bank-data-analysis

September 23, 2022

1 Bank Data Analysis

1.1 Goals

Goal is to analyze the supplied data and answer some questions. The questions will be outlined in the notebook with prefix [Qi] where i is index. Question will also include english translation and original czech version. For example: [Q1] What's the highest age of applicants? (Jaký je nejvyšší věk žadatele?)

1.2 Data Loading

[1]:
```
!pip install -q pandas openpyxl matplotlib optbinning seaborn
```

[2]:
```
!ls ../data
```

```
external  raw
```

[3]:
```
# constants
DATA_PATH = "../data/raw/data.xlsx"

# imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[4]:
```
df = pd.read_excel(DATA_PATH)
```

1.3 Data Exploration

We explore the dataset and answer some basic questions. But we only focus on some columns more in detial.

[5]:
```
df
```

[5]:
```
      CODE_ZIP  AMT_NET_INCOME  AMT_REQUESTED_TICKET  \
0        18100           22000                  8000
1        79501           28000                 10000
2        69661           10800                  1000
3        43111           10000                  6000
```

4	74201	32000	8000
…	…	…	…
4995	74743	13500	15000
4996	69605	23700	3000
4997	74706	50000	15000
4998	28903	6000	1000
4999	74253	20000	15000

	TEXT_BANK	NUM_AGE	TEXT_GENDER \
0	Česká spořitelna, a.s.	37	Muž
1	Komerční banka, a.s.	58	Muž
2	Československá obchodní banka, a.s.	32	Muž
3	Československá obchodní banka, a.s.	24	Žena
4	Česká spořitelna, a.s.	34	Muž
…	…	…	…
4995	Equa bank a.s.	26	Žena
4996	Fio banka, a.s.	26	Žena
4997	Fio banka, a.s.	27	Muž
4998	MONETA Money Bank, a.s.	20	Žena
4999	MONETA Money Bank, a.s.	51	Žena

	NFLAG_MOBILEDEVICE	CODE_IP_1	NUM_LEVEN_EMAIL	NFLAG_EMAIL_NUMERAL \
0	0	178	40	0
1	0	85	88	0
2	1	131	16	0
3	1	78	50	1
4	1	109	92	0
…	…	…	…	…
4995	1	37	90	1
4996	1	37	93	0
4997	0	185	78	1
4998	1	37	36	0
4999	0	109	40	0

	CNT_REJECTED	NUM_DAYS_CREDIT_HISTORY	TARGET
0	1	450	0
1	1	7100	0
2	1	750	0
3	1	0	0
4	1	1950	0
…	…	…	…
4995	1	250	0
4996	1	700	0
4997	1	650	0
4998	1	0	0
4999	1	6450	0

```
[5000 rows x 13 columns]
```

[6]:
```python
df.describe()
```

[6]:
```
              CODE_ZIP  AMT_NET_INCOME  AMT_REQUESTED_TICKET      NUM_AGE  \
count      5000.000000    5.000000e+03           5000.000000  5000.000000
mean      49493.461600    2.704153e+04           7929.200000    30.587400
std       20460.774959    2.685846e+05           4532.360954    10.934271
min       10000.000000    3.500000e+03           1000.000000    18.000000
25%       33202.750000    1.700000e+04           4000.000000    23.000000
50%       47124.000000    2.100000e+04           8000.000000    27.000000
75%       69618.000000    2.800000e+04          10000.000000    36.000000
max       83924.000000    1.900060e+07          20000.000000    84.000000

       NFLAG_MOBILEDEVICE    CODE_IP_1  NUM_LEVEN_EMAIL  NFLAG_EMAIL_NUMERAL  \
count          5000.00000  5000.000000      5000.000000          5000.000000
mean              0.65760    98.467200        62.141800             0.310400
std               0.47456    59.923827        28.476332             0.462704
min               0.00000     5.000000         0.000000             0.000000
25%               0.00000    46.000000        36.000000             0.000000
50%               1.00000    86.000000        71.000000             0.000000
75%               1.00000   176.000000        90.000000             1.000000
max               1.00000   217.000000        96.000000             1.000000

       CNT_REJECTED  NUM_DAYS_CREDIT_HISTORY       TARGET
count   5000.000000               5000.00000  5000.000000
mean       1.001000               1539.89000     0.099400
std        0.938496               2672.32718     0.299228
min        0.000000                  0.00000     0.000000
25%        1.000000                150.00000     0.000000
50%        1.000000               1100.00000     0.000000
75%        1.000000               2100.00000     0.000000
max       20.000000              43700.00000     1.000000
```

[7]:
```python
df["CODE_ZIP"]
```

[7]:
```
0       18100
1       79501
2       69661
3       43111
4       74201
        …
4995    74743
4996    69605
4997    74706
4998    28903
4999    74253
```

```
Name: CODE_ZIP, Length: 5000, dtype: int64
```

[8]:
```
df["CODE_ZIP"].value_counts()
```

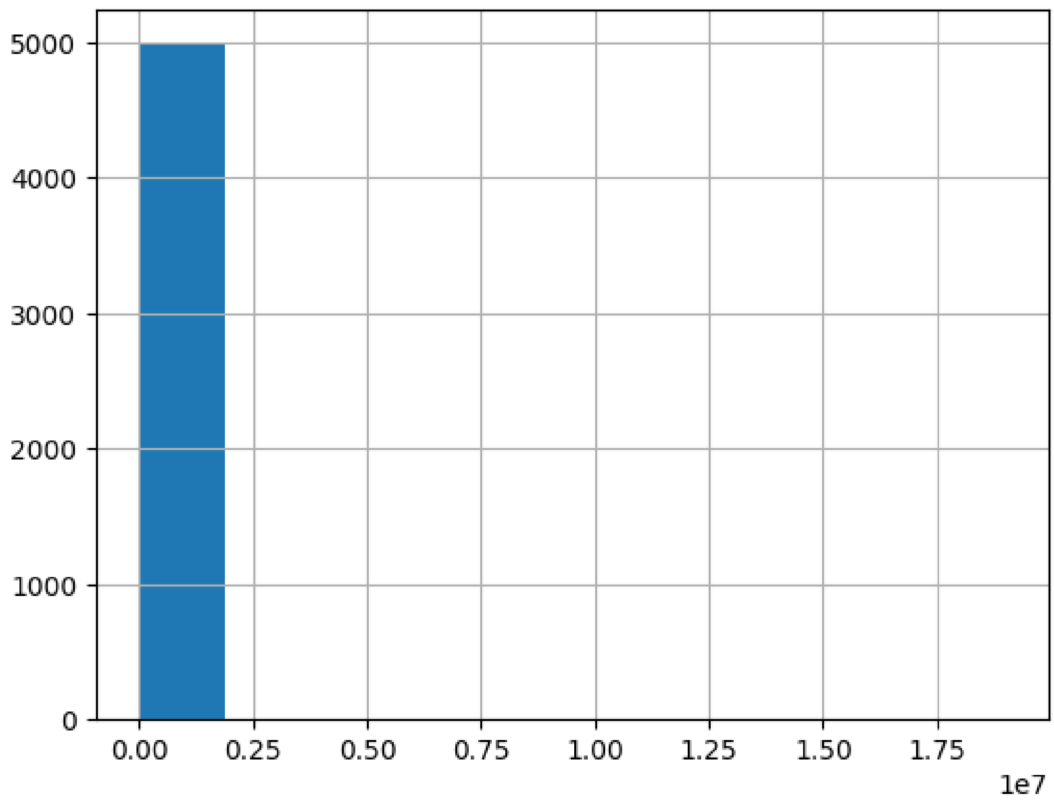
[8]:
```
70030    77
73601    62
43401    51
77900    48
70800    44
         ..
56956     1
26761     1
51233     1
28127     1
74253     1
Name: CODE_ZIP, Length: 1430, dtype: int64
```

[9]:
```
df["AMT_NET_INCOME"].value_counts()
```

[9]:
```
20000    468
25000    356
30000    282
18000    232
15000    230
        …
45200      1
23334      1
13610      1
27100      1
9393       1
Name: AMT_NET_INCOME, Length: 441, dtype: int64
```

[10]:
```
df["AMT_NET_INCOME"].hist()
df["AMT_NET_INCOME"].describe()
```

[10]:
```
count    5.000000e+03
mean     2.704153e+04
std      2.685846e+05
min      3.500000e+03
25%      1.700000e+04
50%      2.100000e+04
75%      2.800000e+04
max      1.900060e+07
Name: AMT_NET_INCOME, dtype: float64
```



[11]:
```
df["AMT_NET_INCOME"].max()
```

[11]: 19000600

[12]:
```
df["AMT_NET_INCOME"].min()
```

[12]: 3500

[13]:
```
df["AMT_NET_INCOME"].median()
```

[13]: 21000.0

[14]:
```
df["AMT_NET_INCOME"].mean()
```

[14]: 27041.529

[15]:
```
df["AMT_NET_INCOME"].sum() / len(df["AMT_NET_INCOME"])
```

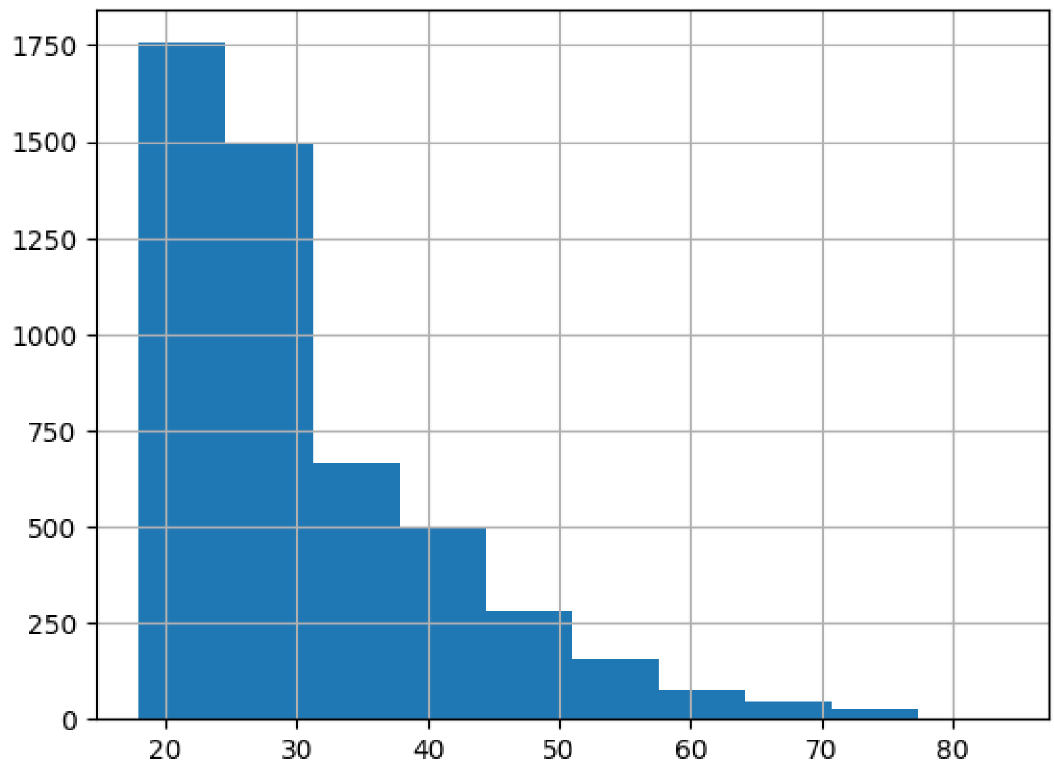
[15]: 27041.529

[16]:
```
df["NUM_AGE"].value_counts()
```

[16]:
```
20    285
23    273
25    270
24    268
27    263
     …
76      2
84      1
83      1
80      1
72      1
Name: NUM_AGE, Length: 62, dtype: int64
```

[17]:
```
df["NUM_AGE"].hist()
df["NUM_AGE"].describe()
```

[17]:
```
count    5000.000000
mean       30.587400
std        10.934271
min        18.000000
25%        23.000000
50%        27.000000
75%        36.000000
max        84.000000
Name: NUM_AGE, dtype: float64
```



[18]:
```
df["NUM_AGE"].max()
```

[18]: 84

[19]:
```
df["NUM_AGE"].min()
```

[19]: 18

[20]:
```
84-18
```

[20]: 66

[21]:
```
df["NUM_AGE"].mode()
```

[21]:
```
0    20
Name: NUM_AGE, dtype: int64
```

[22]:
```
df["NUM_AGE"].mode()
```

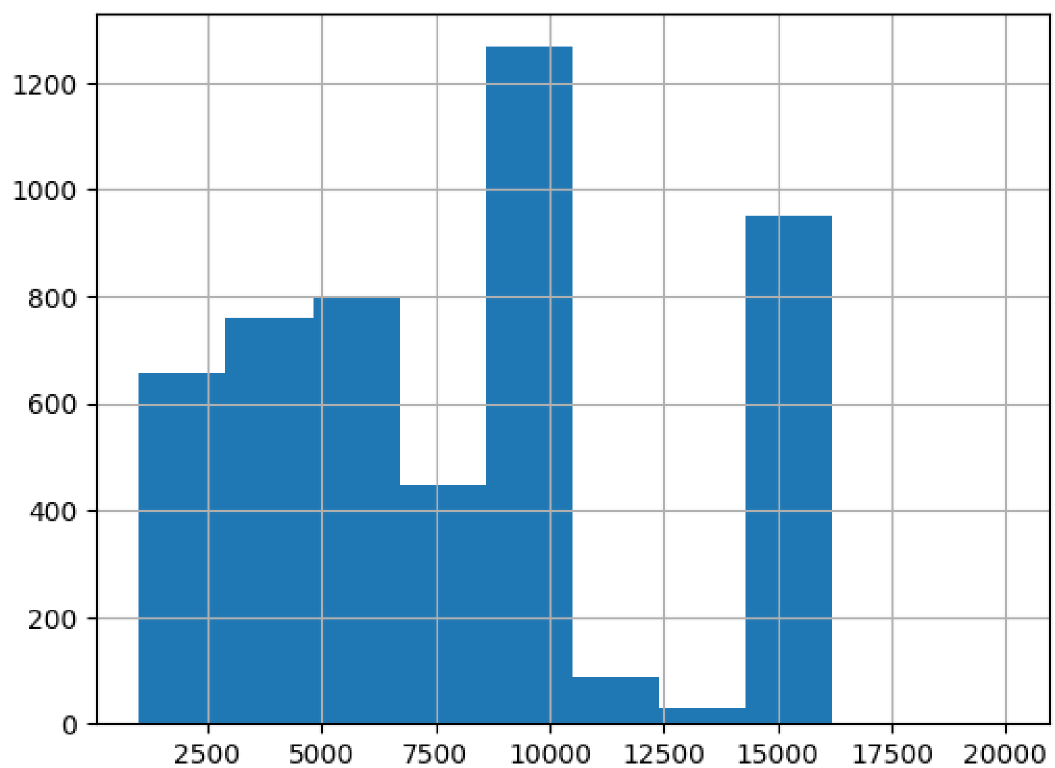
[22]:
```
0    20
Name: NUM_AGE, dtype: int64
```

[23]:
```
df["TEXT_GENDER"].value_counts()
```

[23]:
```
Muž      2897
Žena     2103
Name: TEXT_GENDER, dtype: int64
```

[24]:
```
df["AMT_REQUESTED_TICKET"].hist()
df["AMT_REQUESTED_TICKET"].describe()
```

[24]:
```
count     5000.000000
mean      7929.200000
std       4532.360954
min       1000.000000
25%       4000.000000
50%       8000.000000
75%      10000.000000
max      20000.000000
Name: AMT_REQUESTED_TICKET, dtype: float64
```



[25]:
```
df["TEXT_BANK"].value_counts()
```

[25]:
```
Česká spořitelna, a.s.                                    1254
MONETA Money Bank, a.s.                                    712
Air Bank a.s.                                              677
Československá obchodní banka, a.s.                       610
Komerční banka, a.s.                                       499
Equa bank a.s.                                             349
Raiffeisenbank a.s.                                        282
Fio banka, a.s.                                            239
UniCredit Bank Czech Republic and Slovakia, a.s.           178
mBank S.A., organizační složka                             141
Sberbank CZ, a.s.                                           13
BNP Paribas Personal Finance SA, odštěpný závod              9
Waldviertler Sparkasse Bank AG                               3
Banka CREDITAS a.s.                                          3
Name: TEXT_BANK, dtype: int64
```

[26]:
```
df["NFLAG_MOBILEDEVICE"].value_counts()
```

[26]:
```
1    3288
0    1712
Name: NFLAG_MOBILEDEVICE, dtype: int64
```

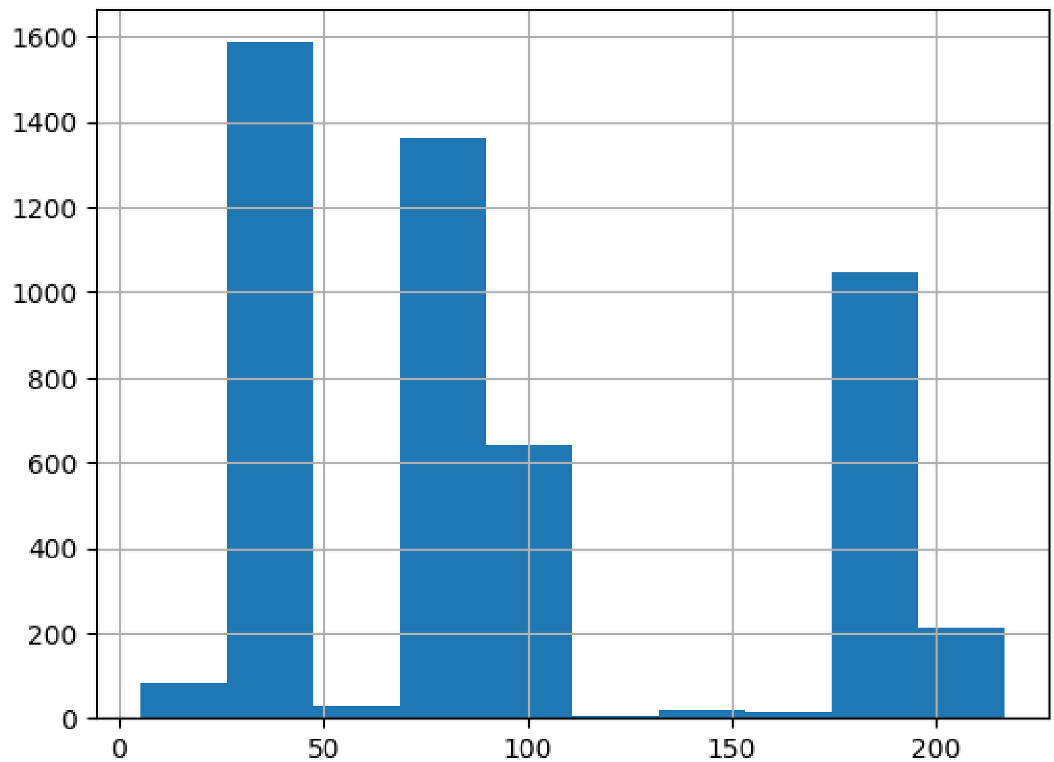
[27]:
```
df["CODE_IP_1"].value_counts()
```

[27]:
```
37     989
46     530
89     455
193    346
109    237
      …
196      1
139      1
100      1
41       1
160      1
Name: CODE_IP_1, Length: 61, dtype: int64
```

[28]:
```
df["CODE_IP_1"].hist()
df["CODE_IP_1"].describe()
```

[28]:
```
count    5000.000000
mean       98.467200
std        59.923827
min         5.000000
25%        46.000000
50%        86.000000
75%       176.000000
```

