# Task final

sijie hu, 11/30/2023

In [1]:
```
# the task:

# The management team at Amalgamated Bank Corp (ABC)
# has asked you to step in as a data analyst.
# They heard about your rapidly developing Python skills
# and would like you help them out.

# They are a bank. Their business consists of issuing loans.
# Their problem is that they know very little about their data.
# They have a data file that has over 300k loans they have issued.
# The dataset describes information about each loan.
# The dataset contains loan amount issued and many other fields
# that describe the client’s credit factors,
# such as whether they own their own home or not, their income,
# how long it has been since they were delinquent on an account,
# how many years since they received their first credit line, etc.

# The problem is that ABC has no idea who their clients are
# and what their data can tell them about their business.
# They have asked for your guidance.
# They have provided a data file and a data dictionary.
# The data dictionary contains a list of fields in the dataset
# and an explanation for each one.
# (To simplify the project, many irrelevant fields
# have been removed from the dataset.
# Those fields still appear in the dictionary, however).

# To help our client, here are the steps to take:

# Cleanse
# Look for null data in the table, and use the appropriate strategy
# to handle null data for each column.
# Explain why this was the strategy that you used.

# Outliers
# Search the data for outliers and remove them.
# Use the appropriate outlier method(s).
# Show all work.

# Who are our clients?
# The ABC Management team has no idea who is their customers are.
# They don’t know anything about the type of employment
# and age, income of their clients.
# They need to know some macro information about their data.
# How much (total) do they have out in loans?
# How much are in default/late?
# What percentage of the business are default and late?
# Along with the information above,
# provide three other demographics of their customers.
# Remember, we are dealing with senior management.
# The charts must be readable, meaningful and at a summary level.
# Use at least one group/by or bin in your analysis

# Who defaults or has problems replaying loans?
```

```
# Create visualizations to show management qualities specific
# to those who are in default/late.
# Show three meaningful visualizations.
# Use at least one group/by or bin in your analysis.

# Prepare the data for a regression analysis
# The ABC management team has heard that it might be possible
# to use their data to make predictions.
# They don't know much about data analytics.
# We are hoping that an example of what is possible
# will help them understand better.
# Prepare the data file to run with a regression analysis.
# Use the techniques and methods discussed in class.
# Run the regression analysis

# Show scoring and a confusion matrix.
# You do not need to split the data.
# Running it as a full dataset is fine.
```

# Table of Contents



# 0. Libraries

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
```

# 1. The base

In [3]:
```
df = pd.read_csv('application_train.csv')
```

# 2. Cleanse

In [4]:
```
# check basics
print(df.info())
print(df.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 37 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   SK_ID_CURR                   307511 non-null  int64
 1   Unnamed: 1                   0 non-null       float64
 2   NAME_CONTRACT_TYPE           307511 non-null  object
 3   CODE_GENDER                  307511 non-null  object
 4   FLAG_OWN_CAR                 307511 non-null  object
 5   FLAG_OWN_REALTY              307511 non-null  object
 6   CNT_CHILDREN                 307511 non-null  int64
 7   AMT_INCOME_TOTAL             307511 non-null  float64
 8   AMT_CREDIT                   307511 non-null  float64
 9   AMT_ANNUITY                  307499 non-null  float64
 10  AMT_GOODS_PRICE              307233 non-null  float64
 11  NAME_TYPE_SUITE              306219 non-null  object
 12  NAME_INCOME_TYPE             307511 non-null  object
 13  NAME_EDUCATION_TYPE          307511 non-null  object
 14  NAME_FAMILY_STATUS           307511 non-null  object
 15  NAME_HOUSING_TYPE            307511 non-null  object
 16  DAYS_BIRTH                   307511 non-null  int64
 17  DAYS_EMPLOYED                307511 non-null  int64
 18  DAYS_REGISTRATION            307511 non-null  float64
 19  DAYS_ID_PUBLISH              307511 non-null  int64
 20  OWN_CAR_AGE                  104582 non-null  float64
 21  FLAG_MOBIL                   307511 non-null  int64
 22  FLAG_EMP_PHONE               307511 non-null  int64
 23  FLAG_WORK_PHONE              307511 non-null  int64
 24  FLAG_CONT_MOBILE             307511 non-null  int64
 25  FLAG_PHONE                   307511 non-null  int64
 26  FLAG_EMAIL                   307511 non-null  int64
 27  OCCUPATION_TYPE              211120 non-null  object
 28  CNT_FAM_MEMBERS              307509 non-null  float64
 29  REG_REGION_NOT_LIVE_REGION   307511 non-null  int64
 30  REG_REGION_NOT_WORK_REGION   307511 non-null  int64
 31  LIVE_REGION_NOT_WORK_REGION  307511 non-null  int64
 32  REG_CITY_NOT_LIVE_CITY       307511 non-null  int64
 33  REG_CITY_NOT_WORK_CITY       307511 non-null  int64
 34  LIVE_CITY_NOT_WORK_CITY      307511 non-null  int64
 35  ORGANIZATION_TYPE            307511 non-null  object
 36  TARGET                       307511 non-null  int64
dtypes: float64(8), int64(18), object(11)
memory usage: 86.8+ MB
None
          SK_ID_CURR  Unnamed: 1   CNT_CHILDREN  AMT_INCOME_TOTAL  \
count  307511.000000         0.0  307511.000000      3.075110e+05
mean   278180.518577         NaN       0.417052      1.687979e+05
std    102790.175348         NaN       0.722121      2.371231e+05
min    100002.000000         NaN       0.000000      2.565000e+04
25%    189145.500000         NaN       0.000000      1.125000e+05
50%    278202.000000         NaN       0.000000      1.471500e+05
75%    367142.500000         NaN       1.000000      2.025000e+05
max    456255.000000         NaN      19.000000      1.170000e+08

         AMT_CREDIT    AMT_ANNUITY  AMT_GOODS_PRICE     DAYS_BIRTH  \
count  3.075110e+05  307499.000000     3.072330e+05  307511.000000
mean   5.990260e+05   27108.573909     5.383962e+05  -16036.995067
std    4.024908e+05   14493.737315     3.694465e+05    4363.988632
min    4.500000e+04    1615.500000     4.050000e+04  -25229.000000
25%    2.700000e+05   16524.000000     2.385000e+05  -19682.000000
50%    5.135310e+05   24903.000000     4.500000e+05  -15750.000000
```

```
75%    8.086500e+05   34596.000000     6.795000e+05  -12413.000000
max    4.050000e+06  258025.500000     4.050000e+06   -7489.000000

       DAYS_EMPLOYED  DAYS_REGISTRATION  ...     FLAG_PHONE     FLAG_EMAIL  \
count  307511.000000      307511.000000  ...  307511.000000  307511.000000
mean    63815.045904       -4986.120328  ...       0.281066       0.056720
std    141275.766519        3522.886321  ...       0.449521       0.231307
min    -17912.000000      -24672.000000  ...       0.000000       0.000000
25%     -2760.000000       -7479.500000  ...       0.000000       0.000000
50%     -1213.000000       -4504.000000  ...       0.000000       0.000000
75%      -289.000000       -2010.000000  ...       1.000000       0.000000
max    365243.000000           0.000000  ...       1.000000       1.000000

       CNT_FAM_MEMBERS  REG_REGION_NOT_LIVE_REGION  \
count    307509.000000               307511.000000
mean          2.152665                    0.015144
std           0.910682                    0.122126
min           1.000000                    0.000000
25%           2.000000                    0.000000
50%           2.000000                    0.000000
75%           3.000000                    0.000000
max          20.000000                    1.000000

       REG_REGION_NOT_WORK_REGION  LIVE_REGION_NOT_WORK_REGION  \
count               307511.000000                307511.000000
mean                    0.050769                     0.040659
std                     0.219526                     0.197499
min                     0.000000                     0.000000
25%                     0.000000                     0.000000
50%                     0.000000                     0.000000
75%                     0.000000                     0.000000
max                     1.000000                     1.000000

       REG_CITY_NOT_LIVE_CITY  REG_CITY_NOT_WORK_CITY  \
count           307511.000000           307511.000000
mean                0.078173                0.230454
std                 0.268444                0.421124
min                 0.000000                0.000000
25%                 0.000000                0.000000
50%                 0.000000                0.000000
75%                 0.000000                0.000000
max                 1.000000                1.000000

       LIVE_CITY_NOT_WORK_CITY         TARGET
count           307511.000000  307511.000000
mean                0.179555       0.080729
std                 0.383817       0.272419
min                 0.000000       0.000000
25%                 0.000000       0.000000
50%                 0.000000       0.000000
75%                 0.000000       0.000000
max                 1.000000       1.000000

[8 rows x 26 columns]
```

In [5]:
```
df.head()
```

Out[5]:

| | SK_ID_CURR | Unnamed: 1 | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY |
|---|---|---|---|---|---|---|
| **0** | 100002 | NaN | Cash loans | M | N | Y |
| **1** | 100003 | NaN | Cash loans | F | N | N |
| **2** | 100004 | NaN | Revolving loans | M | Y | Y |
| **3** | 100006 | NaN | Cash loans | F | N | Y |
| **4** | 100007 | NaN | Cash loans | M | N | Y |

5 rows × 37 columns

In [6]:
```
# check if any column is totally empty
def delete_empty_column(df):
    del_column = []

    for i in df.columns:
        if i.find('Unnamed') >= 0:
            del_column.append(i)

    dfnew = df.drop(columns=del_column)

    return dfnew

# delete
df = delete_empty_column(df)
df.head()
```

Out[6]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILI |
|---|---|---|---|---|---|---|
| **0** | 100002 | Cash loans | M | N | Y | |
| **1** | 100003 | Cash loans | F | N | N | |
| **2** | 100004 | Revolving loans | M | Y | Y | |
| **3** | 100006 | Cash loans | F | N | Y | |
| **4** | 100007 | Cash loans | M | N | Y | |

5 rows × 36 columns

In [7]:
```
# check if there is any NaN in any column, and how many
# turns out we have some columns with NaN
df.isna().sum()
```

Out[7]:
```
SK_ID_CURR                       0
NAME_CONTRACT_TYPE               0
CODE_GENDER                      0
FLAG_OWN_CAR                     0
FLAG_OWN_REALTY                  0
CNT_CHILDREN                     0
AMT_INCOME_TOTAL                 0
AMT_CREDIT                       0
AMT_ANNUITY                     12
AMT_GOODS_PRICE                278
NAME_TYPE_SUITE               1292
NAME_INCOME_TYPE                 0
NAME_EDUCATION_TYPE              0
NAME_FAMILY_STATUS               0
NAME_HOUSING_TYPE                0
DAYS_BIRTH                       0
DAYS_EMPLOYED                    0
DAYS_REGISTRATION                0
DAYS_ID_PUBLISH                  0
OWN_CAR_AGE                 202929
FLAG_MOBIL                       0
FLAG_EMP_PHONE                   0
FLAG_WORK_PHONE                  0
FLAG_CONT_MOBILE                 0
FLAG_PHONE                       0
FLAG_EMAIL                       0
OCCUPATION_TYPE              96391
CNT_FAM_MEMBERS                  2
REG_REGION_NOT_LIVE_REGION       0
REG_REGION_NOT_WORK_REGION       0
LIVE_REGION_NOT_WORK_REGION      0
REG_CITY_NOT_LIVE_CITY           0
REG_CITY_NOT_WORK_CITY           0
LIVE_CITY_NOT_WORK_CITY          0
ORGANIZATION_TYPE                0
TARGET                           0
dtype: int64
```

In [8]:
```
# deal with AMT_ANNUITY, AMT_GOODS_PRICE, NAME_TYPE_SUITE, OWN_CAR_AGE, OCCUPATION_TYPE, CNT_FAM_

# NAME_TYPE_SUITE
# Who was accompanying client when he was applying for the loan
# 1292, too many to drop. replace with 'Unknown'
# the value is not used in the column, same data type - str
df['NAME_TYPE_SUITE'].fillna('Unknown', inplace=True)

# OCCUPATION_TYPE
# What kind of occupation does the client have
# 96391, a lot of blanks
# replace blank with 'Unknown'. it is not used in there. same data type - str
df['OCCUPATION_TYPE'].fillna('Unknown', inplace=True)

# OWN_CAR_AGE
# Age of client's car
# 0 is already there
# replace blank with -1. same data type - int. easy to find.
# basically means 'data not available' to us
df['OWN_CAR_AGE'].fillna(-1, inplace=True)

# AMT_ANNUITY, AMT_GOODS_PRICE, CNT_FAM_MEMBERS
# 12, 278, 2 not a significant number of records
```

```
# also does not make sense to be empty - loan amount is essential
# does not make sense not having it
# just drop them
df.dropna(inplace=True)

# check again
# Voila! all NaN are gone
df.isna().sum()
```

Out[8]:

```
SK_ID_CURR                    0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
FLAG_OWN_REALTY               0
CNT_CHILDREN                  0
AMT_INCOME_TOTAL              0
AMT_CREDIT                    0
AMT_ANNUITY                   0
AMT_GOODS_PRICE               0
NAME_TYPE_SUITE               0
NAME_INCOME_TYPE              0
NAME_EDUCATION_TYPE           0
NAME_FAMILY_STATUS            0
NAME_HOUSING_TYPE             0
DAYS_BIRTH                    0
DAYS_EMPLOYED                 0
DAYS_REGISTRATION             0
DAYS_ID_PUBLISH               0
OWN_CAR_AGE                   0
FLAG_MOBIL                    0
FLAG_EMP_PHONE                0
FLAG_WORK_PHONE               0
FLAG_CONT_MOBILE              0
FLAG_PHONE                    0
FLAG_EMAIL                    0
OCCUPATION_TYPE               0
CNT_FAM_MEMBERS               0
REG_REGION_NOT_LIVE_REGION    0
REG_REGION_NOT_WORK_REGION    0
LIVE_REGION_NOT_WORK_REGION   0
REG_CITY_NOT_LIVE_CITY        0
REG_CITY_NOT_WORK_CITY        0
LIVE_CITY_NOT_WORK_CITY       0
ORGANIZATION_TYPE             0
TARGET                        0
dtype: int64
```

# 3. Outliers

## General info

In [9]:

```
# 307221 is the total records at this point
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 307221 entries, 0 to 307510
Data columns (total 36 columns):
 #   Column                       Non-Null Count   Dtype  
---  ------                       --------------   -----  
 0   SK_ID_CURR                   307221 non-null  int64  
 1   NAME_CONTRACT_TYPE           307221 non-null  object 
 2   CODE_GENDER                  307221 non-null  object 
 3   FLAG_OWN_CAR                 307221 non-null  object 
 4   FLAG_OWN_REALTY              307221 non-null  object 
 5   CNT_CHILDREN                 307221 non-null  int64  
 6   AMT_INCOME_TOTAL             307221 non-null  float64
 7   AMT_CREDIT                   307221 non-null  float64
 8   AMT_ANNUITY                  307221 non-null  float64
 9   AMT_GOODS_PRICE              307221 non-null  float64
 10  NAME_TYPE_SUITE              307221 non-null  object 
 11  NAME_INCOME_TYPE             307221 non-null  object 
 12  NAME_EDUCATION_TYPE          307221 non-null  object 
 13  NAME_FAMILY_STATUS           307221 non-null  object 
 14  NAME_HOUSING_TYPE            307221 non-null  object 
 15  DAYS_BIRTH                   307221 non-null  int64  
 16  DAYS_EMPLOYED                307221 non-null  int64  
 17  DAYS_REGISTRATION            307221 non-null  float64
 18  DAYS_ID_PUBLISH              307221 non-null  int64  
 19  OWN_CAR_AGE                  307221 non-null  float64
 20  FLAG_MOBIL                   307221 non-null  int64  
 21  FLAG_EMP_PHONE               307221 non-null  int64  
 22  FLAG_WORK_PHONE              307221 non-null  int64  
 23  FLAG_CONT_MOBILE             307221 non-null  int64  
 24  FLAG_PHONE                   307221 non-null  int64  
 25  FLAG_EMAIL                   307221 non-null  int64  
 26  OCCUPATION_TYPE              307221 non-null  object 
 27  CNT_FAM_MEMBERS              307221 non-null  float64
 28  REG_REGION_NOT_LIVE_REGION   307221 non-null  int64  
 29  REG_REGION_NOT_WORK_REGION   307221 non-null  int64  
 30  LIVE_REGION_NOT_WORK_REGION  307221 non-null  int64  
 31  REG_CITY_NOT_LIVE_CITY       307221 non-null  int64  
 32  REG_CITY_NOT_WORK_CITY       307221 non-null  int64  
 33  LIVE_CITY_NOT_WORK_CITY      307221 non-null  int64  
 34  ORGANIZATION_TYPE            307221 non-null  object 
 35  TARGET                       307221 non-null  int64  
dtypes: float64(7), int64(18), object(11)
memory usage: 86.7+ MB
```

In [10]:

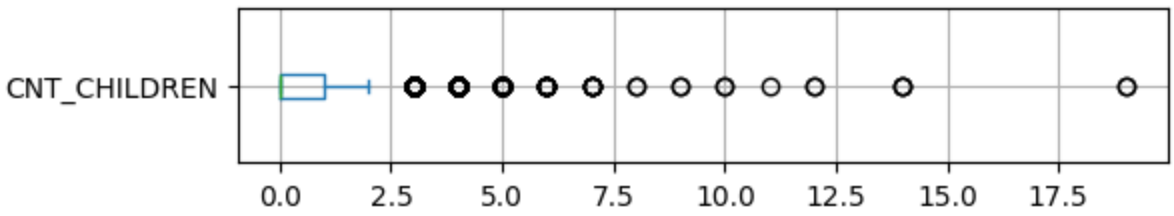
```
# it is good that SK_ID_CURR has all values unique
# theoretically SK_ID_CURR is the PK in database

