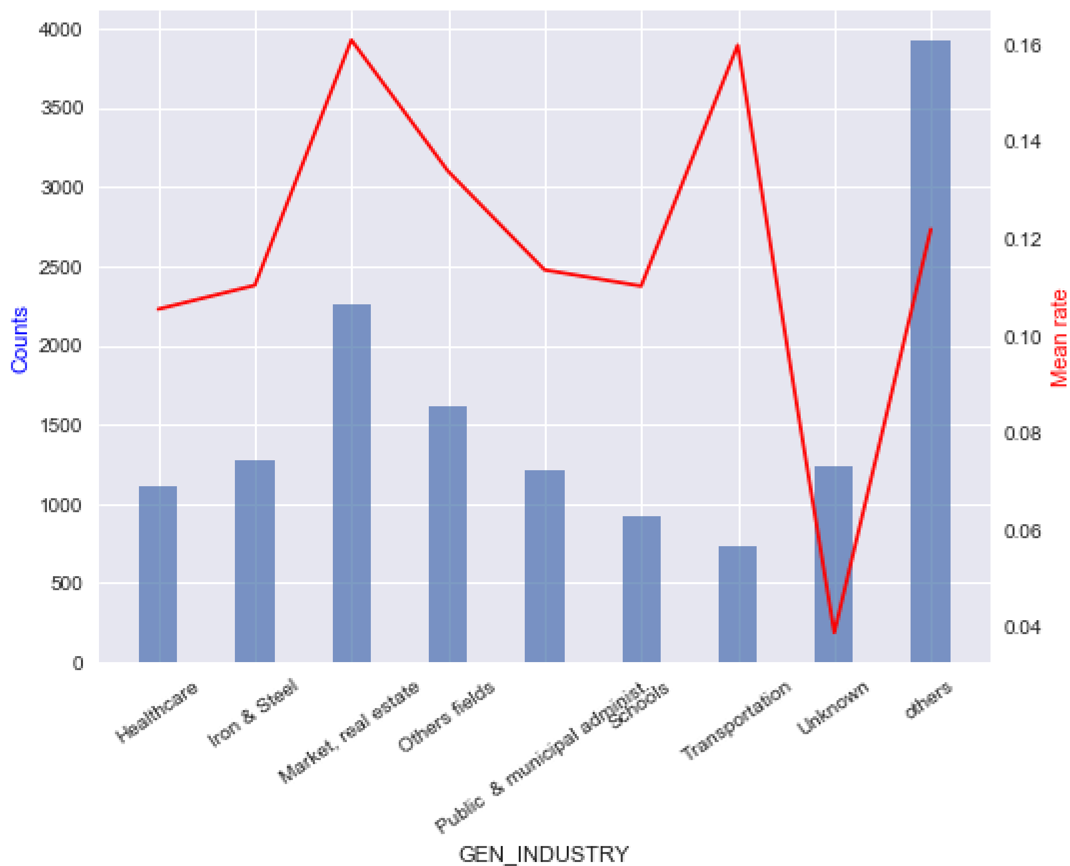
In [75]:
```
data['GEN_INDUSTRY'].value_counts(dropna=False, normalize=True)
```

```
Out[75]: Market, real estate                 0.157957
         Others fields                       0.113477
         Iron & Steel                        0.089451
         Unknown                             0.086579
         Public  & municipal administ.       0.084477
         Healthcare                          0.077683
         Schools                             0.064164
         Transportation                      0.051695
         Agriculture                         0.046372
         Construction - Raw Materials        0.037896
         Municipal economy/Road service      0.035724
         Restaurant & Catering               0.027249
         Scientific & Technical Instr.       0.026898
         Oil & Gas Operations                0.014780
         Assembly production                 0.011418
         Regional Banks                      0.010857
         Recreational Activities             0.009526
         Detective                           0.009316
         Oil Well Services & Equipment       0.009316
         Information service                 0.006795
         Beauty shop                         0.006514
         Software & Programming              0.005534
         Chemistry/Perfumery/Pharmaceut      0.004273
         Mass media                          0.003362
         Personal Services                   0.002732
         Insurance (Accident & Health)       0.001821
         Hotels & Motels                     0.001121
         Real Estate Operations              0.000771
         Business Services                   0.000771
         Trucking                            0.000700
         Staff recruitment                   0.000560
         Marketing                           0.000210
         Name: GEN_INDUSTRY, dtype: float64
```

```
In [76]: data['GEN_INDUSTRY'].cat.add_categories(['others'], inplace=True)
         data.loc[data['GEN_INDUSTRY'].isin(['Market, real estate', 'Others fields',
                                             'Public  & municipal administ.', 'Healthc
                  'GEN_INDUSTRY'] = 'others'
         data['GEN_INDUSTRY'] = data['GEN_INDUSTRY'].cat.remove_unused_categories()
```

```
In [77]: functions.feature_stat(data, 'GEN_INDUSTRY', 'TARGET')
         functions.calc_iv(data, 'TARGET', 'GEN_INDUSTRY')[0]
```

```
Counts:
GEN_INDUSTRY
Healthcare                        1109
Iron & Steel                      1277
Market, real estate               2255
Others fields                     1620
Public  & municipal administ.     1206
Schools                            916
Transportation                     738
Unknown                           1236
others                            3919
Name: TARGET, dtype: int64
Frequencies:
others                            0.274517
Market, real estate               0.157957
Others fields                     0.113477
Iron & Steel                      0.089451
Unknown                           0.086579
Public  & municipal administ.     0.084477
Healthcare                        0.077683
Schools                           0.064164
Transportation                    0.051695
Name: GEN_INDUSTRY, dtype: float64
```




```
IV:  0.113378430613
```

Out[77]:

	% responders	% non-responders	WOE	DG-DB	IV
Market, real estate	0.211047	0.150685	0.336887	0.060362	0.020335
others	0.277907	0.274052	0.013968	0.003855	0.000054
Schools	0.058721	0.064909	-0.100193	-0.006188	0.000620
Public & municipal administ.	0.079651	0.085139	-0.066624	-0.005487	0.000366
Others fields	0.126163	0.111739	0.121404	0.014423	0.001751
Iron & Steel	0.081977	0.090475	-0.098634	-0.008498	0.000838
Unknown	0.027907	0.094616	-1.220951	-0.066709	0.081449
Transportation	0.068605	0.049379	0.328839	0.019226	0.006322
Healthcare	0.068023	0.079006	-0.149675	-0.010983	0.001644

FAMILY_INCOME

In [78]:

```
data['FAMILY_INCOME'].value_counts(dropna=False, normalize=True)
```