```
max       217.000000
Name: CODE_IP_1, dtype: float64
```

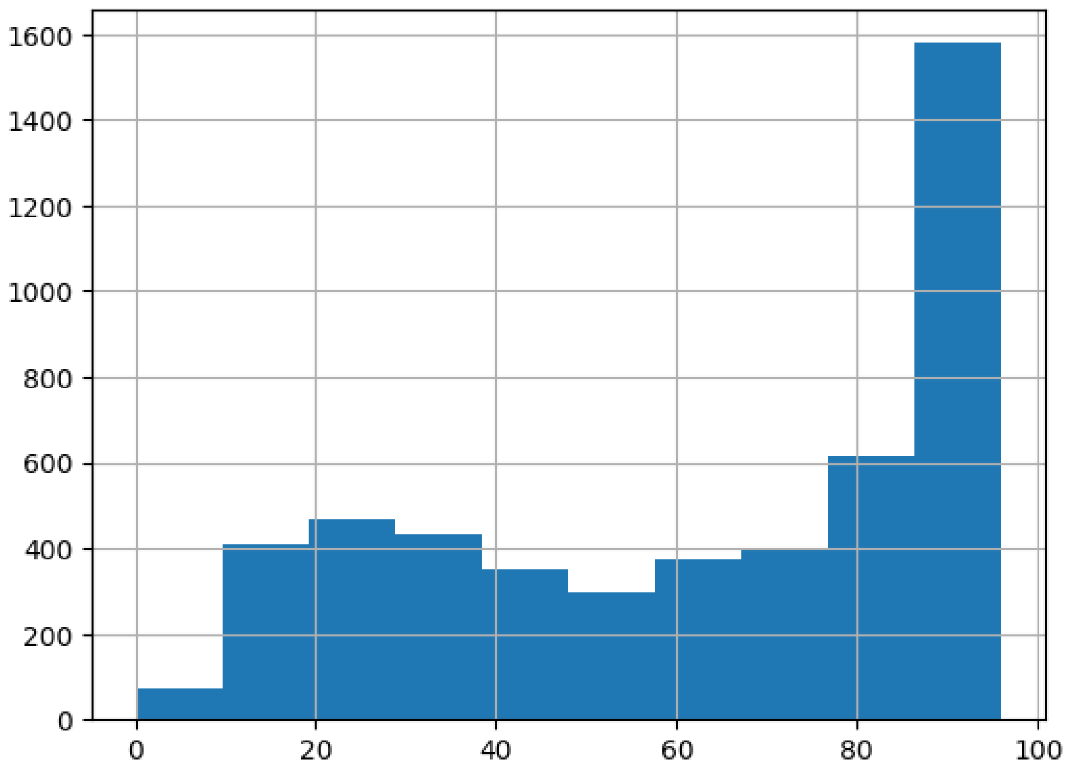


[29]:
```python
df["NUM_LEVEN_EMAIL"].value_counts()
```

[29]:
```
93    335
94    255
92    212
91    185
50    155
     …
81      2
6       1
61      1
52      1
21      1
Name: NUM_LEVEN_EMAIL, Length: 84, dtype: int64
```

[30]:
```python
df["NUM_LEVEN_EMAIL"].hist()
df["NUM_LEVEN_EMAIL"].describe()
```

[30]:
```
count    5000.000000
mean       62.141800
std        28.476332
min         0.000000
25%        36.000000
50%        71.000000
75%        90.000000
max        96.000000
Name: NUM_LEVEN_EMAIL, dtype: float64
```



[31]:
```
df["NFLAG_EMAIL_NUMERAL"].value_counts()
```

[31]:
```
0    3448
1    1552
Name: NFLAG_EMAIL_NUMERAL, dtype: int64
```

[32]:
```
df["CNT_REJECTED"].value_counts()
```

[32]:
```
1     3972
0      729
2      146
3       69
```

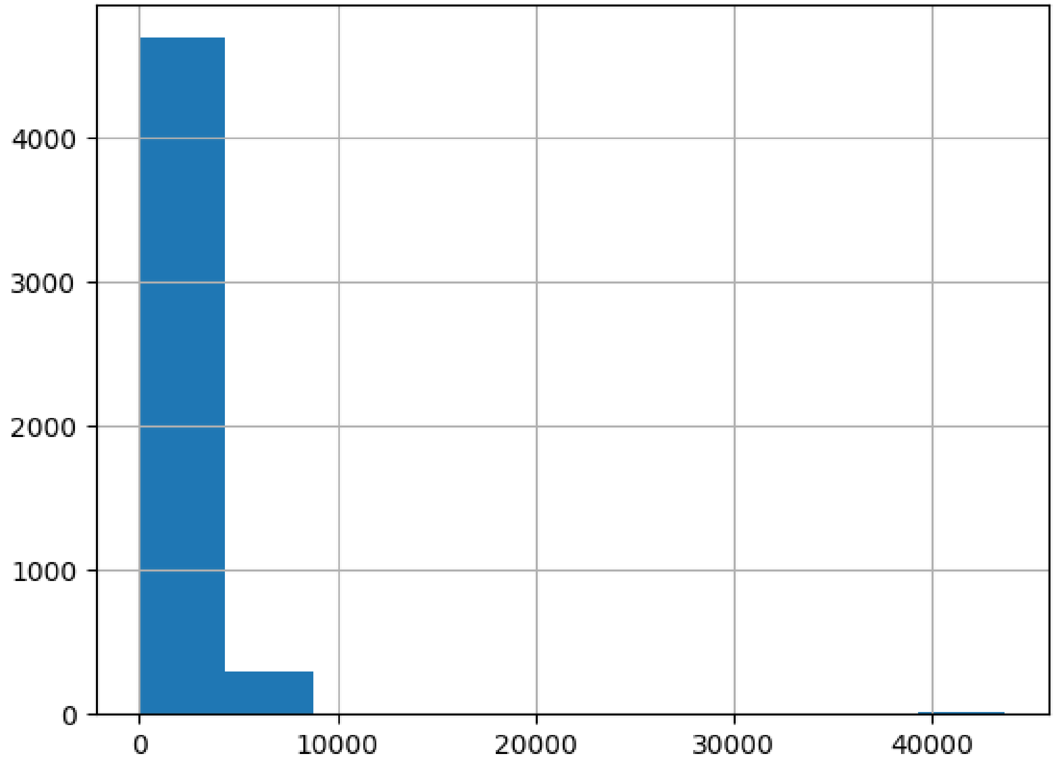
```
4        32
5        15
6         9
7         7
8         7
10        4
12        2
11        2
13        2
14        1
17        1
9         1
20        1
Name: CNT_REJECTED, dtype: int64
```

[33]:

```
df["NUM_DAYS_CREDIT_HISTORY"].hist()
df["NUM_DAYS_CREDIT_HISTORY"].describe()
```

[33]:

```
count     5000.00000
mean      1539.89000
std       2672.32718
min          0.00000
25%        150.00000
50%       1100.00000
75%       2100.00000
max      43700.00000
Name: NUM_DAYS_CREDIT_HISTORY, dtype: float64
```



[34]:
```
binned_age = pd.cut(
    df["NUM_AGE"],
    [18, 28, 38, 48, 58, 68, 78, 88],
    labels=["18-28", "29-38", "39-48", "49-58", "59-68", "69-78", "79-88"]
)
binned_age.value_counts()
```

[34]:
```
18-28    2559
29-38    1242
39-48     624
49-58     235
59-68      98
69-78      44
79-88       3
Name: NUM_AGE, dtype: int64
```

[35]:
```
pd.crosstab(binned_age, df["TEXT_GENDER"])
```

[35]:
```
TEXT_GENDER   Muž  Žena
NUM_AGE
18-28        1567   992
29-38         757   485
```

```
39-48          313   311
49-58          115   120
59-68           38    60
69-78           11    33
79-88            0     3
```

We have 5000 rows (samples) and 13 columns (features). One row should correspond to one applicant. The features: - CODE_ZIP – zip code of location of applicant, 1430 unique zip codes - AMT_NET_INCOME - average monthly income in crowns, mean is 27041.529 and median is 21000, this should most likely represent income after taxes - AMT_REQUESTED_TICKET - average monthly requested ticket - TEXT_BANK - bank of the appliccant, we have 14 banks with most in Ceska sporitelna - NUM_AGE - numeric age from 18 to 84 - TEXT_GENDER - gender in format "Muž" "Žena" with more men - NFLAG_MOBILEDEVICE - flag if applicant uses mobile device, more applicants use it (approx 2:1 for use:dont use) - CODE_IP_1 - no idea what this means - NUM_LEVEN_EMAIL - no idea - NFLAG_EMAIL_NUMERAL - whether applicant uses email - CNT_REJECTED - I guess this should be whether last one was rejected? - NUM_DAYS_CREDIT_HISTORY - number of days of credit history - TARGET - whether loan wasnt paid on time and properly

[Q1] What's the highest age of applicants? (Jaký je nejvyšší věk žadatele?)

[A1] Highest age is 84 years. We just take the maximum value of NUM_AGE column.

[Q2] What is the mode age of applicant? (Jaký je modus věku žadatele?) Mode age of applicant is 20 years. Here we take the age that occurs most often.

[Q3] What is the average income of applicant and how does that differ fro the average in Czech republic? (Jaký je průměrný příjem žadatele a jak se liší od průměru v ČR?)

[A3] Average income of applicant is 27041.529. This should represent income that arrives to applicants bank account. We could calculate is as sum of average income for each applicant divided by number of applicants. 40086 is the average monthly GROSS income in Czech republic (https://www.czso.cz/csu/czso/cri/prumerne-mzdy-2-ctvrtleti-2022). I wasnt able to find information about salary after taxes (čistá mzda), thus I use online calculator (https://www.vypocet.cz/cista-mzda) to calculate it from the found gross income (we ignore kids/students etc..). The result is: 32231. Thus the average monthly income in Czech republic currently is higher than the one in the dataset. However this can be caused by me using the most recent statistics while the dataset contains bit more historic data.

[Q4] In what age groups are more men than women? (Ve kterých věkových skupinách (18-28, 29-38, 39-48, ..) je více mužů než žen?)

[A4] In age groups 18-28, 29-38, and 39-48. I calculated this by creating age bins and then contingency table to count all possible combinations of age bins with gender.

1.4 Advanced Target Analysis

We analyse the target variable.

[36]:
```python
df["TARGET"].value_counts()
```

[36]:
```
0    4503
1     497
Name: TARGET, dtype: int64
```

[37]:
```python
def get_target_rate(df):

    return df["TARGET"].value_counts(normalize=True)[1]