# to deal with the outliers
# we deal with columns that have a lot of unique values
# the columns that have 2 unique values are likely binary columns
# will convert them to 0/1 if they are not
# later in the regression process
df.nunique()
```

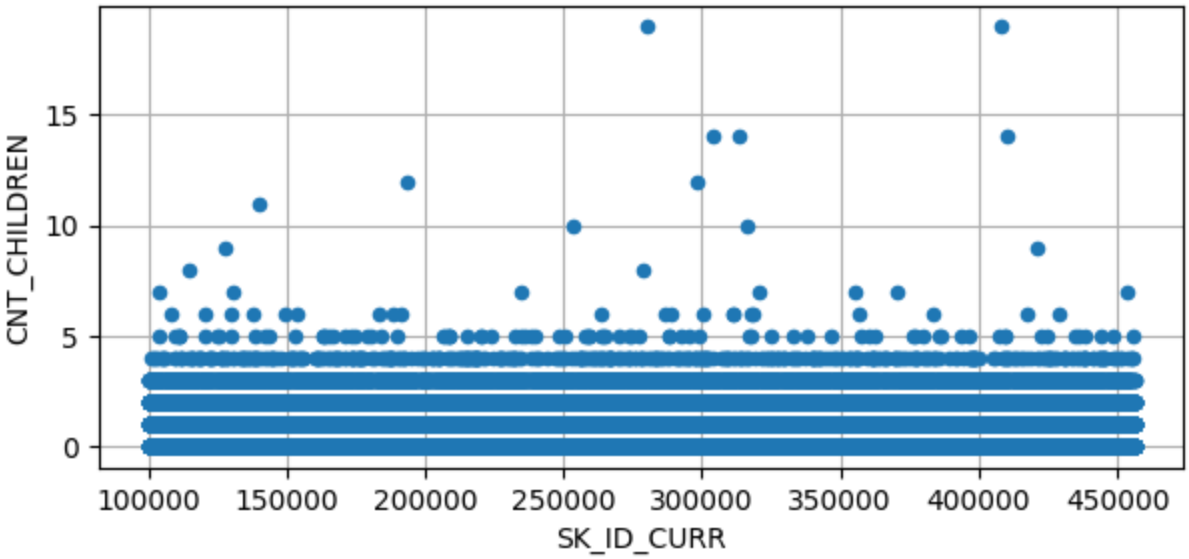
Out[10]:
```
SK_ID_CURR                  307221
NAME_CONTRACT_TYPE               2
CODE_GENDER                      3
FLAG_OWN_CAR                     2
FLAG_OWN_REALTY                  2
CNT_CHILDREN                    15
AMT_INCOME_TOTAL              2547
AMT_CREDIT                    5603
AMT_ANNUITY                  13672
AMT_GOODS_PRICE               1002
NAME_TYPE_SUITE                  8
NAME_INCOME_TYPE                 8
NAME_EDUCATION_TYPE              5
NAME_FAMILY_STATUS               5
NAME_HOUSING_TYPE                6
DAYS_BIRTH                   17460
DAYS_EMPLOYED                12572
DAYS_REGISTRATION            15688
DAYS_ID_PUBLISH               6168
OWN_CAR_AGE                     63
FLAG_MOBIL                       2
FLAG_EMP_PHONE                   2
FLAG_WORK_PHONE                  2
FLAG_CONT_MOBILE                 2
FLAG_PHONE                       2
FLAG_EMAIL                       2
OCCUPATION_TYPE                 19
CNT_FAM_MEMBERS                 17
REG_REGION_NOT_LIVE_REGION       2
REG_REGION_NOT_WORK_REGION       2
LIVE_REGION_NOT_WORK_REGION      2
REG_CITY_NOT_LIVE_CITY           2
REG_CITY_NOT_WORK_CITY           2
LIVE_CITY_NOT_WORK_CITY          2
ORGANIZATION_TYPE               58
TARGET                           2
dtype: int64
```

## CNT_CHILDREN

In [11]:
```
# not very common to have >= 7 children
df.plot.box(column='CNT_CHILDREN', vert=False, figsize=(6,1), zorder=2, grid=True)
df.plot.scatter(x='SK_ID_CURR', y='CNT_CHILDREN', figsize=(7,3), zorder=2, grid=True)
```

Out[11]:
```
<Axes: xlabel='SK_ID_CURR', ylabel='CNT_CHILDREN'>
```






In [12]:
```
# seems ok to remove the top 25%, but let's investigate moretop
# q75 is 1 child
df['CNT_CHILDREN'].describe()
```

Out[12]:
```
count    307221.000000
mean          0.416977
std           0.722047
min           0.000000
25%           0.000000
50%           0.000000
75%           1.000000
max          19.000000
Name: CNT_CHILDREN, dtype: float64
```

In [13]:
```
# let's try to invent function that will potentially work on all columns
# first find outliers, confirm the number and percentage
# combine with the box and scatter plot analysis
# then another function to remove the outliers

# all boundaries are exclusive
def find_outlier(column, q):
    # regular IQR analysis
    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)
    IQR = Q3 - Q1

    below = Q1 - 1.5 * IQR
    above = Q3 + 1.5 * IQR

    below_count = len(column[column < below])
    above_count = len(column[column > above])

    # custom Q analysis
    qresult = column.quantile(q)
    lentop = len(column[column > qresult])
    lentotal = len(column)

    percent = lentop / lentotal * 100
    percent_str = f'{percent:.2f}%'

    # report
    print('Report:\n'
          f'1.5 IQR below is: {below}, 1.5 IQR above is: {above}\n'
```

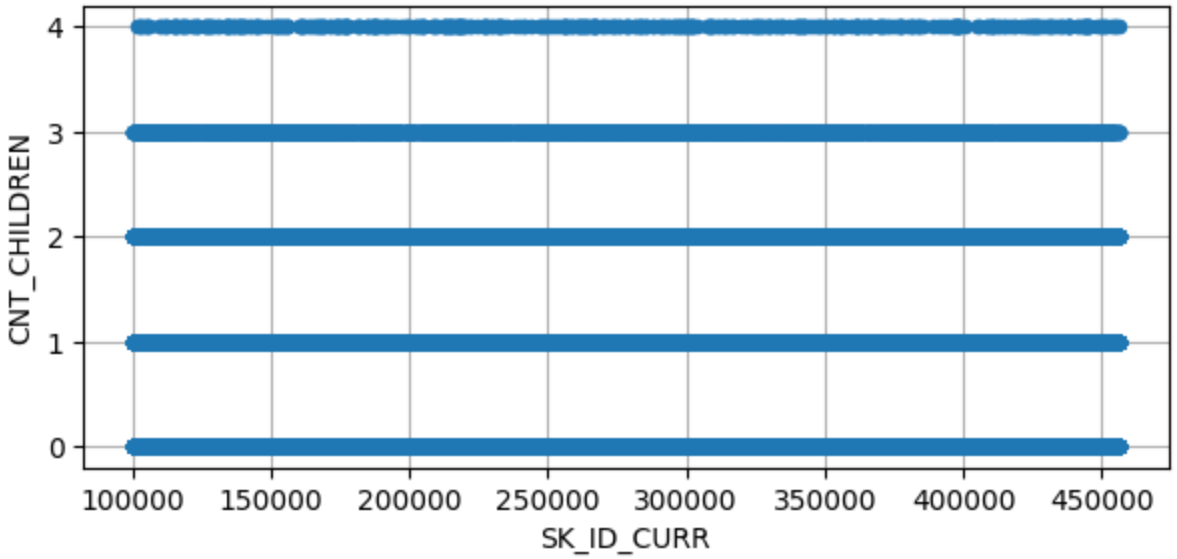
```
            f'below count: {below_count}, above count: {above_count}\n'
            f'q{q*100} is: {qresult}, count: {lentop}, percent: {percent_str}\n'
            f'total: {lentotal}')

    return None

find_outlier(df['CNT_CHILDREN'], 0.99)
```

```
Report:
1.5 IQR below is: -1.5, 1.5 IQR above is: 2.5
below count: 0, above count: 4264
q99.0 is: 3.0, count: 553, percent: 0.18%
total: 307221
```

In [14]:
```
# q99 is 3
# seems ok to remove >= 5, based on the plot and the quantile analysis
# those 15+ children may be input mistakes
# it is very possible to have 4 children
# and the plot seems dense enough, so keep them
# all in all, we keep most of the records

# the method we use:
# 1. common sense
# 2. 1.5 IQR method
# 3. try not to delete too many records

# let's define another function so we can reuse it
# it also prints how many we have removed
def remove_outlier(df, column, point):
    print(f'records removed: {len(df[df[column] > point])}')

    dfnew = df[df[column] <= point]

    return dfnew

# the beauty is we can keep running this function
# and the result will not decrease
# gone is gone
# no risk of running the cells again
# the cutting point - 5 here - is inclusive
df = remove_outlier(df, 'CNT_CHILDREN', 4)
```

```
records removed: 126
```

In [15]:
```
# only removed 126 records
# check the result
df.plot.scatter(x='SK_ID_CURR', y='CNT_CHILDREN', figsize=(7,3), zorder=2, grid=True)
plt.show()

len(df)
```



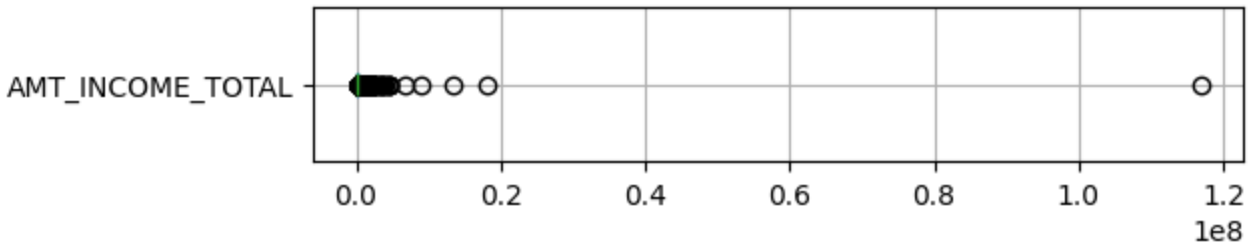

Out[15]: 307095

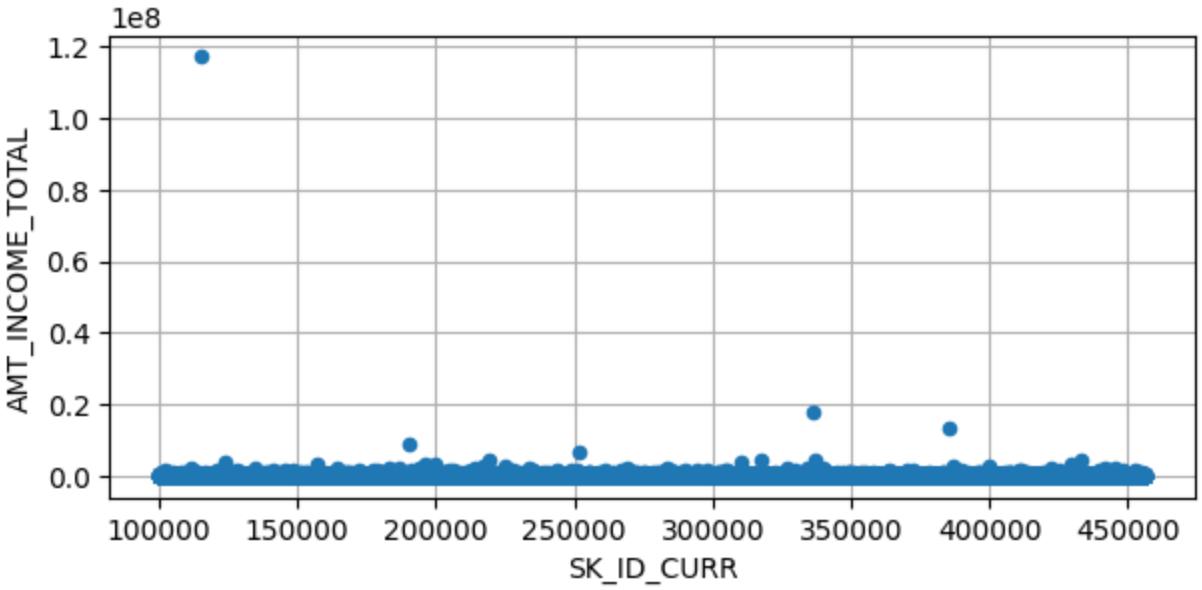
In [16]:
```
# 307095 now compared to 307221 where we started
# let's continue
```

## AMT_INCOME_TOTAL

In [17]:
```
# check income total
# definitely remove the 120 million guys?
df.plot.box(column='AMT_INCOME_TOTAL', vert=False, figsize=(6,1), zorder=2, grid=True)
df.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=True)
```

Out[17]: <Axes: xlabel='SK_ID_CURR', ylabel='AMT_INCOME_TOTAL'>



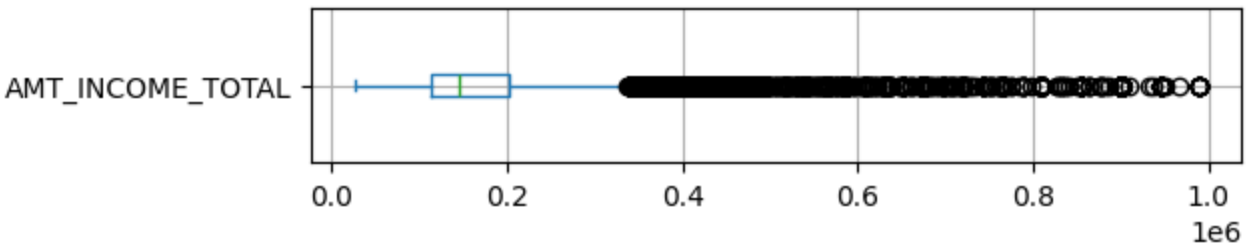
In [18]:
```
# use our function
find_outlier(df['AMT_INCOME_TOTAL'], 0.99)
```

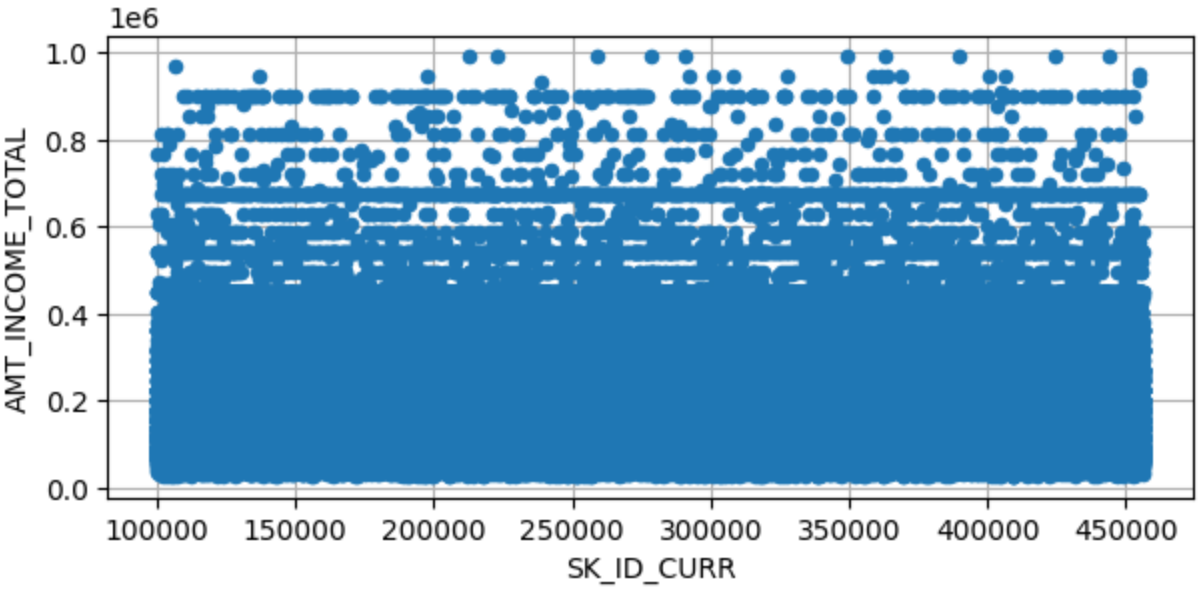
```
Report:
1.5 IQR below is: -22500.0, 1.5 IQR above is: 337500.0
below count: 0, above count: 14024
q99.0 is: 472500.0, count: 3011, percent: 0.98%
total: 307095
```

In [19]:
```
# 3011 is a little too much, maybe
# try again
find_outlier(df['AMT_INCOME_TOTAL'], 0.999)
```

```
Report:
1.5 IQR below is: -22500.0, 1.5 IQR above is: 337500.0
below count: 0, above count: 14024
q99.9 is: 900000.0, count: 278, percent: 0.09%
total: 307095
```

In [20]:
```
# so one million seems to be the cut point
# but check those guys before removal
# because they may have significant amount of loans if they have that much income