Out[78]:

```
10000-20000    0.471070
20000-50000    0.405015
5000-10000     0.096526
50000+         0.025077
up to 5000     0.002312
Name: FAMILY_INCOME, dtype: float64
```

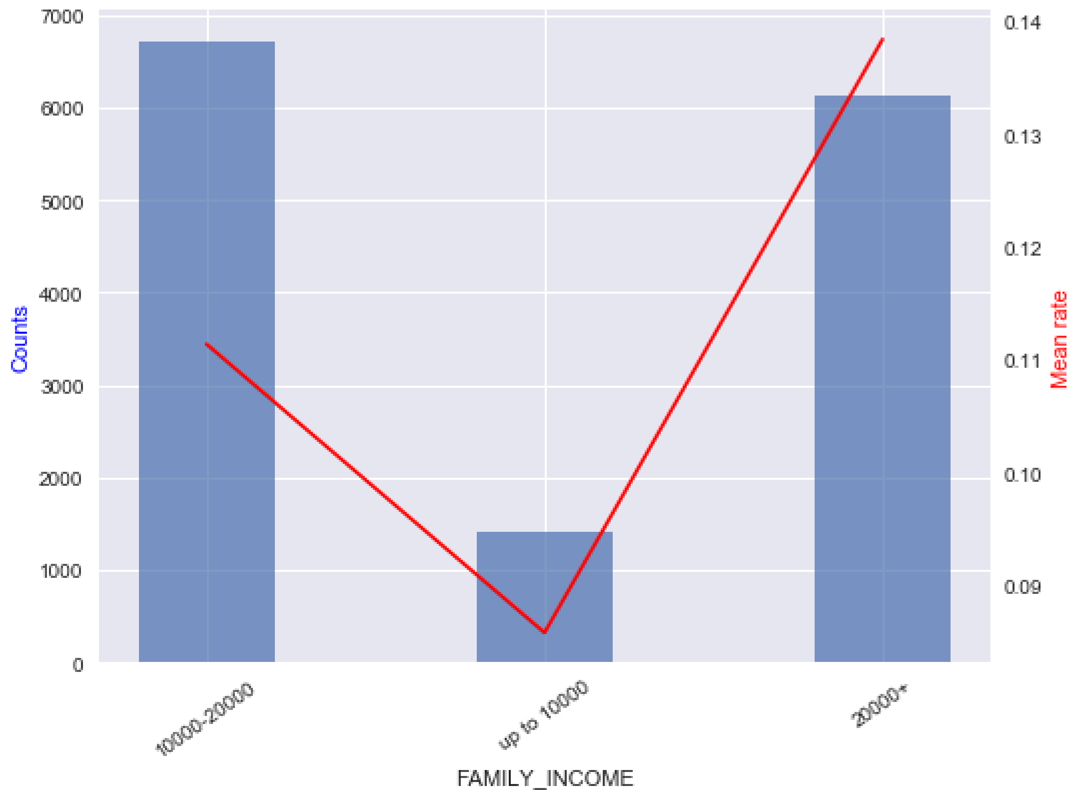
In [79]:

```
data['FAMILY_INCOME'].cat.add_categories(['up to 10000', '20000+'], inplace=
data.loc[data['FAMILY_INCOME'].isin(['up to 5000', '5000-10000']), 'FAMILY_I
data.loc[data['FAMILY_INCOME'].isin(['20000-50000', '50000+']), 'FAMILY_INCO
data['FAMILY_INCOME'] = data['FAMILY_INCOME'].cat.remove_unused_categories()
```

In [80]:

```
functions.feature_stat(data, 'FAMILY_INCOME', 'TARGET')
functions.calc_iv(data, 'TARGET', 'FAMILY_INCOME')[0]
```

```
Counts:
FAMILY_INCOME
10000-20000    6725
up to 10000    1411
20000+         6140
Name: TARGET, dtype: int64
Frequencies:
10000-20000    0.471070
20000+         0.430092
up to 10000    0.098837
Name: FAMILY_INCOME, dtype: float64
```




```
IV:  0.0274921611768
```

Out[80]:

	% responders	% non-responders	WOE	DG-DB	IV
10000-20000	0.435465	0.475948	-0.088893	-0.040483	0.003599
20000+	0.494186	0.421313	0.159537	0.072874	0.011626
up to 10000	0.070349	0.102740	-0.378733	-0.032391	0.012267

LOAN_NUM_TOTAL

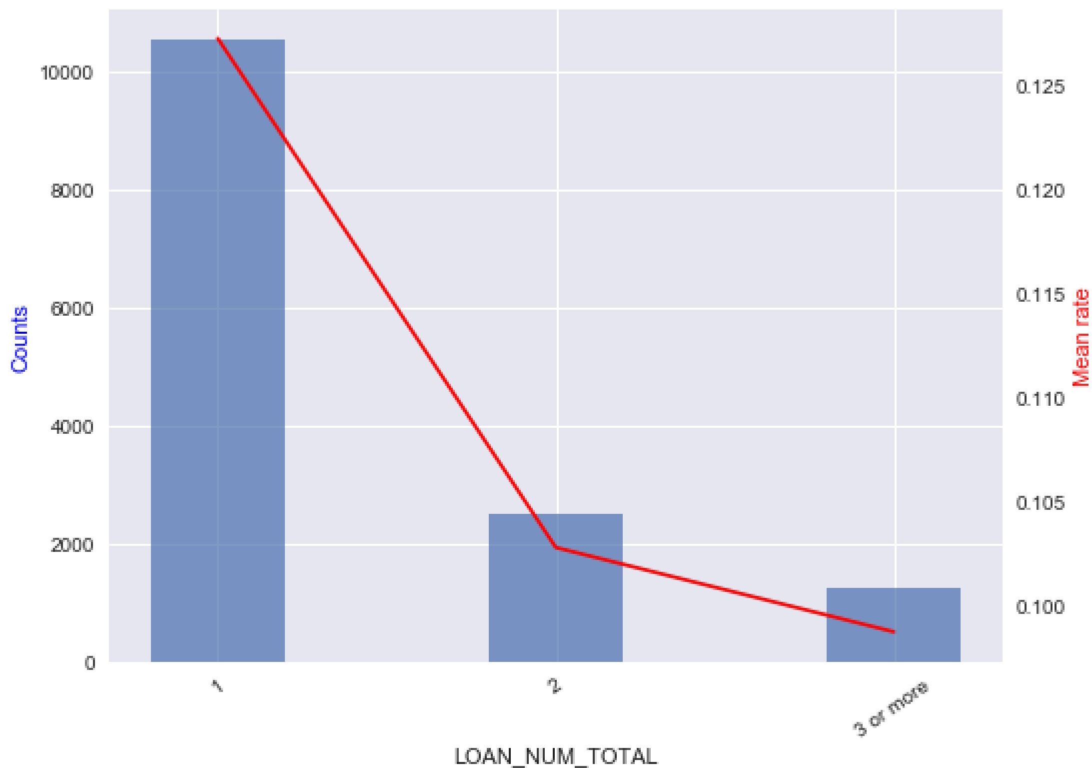
In [81]:
```
data['LOAN_NUM_TOTAL'].value_counts(dropna=False, normalize=True)
```