get_target_rate(df)
```

[37]:
```
0.0994
```

[38]:
```python
pd.crosstab( df["TEXT_BANK"], df["TARGET"], normalize="index").
 ↪sort_values(by=1, ascending=False)
```

[38]:
```
TARGET                                                0         1
TEXT_BANK
BNP Paribas Personal Finance SA, odštěpný závod   0.777778  0.222222
Raiffeisenbank a.s.                               0.843972  0.156028
mBank S.A., organizační složka                    0.879433  0.120567
Česká spořitelna, a.s.                            0.886762  0.113238
UniCredit Bank Czech Republic and Slovakia, a.s.  0.893258  0.106742
Air Bank a.s.                                     0.895126  0.104874
Fio banka, a.s.                                   0.907950  0.092050
Komerční banka, a.s.                              0.915832  0.084168
Equa bank a.s.                                    0.916905  0.083095
MONETA Money Bank, a.s.                           0.919944  0.080056
Československá obchodní banka, a.s.               0.927869  0.072131
Banka CREDITAS a.s.                               1.000000  0.000000
Sberbank CZ, a.s.                                 1.000000  0.000000
Waldviertler Sparkasse Bank AG                    1.000000  0.000000
```

[Q5] Ve které bance je největší target rate (tedy poměr počtu TARGET=1 na celku)?

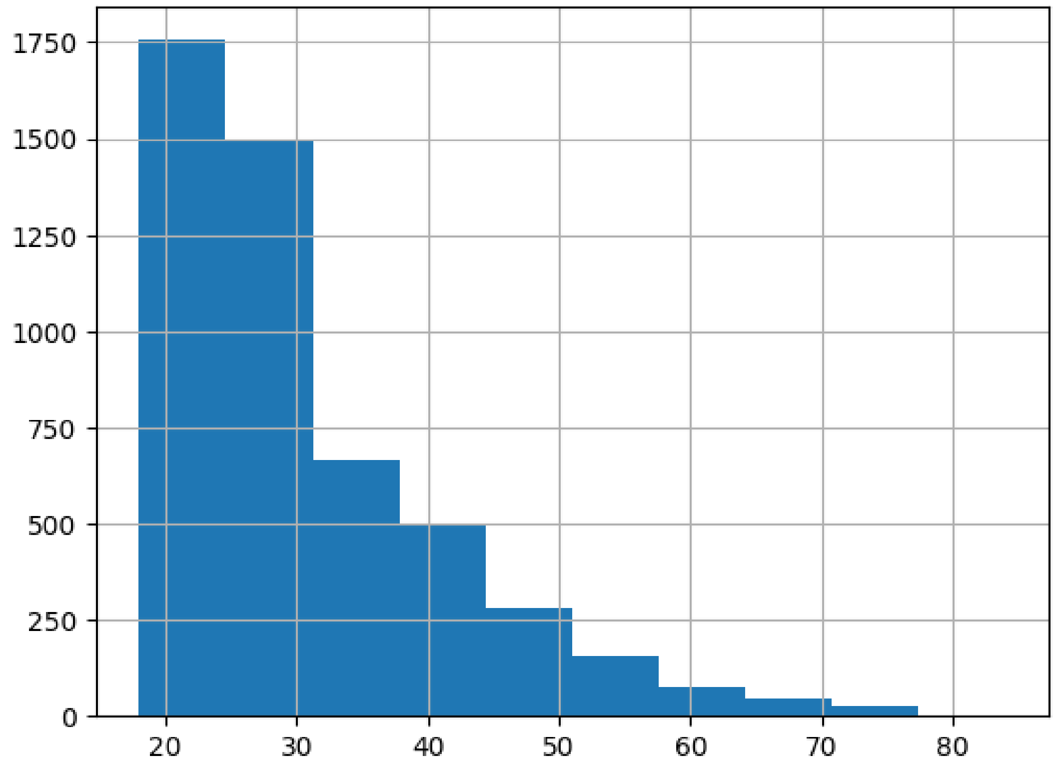
[A5] In bank BNP Paribas Personal Finance SA, odštěpný závod. We create contingency table, normalize it and take the one with highest ratio.

[39]:
```python
df.columns
```

[39]:
```
Index(['CODE_ZIP', 'AMT_NET_INCOME', 'AMT_REQUESTED_TICKET', 'TEXT_BANK',
       'NUM_AGE', 'TEXT_GENDER', 'NFLAG_MOBILEDEVICE', 'CODE_IP_1',
       'NUM_LEVEN_EMAIL', 'NFLAG_EMAIL_NUMERAL', 'CNT_REJECTED',
       'NUM_DAYS_CREDIT_HISTORY', 'TARGET'],
      dtype='object')
```

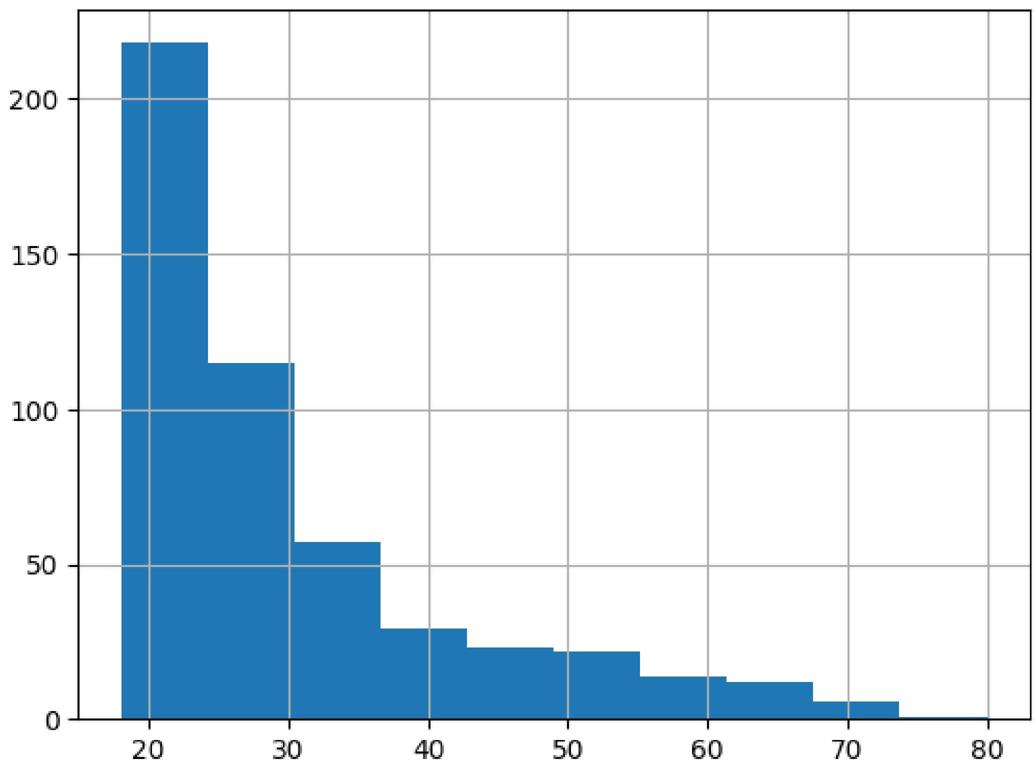
[40]:
```python
df["NUM_AGE"].hist()
df["NUM_AGE"].describe()
```

[40]:
```
count    5000.000000
mean       30.587400
std        10.934271
min        18.000000
25%        23.000000
50%        27.000000
75%        36.000000
max        84.000000
Name: NUM_AGE, dtype: float64
```



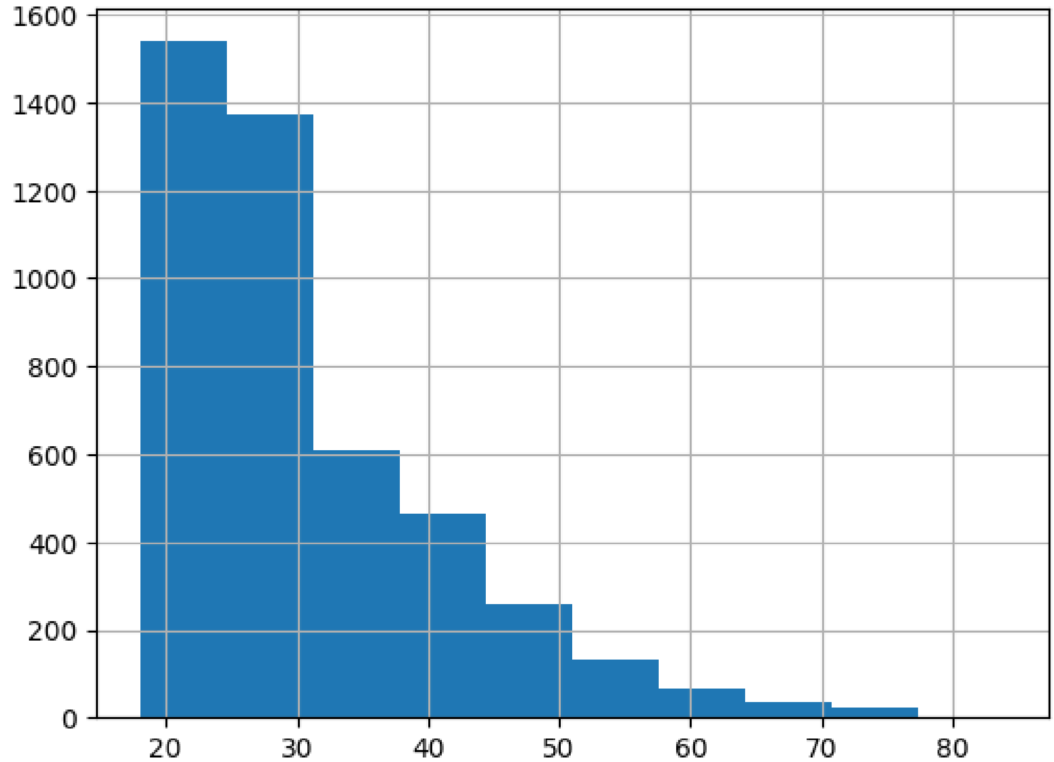
[41]:
```
df[df["TARGET"] == 1]["NUM_AGE"].hist()
df[df["TARGET"] == 1]["NUM_AGE"].describe()
```

[41]:
```
count    497.000000
mean      30.028169
std       12.605651
min       18.000000
25%       21.000000
50%       26.000000
75%       35.000000
max       80.000000
Name: NUM_AGE, dtype: float64
```



[42]:
```
df[df["TARGET"] == 0]["NUM_AGE"].hist()
df[df["TARGET"] == 0]["NUM_AGE"].describe()
```

[42]:
```
count    4503.000000
mean       30.649123
std        10.733677
min        18.000000
25%        23.000000
50%        27.000000
75%        36.000000
max        84.000000
Name: NUM_AGE, dtype: float64
```



We can see that if we divide dataset by target the age distribution is similar tho not identical. Next we use optimal binning library.

[43]:
```
from optbinning import OptimalBinning
x = df["NUM_AGE"].values
y = df["TARGET"]
optb = OptimalBinning(name="NUM_AGE", dtype="numerical", solver="cp").fit(x, y)
```

[44]:
```
optb.status
```

[44]:
```
'OPTIMAL'
```

[45]:
```
optb.splits
```

[45]:
```
array([19.5, 20.5, 23.5, 26.5, 30.5, 36.5, 40.5, 51.5])
```

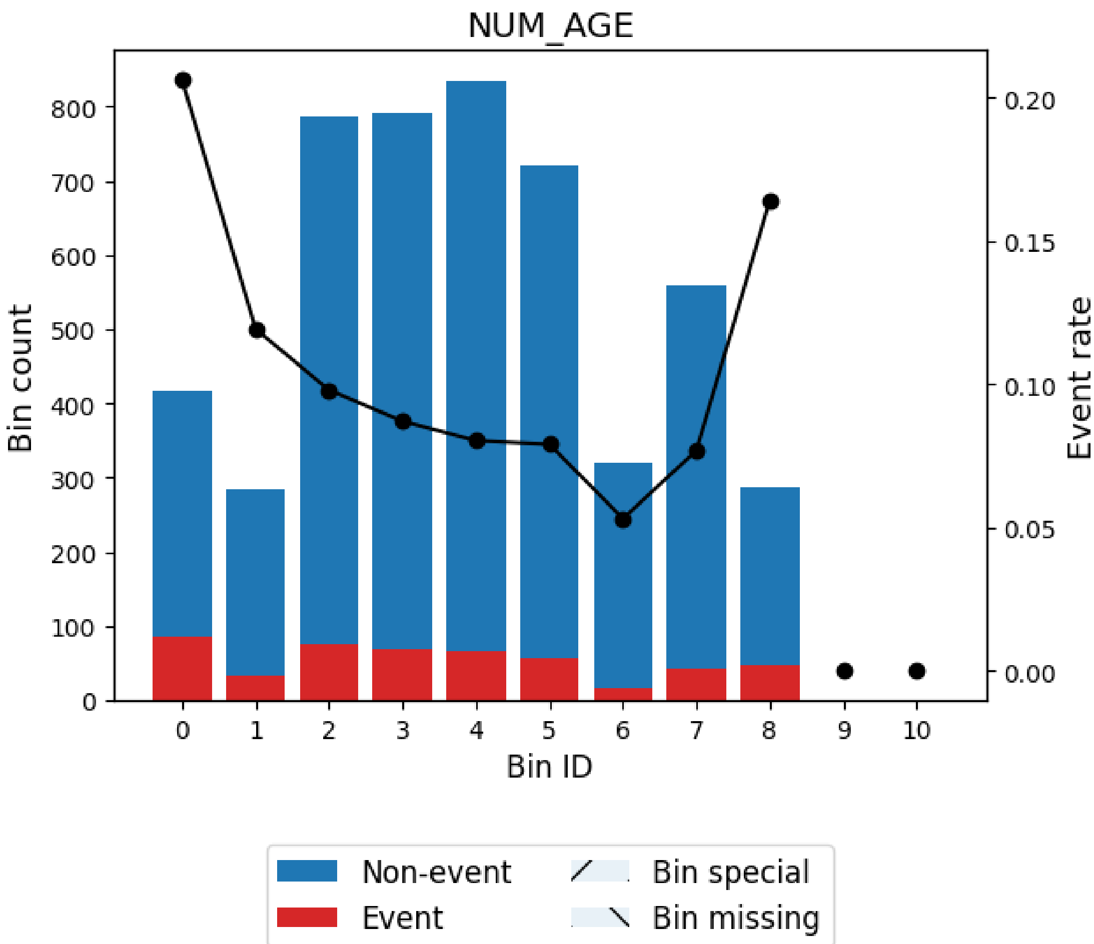
[46]:
```
optb.binning_table.build()
```

[46]:
```
                          Bin  Count  Count (%)  Non-event  Event  Event rate  \
0           (-inf, 19.50)    417     0.0834        331     86    0.206235
1          [19.50, 20.50)    285     0.0570        251     34    0.119298
2          [20.50, 23.50)    786     0.1572        709     77    0.097964
```

3	[23.50, 26.50)	792	0.1584	723	69	0.087121
4	[26.50, 30.50)	834	0.1668	767	67	0.080336
5	[30.50, 36.50)	721	0.1442	664	57	0.079057
6	[36.50, 40.50)	320	0.0640	303	17	0.053125
7	[40.50, 51.50)	559	0.1118	516	43	0.076923
8	[51.50, inf)	286	0.0572	239	47	0.164336
9	Special	0	0.0000	0	0	0.000000
10	Missing	0	0.0000	0	0	0.000000
Totals		5000	1.0000	4503	497	0.099400

	WoE	IV	JS
0	-0.856138	0.085213	0.010338
1	-0.204817	0.002595	0.000324
2	0.016141	0.000041	0.000005
3	0.145394	0.003159	0.000395
4	0.233885	0.008308	0.001036
5	0.251322	0.008236	0.001027
6	0.67661	0.022384	0.002746
7	0.280998	0.007888	0.000983
8	-0.577593	0.023965	0.002955
9	0.0	0.000000	0.000000
10	0.0	0.000000	0.000000
Totals		0.161789	0.019807

[47]:
```
optb.binning_table.plot(metric="event_rate")
```



[48]:
```
df["BIN_AGE"] = optb.transform(x, metric="bins")
```

[49]:
```
pd.crosstab(df["BIN_AGE"], df["TARGET"], normalize="index").sort_values(by=1,␣
↪ascending=False)
```

[49]:
```
TARGET                 0         1
BIN_AGE
(-inf, 19.50)   0.793765  0.206235
[51.50, inf)    0.835664  0.164336
[19.50, 20.50)  0.880702  0.119298
[20.50, 23.50)  0.902036  0.097964
[23.50, 26.50)  0.912879  0.087121
[26.50, 30.50)  0.919664  0.080336
[30.50, 36.50)  0.920943  0.079057
[40.50, 51.50)  0.923077  0.076923
[36.50, 40.50)  0.946875  0.053125
```

[Q6] Try to find ideal age categories to analyze target rate. (Pokuste se vytvořit vhodné věkové kategorie pro zkoumání target rate.)

[A6] We used the optimal binning library which uses mathematical programming to find the optimal bins regarding the target variable (see https://arxiv.org/pdf/2001.08025.pdf and https://github.com/guillermo-navas-palencia/optbinning). The found bins are 0-19, 20, 21-23, 23-26, 26-30, 31-36, 37-41, 41-51, 52+. The highest target rate is for 0-19 and lowest for 37-41.

[50]:
```
target_rate_per_age_and_bank = pd.crosstab(
    [df["TEXT_BANK"], df["BIN_AGE"]], df["TARGET"], normalize="index"
).drop(columns=[0]).rename(columns={1: "TARGET_RATE"})
target_rate_per_age_and_bank.sort_values(by="TARGET_RATE", ascending=False)
```

[50]:
```
TARGET                                                            TARGET_RATE
TEXT_BANK                                           BIN_AGE
Raiffeisenbank a.s.                                 [51.50, inf)     0.562500
BNP Paribas Personal Finance SA, odštěpný závod     [26.50, 30.50)   0.400000
UniCredit Bank Czech Republic and Slovakia, a.s.    (-inf, 19.50)    0.320000
Fio banka, a.s.                                     (-inf, 19.50)    0.307692
mBank S.A., organizační složka                      [51.50, inf)     0.300000
…                                                                     …
Waldviertler Sparkasse Bank AG                      [30.50, 36.50)   0.000000
Komerční banka, a.s.                                [51.50, inf)     0.000000
BNP Paribas Personal Finance SA, odštěpný závod     [51.50, inf)     0.000000
Komerční banka, a.s.                                [36.50, 40.50)   0.000000
Sberbank CZ, a.s.                                   [26.50, 30.50)   0.000000

[105 rows x 1 columns]
```

[51]:
```
target_rate_per_age_and_bank.reset_index()
```

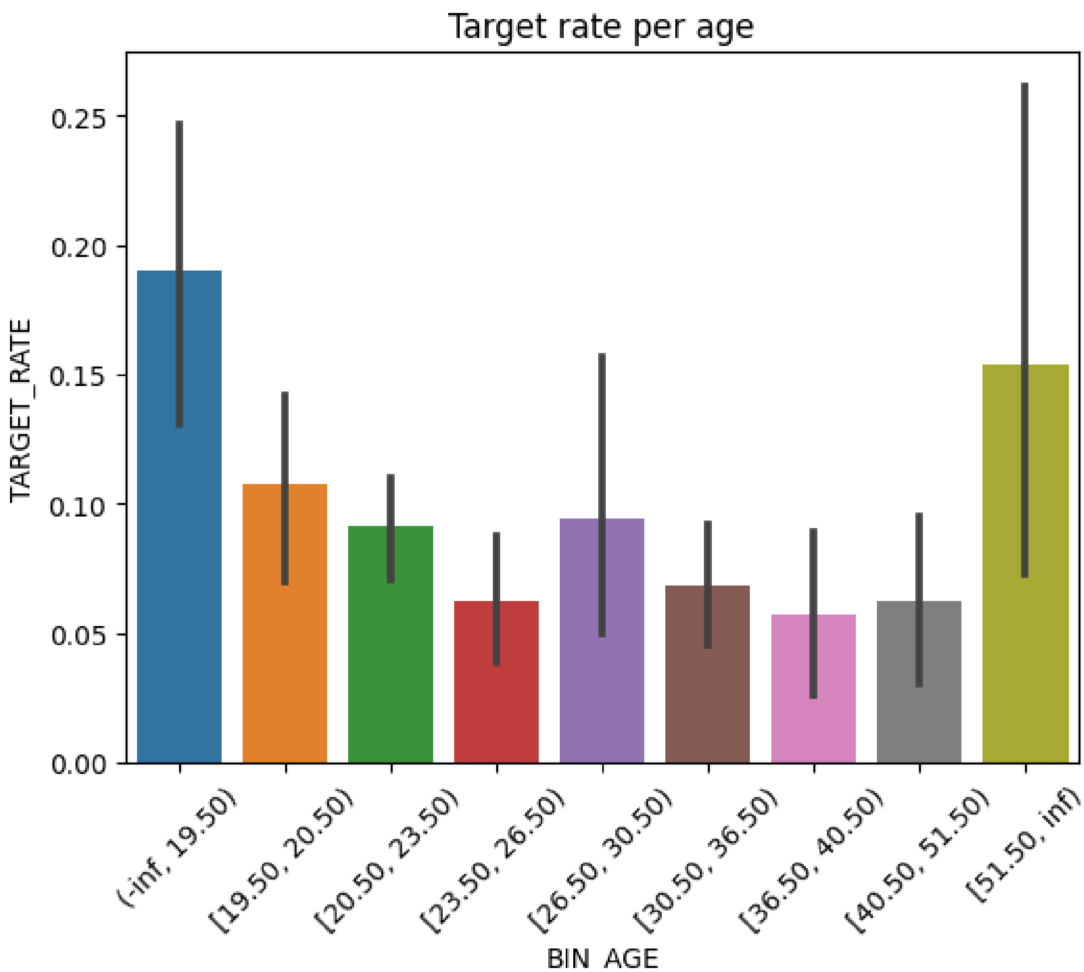
[51]:
```
TARGET               TEXT_BANK         BIN_AGE  TARGET_RATE
0               Air Bank a.s.    (-inf, 19.50)     0.283582
1               Air Bank a.s.   [19.50, 20.50)     0.166667
2               Air Bank a.s.   [20.50, 23.50)     0.075630
3               Air Bank a.s.   [23.50, 26.50)     0.091667
4               Air Bank a.s.   [26.50, 30.50)     0.094828
..                        …                …          …
100     Česká spořitelna, a.s.  [26.50, 30.50)     0.065657
101     Česká spořitelna, a.s.  [30.50, 36.50)     0.082873
102     Česká spořitelna, a.s.  [36.50, 40.50)     0.073529
103     Česká spořitelna, a.s.  [40.50, 51.50)     0.139073
104     Česká spořitelna, a.s.    [51.50, inf)     0.213483