# quick check the folks with income under 1 mil
# probably can still remove some of the top ones
# after all, annual income of 1 mil is very very rich
df_less_mil = df[df['AMT_INCOME_TOTAL'] <= 1000000]

df_less_mil.plot.box(column='AMT_INCOME_TOTAL', vert=False, figsize=(6,1), zorder=2, grid=True)
df_less_mil.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=Tru
plt.show()

len(df_less_mil)
```

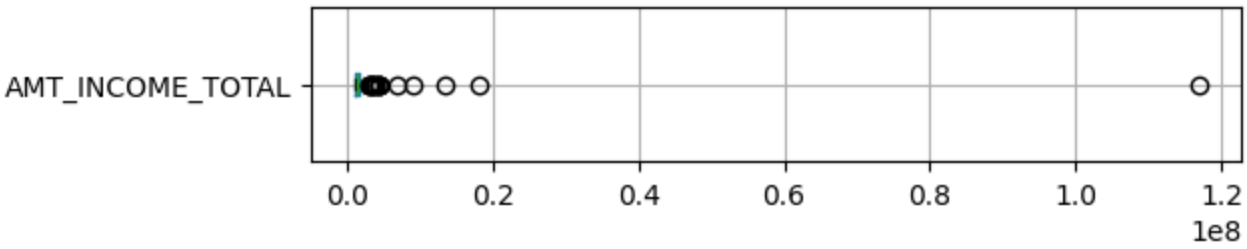


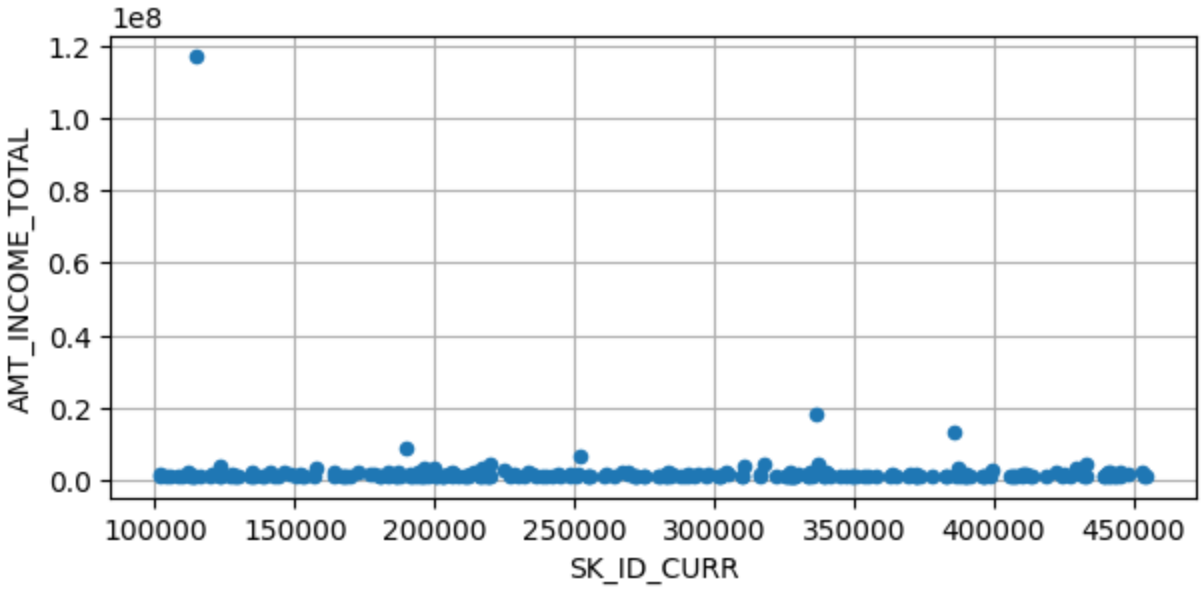



Out[20]: 306845

## 1. the millionaire anaysis

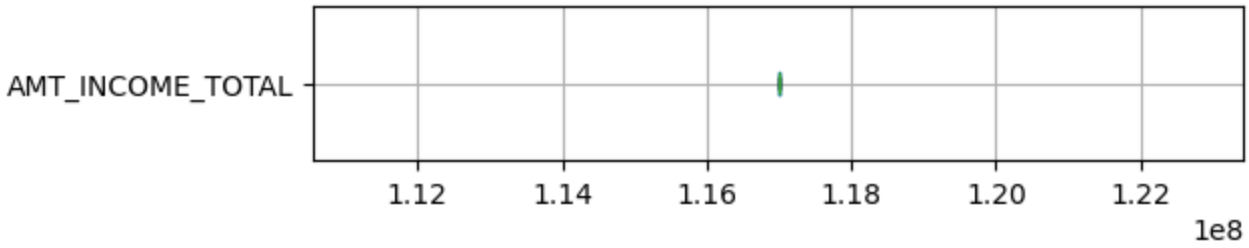
In [21]:
```
df_more_mil = df[df['AMT_INCOME_TOTAL'] > 1000000]

# same as plot.box, a little less typing
# seems fine to omit the zorder and grid params
# we will keep optimizing the code when we proceeed
df_more_mil.boxplot('AMT_INCOME_TOTAL', vert=False, figsize=(6,1))
df_more_mil.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=Tru
plt.show()

len(df_more_mil)
```

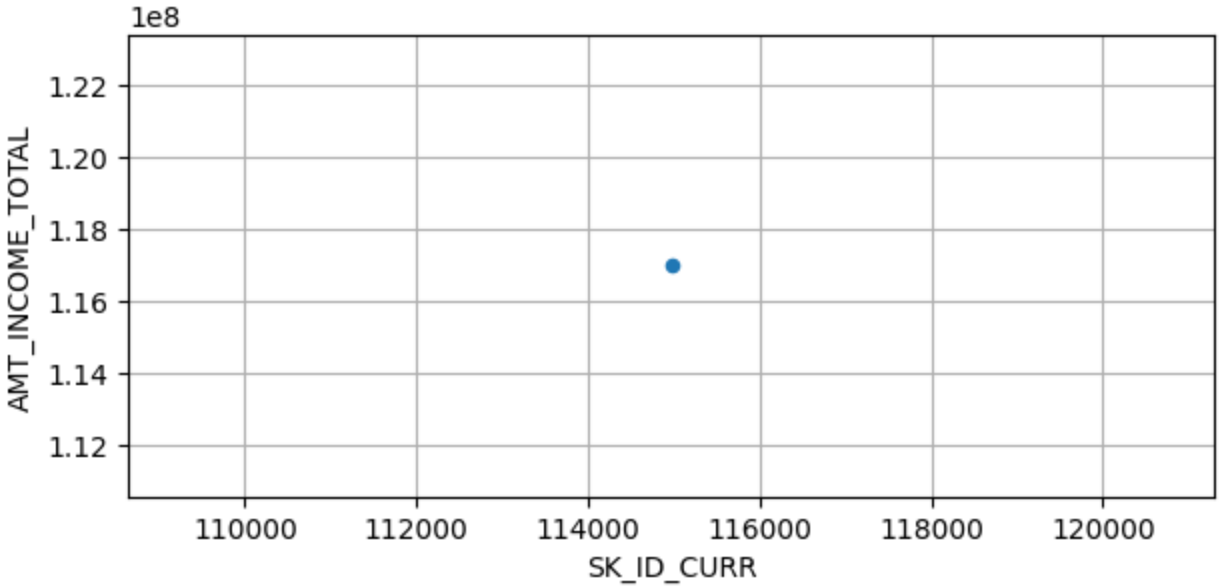



Out[21]: 250

In [22]:
```
# check that 120 mil guy
df_temp = df[df['AMT_INCOME_TOTAL'] > 110000000]

df_temp.boxplot('AMT_INCOME_TOTAL', vert=False, figsize=(6,1))
df_temp.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=True)
plt.show()

len(df_temp)
```




Out[22]: 1

In [23]:
```
# just 1 guy
# check other information about him/her
# turns out it's her, actually

df_temp
```

Out[23]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_ |
|---|---|---|---|---|---|---|
| **12840** | 114967 | Cash loans | F | N | Y | |

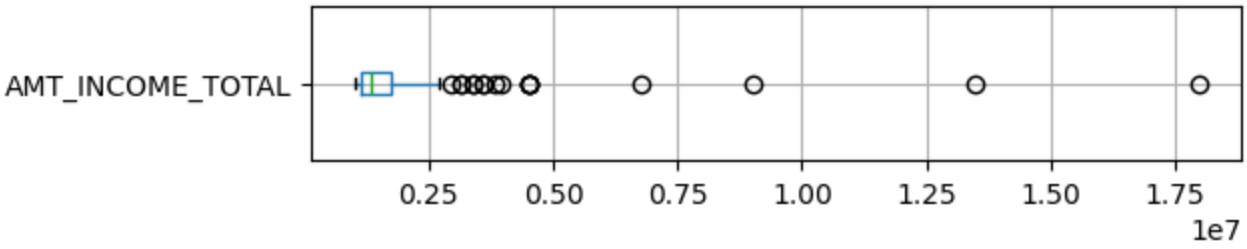
1 rows × 36 columns

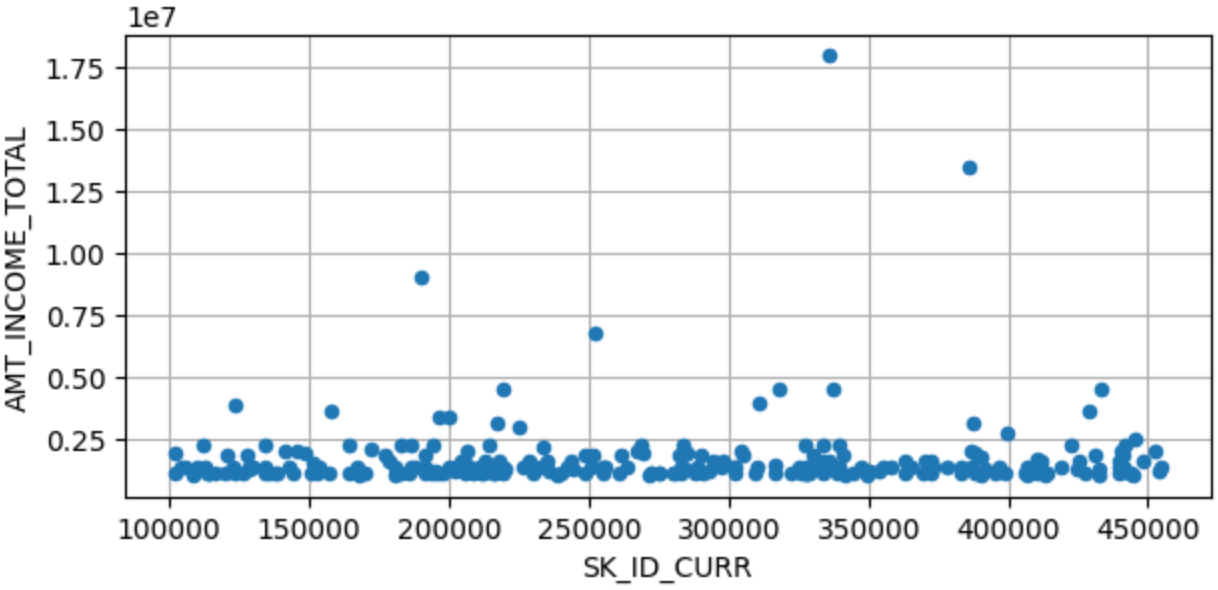
In [24]:
```
# she just sits in the middle, in terms of the stats
# so the income must be a typo
# will drop
df[['AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE']].describe()
```

Out[24]:

| | AMT_CREDIT | AMT_ANNUITY | AMT_GOODS_PRICE |
|---|---|---|---|
| **count** | 3.070950e+05 | 307095.000000 | 3.070950e+05 |
| **mean** | 5.993361e+05 | 27120.611972 | 5.384209e+05 |
| **std** | 4.025330e+05 | 14492.454729 | 3.694647e+05 |
| **min** | 4.500000e+04 | 1615.500000 | 4.050000e+04 |
| **25%** | 2.700000e+05 | 16551.000000 | 2.385000e+05 |
| **50%** | 5.146020e+05 | 24916.500000 | 4.500000e+05 |
| **75%** | 8.086500e+05 | 34596.000000 | 6.795000e+05 |
| **max** | 4.050000e+06 | 258025.500000 | 4.050000e+06 |

In [25]:
```
# check other millionaires
df_more_mil = df[ (df['AMT_INCOME_TOTAL'] > 1000000) & (df['AMT_INCOME_TOTAL'] < 110000000) ]

df_more_mil.boxplot('AMT_INCOME_TOTAL', vert=False, figsize=(6,1))
df_more_mil.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=Tru
plt.show()

len(df_more_mil)
```

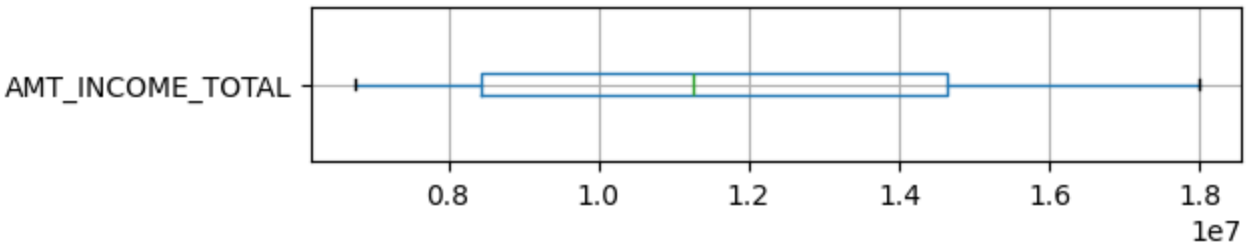


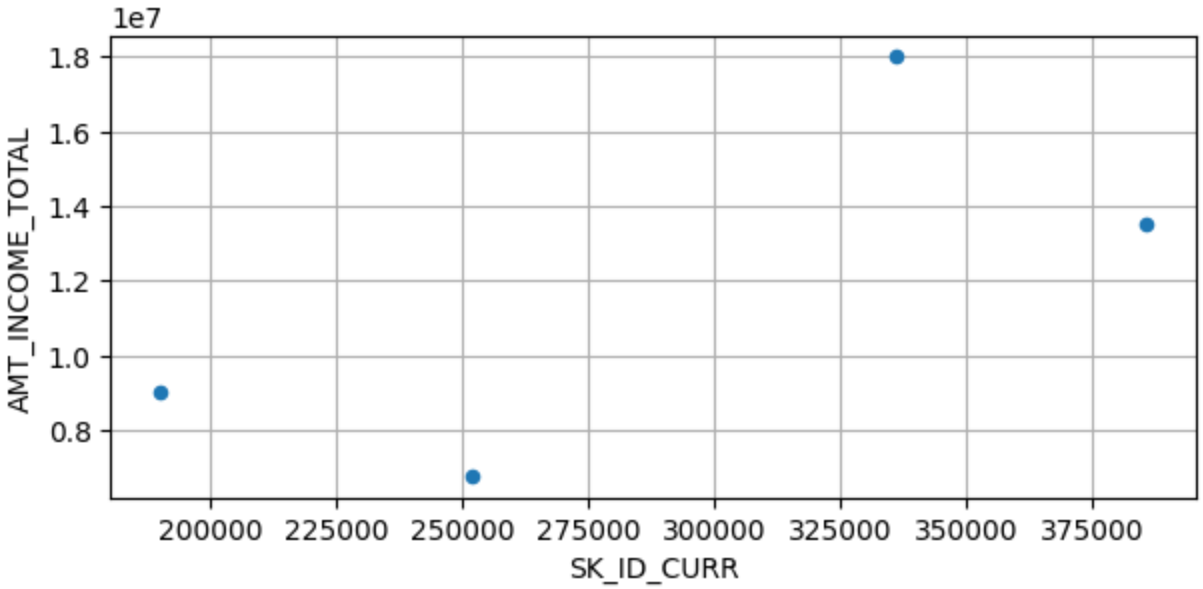




Out[25]: 249

In [26]:
```
# get details about the top 4 dots

df_temp2 = df_more_mil[df_more_mil['AMT_INCOME_TOTAL'] > 0.6*10000000]

df_temp2.boxplot('AMT_INCOME_TOTAL', vert=False, figsize=(6,1))
df_temp2.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=True)
```