Out[81]:
```
1     0.738232
2     0.174489
3     0.058350
4     0.018282
5     0.007005
6     0.002452
7     0.000981
8     0.000140
11    0.000070
Name: LOAN_NUM_TOTAL, dtype: float64
```

In [82]:
```
data['LOAN_NUM_TOTAL'].cat.add_categories(['3 or more'], inplace=True)
data.loc[data['LOAN_NUM_TOTAL'].isin([1, 2]) == False, 'LOAN_NUM_TOTAL'] = '
data['LOAN_NUM_TOTAL'] = data['LOAN_NUM_TOTAL'].cat.remove_unused_categories
```

In [83]:
```
functions.feature_stat(data, 'LOAN_NUM_TOTAL', 'TARGET')
functions.calc_iv(data, 'TARGET', 'LOAN_NUM_TOTAL')[0]
```

```
Counts:
LOAN_NUM_TOTAL
1            10539
2             2491
3 or more     1246
Name: TARGET, dtype: int64
Frequencies:
1            0.738232
2            0.174489
3 or more    0.087279
Name: LOAN_NUM_TOTAL, dtype: float64
```




```
IV:  0.0121634889441
```

Out[83]:

	% responders	% non-responders	WOE	DG-DB	IV
1	0.779651	0.732558	0.062304	0.047093	0.002934
2	0.148837	0.178003	-0.178945	-0.029165	0.005219
3 or more	0.071512	0.089439	-0.223700	-0.017928	0.004010

LOAN_NUM_TOTAL

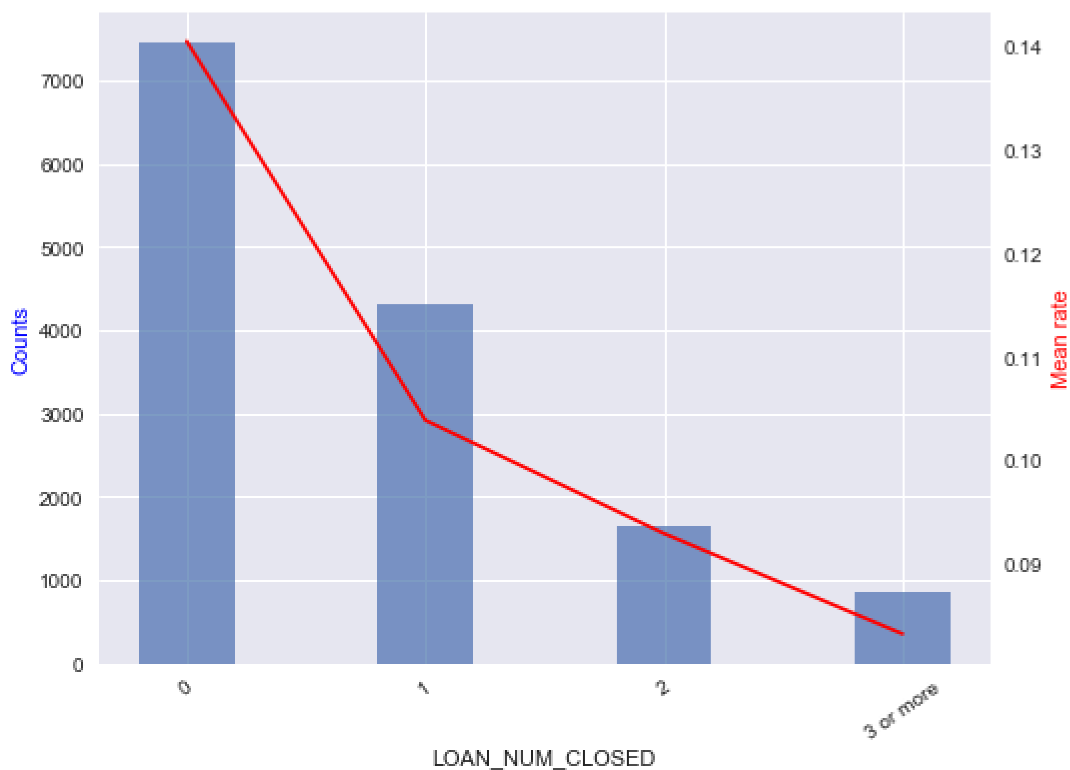
In [84]:
```
data['LOAN_NUM_CLOSED'].value_counts(dropna=False, normalize=True)
```

```
Out[84]: 0     0.522275
         1     0.302045
         2     0.115999
         3     0.039857
         4     0.013379
         5     0.004133
         6     0.001821
         7     0.000280
         8     0.000140
         11    0.000070
         Name: LOAN_NUM_CLOSED, dtype: float64
```

```
In [85]: data['LOAN_NUM_CLOSED'].cat.add_categories(['3 or more'], inplace=True)
         data.loc[data['LOAN_NUM_CLOSED'].isin([0, 1, 2]) == False, 'LOAN_NUM_CLOSED'
         data['LOAN_NUM_CLOSED'] = data['LOAN_NUM_CLOSED'].cat.remove_unused_categori
```

```
In [86]: functions.feature_stat(data, 'LOAN_NUM_CLOSED', 'TARGET')
         functions.calc_iv(data, 'TARGET', 'LOAN_NUM_CLOSED')[0]
```

```
Counts:
LOAN_NUM_CLOSED
0            7456
1            4312
2            1656
3 or more     852
Name: TARGET, dtype: int64
Frequencies:
0            0.522275
1            0.302045
2            0.115999
3 or more    0.059681
Name: LOAN_NUM_CLOSED, dtype: float64
```



```
IV:  0.0424898763872
```

Out[86]:

	% responders	% non-responders	WOE	DG-DB	IV
1	0.260465	0.307741	-0.166791	-0.047276	0.007885
2	0.089535	0.119624	-0.289726	-0.030089	0.008718
0	0.608721	0.510433	0.176100	0.098288	0.017308
3 or more	0.041279	0.062201	-0.410021	-0.020922	0.008579

LOAN_DLQ_NUM

In [87]:

```
data['LOAN_DLQ_NUM'].value_counts(dropna=False, normalize=True)
```