[105 rows x 3 columns]
```

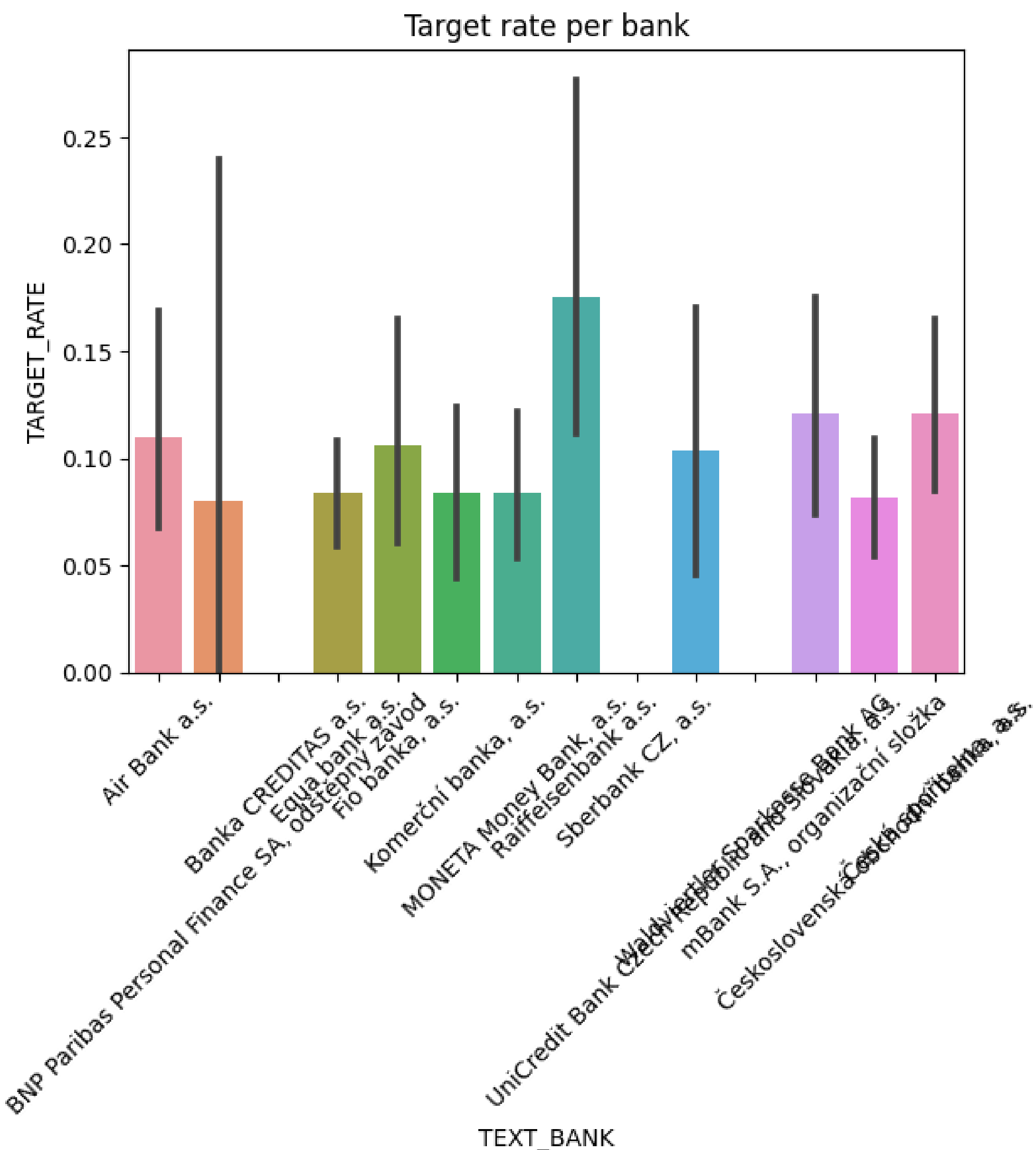
[52]:
```
sns.barplot(data=target_rate_per_age_and_bank.reset_index(), x="BIN_AGE",␣
 ↪y="TARGET_RATE")
plt.xticks(rotation=45)
```

```
plt.title("Target rate per age")
```

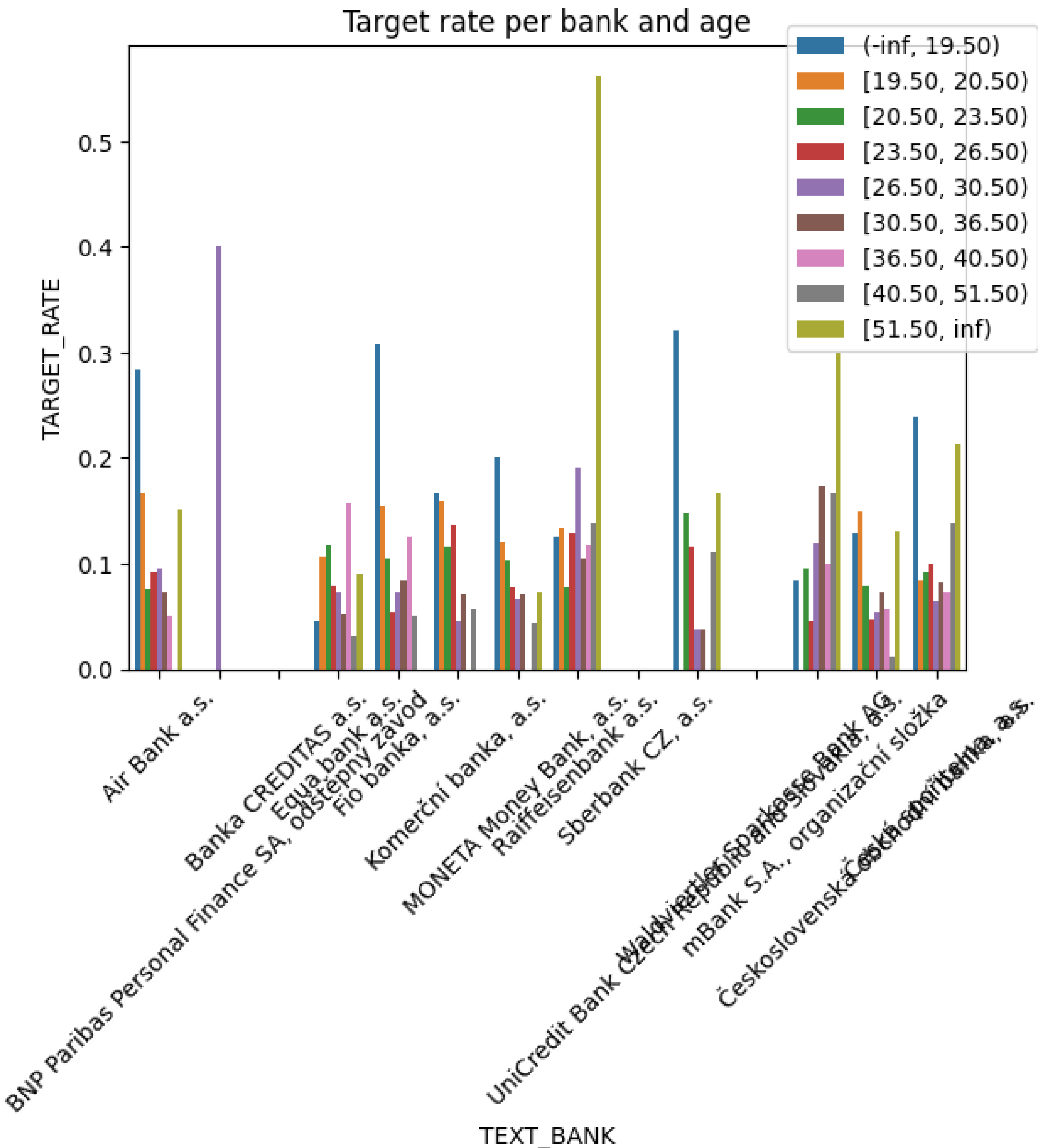
[52]: Text(0.5, 1.0, 'Target rate per age')



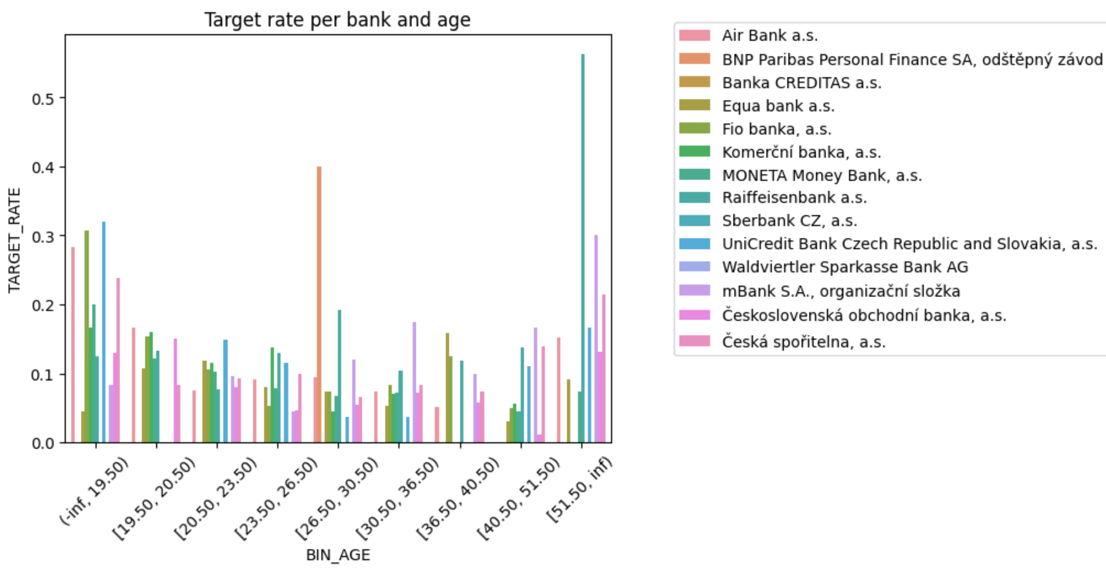
[53]:
```
sns.barplot(data=target_rate_per_age_and_bank.reset_index(), x="TEXT_BANK",␣
 ↪y="TARGET_RATE")
plt.xticks(rotation=45)
plt.title("Target rate per bank")
plt.show()
```



[54]:
```python
sns.barplot(data=target_rate_per_age_and_bank.reset_index(), x="TEXT_BANK", y="TARGET_RATE", hue="BIN_AGE")
plt.xticks(rotation=45)
plt.title("Target rate per bank and age")
plt.legend(bbox_to_anchor=(1.1, 1.05))
plt.show()
```



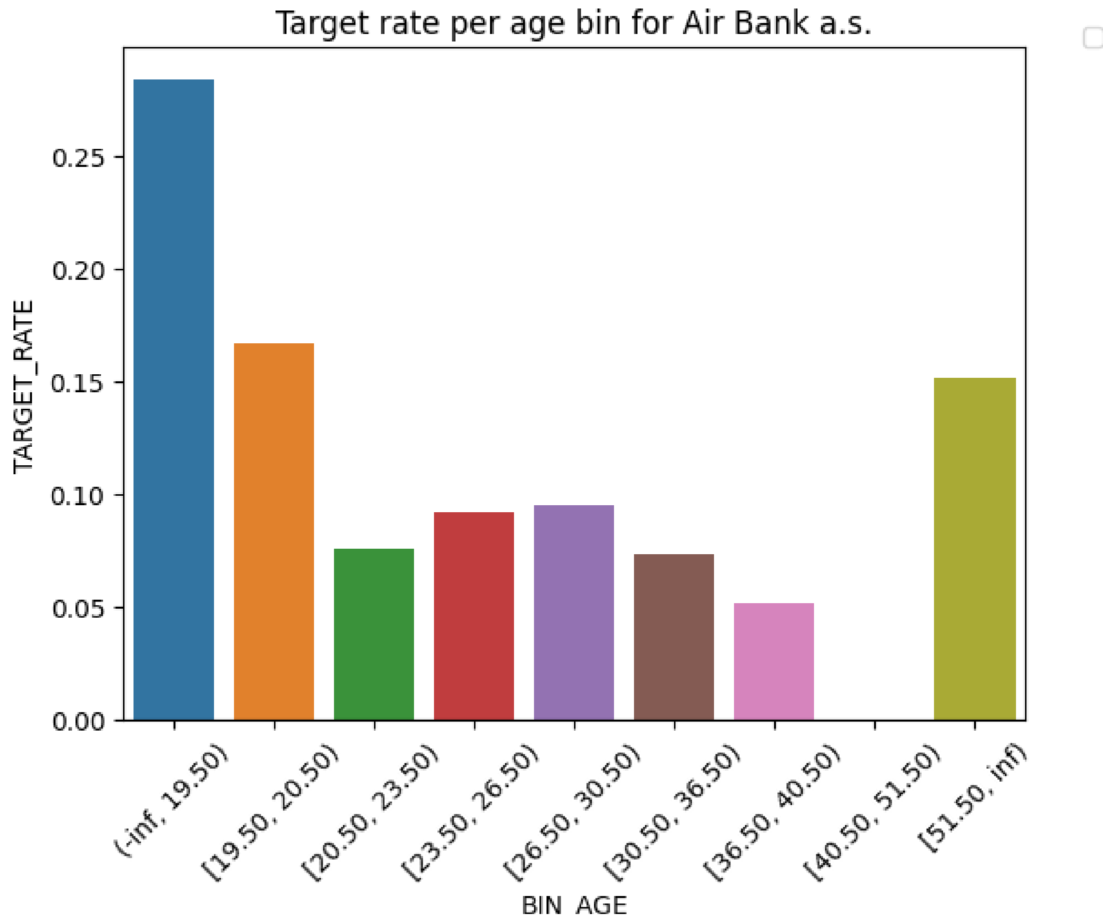