```
plt.show()

len(df_temp2)
```




Out[26]: 4

In [27]:
```
# 4 dots are 4 people exactly
# check the details

df_temp2
```

Out[27]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT |
|---|---|---|---|---|---|---|
| **77768** | 190160 | Cash loans | F | Y | N | |
| **131127** | 252084 | Cash loans | M | Y | N | |
| **203693** | 336147 | Cash loans | M | Y | Y | |
| **246858** | 385674 | Cash loans | M | Y | Y | |

4 rows × 36 columns

In [28]:
```
# compare to the average
df[['AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE']].describe()
```

Out[28]:

| | AMT_CREDIT | AMT_ANNUITY | AMT_GOODS_PRICE |
|---|---|---|---|
| **count** | 3.070950e+05 | 307095.000000 | 3.070950e+05 |
| **mean** | 5.993361e+05 | 27120.611972 | 5.384209e+05 |
| **std** | 4.025330e+05 | 14492.454729 | 3.694647e+05 |
| **min** | 4.500000e+04 | 1615.500000 | 4.050000e+04 |
| **25%** | 2.700000e+05 | 16551.000000 | 2.385000e+05 |
| **50%** | 5.146020e+05 | 24916.500000 | 4.500000e+05 |
| **75%** | 8.086500e+05 | 34596.000000 | 6.795000e+05 |
| **max** | 4.050000e+06 | 258025.500000 | 4.050000e+06 |

In [29]:
```
# check the millionaire group's total loan amount
# compared to the bank's total loan amount
# see if the percentage is significant
df_more_mil['AMT_CREDIT'].sum() / ( df_more_mil['AMT_CREDIT'].sum() + \
                                    df_less_mil['AMT_CREDIT'].sum() ) * 100
```

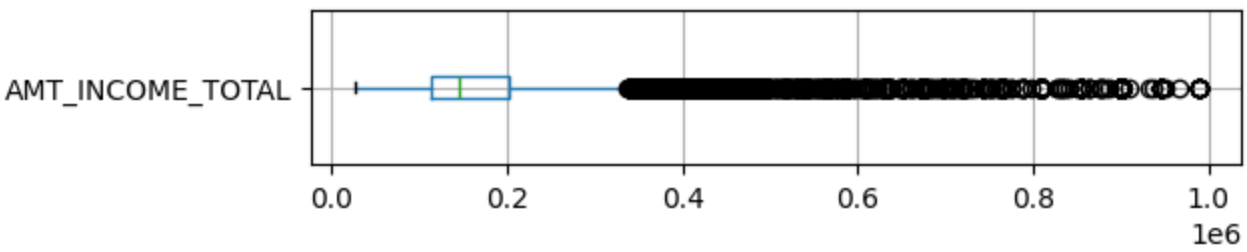
Out[29]:
```
0.1574627552598572
```

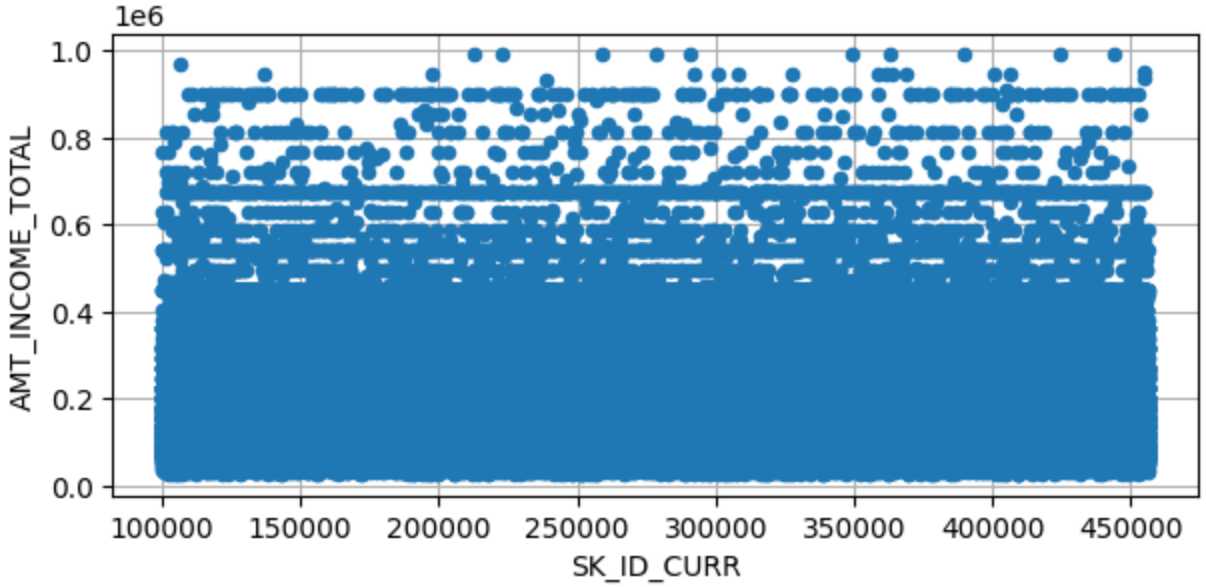
In [30]:
```
len(df_more_mil) / ( len(df_more_mil) + len(df_less_mil) ) * 100
```

Out[30]:
```
0.08108266524256416
```

In [31]:
```
# make a decision here about those 250 people:
# it is true that the amount percentage 0.15% is higher than the count percentage 0.08%
# but those millionaires do not have significantly more loan amount than others
# some might be typo, some might be just regular loans

# might be ok to remove those whose income > 1 mil
# still a majority of records is left with income <= 1mil
# if we need more demographics info about those multi millionaires
# we can run an analysis separately. only 250 records, 1 is probably typo
# let's do the removal
df = remove_outlier(df, 'AMT_INCOME_TOTAL', 1000000)

# check the result
df.boxplot('AMT_INCOME_TOTAL', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=True)
plt.show()

len(df)
```

```
records removed: 250
```






Out[31]: 306845

In [32]:
```
# 306845 now compared to 307221 where we started
```

## 2. reduce further

In [33]:
```
# recall
# 1.5 IQR above is: 337500.0
# q99.0 is: 472500.0, count: 3011, percent: 0.98%
# how about we delete those above 500k
# check how many there are first

len(df[df['AMT_INCOME_TOTAL'] > 500000])
```

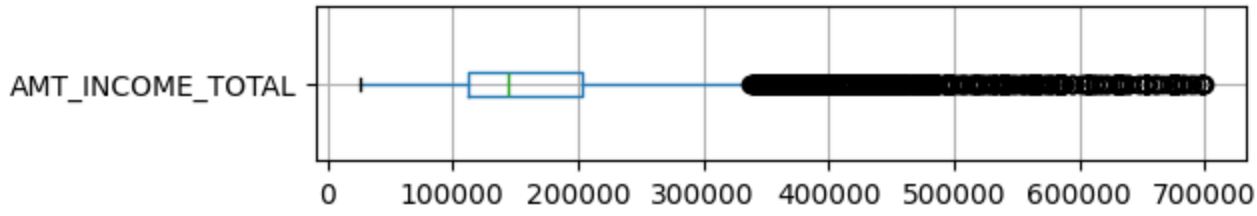
Out[33]: 2449

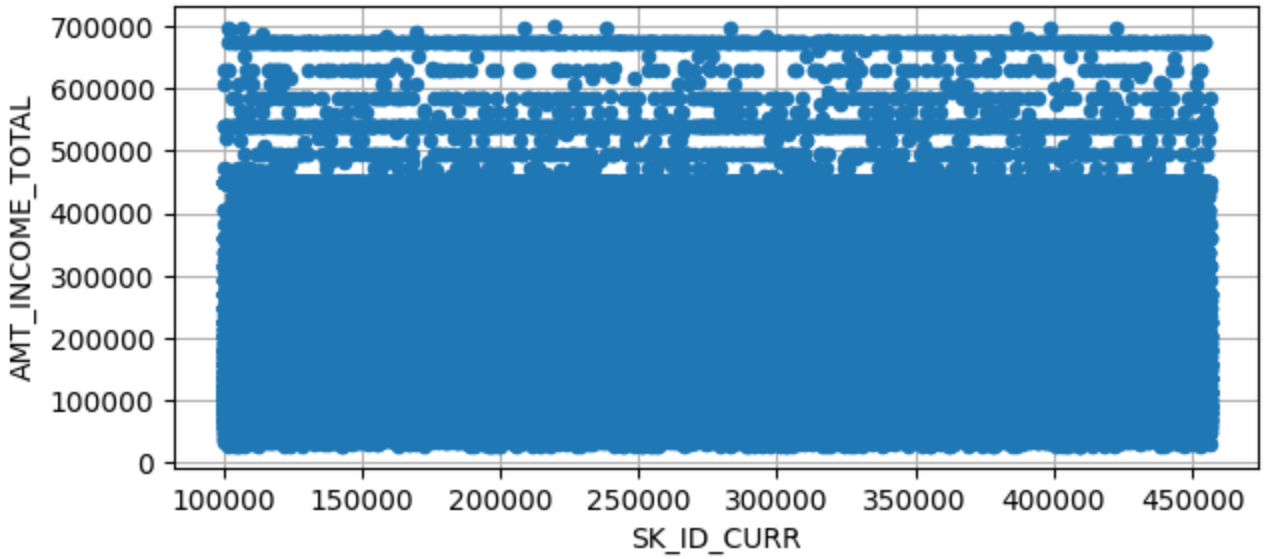
In [34]:
```
# maybe too many
# try 700k

len(df[df['AMT_INCOME_TOTAL'] > 700000])
```

Out[34]: 486

In [35]:
```
# let's do the removal
df = remove_outlier(df, 'AMT_INCOME_TOTAL', 700000)

# check the result
df.boxplot('AMT_INCOME_TOTAL', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_INCOME_TOTAL', figsize=(7,3), zorder=2, grid=True)
plt.show()

len(df)
```

```
records removed: 486
```





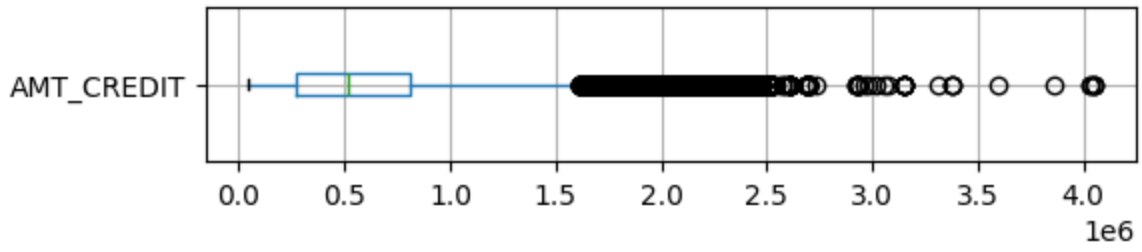

Out[35]: 306359

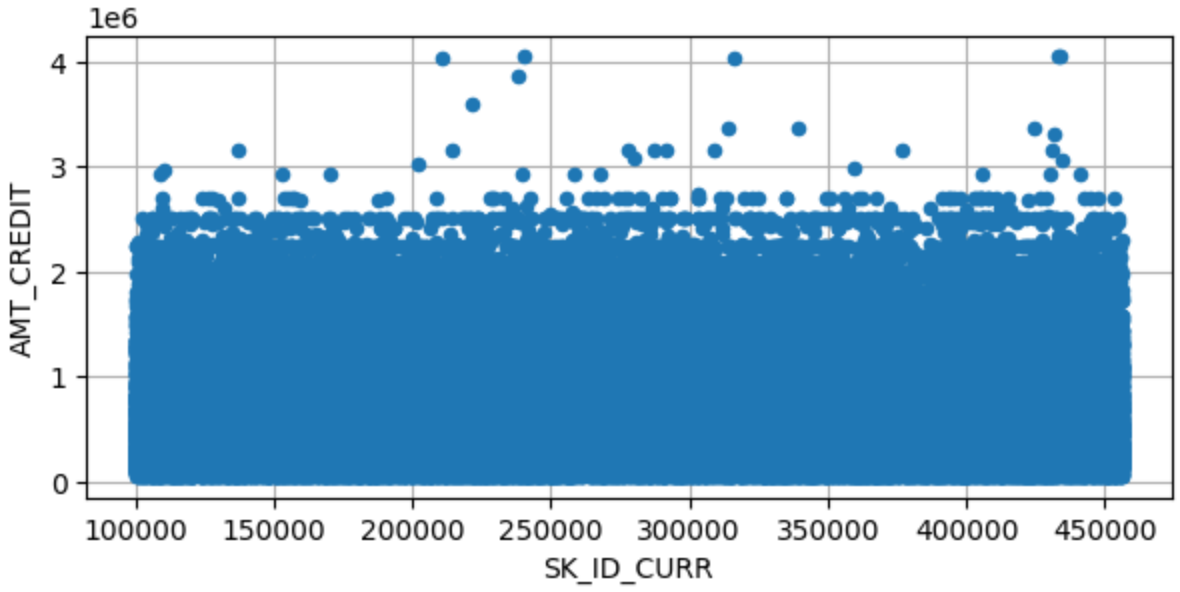
In [36]:
```
# 306359 now compared to 307221 where we started
```

## AMT_CREDIT

In [37]:
```
# check credit total
# repeat our process

# 1 chart
df.boxplot(column='AMT_CREDIT', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_CREDIT', figsize=(7,3), zorder=2, grid=True)
```

Out[37]: <Axes: xlabel='SK_ID_CURR', ylabel='AMT_CREDIT'>



In [38]:
```
# 2 check outlier
find_outlier(df['AMT_CREDIT'], 0.99)
```

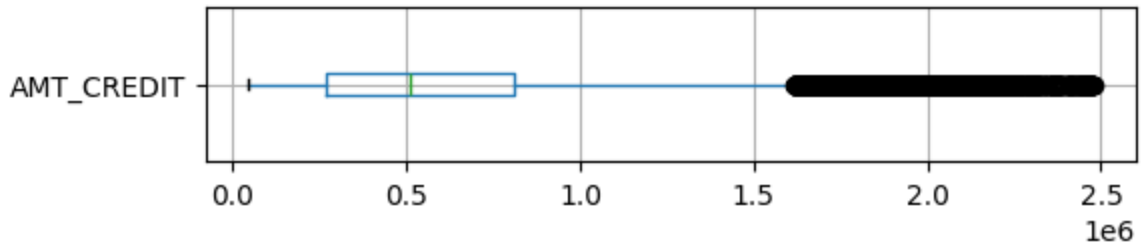
```
Report:
1.5 IQR below is: -537975.0, 1.5 IQR above is: 1616625.0
below count: 0, above count: 6396
q99.0 is: 1823242.5, count: 3057, percent: 1.00%
total: 306359
```

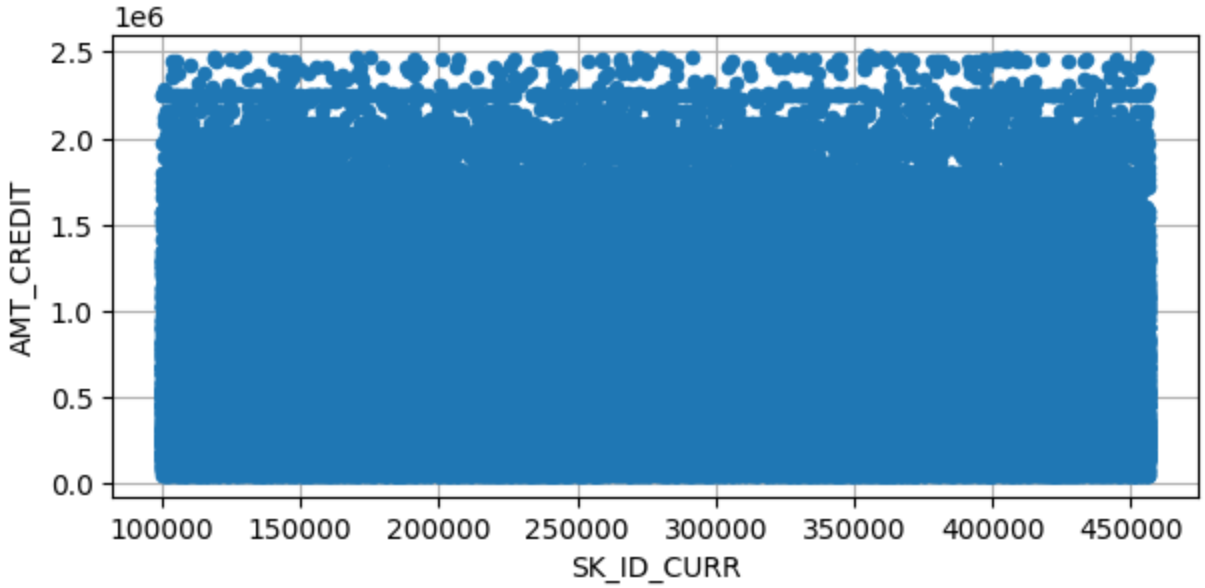
In [39]:
```
find_outlier(df['AMT_CREDIT'], 0.999)
```

```
Report:
1.5 IQR below is: -537975.0, 1.5 IQR above is: 1616625.0
below count: 0, above count: 6396
q99.9 is: 2517300.0, count: 117, percent: 0.04%
total: 306359
```

In [40]:
```
# 3 it is a little arbitrary but let's cut 2.5 * 1e6
# the scatter plot looks much looser above it
df = remove_outlier(df, 'AMT_CREDIT', 2500000)

# check the result
df.boxplot('AMT_CREDIT', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_CREDIT', figsize=(7,3), zorder=2, grid=True)
plt.show()

len(df)
```

```
records removed: 331
```



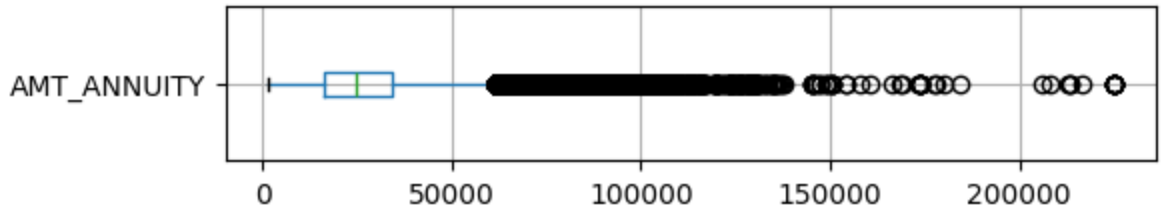

Out[40]: 306028

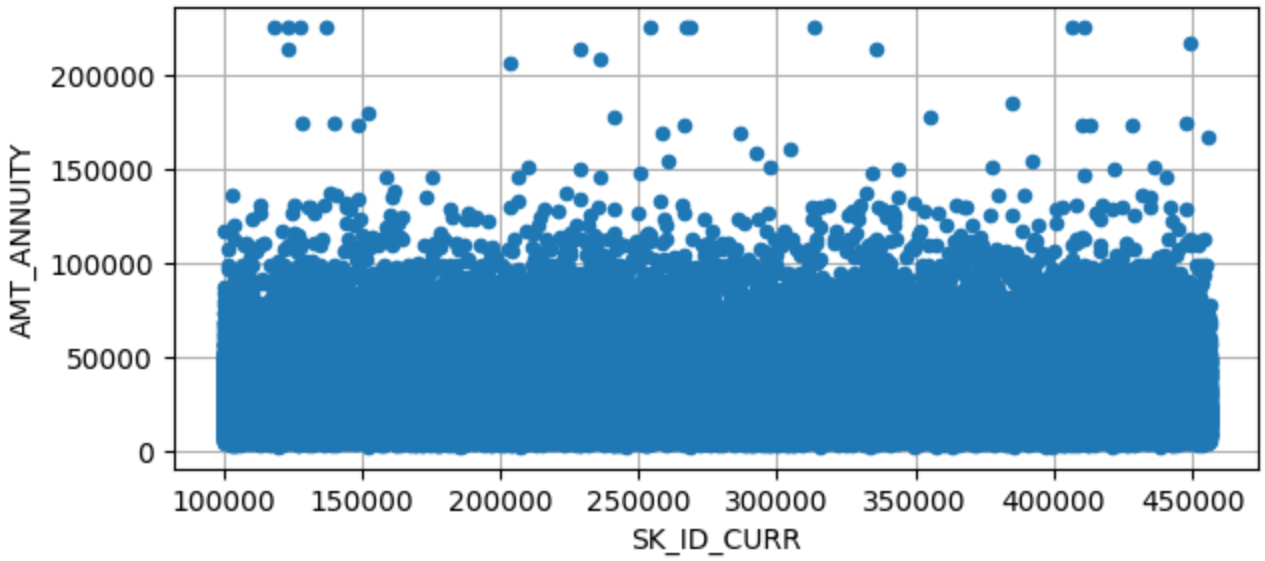
In [41]:
```
# 306028 now, (307221)
```

## AMT_ANNUITY

In [42]:
```
# we can almost copy paste this template as follows:
# 1 chart
df.boxplot(column='AMT_ANNUITY', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_ANNUITY', figsize=(7,3), zorder=2, grid=True)