Out[87]:

```
0     0.871603
1     0.094284
2     0.018633
3     0.006514
4     0.003362
5     0.002662
6     0.001121
7     0.000911
9     0.000280
8     0.000210
13    0.000140
10    0.000140
12    0.000070
11    0.000070
Name: LOAN_DLQ_NUM, dtype: float64
```

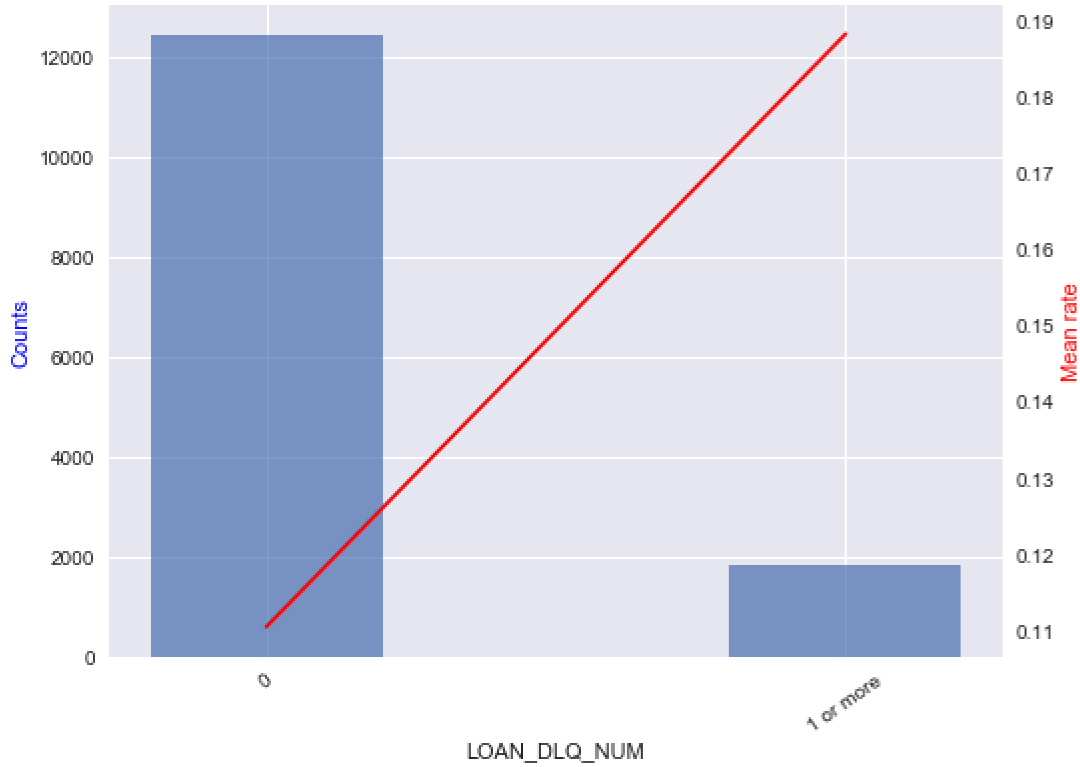
In [88]:

```
data['LOAN_DLQ_NUM'].cat.add_categories(['1 or more'], inplace=True)
data.loc[data['LOAN_DLQ_NUM'].isin([0]) == False, 'LOAN_DLQ_NUM'] = '1 or mo
data['LOAN_DLQ_NUM'] = data['LOAN_DLQ_NUM'].cat.remove_unused_categories()
```

In [89]:

```
functions.feature_stat(data, 'LOAN_DLQ_NUM', 'TARGET')
functions.calc_iv(data, 'TARGET', 'LOAN_DLQ_NUM')[0]
```

```
Counts:
LOAN_DLQ_NUM
0            12443
1 or more     1833
Name: TARGET, dtype: int64
Frequencies:
0            0.871603
1 or more    0.128397
Name: LOAN_DLQ_NUM, dtype: float64
```




```
IV:  0.0512098860054
```

Out[89]:

	% responders	% non-responders	WOE	DG-DB	IV
1 or more	0.200581	0.118509	0.526231	0.082072	0.043189
0	0.799419	0.881491	-0.097730	-0.082072	0.008021

LOAN_MAX_DLQ

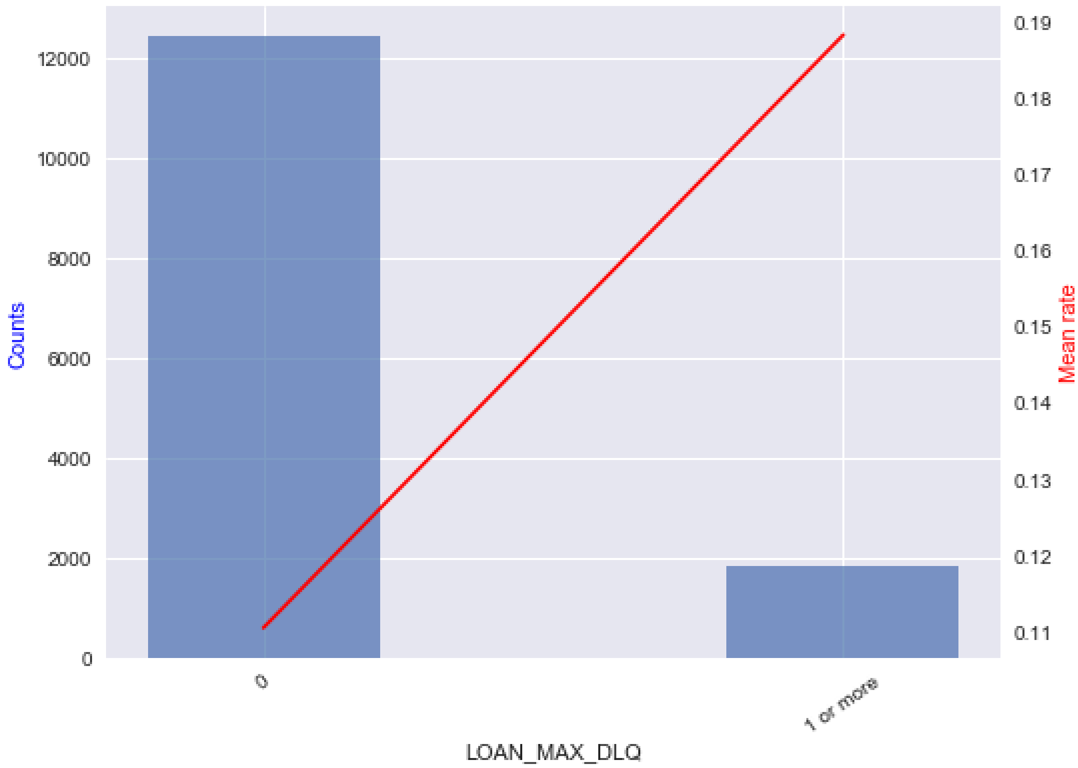
In [90]:
```
data['LOAN_MAX_DLQ'].value_counts(dropna=False, normalize=True)
```