```
[55]: sns.barplot(data=target_rate_per_age_and_bank.reset_index(), x="BIN_AGE",␣
        ↪y="TARGET_RATE", hue="TEXT_BANK")
      plt.xticks(rotation=45)
      plt.title("Target rate per bank and age")
      plt.legend(bbox_to_anchor=(1.1, 1.05))
      plt.show()
```



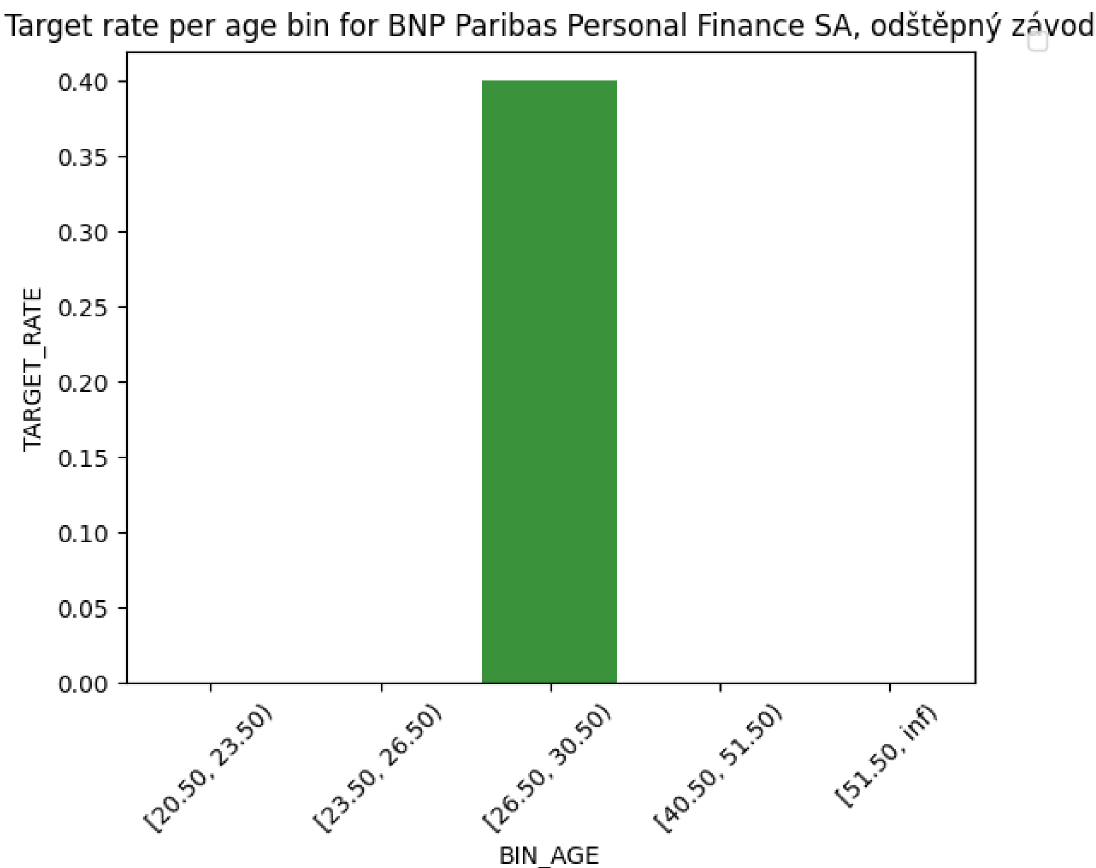
[56]:
```
for b in target_rate_per_age_and_bank.reset_index()["TEXT_BANK"].unique():

    sns.barplot(data=target_rate_per_age_and_bank.loc[b].reset_index(),␣
↪x="BIN_AGE", y="TARGET_RATE")
    plt.xticks(rotation=45)
    plt.title(f"Target rate per age bin for {b}")
    plt.legend(bbox_to_anchor=(1.1, 1.05))
    plt.show()
```

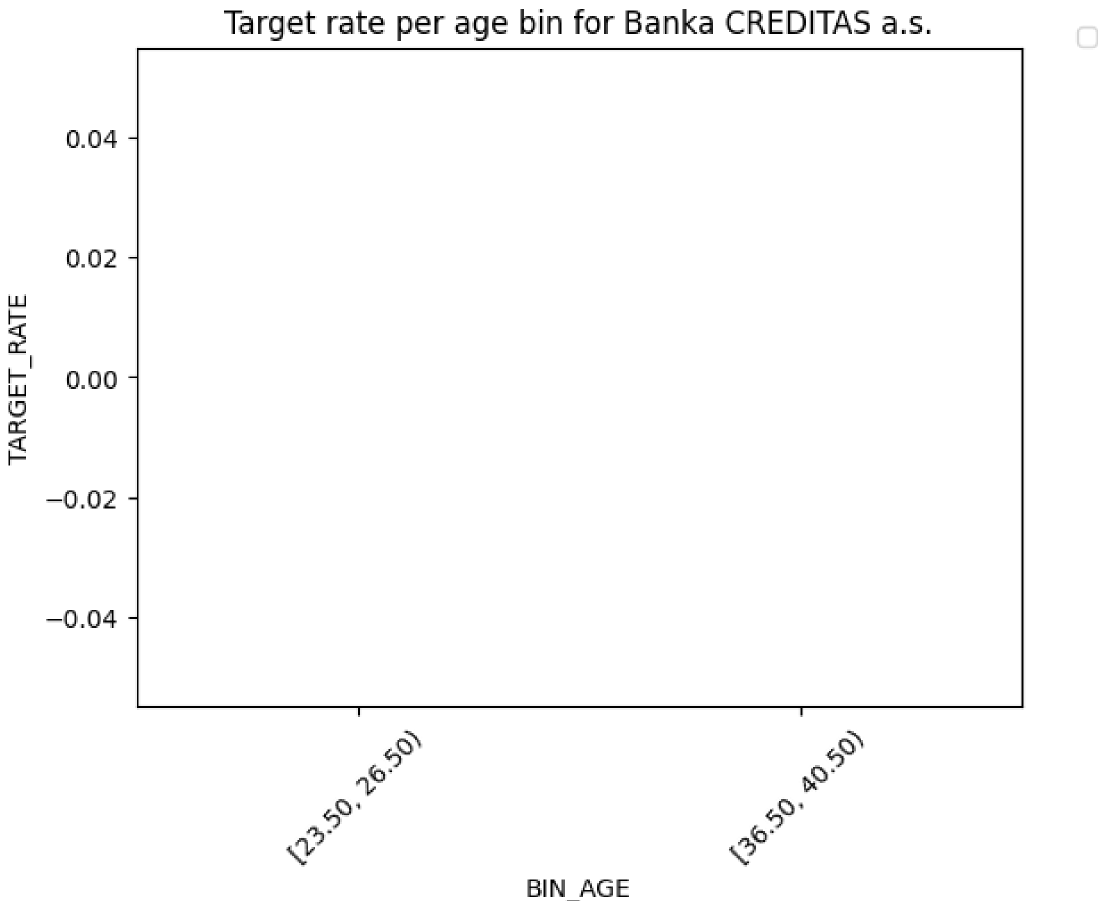
```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