# 2 check outlier
find_outlier(df['AMT_ANNUITY'], 0.99)
find_outlier(df['AMT_ANNUITY'], 0.999)
```

```
Report:
1.5 IQR below is: -10579.5, 1.5 IQR above is: 61672.5
below count: 0, above count: 6922
q99.0 is: 69165.0, count: 3056, percent: 1.00%
total: 306028
Report:
1.5 IQR below is: -10579.5, 1.5 IQR above is: 61672.5
below count: 0, above count: 6922
q99.9 is: 106947.0, count: 301, percent: 0.10%
total: 306028
```

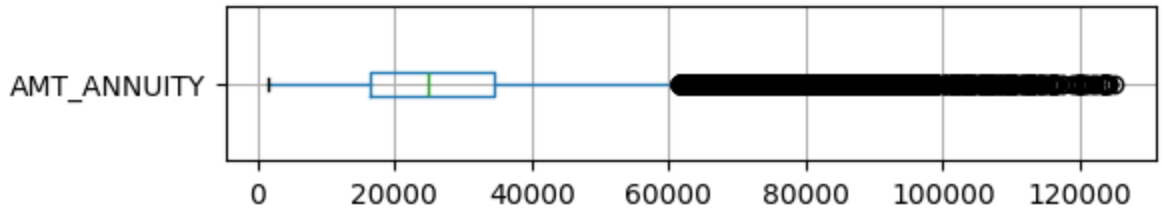


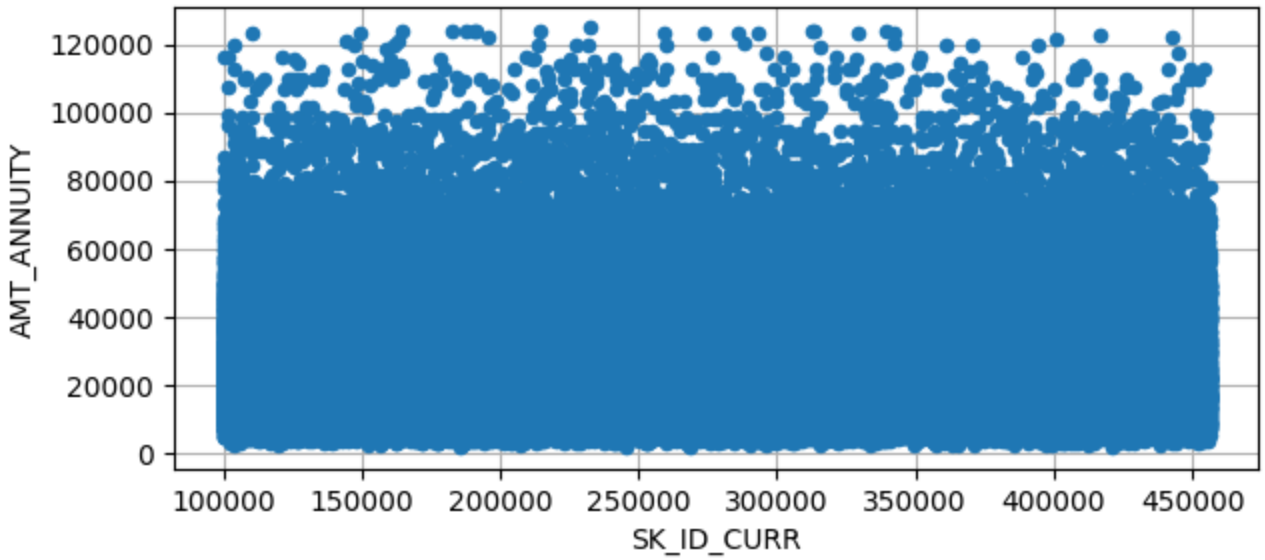




In [43]:
```
# 3 cut 125000 mostly based on the scatter plot
# there is no common sense number as to
# how much annuity should be
df = remove_outlier(df, 'AMT_ANNUITY', 125000)

# check the result
df.boxplot('AMT_ANNUITY', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_ANNUITY', figsize=(7,3), zorder=2, grid=True)

len(df)
```

```
records removed: 121
```

Out[43]: 305907



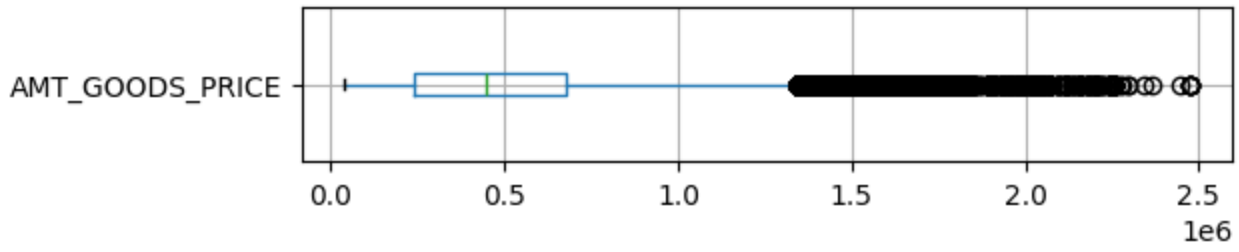



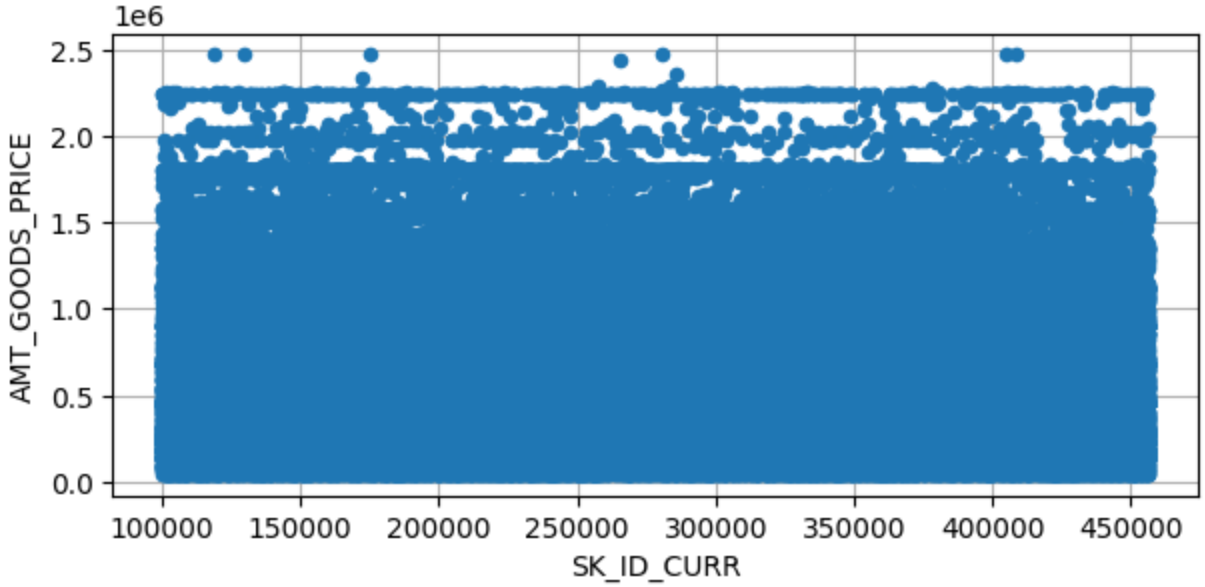

In [44]:
```
# 305907 now, (307221)
```

## AMT_GOODS_PRICE

In [45]:
```
# template:
# 1 chart
df.boxplot(column='AMT_GOODS_PRICE', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_GOODS_PRICE', figsize=(7,3),
                zorder=2, grid=True)

# 2 check outlier
find_outlier(df['AMT_GOODS_PRICE'], 0.99)
find_outlier(df['AMT_GOODS_PRICE'], 0.999)
```

```
Report:
1.5 IQR below is: -423000.0, 1.5 IQR above is: 1341000.0
below count: 0, above count: 14022
q99.0 is: 1799730.0000000105, count: 3060, percent: 1.00%
total: 305907
Report:
1.5 IQR below is: -423000.0, 1.5 IQR above is: 1341000.0
below count: 0, above count: 14022
q99.9 is: 2250000.0, count: 47, percent: 0.02%
total: 305907
```

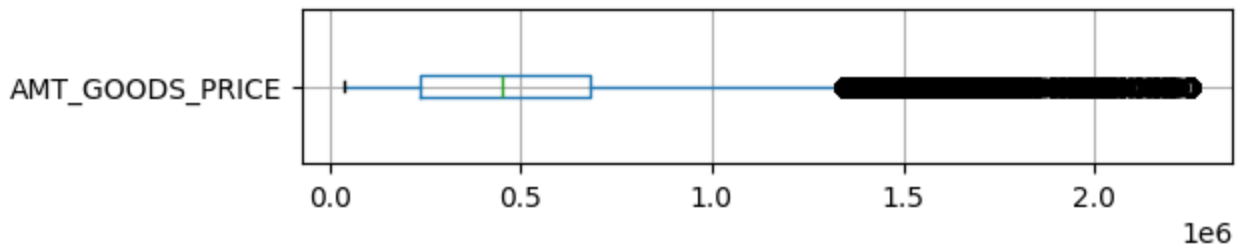


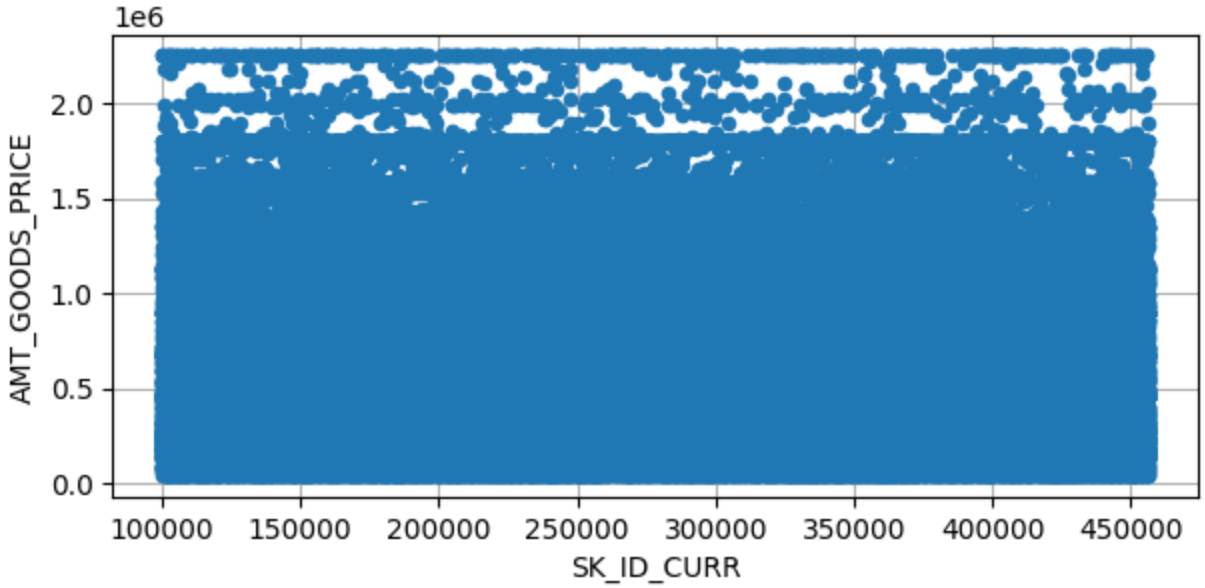



In [46]:
```
# 3 cut 2250000 or q999
df = remove_outlier(df, 'AMT_GOODS_PRICE', 2250000)

# check the result
df.boxplot('AMT_GOODS_PRICE', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='AMT_GOODS_PRICE', figsize=(7,3), zorder=2, grid=True)

len(df)
```

```
records removed: 47
```

Out[46]: 305860



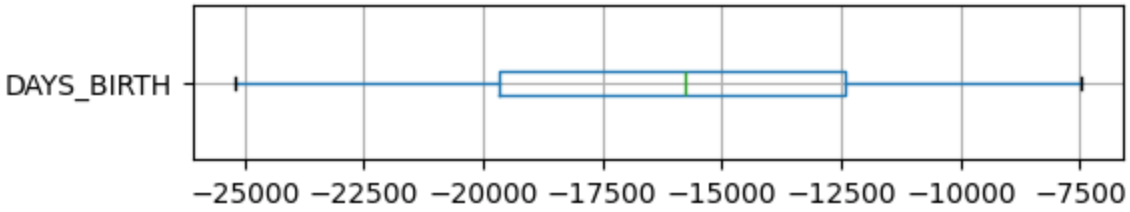

In [47]:
```
# 305860 now, (307221)
```

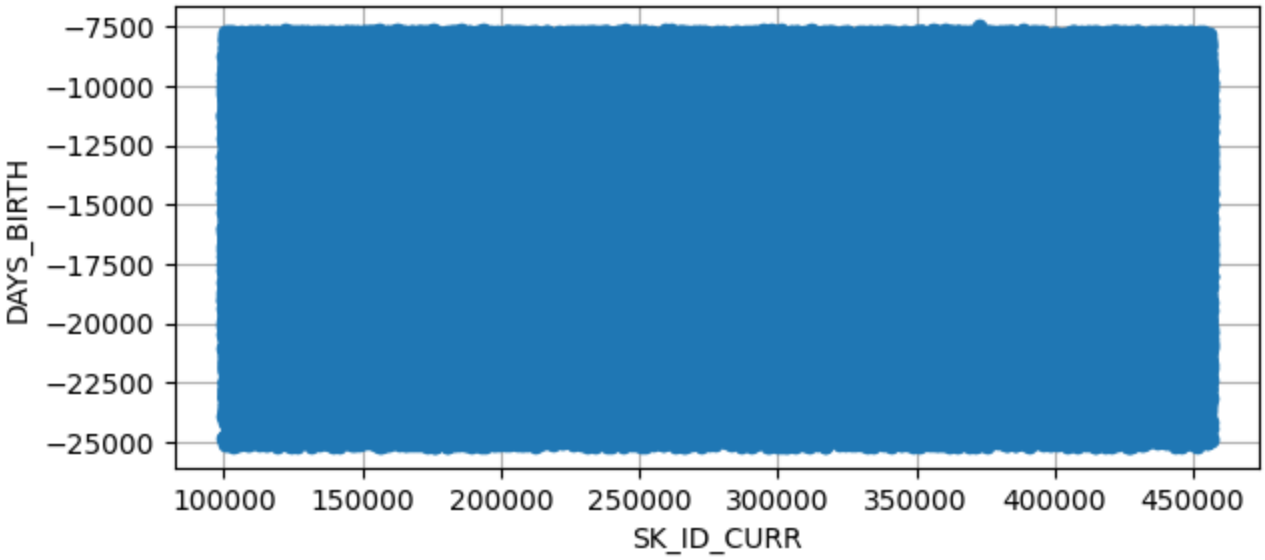
# DAYS_BIRTH

## 1. outlier

In [48]:
```
# template:
# 1 chart
df.boxplot(column='DAYS_BIRTH', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_BIRTH', figsize=(7,3), zorder=2, grid=True)

# 2 check outlier
find_outlier(df['DAYS_BIRTH'], 0.99)
find_outlier(df['DAYS_BIRTH'], 0.999)
```

```
Report:
1.5 IQR below is: -30606.0, 1.5 IQR above is: -1494.0
below count: 0, above count: 0
q99.0 is: -8262.0, count: 3053, percent: 1.00%
total: 305860
Report:
1.5 IQR below is: -30606.0, 1.5 IQR above is: -1494.0
below count: 0, above count: 0
q99.9 is: -7759.0, count: 304, percent: 0.10%
total: 305860
```




## 2. convert

In [49]:
```
# looks ok
# 305860 still
# however it is a little weird to have days to measure age
# let's convert that to years