Out[90]:
```
0    0.871603
1    0.125525
2    0.002171
3    0.000490
8    0.000070
6    0.000070
4    0.000070
Name: LOAN_MAX_DLQ, dtype: float64
```

In [91]:
```
data['LOAN_MAX_DLQ'].cat.add_categories(['1 or more'], inplace=True)
data.loc[data['LOAN_MAX_DLQ'].isin([0]) == False, 'LOAN_MAX_DLQ'] = '1 or mo
data['LOAN_MAX_DLQ'] = data['LOAN_MAX_DLQ'].cat.remove_unused_categories()
```

In [92]:
```
functions.feature_stat(data, 'LOAN_MAX_DLQ', 'TARGET')
functions.calc_iv(data, 'TARGET', 'LOAN_MAX_DLQ')[0]
```

```
Counts:
LOAN_MAX_DLQ
0              12443
1 or more       1833
Name: TARGET, dtype: int64
Frequencies:
0              0.871603
1 or more      0.128397
Name: LOAN_MAX_DLQ, dtype: float64
```




```
IV:  0.0512098860054
```

Out[92]:

	% responders	% non-responders	WOE	DG-DB	IV
1 or more	0.200581	0.118509	0.526231	0.082072	0.043189
0	0.799419	0.881491	-0.097730	-0.082072	0.008021

In [93]:

```
data.head(10)
```

Out[93]:

	AGREEMENT_RK	TARGET	AGE	SOCSTATUS_WORK_FL	SOCSTATUS_PENS_
1	59910230	0	(30.0, 34.0]	1	
2	59910525	0	(50.0, 54.0]	1	
3	59910803	0	(38.0, 42.0]	1	
4	59911781	0	(26.0, 30.0]	1	
5	59911784	0	(26.0, 30.0]	1	
7	59912034	0	(38.0, 42.0]	1	
9	59912659	0	(42.0, 50.0]	1	
10	59912692	0	(50.0, 54.0]	1	
11	59913108	1	(0.0, 26.0]	1	
12	59913134	1	(54.0, 67.0]	0	

This is it, all the variables are transformed. I didn't do anything to several variables which are flags, but they are good as they are.

Feature selection based on IV

Now it is time to choose columns. It could be done before, while processing separate columns, but I prefer to do this for all columns at once. I calculate IV for all columns and use only those which have value higher that threshold (0.02 in this case).

In [94]:

```
columns_to_try = [col for col in list(data.columns) if col not in ('AGREEMEN
```

In [95]:

```
ivs = []
for col in columns_to_try:
    data[col] = data[col].astype('category')
    if data[col].isnull().any():
        print(col)
        if 'Unknown' not in data[col].cat.categories:
            data[col].cat.add_categories(['Unknown'], inplace=True)
        data[col].fillna('Unknown', inplace=True)
    data[col] = data[col].cat.remove_unused_categories()
```

```
    _, iv = functions.calc_iv(data, 'TARGET', col)
    ivs.append((col, np.round(iv, 4)))
```

In [96]:
```
good_cols = [i[0] for i in sorted(ivs, key=lambda tup: tup[1], reverse=True)
for i in ['TARGET', 'AGREEMENT_RK']:
    good_cols.append(i)
```

In [97]:
```
good_cols
```

Out[97]:
```
['AGE',
 'GEN_INDUSTRY',
 'WORK_TIME',
 'PERSONAL_INCOME',
 'GEN_PHONE_FL',
 'SOCSTATUS_PENS_FL',
 'SOCSTATUS_WORK_FL',
 'LOAN_AVG_DLQ_AMT',
 'LOAN_DLQ_NUM',
 'LOAN_MAX_DLQ',
 'LOAN_MAX_DLQ_AMT',
 'FACT_LIVING_TERM',
 'LOAN_NUM_CLOSED',
 'FST_PAYMENT',
 'TERM',
 'Income_to_limit',
 'LOAN_NUM_PAYM',
 'FAMILY_INCOME',
 'REG_FACT_POST_TP_FL',
 'TARGET',
 'AGREEMENT_RK']
```

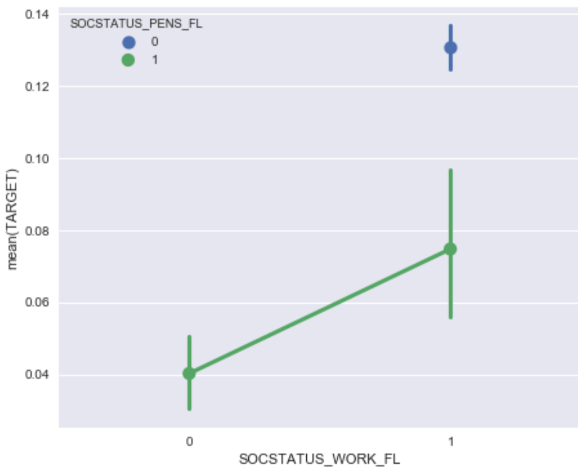
Some additional visualization

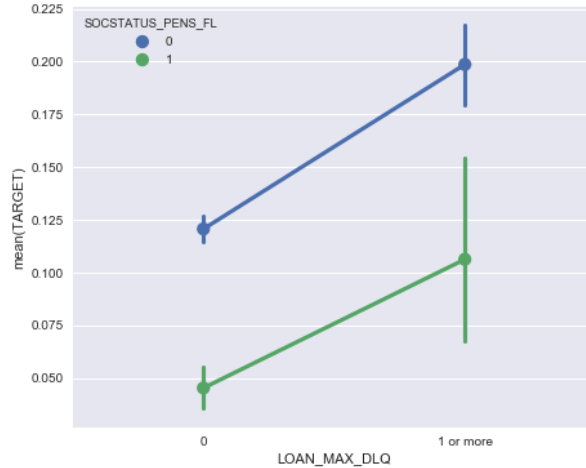
Plotting variables by themselves is useful, but visualizing their interactions can unveil interesting things. There are some examples below.

Pointplots show mean target rate for pairs of variables. I show only several plots as there are too many possible combinations.