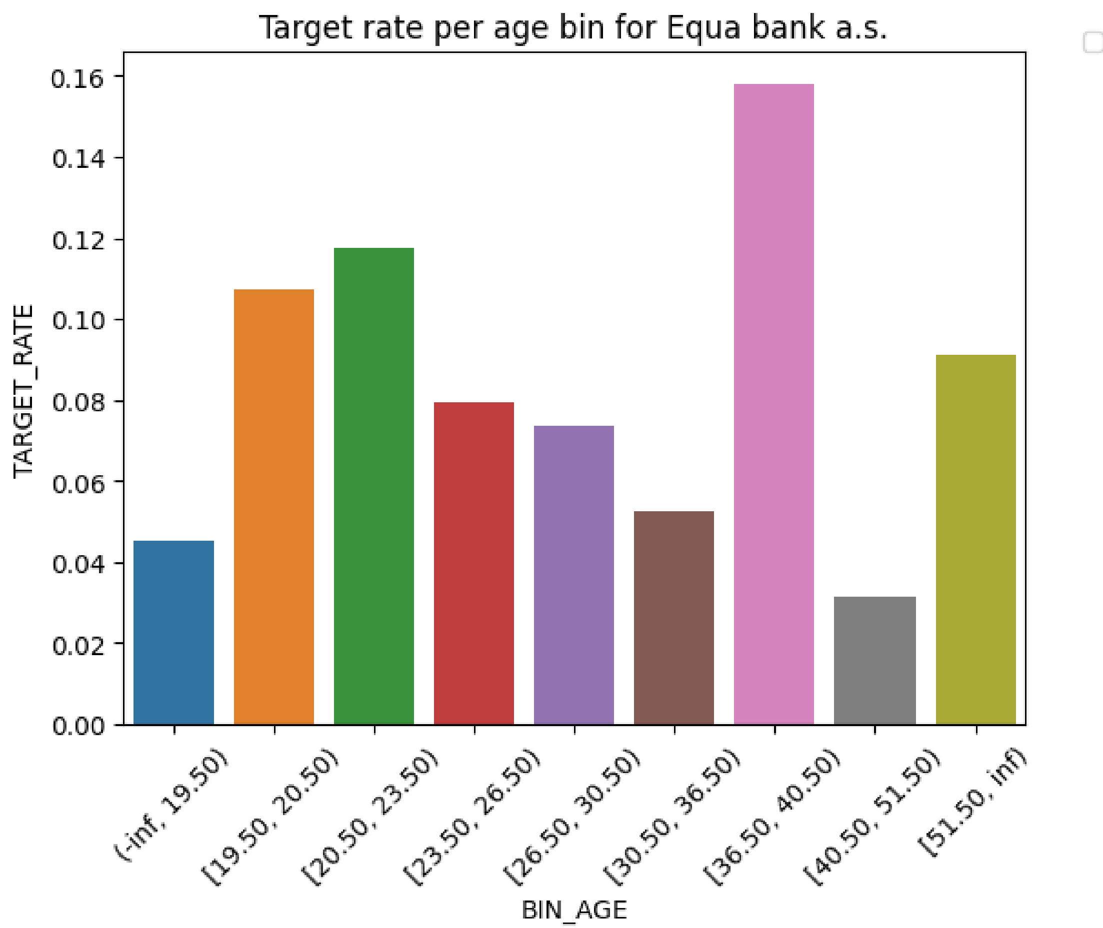

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



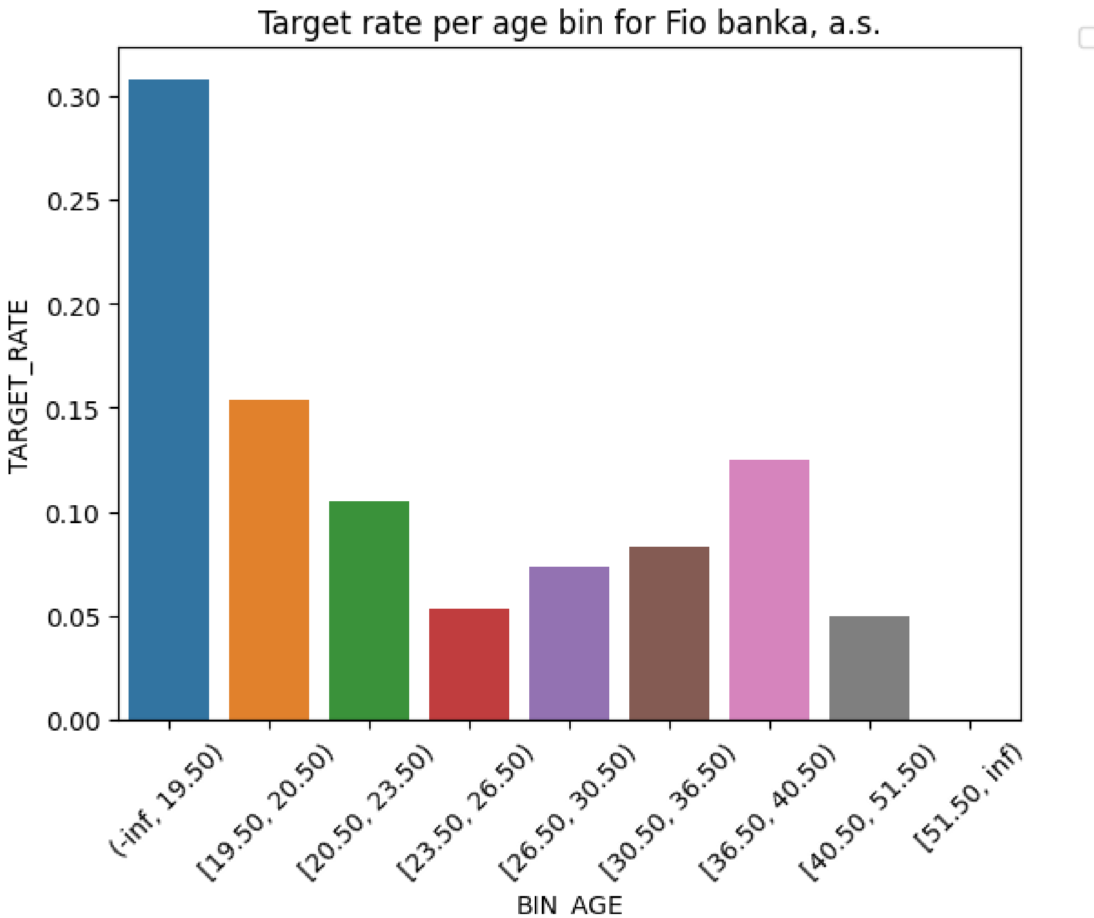

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



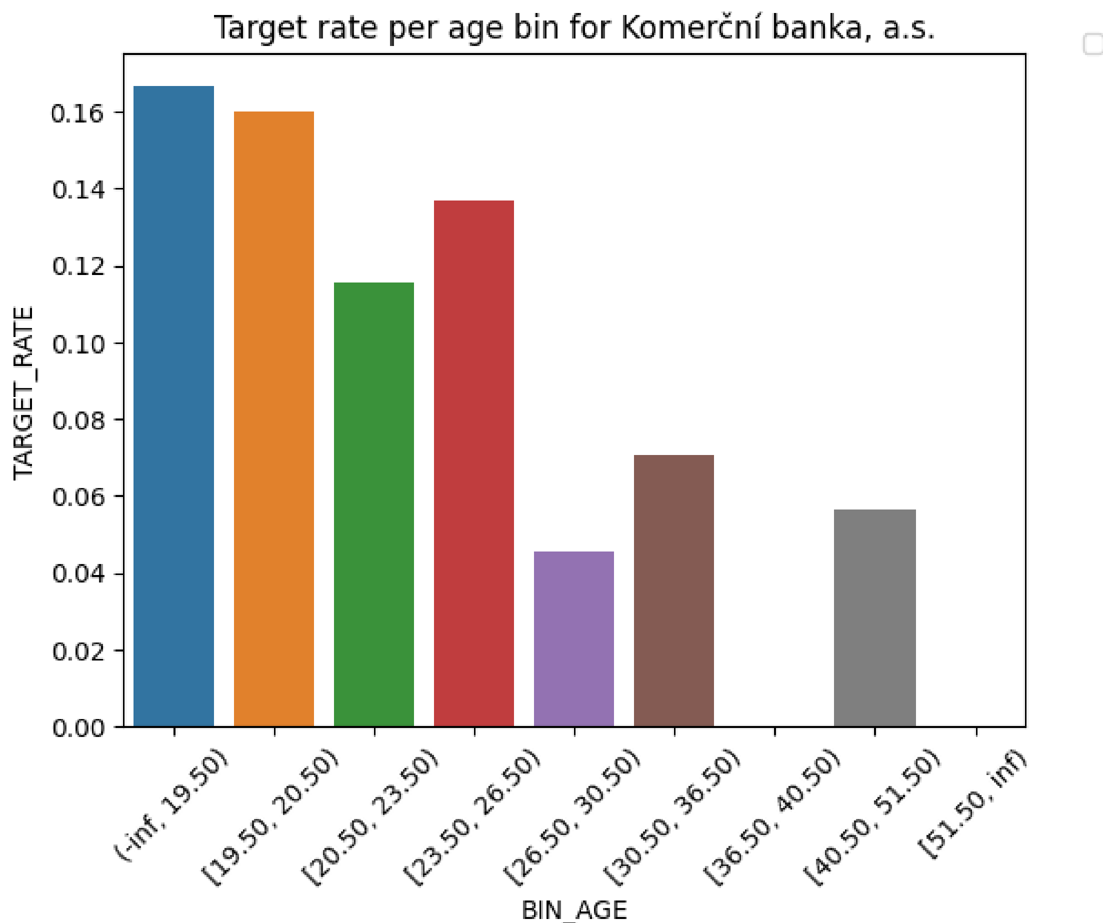

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



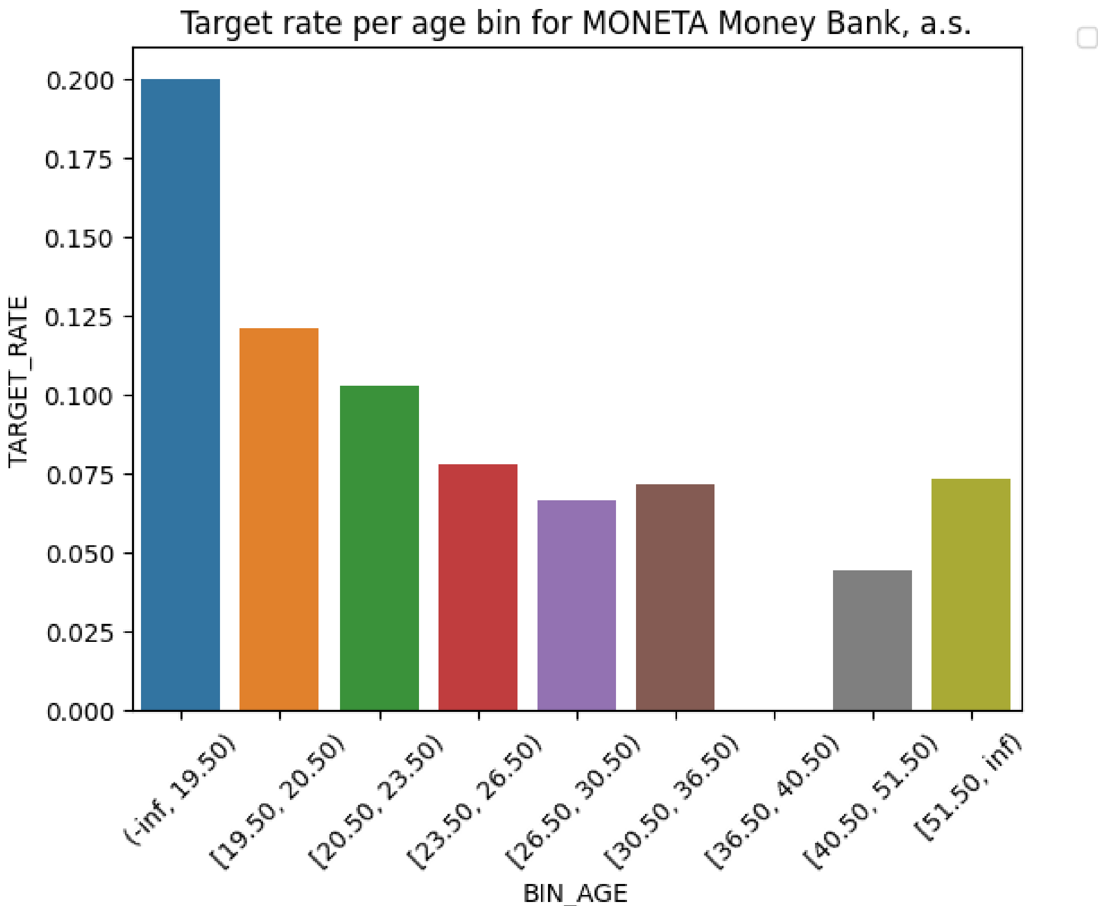

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



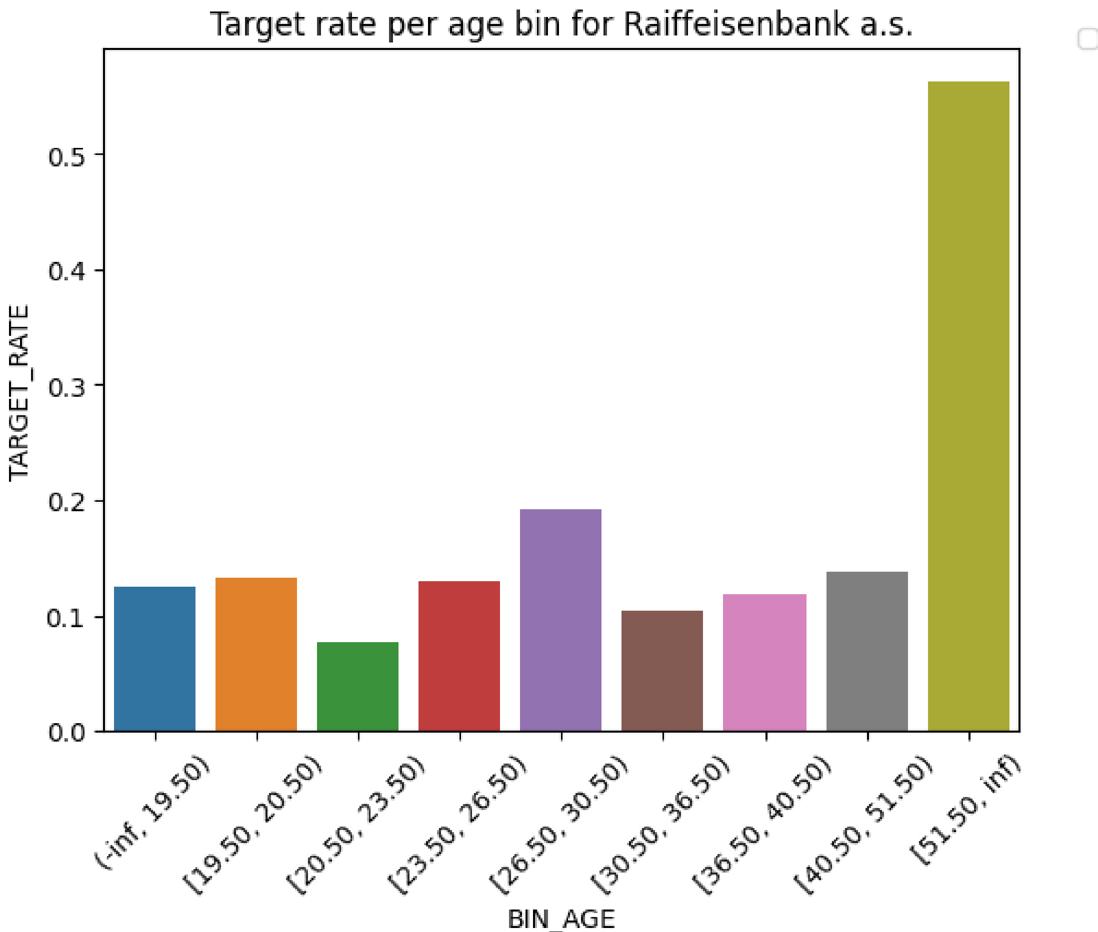

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



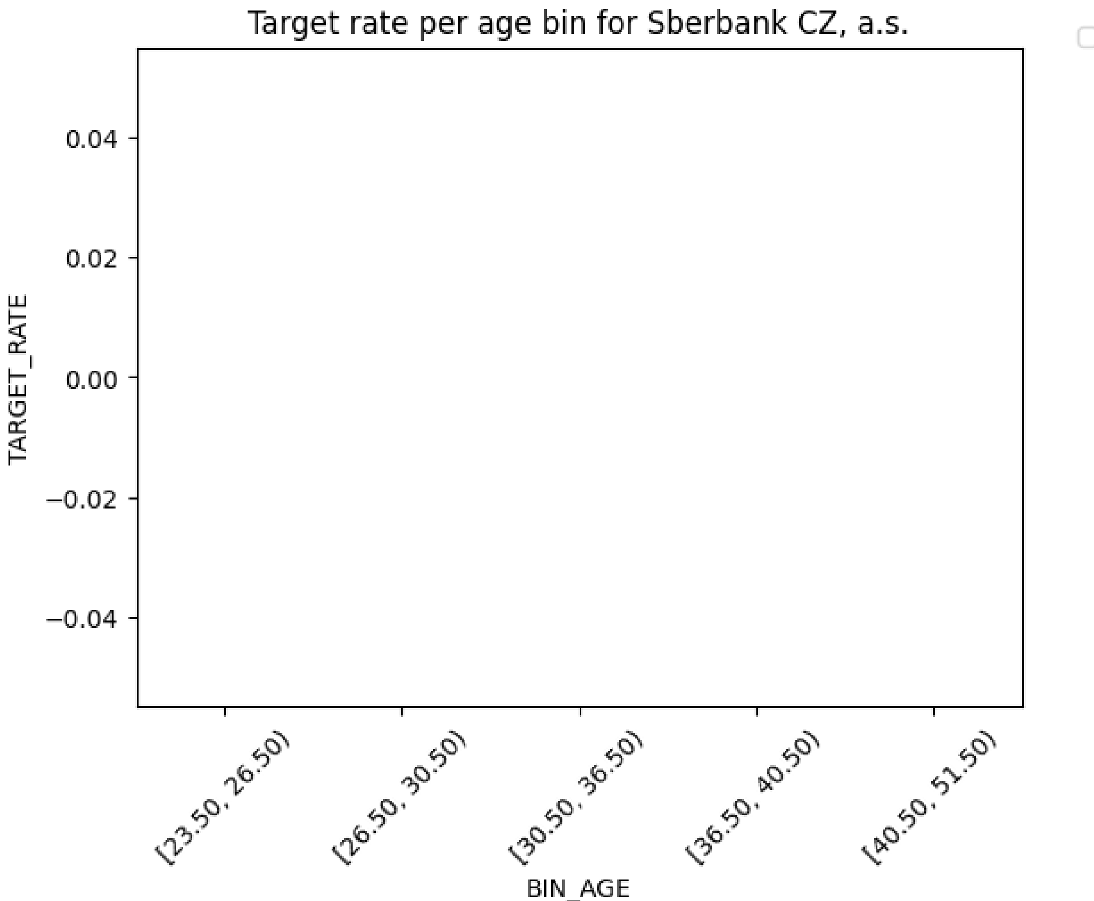

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



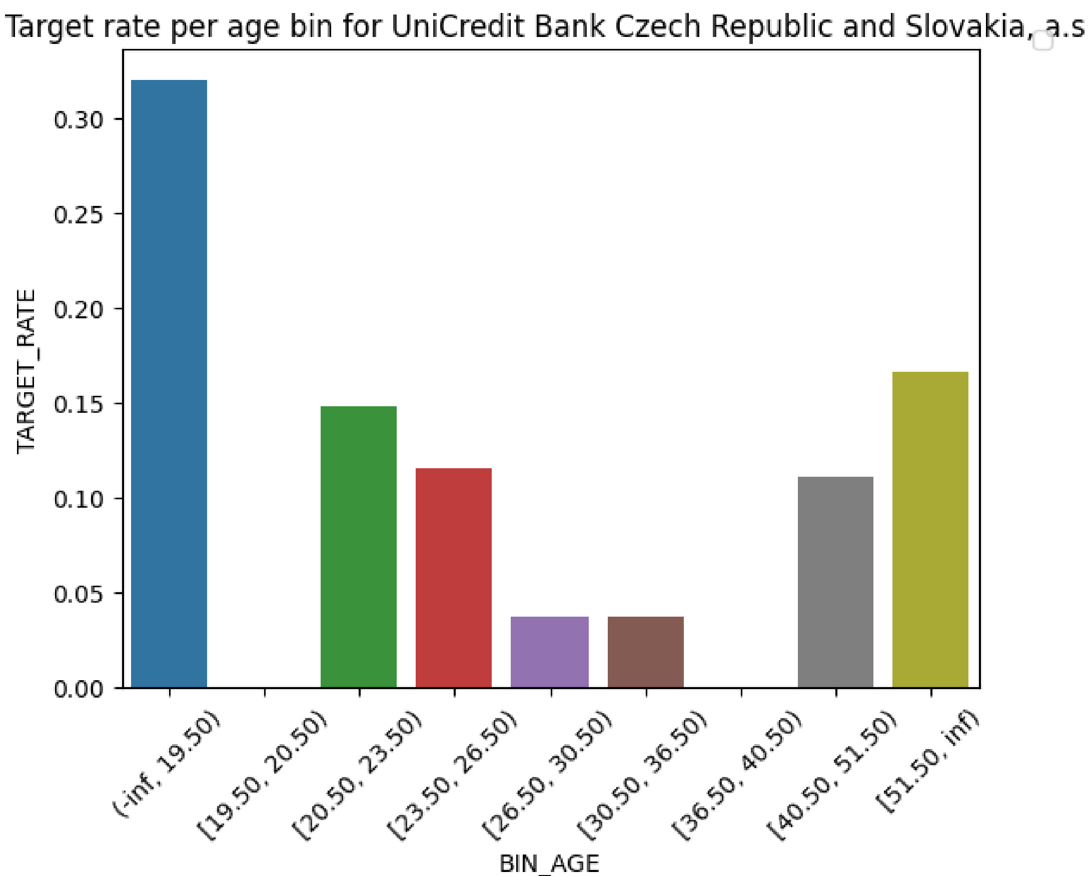

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



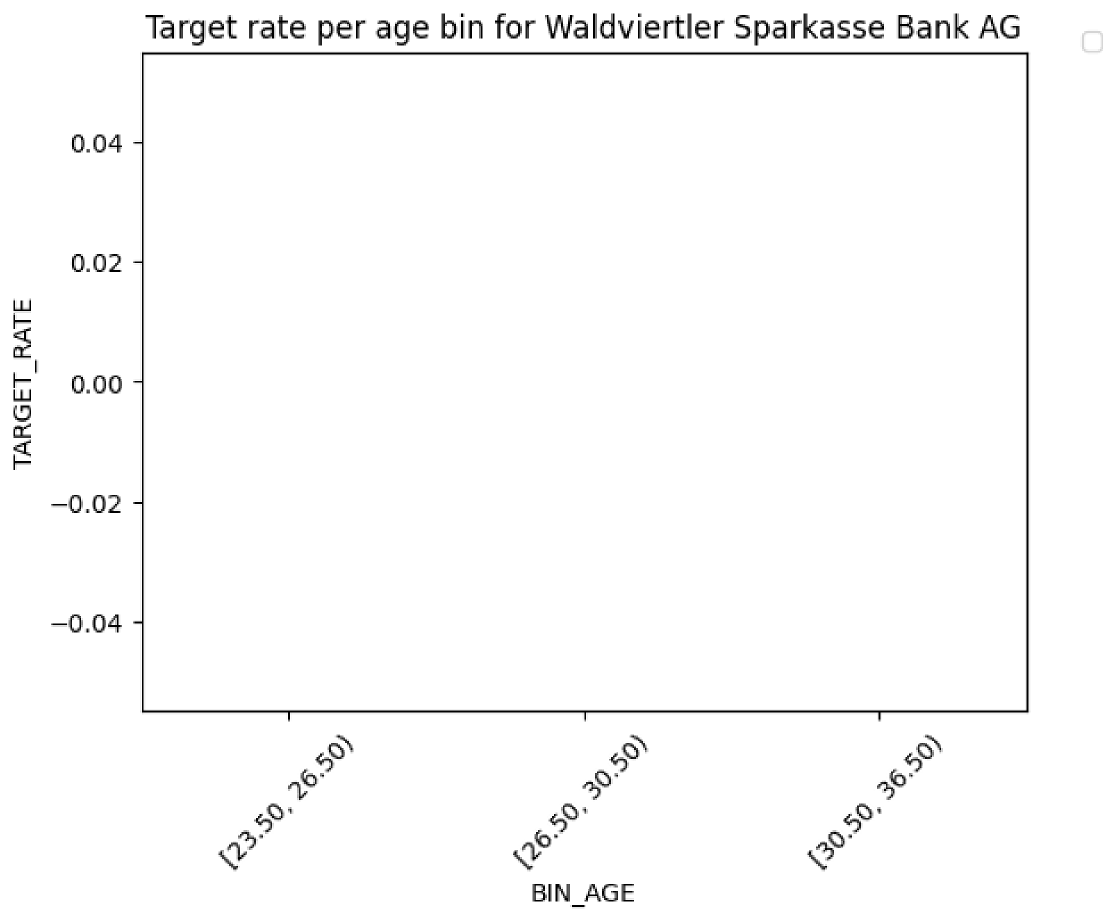

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



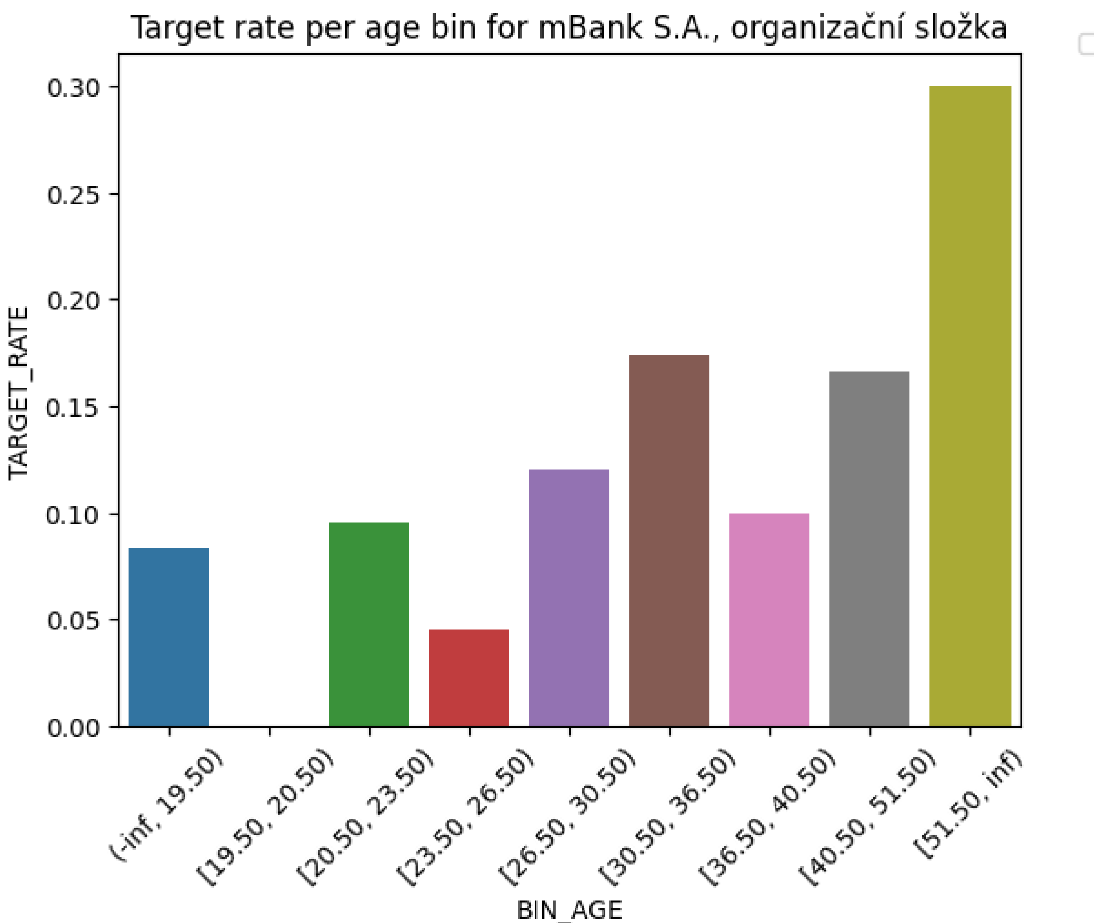

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



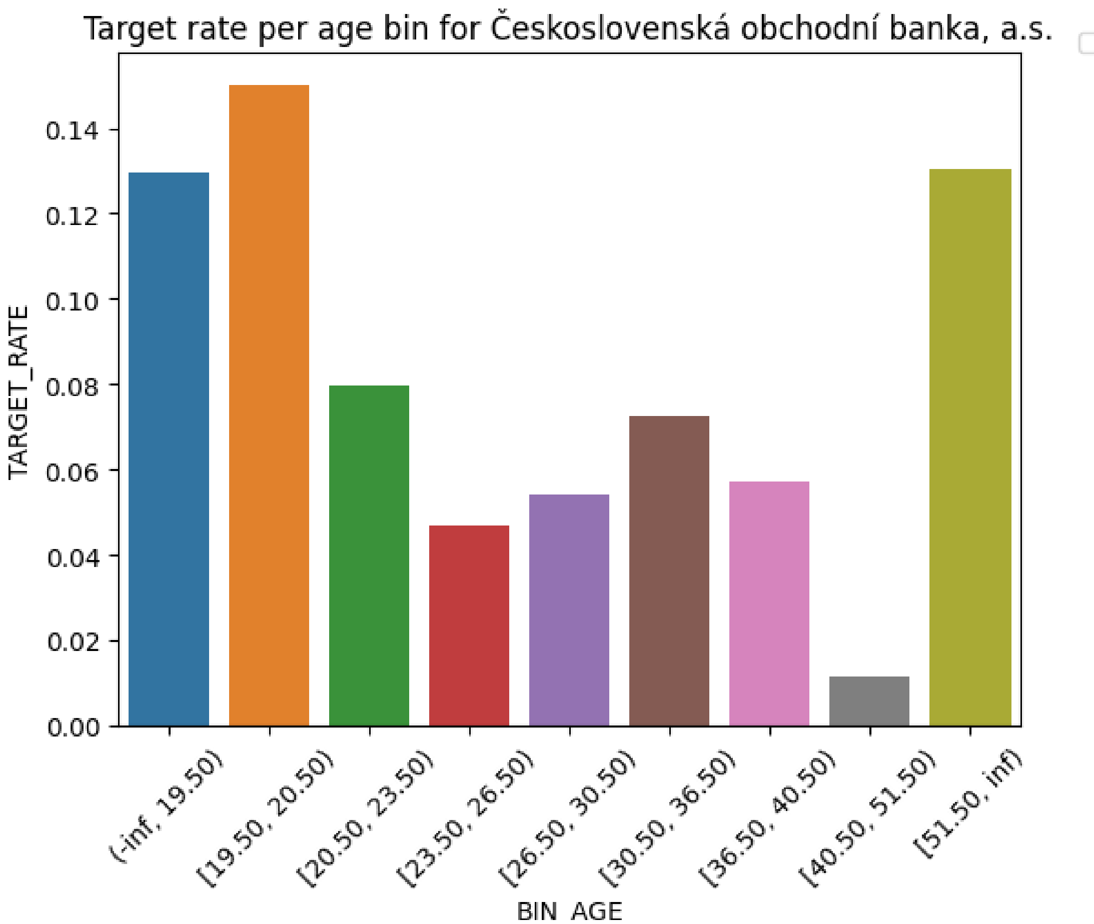

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



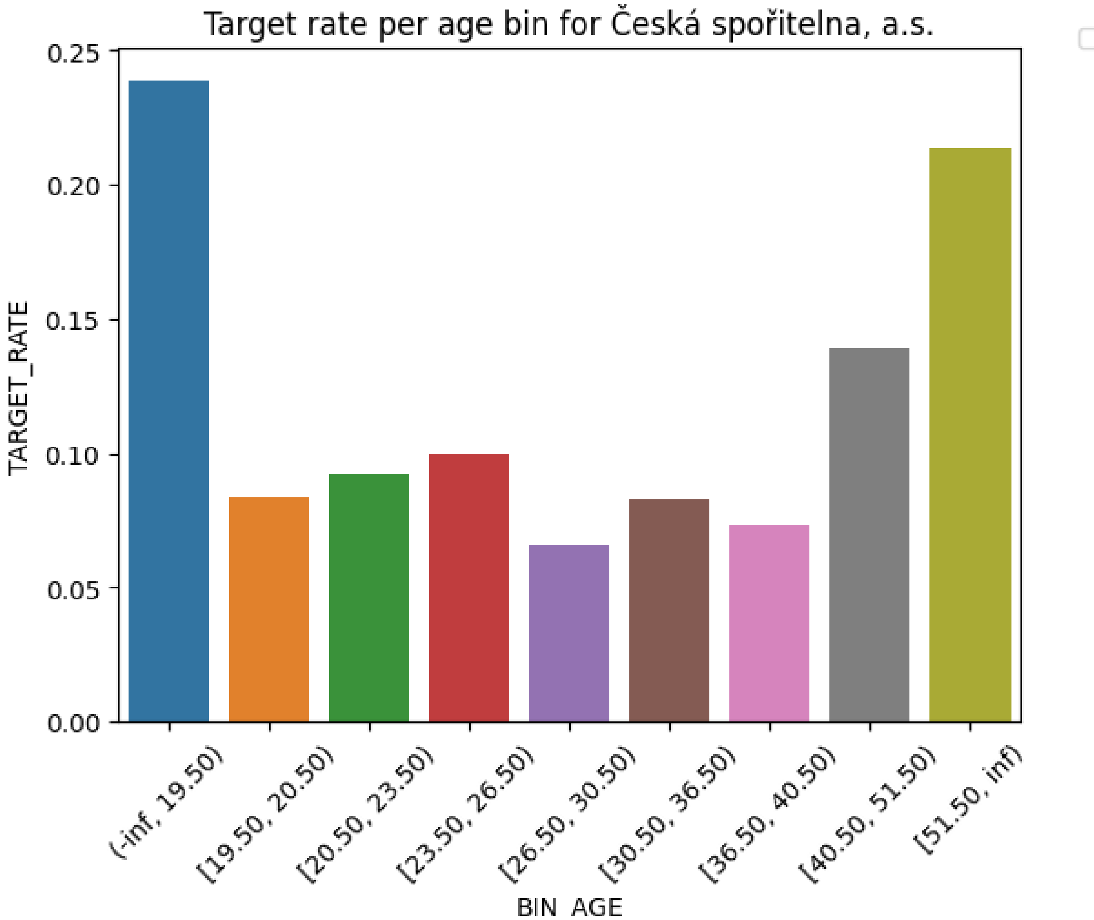

```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```




```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```




```
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



[Q7] How does target rate differ for different banks according to age? (Jak se liší výsledky target rate podle jednotlivých bank v závislosti na věku?)

[A7] We can leverage our binned age and bank to create contingency table and then extract the target rate (ratio of True target to False+True). Further we can create barplots here (where y is target rate and x/hue are age bin and bank). Then we can inspect the numbers and see differences: - for example air bank, and fio have the highest target rate for people up to 19 years old (including) - obchodni banka has highest target rate for 20 years old - raiffeisen for people from 52 years - equa bank for 37-40 years old Further we could focus more on some banks and look at the trends more or even inspect histograms of age per target and bank (two histograms per each bank). We could also leverage two-way ANOVA to test difference between numerical age according to interaction between TARGET and BANK. But I think the plots tell us more about the differences in target rate.

1.5 Approval criterions

[57]:
```