# loc to replace value, directly use [] will have warning
# since df is a slice of the original df, not copy
df.loc[:, 'DAYS_BIRTH']
```

Out[49]:
```
0         -9461
1        -16765
2        -19046
3        -19005
4        -19932
           ...
307506    -9327
307507   -20775
307508   -14966
307509   -11961
307510   -16856
Name: DAYS_BIRTH, Length: 305860, dtype: int64
```

In [50]:
```
# to prevent this from being run again, use if
if df['DAYS_BIRTH'].dtype == 'int64':
    df.loc[:, 'DAYS_BIRTH'] = df['DAYS_BIRTH'] / -365

df['DAYS_BIRTH']
```

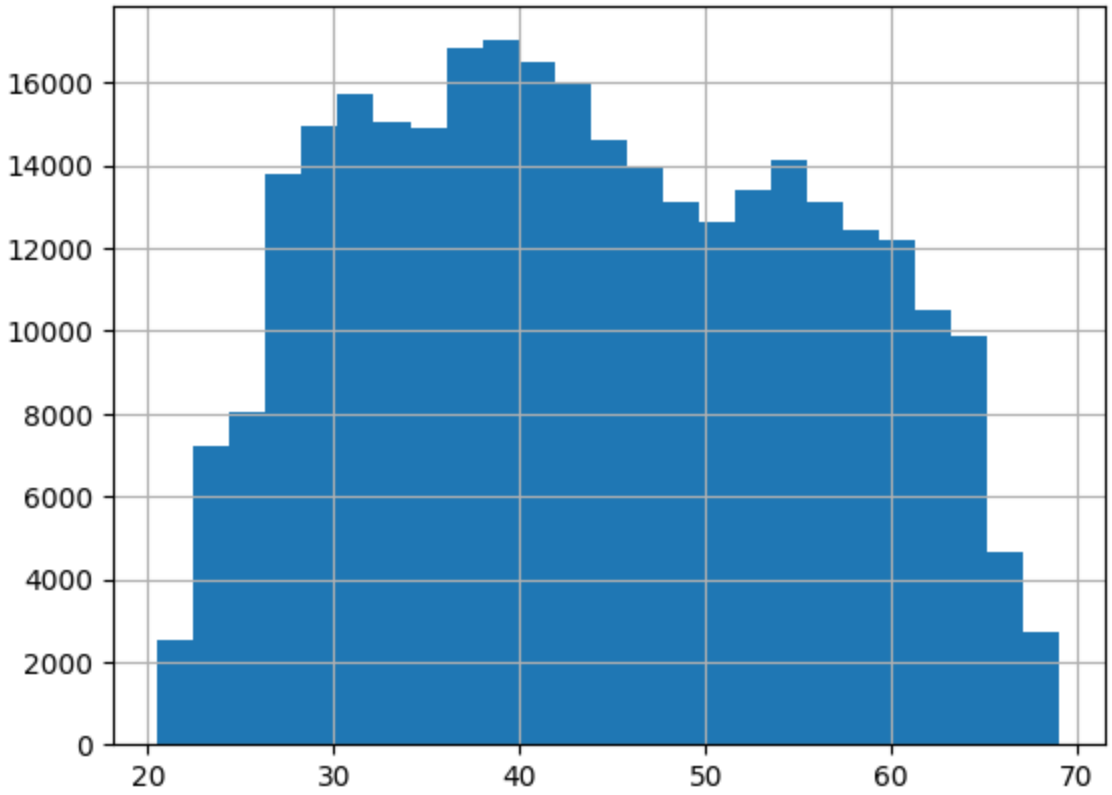
Out[50]:
```
0         25.920548
1         45.931507
2         52.180822
3         52.068493
4         54.608219
             ...
307506    25.553425
307507    56.917808
307508    41.002740
307509    32.769863
307510    46.180822
Name: DAYS_BIRTH, Length: 305860, dtype: float64
```

In [51]:
```
# change the column name as well
df = df.rename(columns={'DAYS_BIRTH': 'AGE'})
df['AGE']
```

Out[51]:
```
0         25.920548
1         45.931507
2         52.180822
3         52.068493
4         54.608219
             ...
307506    25.553425
307507    56.917808
307508    41.002740
307509    32.769863
307510    46.180822
Name: AGE, Length: 305860, dtype: float64
```

In [52]:
```
# check hist
df['AGE'].hist(bins=25)
```

Out[52]:
```
<Axes: >
```



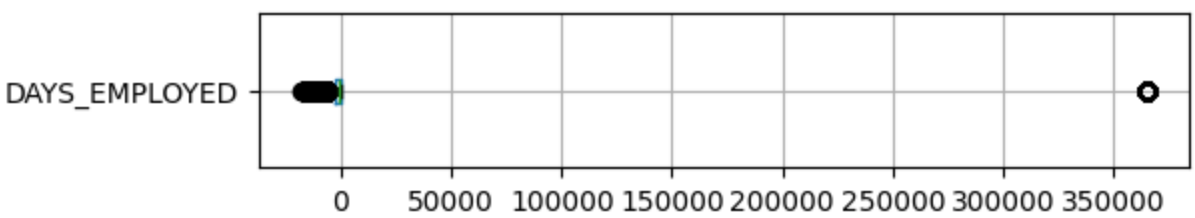

In [53]:
```
# looks good for 'Age' according to common sense
# 305860 now, (307221)
```

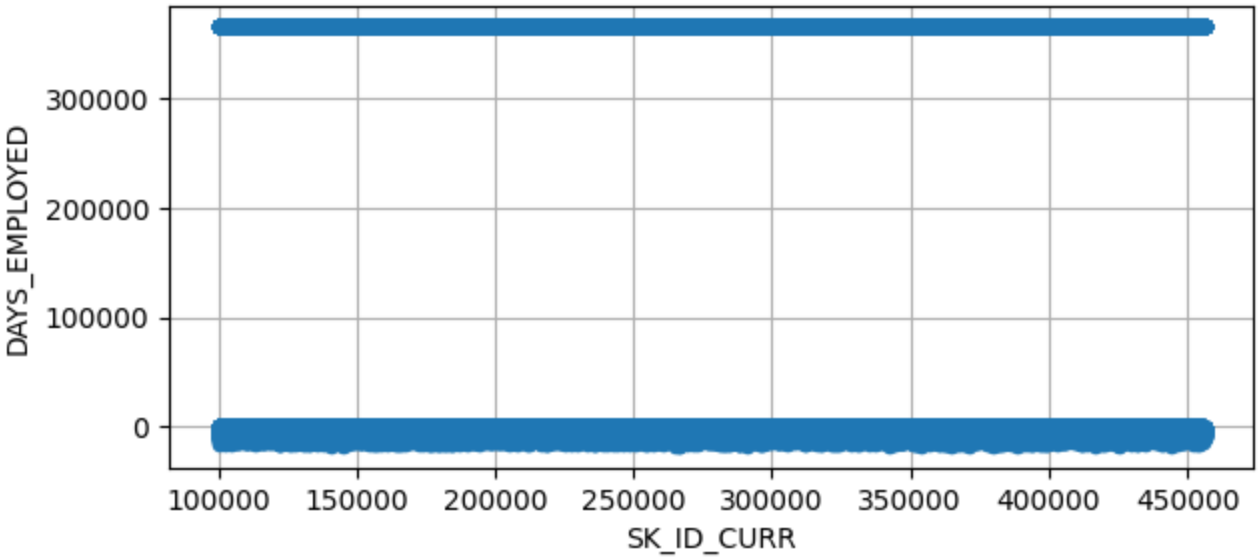
## DAYS_EMPLOYED

### 1. outlier

In [54]:
```
# template:
# 1 chart
df.boxplot(column='DAYS_EMPLOYED', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_EMPLOYED', figsize=(7,3), zorder=2, grid=True)

# 2 check outlier
find_outlier(df['DAYS_EMPLOYED'], 0.99)
find_outlier(df['DAYS_EMPLOYED'], 0.999)
```

```
Report:
1.5 IQR below is: -6462.0, 1.5 IQR above is: 3418.0
below count: 16750, above count: 55261
q99.0 is: 365243.0, count: 0, percent: 0.00%
total: 305860
Report:
1.5 IQR below is: -6462.0, 1.5 IQR above is: 3418.0
below count: 16750, above count: 55261
q99.9 is: 365243.0, count: 0, percent: 0.00%
total: 305860
```

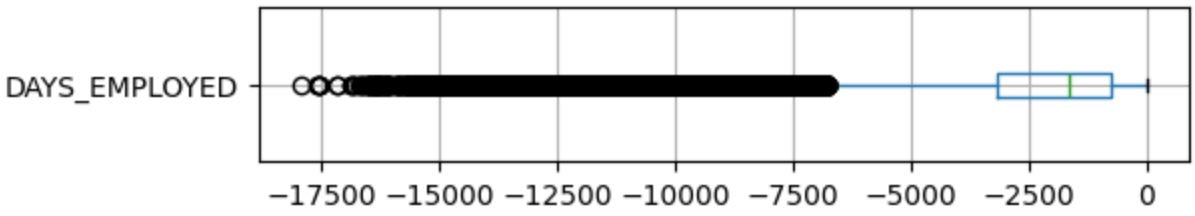


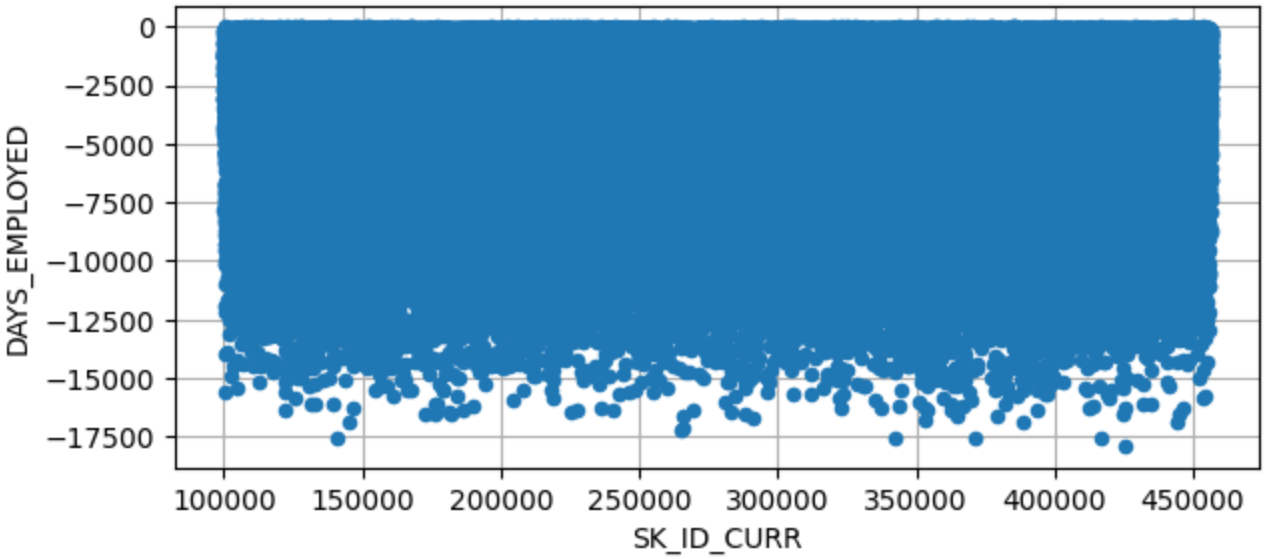



In [55]:
```
# it is weird. everything should be <0
# change those sky high outliers to value of 1, same int type, but basically an invalid value
# not sure why the original data has this 350000ish value
# which is 1000 years!
# too many records set to this huge number
# guess this means those people are unemployed
df.loc[df['DAYS_EMPLOYED']>200000, 'DAYS_EMPLOYED'] = 1
```

In [56]:
```
# ignore the ones with value of 1 for a temporary df
df_temp = df[df['DAYS_EMPLOYED'] <= 0]

# check the result
df_temp.boxplot('DAYS_EMPLOYED', figsize=(6,1), vert=False)
df_temp.plot.scatter(x='SK_ID_CURR', y='DAYS_EMPLOYED', figsize=(7,3), zorder=2, grid=True)

len(df_temp)
```

Out[56]: 250599






In [57]:
```
# looks kinda ok
# but we can remove some of the bottoms
```

In [58]:
```
# at this point, values become negative
# it is probably wise to revise our functions
# so they can work both ways - negative and positive
# copy the original functions from the 'CNT_CHILDREN' section
# revise as below

# if q < 0.2 it means we are looking at the bottom, not the top
def find_outlier(column, q):
    # regular IQR analysis
    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)
    IQR = Q3 - Q1

    below = Q1 - 1.5 * IQR
    above = Q3 + 1.5 * IQR

    below_count = len(column[column < below])
    above_count = len(column[column > above])

    # custom Q analysis
    qresult = column.quantile(q)

    if q > 0.2:
        lentop = len(column[column > qresult])
    else:
        # actually 'lenbottom'
        lentop = len(column[column < qresult])

    lentotal = len(column)

    percent = lentop / lentotal * 100
    percent_str = f'{percent:.2f}%'

    # report
    print('Report:\n'
          f'1.5 IQR below is: {below}, 1.5 IQR above is: {above}\n'
          f'below count: {below_count}, above count: {above_count}\n'
          f'q{q*100} is: {qresult}, count: {lentop}, percent: {percent_str}\n'
          f'total: {lentotal}')
```

```
    return None

# check is exclusive of the cutting point
# remove is exclusive
# keep is inclusive
def remove_outlier(df, column, point, top=True):
    if top:
        # remove top
        print(f'records removed: {len(df[df[column] > point])}')
        dfnew = df[df[column] <= point]
    else:
        # remove bottom
        print(f'records removed: {len(df[df[column] < point])}')
        dfnew = df[df[column] >= point]

    return dfnew
```

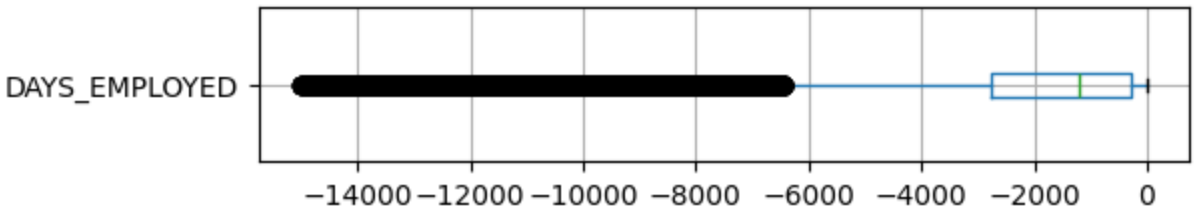
In [59]:
```
find_outlier(df['DAYS_EMPLOYED'], 0.001)
```

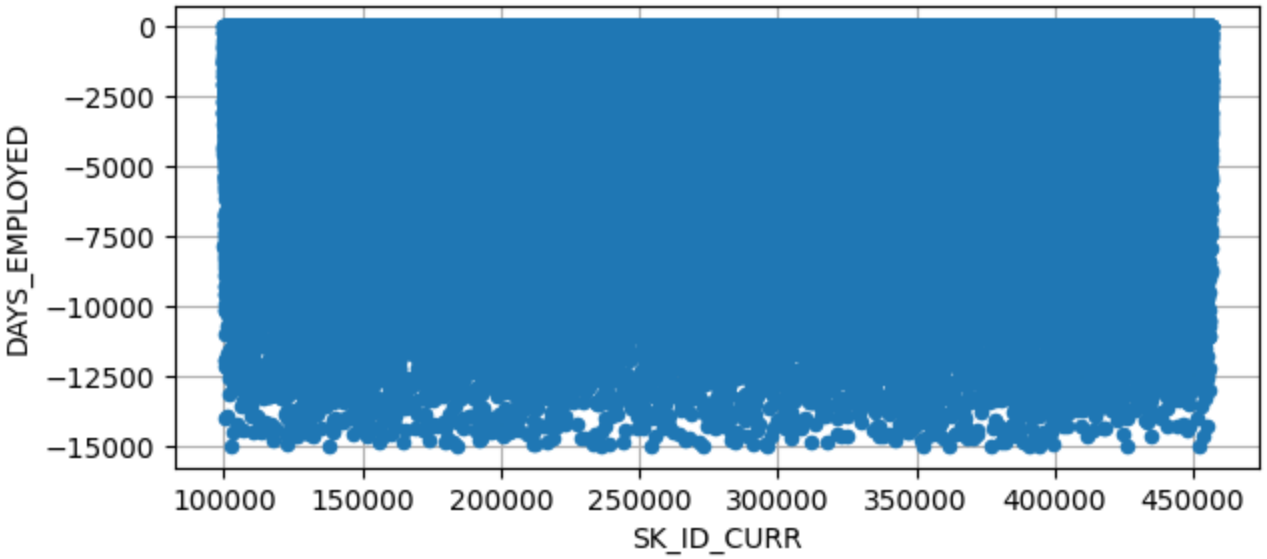
```
Report:
1.5 IQR below is: -6462.0, 1.5 IQR above is: 3418.0
below count: 16750, above count: 0
q0.1 is: -14338.564, count: 306, percent: 0.10%
total: 305860
```

In [60]:
```
# a little arbitrary but let's remove < 15000 or around q0.1
# which is 41 years, seems long enough to be considered
# 'outlier'