In [98]:
```
data_viz = data[good_cols]
fig, ax = plt.subplots(1, 2, figsize = (16, 6))
sns.pointplot(x='SOCSTATUS_WORK_FL', y="TARGET", hue='SOCSTATUS_PENS_FL', da
sns.pointplot(x='LOAN_MAX_DLQ', y="TARGET", hue='SOCSTATUS_PENS_FL', data=da
```

Out[98]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f177fd8fd0>
```





SOCSTATUS_PENS_FL 1 means that person is on pension, 0 otherwise.
SOCSTATUS_WORK_FL 1 means that person works, 0 otherwise.

Three features on the plots above show clear distinctions between mean target rates. It could be a good idea to create new variables showing these interactions.

In [99]:
```
data['work_pens'] = 0
data.loc[data['SOCSTATUS_WORK_FL'] == 0, 'work_pens'] = 1
data.loc[(data['SOCSTATUS_WORK_FL'] == 1) & (data['SOCSTATUS_PENS_FL'] == 1)
data.loc[(data['SOCSTATUS_WORK_FL'] == 1) & (data['SOCSTATUS_PENS_FL'] == 0)
```

In [100…
```
data['pens_dlq'] = 0
data.loc[(data['LOAN_MAX_DLQ'] == 0) & (data['SOCSTATUS_PENS_FL'] == 0), 'pe
data.loc[(data['LOAN_MAX_DLQ'] == '1 or more') & (data['SOCSTATUS_PENS_FL']
data.loc[(data['LOAN_MAX_DLQ'] == 0) & (data['SOCSTATUS_PENS_FL'] == 0), 'pe
data.loc[(data['LOAN_MAX_DLQ'] == '1 or more') & (data['SOCSTATUS_PENS_FL']
```

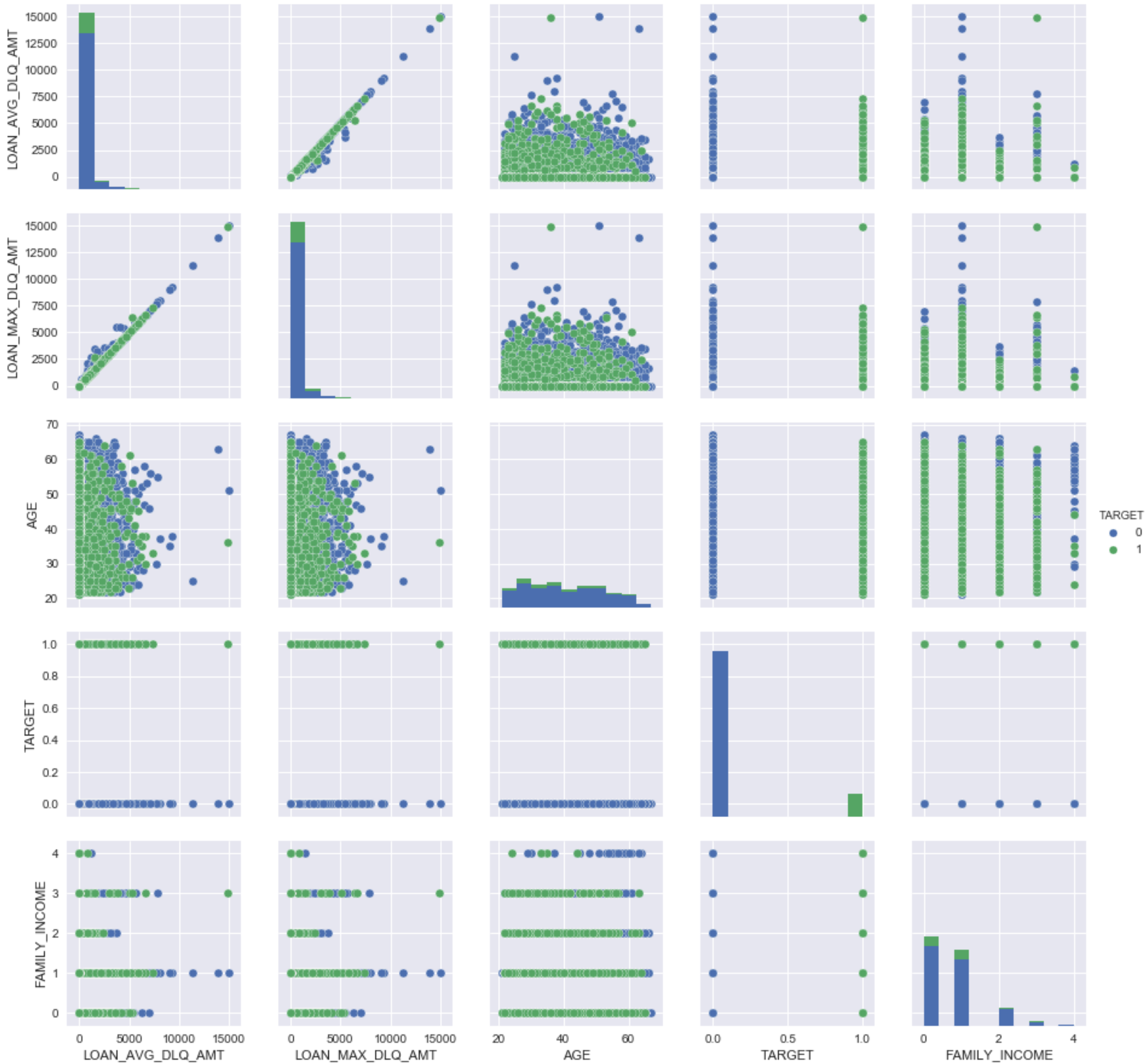
For the next graphs I'll need data, where continuous variables aren't binned. Also it is necessary to do label encoding for categorical variables, as sns.pairplot doesn't work well with them.

In [101…
```
le = preprocessing.LabelEncoder()
for col in ['GENDER', 'CHILD_TOTAL', 'DEPENDANTS', 'EDUCATION', 'MARITAL_STA
            'FAMILY_INCOME', 'LOAN_NUM_TOTAL', 'LOAN_NUM_CLOSED', 'LOAN_DLQ_
    initial_data[col] = initial_data[col].astype('category')
    if (initial_data[col].isnull() == True).any():
        initial_data[col].cat.add_categories(['Unknown'], inplace=True)
        initial_data[col].fillna('Unknown', inplace=True)
    initial_data[col] = le.fit_transform(initial_data[col])
```

In [102…
```
data_viz1 = initial_data[good_cols].drop(['AGREEMENT_RK'], axis=1)
```

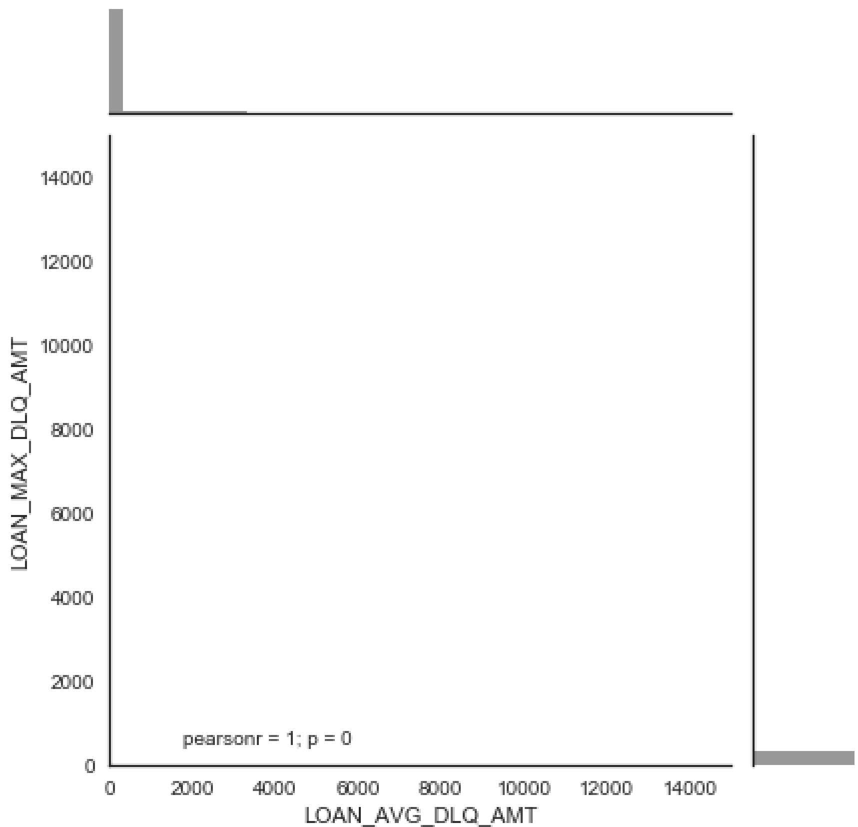
In [103…
```
plt.figure(figsize=(32, 32))
sns.pairplot(data_viz1[['LOAN_AVG_DLQ_AMT', 'LOAN_MAX_DLQ_AMT', 'AGE', 'TARG
```

Out[103…
```
<seaborn.axisgrid.PairGrid at 0x1f17817e208>
<matplotlib.figure.Figure at 0x1f1784a5ba8>
```



I included only several variables in this pairplot, but it shows how variables can interact. Sometimes variables may interact in such a way, that their values cleate visible clusters based on target. New variables can be created based on this. Another use of the graph is to find correlated features. 'LOAN_AVG_DLQ_AMT' and 'LOAN_MAX_DLQ_AMT' seem to be highly correlated, let's have a look.