tab = pd.crosstab(
    df["TEXT_GENDER"], df["TARGET"], margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1]).sort_values(by="TARGET_RATE", ascending=False)
tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[57]:
```
Empty DataFrame
Columns: [0, 1, All, TARGET_RATE]
Index: []
```

[58]:
```
tab = pd.crosstab(
    df["BIN_AGE"], df["TARGET"], margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1]).sort_values(by="TARGET_RATE", ascending=False)
tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[58]:
```
TARGET            0   1  All  TARGET_RATE
BIN_AGE
[19.50, 20.50)  251  34  285     0.119298
[51.50, inf)    239  47  286     0.164336
```

[59]:
```
tab = pd.crosstab(
    [df["BIN_AGE"],df["TEXT_GENDER"]], df["TARGET"], margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1]).sort_values(by="TARGET_RATE", ascending=False)
tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[59]:
```
TARGET                            0   1  All  TARGET_RATE
BIN_AGE        TEXT_GENDER
(-inf, 19.50)  Muž              173  43  216     0.199074
               Žena             158  43  201     0.213930
[23.50, 26.50) Žena             276  20  296     0.067568
[30.50, 36.50) Žena             268  16  284     0.056338
[40.50, 51.50) Muž              241  25  266     0.093985
               Žena             275  18  293     0.061433
```

[60]:
```
tab = pd.crosstab(
    [df["BIN_AGE"],df["TEXT_GENDER"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
```

```
tab.drop(columns=[0,1]).sort_values(by="TARGET_RATE", ascending=False)
tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[60]:

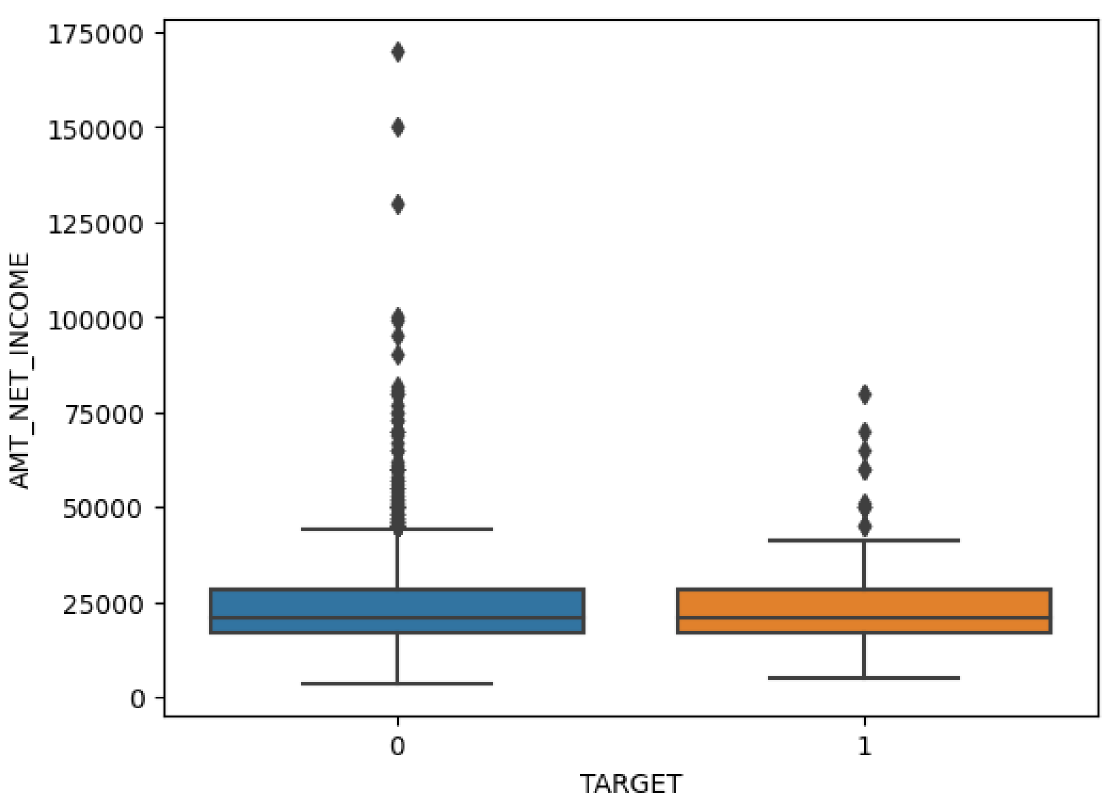
```
TARGET                             0   1  All  TARGET_RATE
BIN_AGE         TEXT_GENDER
(-inf, 19.50)   Muž              173  43  216     0.199074
                Žena             158  43  201     0.213930
[23.50, 26.50)  Žena             276  20  296     0.067568
[30.50, 36.50)  Žena             268  16  284     0.056338
[40.50, 51.50)  Muž              241  25  266     0.093985
                Žena             275  18  293     0.061433
```

[61]:

```
sns.boxplot(df[df["AMT_NET_INCOME"] <= 1e7], x="TARGET", y="AMT_NET_INCOME")
df[df["TARGET"] == 0]["AMT_NET_INCOME"].describe()
```

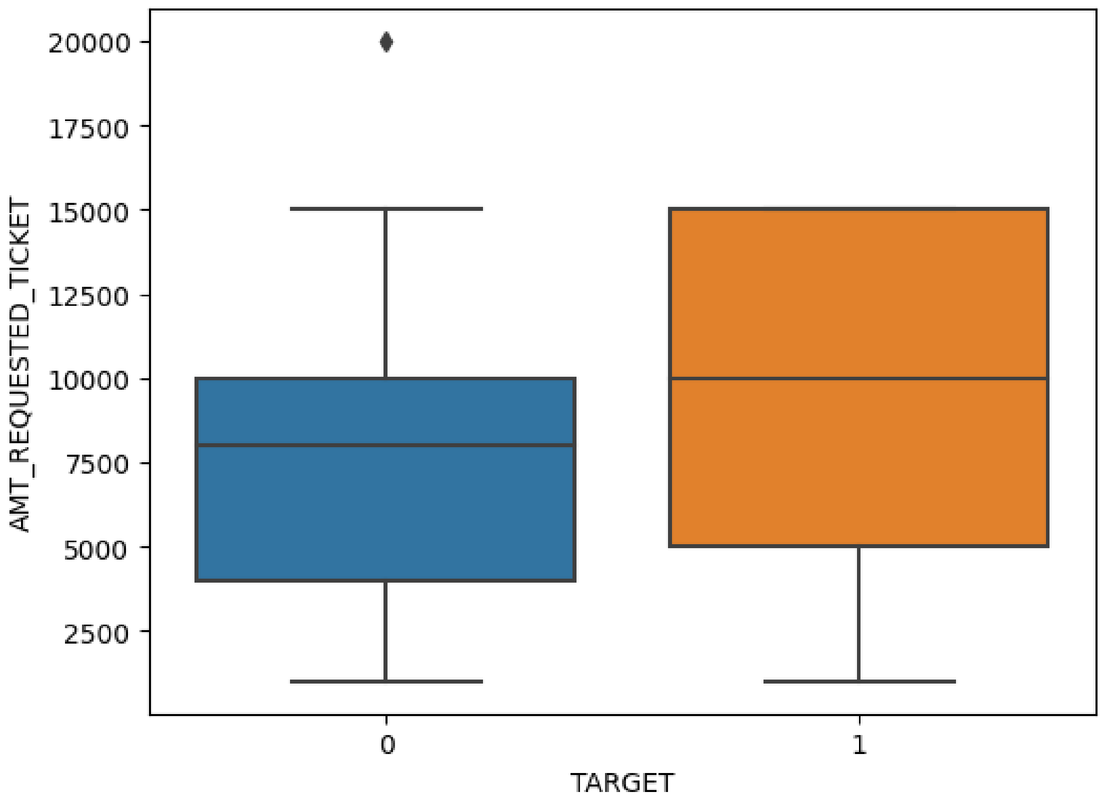
[61]:

```
count    4.503000e+03
mean     2.752179e+04
std      2.830010e+05
min      3.500000e+03
25%      1.700000e+04
50%      2.100000e+04
75%      2.800000e+04
max      1.900060e+07
Name: AMT_NET_INCOME, dtype: float64
```



[62]:
```
sns.boxplot(df, x="TARGET", y="AMT_REQUESTED_TICKET")
df[df["TARGET"] == 0]["AMT_REQUESTED_TICKET"].describe()
```

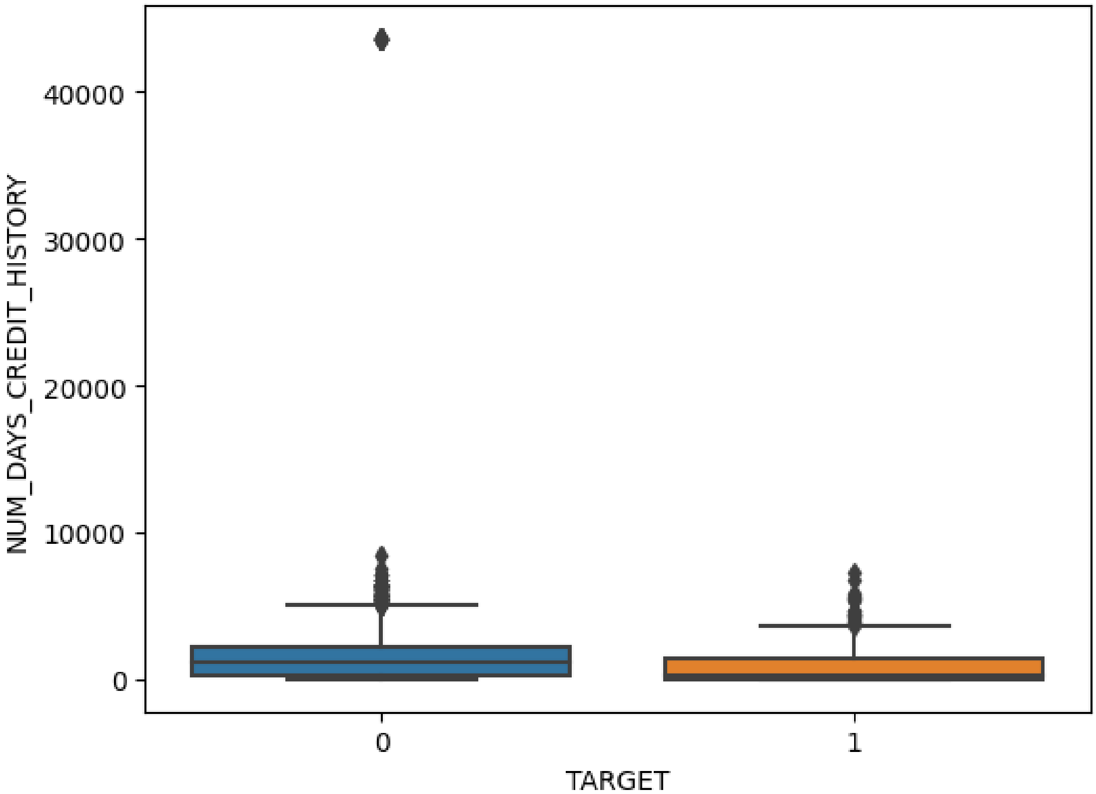
[62]:
```
count     4503.000000
mean      7782.145237
std       4532.700782
min       1000.000000
25%       4000.000000
50%       8000.000000
75%      10000.000000
max      20000.000000
Name: AMT_REQUESTED_TICKET, dtype: float64
```



[63]:
```
sns.boxplot(df, x="TARGET", y="NUM_DAYS_CREDIT_HISTORY")
df[df["TARGET"] == 0]["NUM_DAYS_CREDIT_HISTORY"].describe()
```

[63]:
```
count     4503.000000
mean      1615.056629
std       2775.935379
```

```
min          0.000000
25%        200.000000
50%       1150.000000
75%       2150.000000
max      43700.000000
Name: NUM_DAYS_CREDIT_HISTORY, dtype: float64
```



[64]:

```
# candidates
# >= 1615 CREDIT HISTORY
# > 10 000 AMT_REQUESTED_TICKET
# > 80 000AMT_NET_INCOME
credit_history_rule = df["NUM_DAYS_CREDIT_HISTORY"] <= 1615 # under mean of␣
 ↪TARGET=0
ticket_rule = df["AMT_REQUESTED_TICKET"] > 10000 # all above that are approved
income_rule = df["AMT_NET_INCOME"] <= 80000 # some outliers are above that only␣
 ↪for reject
```

[65]:

```
tab = pd.crosstab(
    income_rule,
    df["TARGET"],
    margins=True
```

```
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab
#tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[65]:

```
TARGET            All  TARGET_RATE
AMT_NET_INCOME
True             4990     0.099599
All              5000     0.099400
False              10     0.000000
```

[66]:

```
tab = pd.crosstab(
    ticket_rule,
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab
#tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[66]:

```
TARGET                  All  TARGET_RATE
AMT_REQUESTED_TICKET
True                   1070     0.134579
All                    5000     0.099400
False                  3930     0.089822
```

[67]:

```
tab = pd.crosstab(
    credit_history_rule,
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab
#tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[67]:

```
TARGET                     All  TARGET_RATE
NUM_DAYS_CREDIT_HISTORY
True                      3213     0.124494
All                       5000     0.099400
False                     1787     0.054281
```

[68]:
```
tab = pd.crosstab(
    [credit_history_rule, ticket_rule, income_rule],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab
#tab[(tab["All"] >= 0.04 * 5000) & (tab["All"] <= 0.06 * 5000)]
```

[68]:
```
TARGET                                                         All  TARGET_RATE
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME
True                    True                 True              611     0.188216
                        False                True             2596     0.109784
All                                                           5000     0.099400
False                   True                 True              455     0.063736
                        False                True             1328     0.051205
                                             False               1     0.000000
                        True                 False               3     0.000000
True                    False                False               5     0.000000
                        True                 False               1     0.000000
```

[69]:
```
tab = pd.crosstab(
    [credit_history_rule, ticket_rule, income_rule, df["CNT_REJECTED"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab[(tab["All"] >= 0.04 * 5000)]
```

[69]:
```
TARGET                                                                       All
\
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME CNT_REJECTED
True                    True                 True           1                493
                        False                True           0                462
                                                            1               1949
All                                                                         5000
False                   True                 True           1                391
                        False                True           1               1131

TARGET
TARGET_RATE
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME CNT_REJECTED
True                    True                 True           1
```

```
0.190669
                        False                True           0
0.110390
                                                            1
0.100051
All
0.099400
False                   True                 True           1
0.061381
                        False                True           1
0.049514
```

[70]:
```
tab = pd.crosstab(
    [credit_history_rule, ticket_rule, income_rule, df["BIN_AGE"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab[(tab["All"] >= 0.04 * 5000)]
```

[70]:
```
TARGET                                                                          All
\
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME BIN_AGE
True                    False                True           (-inf, 19.50)       370
                                                            [19.50, 20.50)      247
All                                                                            5000
True                    False                True           [30.50, 36.50)      216
                                                            [23.50, 26.50)      511
                                                            [20.50, 23.50)      635
                                                            [26.50, 30.50)      371
False                   False                True           [26.50, 30.50)      279
                                                            [40.50, 51.50)      291
                                                            [30.50, 36.50)      319

TARGET
TARGET_RATE
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME BIN_AGE
True                    False                True           (-inf, 19.50)
0.200000
                                                            [19.50, 20.50)
0.113360
All
0.099400
True                    False                True           [30.50, 36.50)
0.092593
```

```
                                                    [23.50, 26.50)
0.090020
                                                    [20.50, 23.50)
0.086614
                                                    [26.50, 30.50)
0.086253
False                False              True        [26.50, 30.50)
0.053763
                                                    [40.50, 51.50)
0.041237
                                                    [30.50, 36.50)
0.037618
```

[71]:
```python
tab = pd.crosstab(
    [credit_history_rule, ticket_rule, income_rule, df["BIN_AGE"],␣
 ↪df["CNT_REJECTED"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab[(tab["All"] >= 0.04 * 5000)]
```

[71]:
```
TARGET
All  \
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME BIN_AGE
CNT_REJECTED
True                 False              True        (-inf, 19.50)  1
252
All
5000
True                 False              True        [23.50, 26.50) 1
376
                                                    [20.50, 23.50) 1
465
                                                    [26.50, 30.50) 1
291
False                False              True        [26.50, 30.50) 1
229
                                                    [40.50, 51.50) 1
249
                                                    [30.50, 36.50) 1
274

TARGET
TARGET_RATE
```

```
NUM_DAYS_CREDIT_HISTORY AMT_REQUESTED_TICKET AMT_NET_INCOME BIN_AGE
CNT_REJECTED
True                    False                True           (-inf, 19.50)  1
0.182540
All
0.099400
True                    False                True           [23.50, 26.50) 1
0.090426
                                                            [20.50, 23.50) 1
0.077419
                                                            [26.50, 30.50) 1
0.072165
False                   False                True           [26.50, 30.50) 1
0.048035
                                                            [40.50, 51.50) 1
0.044177
                                                            [30.50, 36.50) 1
0.029197
```

[72]:
```python
tab = pd.crosstab(
    [credit_history_rule, income_rule, df["BIN_AGE"], df["CNT_REJECTED"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab[(tab["All"] >= 0.04 * 5000)]
```

[72]:
```
TARGET                                                                All  \
NUM_DAYS_CREDIT_HISTORY AMT_NET_INCOME BIN_AGE        CNT_REJECTED
True                    True           (-inf, 19.50)  1               282
                                       [30.50, 36.50) 1               231
                                       [19.50, 20.50) 1               202
All                                                                  5000
True                    True           [23.50, 26.50) 1               470
                                       [26.50, 30.50) 1               375
                                       [20.50, 23.50) 1               567
False                   True           [26.50, 30.50) 1               293
                                       [40.50, 51.50) 1               346
                                       [30.50, 36.50) 1               378

TARGET                                                               TARGET_RATE
NUM_DAYS_CREDIT_HISTORY AMT_NET_INCOME BIN_AGE        CNT_REJECTED
True                    True           (-inf, 19.50)  1                 0.184397
                                       [30.50, 36.50) 1                 0.108225
                                       [19.50, 20.50) 1                 0.103960
```

```
All                                                                    0.099400
True                    True            [23.50, 26.50) 1               0.095745
                                        [26.50, 30.50) 1               0.090667
                                        [20.50, 23.50) 1               0.086420
False                   True            [26.50, 30.50) 1               0.051195
                                        [40.50, 51.50) 1               0.040462
                                        [30.50, 36.50) 1               0.039683
```

[73]:
```
tab = pd.crosstab(
    [credit_history_rule, income_rule, df["BIN_AGE"], df["NFLAG_MOBILEDEVICE"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab[(tab["All"] >= 0.04 * 5000)]
```

[73]:
```
TARGET                                                                    All
\
NUM_DAYS_CREDIT_HISTORY AMT_NET_INCOME BIN_AGE        NFLAG_MOBILEDEVICE
True                    True            (-inf, 19.50)  1                  319
                                        [19.50, 20.50) 1                  222
                                        [26.50, 30.50) 1                  320
                                        [20.50, 23.50) 1                  555
                                        [23.50, 26.50) 1                  434
All                                                                      5000
False                   True            [26.50, 30.50) 1                  262
                                        [40.50, 51.50) 0                  207
True                    True            [20.50, 23.50) 0                  209
False                   True            [30.50, 36.50) 1                  289

TARGET
TARGET_RATE
NUM_DAYS_CREDIT_HISTORY AMT_NET_INCOME BIN_AGE        NFLAG_MOBILEDEVICE
True                    True            (-inf, 19.50)  1
0.200627
                                        [19.50, 20.50) 1

0.117117
                                        [26.50, 30.50) 1

0.115625
                                        [20.50, 23.50) 1

0.109910
                                        [23.50, 26.50) 1

0.101382
All
0.099400
```

```
False                   True            [26.50, 30.50) 1
0.057252
                                        [40.50, 51.50) 0
0.053140
True                    True            [20.50, 23.50) 0
0.052632
False                   True            [30.50, 36.50) 1
0.041522
```

[74]:
```python
tab = pd.crosstab(
    [credit_history_rule, income_rule, df["BIN_AGE"], df["NFLAG_MOBILEDEVICE"],␣
 ↪df["CNT_REJECTED"]],
    df["TARGET"],
    margins=True
)
tab["TARGET_RATE"] = tab[1] / tab["All"]
tab.drop(columns=[0,1], inplace=True)
tab.sort_values(by="TARGET_RATE", ascending=False, inplace=True)
tab[(tab["All"] >= 0.04 * 5000)]
```

[74]:
```
TARGET
All  \
NUM_DAYS_CREDIT_HISTORY AMT_NET_INCOME BIN_AGE        NFLAG_MOBILEDEVICE
CNT_REJECTED
True                    True           (-inf, 19.50)  1                  1
221
                                       [26.50, 30.50) 1                  1
251
                                       [23.50, 26.50) 1                  1
334
All
5000
True                    True           [20.50, 23.50) 1                  1
416
False                   True           [26.50, 30.50) 1                  1
211
                                       [30.50, 36.50) 1                  1
251

TARGET
TARGET_RATE
NUM_DAYS_CREDIT_HISTORY AMT_NET_INCOME BIN_AGE        NFLAG_MOBILEDEVICE
CNT_REJECTED
True                    True           (-inf, 19.50)  1                  1
0.194570
                                       [26.50, 30.50) 1                  1
0.107570
```

```
                                        [23.50, 26.50) 1                   1
0.101796
All
0.099400
True                    True            [20.50, 23.50) 1                   1
0.098558
False                   True            [26.50, 30.50) 1                   1
0.047393
                                        [30.50, 36.50) 1                   1
0.035857
```

[Q8] Design the best possible rules that we can use for variables to choose 4-6% records for them to have the best possible target rate. (Navrhněte co nejlepší pravidla, jak pomocí vysvětlujících proměnných ze vzorku vybrat 4-6% záznamů tak, aby ve vybrané sadě byl co největší target rate.)

[A8] Here we experiment with different simple rules and adding them together. For the numerical values I looked at box plots of NUM_DAYS_CREDIT_HISTORY, AMT_REQUESTED_TICKET, AMT_NET_INCOME. I could see most above 10000 requested ticket are approved, and more under 1615 credit history are approved, while there are some outliers that above 80000 income are only rejected. We create three boolean rules out of these values. Then we can also look at other categorical features like binned age, gender, .. Next we just calculate target rates for some promising candidates while moving down to 5% of samples. We have two promisign results: - taking only women are up to 19 years old achieves 21% target rate - takingn people with less credit history than 1615, more income than 10000, age up to 19 years old, mobile device, and CNT_REJECTED we achieve 19.5% target rate

1.6 Feature engineering

[75]:
```python
psc_external_data = pd.read_csv("../data/external/zv_cobce_psc.csv",␣
 ↪encoding='iso-8859-2', sep=";")
psc2okres = psc_external_data[["psc", "nazokresu"]]
psc2okres.set_index("psc", inplace=True)
psc2okres = psc2okres.to_dict()["nazokresu"]
```

[76]:
```python
set(df["CODE_ZIP"].to_list()) - set(psc2okres.keys())
```

[76]:
```
{10003,
 11700,
 13401,
 16003,
 19008,
 20306,
 25002,
 27234,
 28003,
 28801,
 37003,
```

```
 37012,
 37705,
 41502,
 43002,
 43007,
 44401,
 46361,
 53335,
 56003,
 60407,
 62900,
 68176,
 68356,
 69640,
 69823,
 73000,
 75615,
 77095,
 77200,
 78343,
 79364,
 79900,
 83924}
```

[77]:
```
def add_okres(df, psc2okres, okres_colname="OKRES", psc_colname="CODE_ZIP"):

    df[okres_colname] = df[psc_colname].apply(lambda x: psc2okres.get(x,␣
 ↪"UNKNOWN"))
    return df

df = add_okres(df, psc2okres)
```

[Q9] (Obohaťte data tak, že přidáte jeden nový atribut odvozený z PSČ, tedy třeba počet obyvatel, okres, kraj nebo cokoliv jiného. Můžete použít jen veřejné zdroje, ty uveďte.)

[A9] We add data from ceska posta (https://www.ceskaposta.cz/ke-stazeni/zakaznicke-vystupy) which should be reliable. However some PSC is missing there (invalid data? new psc?) so we replace it with special UNKNOWN value.

1.7 Modeling

[Q10] Which mathematical model would u recommend to model TARGET variable based on other variables and why would you choose this method? If u want u can create model and comment it. (Jaký matematický model byste doporučili pro modelování cílové proměnné TARGET za základě ostatních vysvětlujících proměnných a proč byste zvolili právě tuto metodu? Pokud máte čas a chuť, tak nějaký model vytvořte a okomentujte jeho vhodnost po použití při schvalování úvěrů)

[A10] We dont have much data available and in this task we should focus on interpretability of our model. Thus I would choose model that can be easily explained to the "customer". My choices would be either logistic regression or nearest neighbours classifier. Obviously we would need to split our data into train and test sets (we should have actually done that right in the beginning before analysis if we know we gonna model). For the features, we would take the ones we already know work (age, bank), the ones which are logicaly needed (income and requested ticket) as our baseline. Then we would consider other features (if they are not correlated like mobile phone with age might be) andd if we can actually legally use the features (can gender and okres be used?). For evaluation metric we would need to take into account the disbalance of accepted and rejected loans by not using accuracy.

1.8 Conclusion (feedback)

Analysis took me 5hours. Issue was that I started the analysis, suddenly I didnt have time.. then I went back to the analysis week later. This meant I had to once again get into the project. The most frustrating was question 8. I had no idea whats the best way to find ideal rules (besides experimenting or doing some bruteforce). Also question 7 was quite hard (I had issue thinking how to decide and answer this).

[ ]:

```

```