# cut at 15000
df = remove_outlier(df, 'DAYS_EMPLOYED', -15000, top=False)

# check the result
df.boxplot('DAYS_EMPLOYED', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_EMPLOYED', figsize=(7,3), zorder=2, grid=True)

len(df)
```

```
records removed: 162
```

Out[60]: 305698






## 2. convert

In [61]:
```
# again, convert to years from days
df['DAYS_EMPLOYED']
```

Out[61]:
```
0         -637
1        -1188
2         -225
3        -3039
4        -3038
          ...
307506    -236
307507       1
307508   -7921
307509   -4786
307510   -1262
Name: DAYS_EMPLOYED, Length: 305698, dtype: int64
```

In [62]:
```
# to prevent this from being run again, use if
if df['DAYS_EMPLOYED'].dtype == 'int64':
    df.loc[:, 'DAYS_EMPLOYED'] = df['DAYS_EMPLOYED'] / -365

df['DAYS_EMPLOYED']
```

Out[62]:
```
0          1.745205
1          3.254795
2          0.616438
3          8.326027
4          8.323288
             ...
307506     0.646575
307507    -0.002740
307508    21.701370
307509    13.112329
307510     3.457534
Name: DAYS_EMPLOYED, Length: 305698, dtype: float64
```

In [63]:
```
# rename
df = df.rename(columns={'DAYS_EMPLOYED': 'AGE_EMPLOYED'})
df['AGE_EMPLOYED']
```

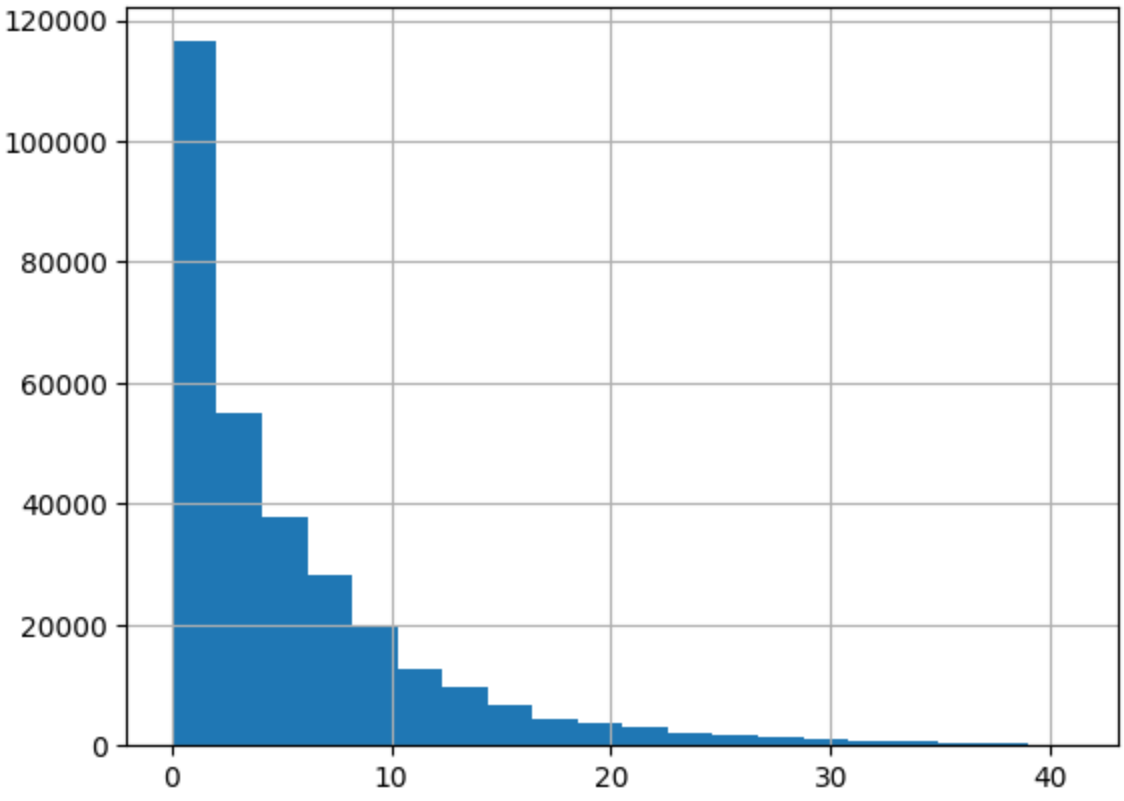
Out[63]:
```
0          1.745205
1          3.254795
2          0.616438
3          8.326027
4          8.323288
            ...
307506     0.646575
307507    -0.002740
307508    21.701370
307509    13.112329
307510     3.457534
Name: AGE_EMPLOYED, Length: 305698, dtype: float64
```

In [64]:
```
# the negative values are from those '-1 day'
# means unemployed
# check how many

len(df[df['AGE_EMPLOYED'] < 0])
```

Out[64]:
```
55261
```

In [65]:
```
# check hist
df['AGE_EMPLOYED'].hist(bins=20)
```

Out[65]:
```
<Axes: >
```




In [66]:
```
# 305698 now, (307221)
```

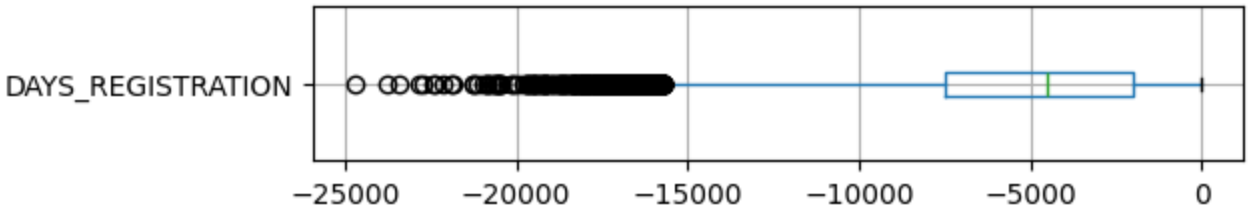
## DAYS_REGISTRATION

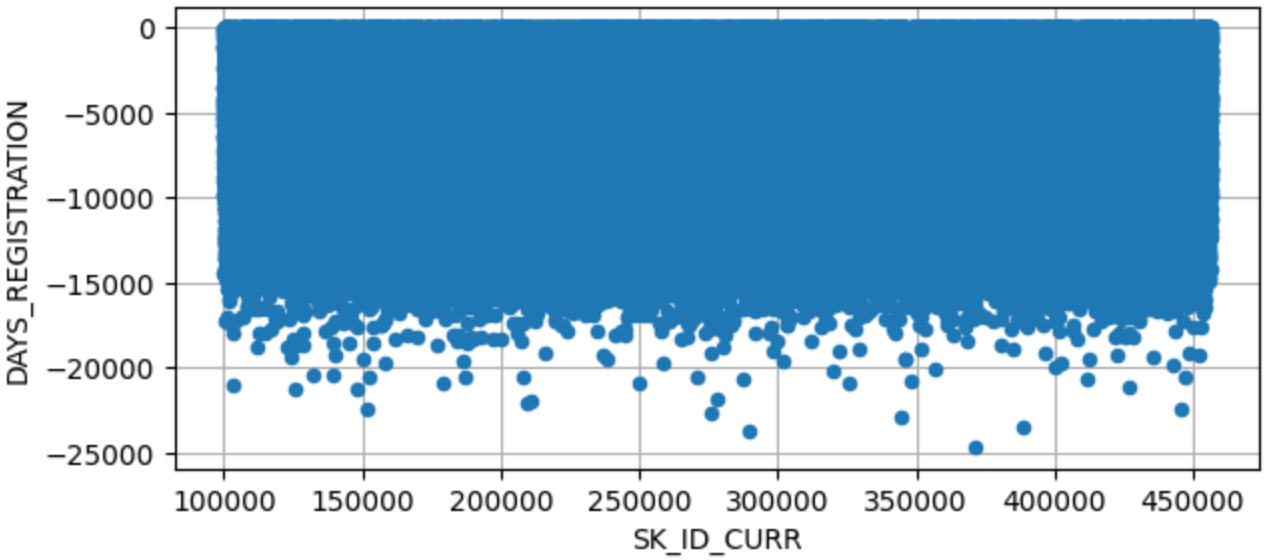
### 1. outlier

In [67]:
```
# template:
# 1 chart
```

```
df.boxplot(column='DAYS_REGISTRATION', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_REGISTRATION', figsize=(7,3), zorder=2, grid=True)

# 2 check outlier
find_outlier(df['DAYS_REGISTRATION'], 0.01)
find_outlier(df['DAYS_REGISTRATION'], 0.001)
```

```
Report:
1.5 IQR below is: -15684.5, 1.5 IQR above is: 6191.5
below count: 650, above count: 0
q1.0 is: -13878.0, count: 3056, percent: 1.00%
total: 305698
Report:
1.5 IQR below is: -15684.5, 1.5 IQR above is: 6191.5
below count: 650, above count: 0
q0.1 is: -16495.212, count: 306, percent: 0.10%
total: 305698
```

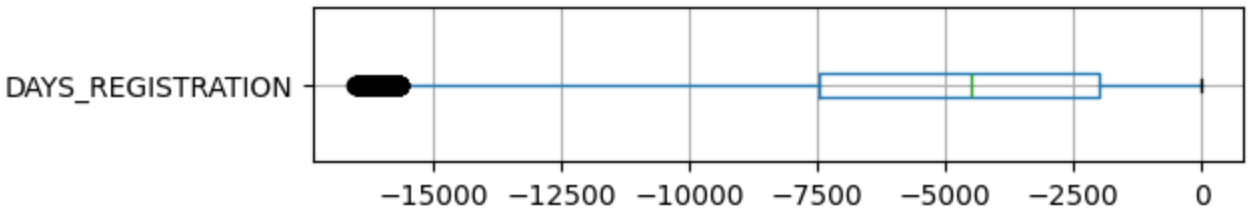


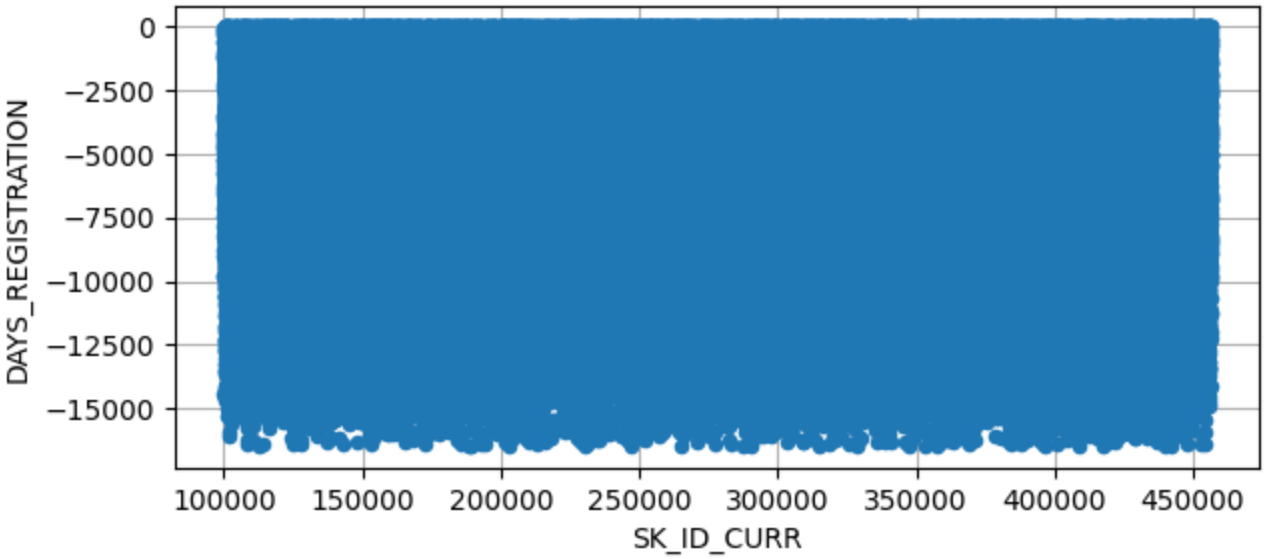




In [68]:
```
# 3 cut at -16500 or q0.1
# 45 years
df = remove_outlier(df, 'DAYS_REGISTRATION', -16500, top=False)

# check the result
df.boxplot('DAYS_REGISTRATION', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_REGISTRATION', figsize=(7,3), zorder=2, grid=True)

len(df)
```

```
records removed: 305
```

Out[68]: 305393






## 2. convert

In [69]:
```
# 1. check
df['DAYS_REGISTRATION']
```

Out[69]:
```
0         -3648.0
1         -1186.0
2         -4260.0
3         -9833.0
4         -4311.0
             ...
307506    -8456.0
307507    -4388.0
307508    -6737.0
307509    -2562.0
307510    -5128.0
Name: DAYS_REGISTRATION, Length: 305393, dtype: float64
```

In [70]:
```
# 2. convert. it is already float dtype
# so use some other method to detect if it is already converted

if df['DAYS_REGISTRATION'].min() < -1000:
    df.loc[:, 'DAYS_REGISTRATION'] = df['DAYS_REGISTRATION'] / -365

df['DAYS_REGISTRATION']
```

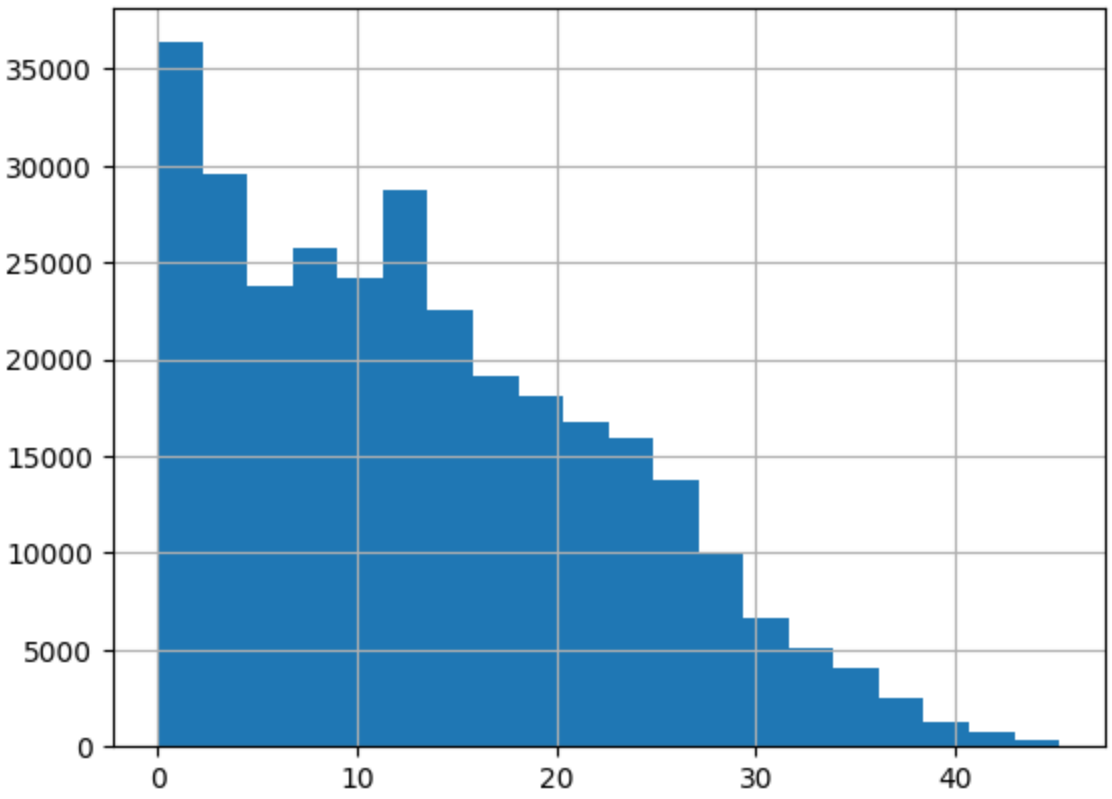
Out[70]:
```
0          9.994521
1          3.249315
2         11.671233
3         26.939726
4         11.810959
              ...
307506    23.167123
307507    12.021918
307508    18.457534
307509     7.019178
307510    14.049315
Name: DAYS_REGISTRATION, Length: 305393, dtype: float64
```

In [71]:
```
# 3. rename
df = df.rename(columns={'DAYS_REGISTRATION': 'AGE_REGISTRATION'})
df['AGE_REGISTRATION']
```

Out[71]:
```
0          9.994521
1          3.249315
2         11.671233
3         26.939726
4         11.810959
             ...
307506    23.167123
307507    12.021918
307508    18.457534
307509     7.019178
307510    14.049315
Name: AGE_REGISTRATION, Length: 305393, dtype: float64
```

In [72]:
```
# 4. hist
df['AGE_REGISTRATION'].hist(bins=20)
```

Out[72]: <Axes: >



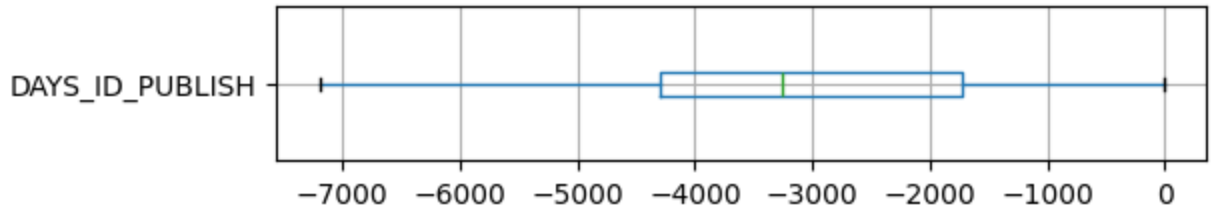

In [73]:
```
# looks good
# 305393 now, (307221)
```

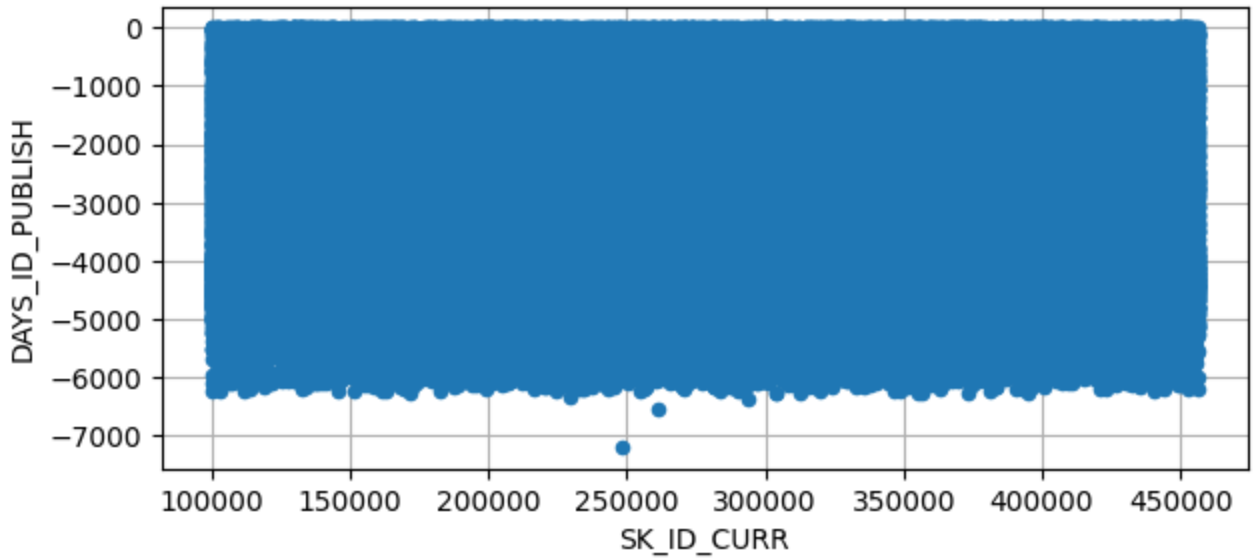
## DAYS_ID_PUBLISH

### 1. outlier

In [74]:
```
# template:
# 1 chart
df.boxplot(column='DAYS_ID_PUBLISH', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_ID_PUBLISH', figsize=(7,3), zorder=2, grid=True)