In [104…
```
with sns.axes_style("white"):
    sns.jointplot(x=data_viz1['LOAN_AVG_DLQ_AMT'], y=data_viz1['LOAN_MAX_DLQ
```



Well, it seems that pearson correlation coefficient is 1 which shows very high correlation. I'll drop one of these columns.

In [105…
```
data.drop(['LOAN_AVG_DLQ_AMT'], axis=1, inplace=True)
```

Let's try selecting variables based on IV again.

In [106…
```
columns_to_try = [col for col in list(data.columns) if col not in ('AGREEMEN
ivs = []
for col in columns_to_try:
    data[col] = data[col].astype('category')
    if data[col].isnull().any():
        print(col)
        if 'Unknown' not in data[col].cat.categories:
            data[col].cat.add_categories(['Unknown'], inplace=True)
        data[col].fillna('Unknown', inplace=True)
    data[col] = data[col].cat.remove_unused_categories()
    _, iv = functions.calc_iv(data, 'TARGET', col)
    ivs.append((col, np.round(iv, 4)))
good_cols = [i[0] for i in sorted(ivs, key=lambda tup: tup[1], reverse=True)
for i in ['TARGET', 'AGREEMENT_RK']:
    good_cols.append(i)
good_cols
```

Out[106… ['AGE',
 'GEN_INDUSTRY',
 'work_pens',
 'WORK_TIME',
 'PERSONAL_INCOME',
 'GEN_PHONE_FL',
 'SOCSTATUS_PENS_FL',
 'SOCSTATUS_WORK_FL',
 'LOAN_DLQ_NUM',
 'LOAN_MAX_DLQ',
 'LOAN_MAX_DLQ_AMT',
 'FACT_LIVING_TERM',
 'LOAN_NUM_CLOSED',
 'FST_PAYMENT',
 'TERM',
 'Income_to_limit',
 'LOAN_NUM_PAYM',
 'FAMILY_INCOME',
 'REG_FACT_POST_TP_FL',
 'TARGET',
 'AGREEMENT_RK']

One of the newly created features proved to be useful! Now it's time to go further. I'll dummify all features.

In [107…
```
columns_dummify = [col for col in good_cols if col not in ('TARGET', 'AGREEM
data = data[good_cols]
for col in columns_dummify:
    data[col] = data[col].astype('category')
    dummies = pd.get_dummies(data[col])
    dummies = dummies.add_prefix('{}_:_'.format(col))
    data.drop([col], axis=1, inplace=True)
    data = data.join(dummies)
```

In [108…
```
X = data.drop(['TARGET', 'AGREEMENT_RK'], axis=1)
Y = data['TARGET']
```

In [109…
```
X.shape
```

Out[109… (14276, 87)

87 variables could be okay, but I think it could be a good idea to reduce the number of them. There are various ways to select features: greedy algorithms, feature importance and so on. As I'm going to use Logistic Regression, I'll use sklearn's RandomizedLogisticRegression for this.

RandomizedLogisticRegression basically runs Logistic Regression several times with various penalties for random coefficients. After the runs high scores are assigned to the most stable features.

In [110…
```
randomized_logistic = linear_model.RandomizedLogisticRegression(C=0.1, selec
                                                                 n_resampling
```

```
X_train_log = randomized_logistic.fit_transform(X=X, y=Y)
randomized_logistic.get_support()
```

Out[110…

```
array([ True, False, False, False,  True,  True, False,  True, False,
       False,  True, False, False, False, False, False, False, False,
       False,  True, False,  True, False,  True, False,  True,  True,
        True,  True,  True, False,  True,  True,  True, False, False,
       False, False, False, False,  True, False, False, False, False,
       False, False, False,  True,  True, False, False,  True,  True,
       False, False, False,  True,  True, False, False,  True, False,
        True,  True, False,  True, False,  True,  True,  True, False,
        True, False,  True, False, False,  True, False, False, False,
        True, False, False, False,  True,  True], dtype=bool)
```

In [111…

```
X_train_log.shape
```

Out[111…

```
(14276, 36)
```

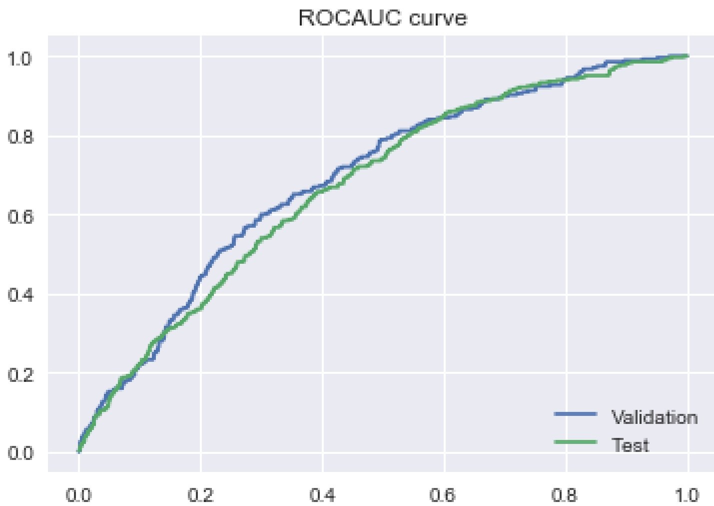
36 from 87 were selected. It's time for the model. I split data into train, test and validation sets. LogisticRegressionCV is used to choose an optimal regularization strength.

In [112…

```
X_train, X_test, y_train, y_test = train_test_split(X_train_log, Y, test_siz
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_siz
logreg = linear_model.LogisticRegressionCV(class_weight='balanced', n_jobs=-
logreg.fit(X_train, y_train)

y_pred_log_val = logreg.predict_proba(X_val)
y_pred_log_val_1 = [i[1] for i in y_pred_log_val]
fpr_val, tpr_val, thresholds_val = roc_curve(y_val, y_pred_log_val_1)
plt.plot(fpr_val, tpr_val, label='Validation')
scores_val = cross_val_score(logreg, X_val, y_val, cv=5, scoring='roc_auc')

y_pred_log_test = logreg.predict_proba(X_test)
y_pred_log_test_1 = [i[1] for i in y_pred_log_test]
fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_pred_log_test_1)
plt.plot(fpr_test, tpr_test, label='Test')
scores_test = cross_val_score(logreg, X_test, y_test, cv=5, scoring='roc_auc

plt.title('ROCAUC curve')
plt.legend(loc='lower right')
```

Out[112…

```
<matplotlib.legend.Legend at 0x1f17ad499e8>
```



In [113…

```
print('Validation auc: ', np.round(auc(fpr_val, tpr_val), 4))
print('Cross-validation: mean value is {0} with std {1}.'.format(np.round(np
                                                                 np.round(np
print('Test auc: ', np.round(auc(fpr_test, tpr_test), 4))
print('Cross-validation: mean value is {0} with std {1}.'.format(np.round(np
                                                                 np.round(np
```

```
Validation auc:  0.6906
Cross-validation: mean value is 0.6612 with std 0.023.
Test auc:  0.6728
Cross-validation: mean value is 0.6593 with std 0.0308.
```

In [114…

```
coefs = pd.DataFrame(list(zip(X[X.columns[randomized_logistic.get_support()]
             columns=['Feature', 'Coefficient'])
coefs
```

Out[114…

	Feature	Coefficient
0	AGE_:_(0.0, 26.0]	0.058152
1	AGE_:_(38.0, 42.0]	0.326568
2	AGE_:_(42.0, 50.0]	-0.049522
3	AGE_:_(54.0, 67.0]	-0.384079
4	GEN_INDUSTRY_:_Market, real estate	0.179091
5	work_pens_:_3	0.515434
6	WORK_TIME_:_(6.5, 21.5]	0.288714
7	WORK_TIME_:_(35.5, 53.5]	0.168606
8	WORK_TIME_:_(85.5, 151.0]	-0.168910
9	WORK_TIME_:_(151.0, 600.0]	-0.381151
10	PERSONAL_INCOME_:_(0.0, 7600.0]	-0.340836
11	PERSONAL_INCOME_:_(7600.0, 9300.0]	-0.285362
12	PERSONAL_INCOME_:_(9300.0, 11000.0]	-0.164639
13	PERSONAL_INCOME_:_(14800.0, 15300.0]	0.277408
14	PERSONAL_INCOME_:_(15300.0, 20800.0]	0.056118
15	PERSONAL_INCOME_:_(20800.0, 44000.0]	0.535057
16	LOAN_DLQ_NUM_:_0	-0.685242
17	FACT_LIVING_TERM_:_(38.5, 85.5]	0.154556
18	FACT_LIVING_TERM_:_(85.5, 131.5]	-0.141100
19	FACT_LIVING_TERM_:_(238.5, 1000.0]	-0.104258
20	LOAN_NUM_CLOSED_:_0	0.178287
21	FST_PAYMENT_:_(0.0, 200.0]	0.310499
22	FST_PAYMENT_:_(200.0, 900.0]	0.216670
23	FST_PAYMENT_:_(1700.0, 2100.0]	-0.207217
24	FST_PAYMENT_:_(3800.0, 6000.0]	-0.440642
25	FST_PAYMENT_:_(6000.0, 75600.0]	-0.405891
26	TERM_:_(4.5, 8.5]	-0.128436
27	TERM_:_(11.5, 36.0]	0.347700
28	Income_to_limit_:_(0.0, 0.515]	-0.014197
29	Income_to_limit_:_(0.515, 0.783]	-0.027910
30	Income_to_limit_:_(1.108, 1.428]	0.245322
31	Income_to_limit_:_(1.962, 2.556]	0.225381
32	LOAN_NUM_PAYM_:_(3.5, 4.5]	0.141627

	Feature	Coefficient
33	LOAN_NUM_PAYM_:_(11.5, 110.0]	-0.174840
34	REG_FACT_POST_TP_FL_:_0	0.220352
35	REG_FACT_POST_TP_FL_:_1	-0.222208

And here we can see how each category influenced the result.

So, this is it. The score is quite high, accuracy on real test set should be lower, but hopefully not much. There are many ways to enchance the model, of course:

- Transform variables with more care - maybe change parameters for DecisionTreeClassifier for specific variables to create better bins;
- Fill missing values with something else;
- Treat outliers instead of dropping rows with them;
- Create more variables bases of feature interaction;
- Try different threshold for feature selection);

And if interpreting variables isn't necessary, then continuous variables can be used without binning. Maybe they can be transformed some way or scaled. More sophisticated algorithms can be used such as a reputable xgboost and so on.