# 2 check outlier
find_outlier(df['DAYS_ID_PUBLISH'], 0.01)
find_outlier(df['DAYS_ID_PUBLISH'], 0.001)
```

```
Report:
1.5 IQR below is: -8166.5, 1.5 IQR above is: 2149.5
below count: 0, above count: 0
q1.0 is: -5446.0, count: 3051, percent: 1.00%
total: 305393
Report:
1.5 IQR below is: -8166.5, 1.5 IQR above is: 2149.5
below count: 0, above count: 0
q0.1 is: -6037.0, count: 305, percent: 0.10%
total: 305393
```



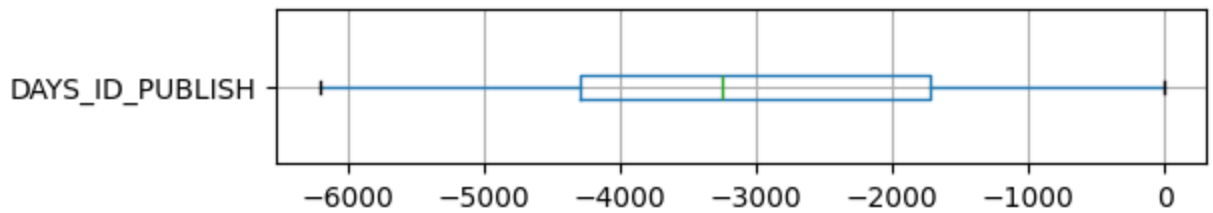

In [75]:
```
find_outlier(df['DAYS_ID_PUBLISH'], 0.0001)
```

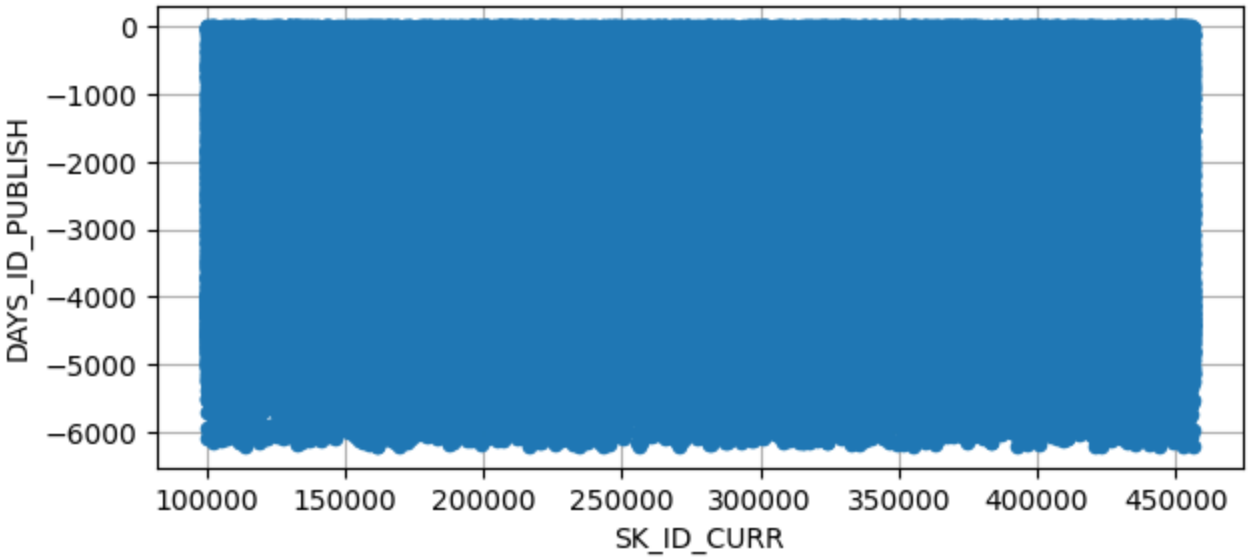
```
Report:
1.5 IQR below is: -8166.5, 1.5 IQR above is: 2149.5
below count: 0, above count: 0
q0.01 is: -6211.4608, count: 31, percent: 0.01%
total: 305393
```

In [76]:
```
# cut at -6211
df = remove_outlier(df, 'DAYS_ID_PUBLISH', -6211, top=False)

# check the result
df.boxplot('DAYS_ID_PUBLISH', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='DAYS_ID_PUBLISH', figsize=(7,3), zorder=2, grid=True)

len(df)
```

```
records removed: 31
```

Out[76]: 305362






## 2. convert

In [77]:
```
# rinse and repeat
# 1. check
df['DAYS_ID_PUBLISH']
```

Out[77]:
```
0        -2120
1         -291
2        -2531
3        -2437
4        -3458
          ...
307506   -1982
307507   -4090
307508   -5150
307509    -931
307510    -410
Name: DAYS_ID_PUBLISH, Length: 305362, dtype: int64
```

In [78]:
```
# 2. convert

if df['DAYS_ID_PUBLISH'].dtype == 'int64':
    df.loc[:, 'DAYS_ID_PUBLISH'] = df['DAYS_ID_PUBLISH'] / -365

df['DAYS_ID_PUBLISH']
```

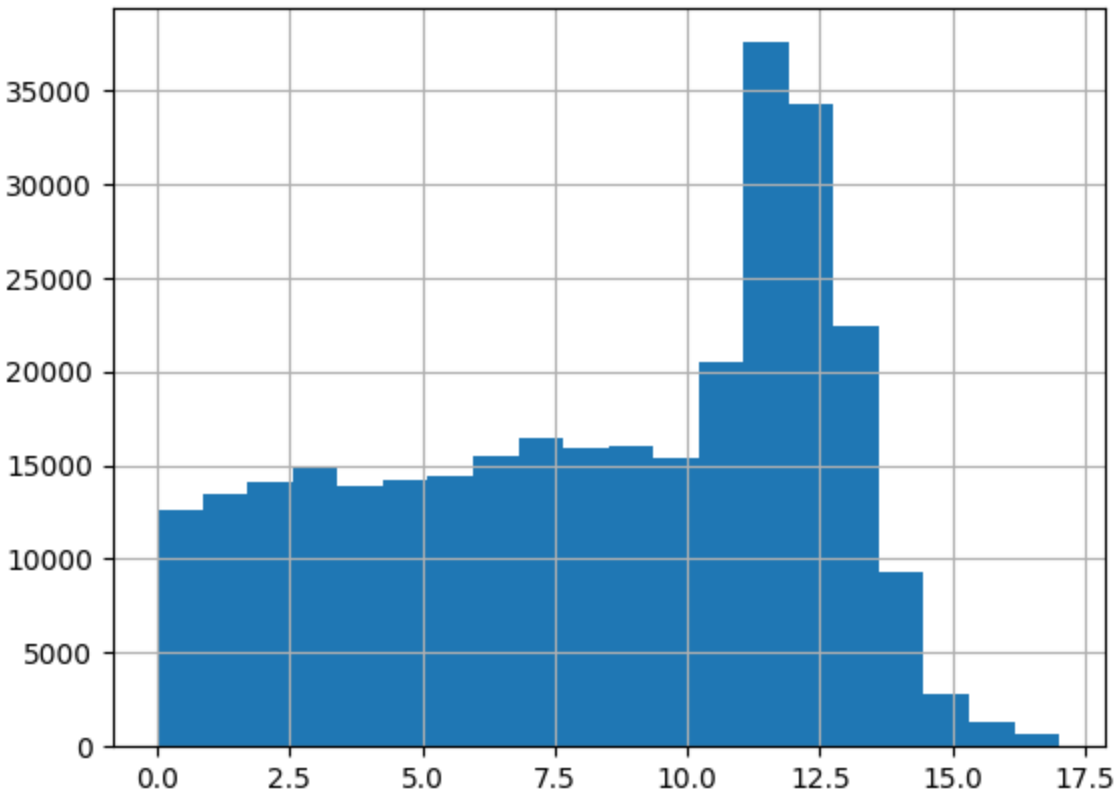
Out[78]:
```
0          5.808219
1          0.797260
2          6.934247
3          6.676712
4          9.473973
             ...
307506     5.430137
307507    11.205479
307508    14.109589
307509     2.550685
307510     1.123288
Name: DAYS_ID_PUBLISH, Length: 305362, dtype: float64
```

In [79]:
```
# 3. rename
df = df.rename(columns={'DAYS_ID_PUBLISH': 'AGE_ID'})
df['AGE_ID']
```

Out[79]:
```
0          5.808219
1          0.797260
2          6.934247
3          6.676712
4          9.473973
             ...
307506     5.430137
307507    11.205479
307508    14.109589
307509     2.550685
307510     1.123288
Name: AGE_ID, Length: 305362, dtype: float64
```

In [80]:
```
# 4. hist
df['AGE_ID'].hist(bins=20)
```

Out[80]:
```
<Axes: >
```




In [81]:
```
# these 'age' columns can be useful in later logistic regression
# 305362 now, (307221)
```

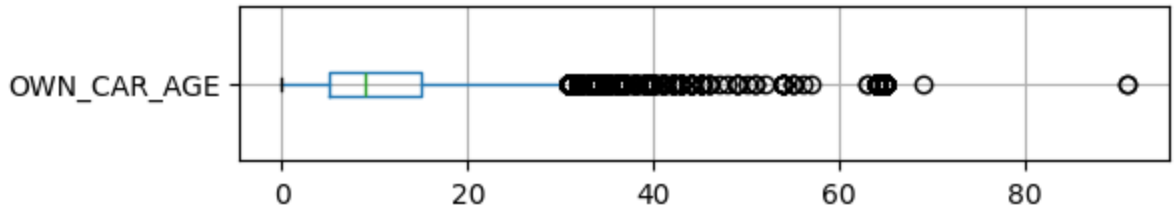
## OWN_CAR_AGE

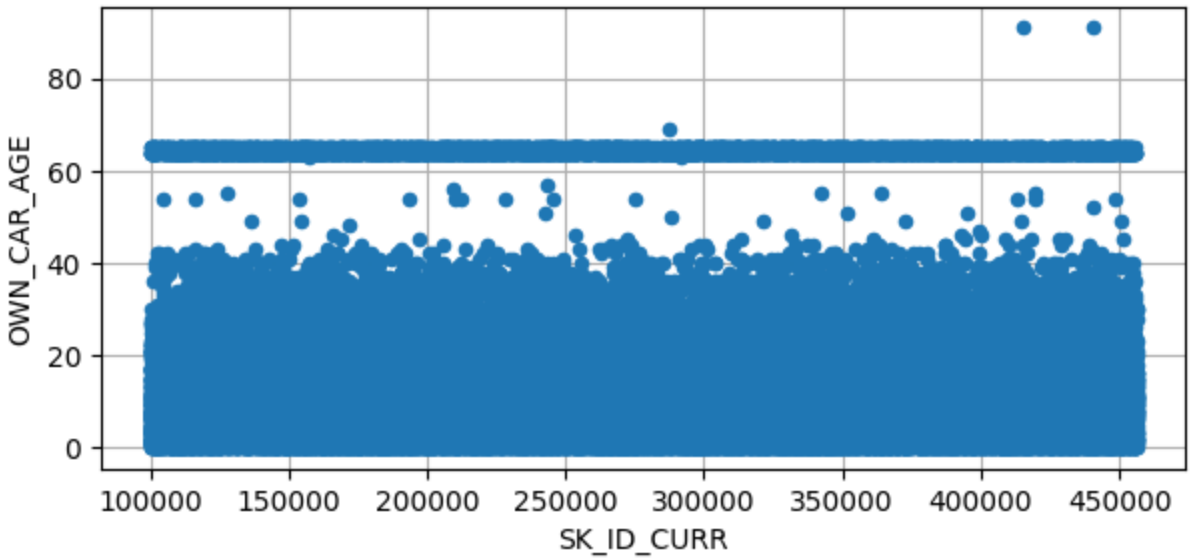
### 1. outlier

In [82]:
```
# recall we set NaN to -1 in this column
# there are a lot of records with -1
# take that out temporarily for q analysis

# template:
# 1 chart
df_car = df[df['OWN_CAR_AGE'] >= 0]
df_car.boxplot(column='OWN_CAR_AGE', figsize=(6,1), vert=False)
df_car.plot.scatter(x='SK_ID_CURR', y='OWN_CAR_AGE', figsize=(7,3), zorder=2, grid=True)
```

```
# 2 check outlier
find_outlier(df_car['OWN_CAR_AGE'], 0.99)
```

```
Report:
1.5 IQR below is: -10.0, 1.5 IQR above is: 30.0
below count: 0, above count: 4920
q99.0 is: 64.0, count: 892, percent: 0.86%
total: 103691
```




In [83]:
```
# the bunch of records just above 60 seems weird
# do some investigation
for i in range(60,70):
    print(i, len(df[df['OWN_CAR_AGE']==i]))
```

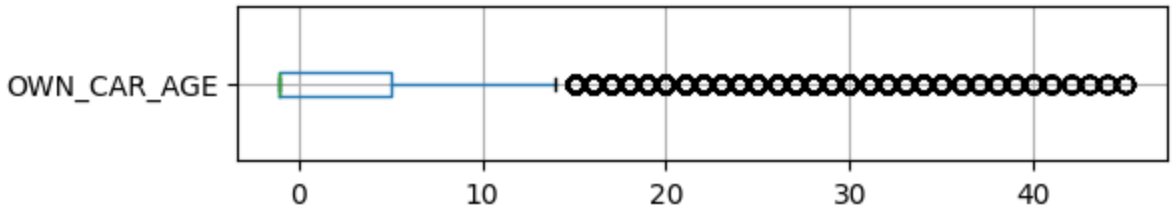
```
60 0
61 0
62 0
63 2
64 2436
65 889
66 0
67 0
68 0
69 1
```

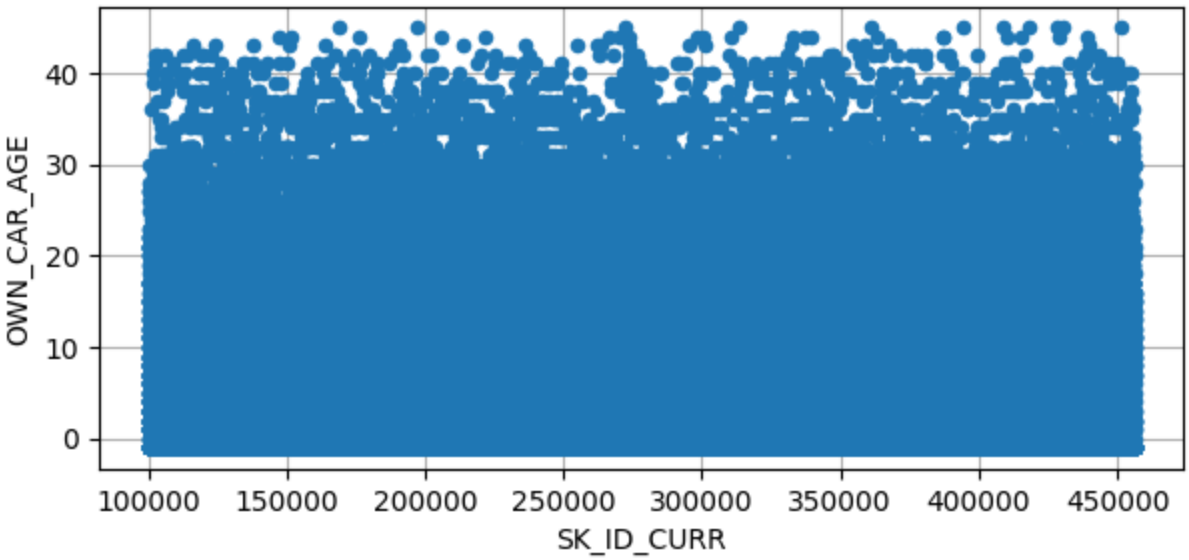
In [84]:
```
# is it a coincidence that there are so many 64 years old cars?
# not sure. but guess we have to cut them
# not a common thing to see 60+ yrs old cars running around
# consider 1.5 IQR above is 30 and look at the scatter plot
# cut 45 should be ok

df = remove_outlier(df, 'OWN_CAR_AGE', 45, top=True)

# check the result
df.boxplot('OWN_CAR_AGE', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='OWN_CAR_AGE', figsize=(7,3), zorder=2, grid=True)
```

```
len(df)
```

```
records removed: 3366
```

Out[84]:
```
301996
```



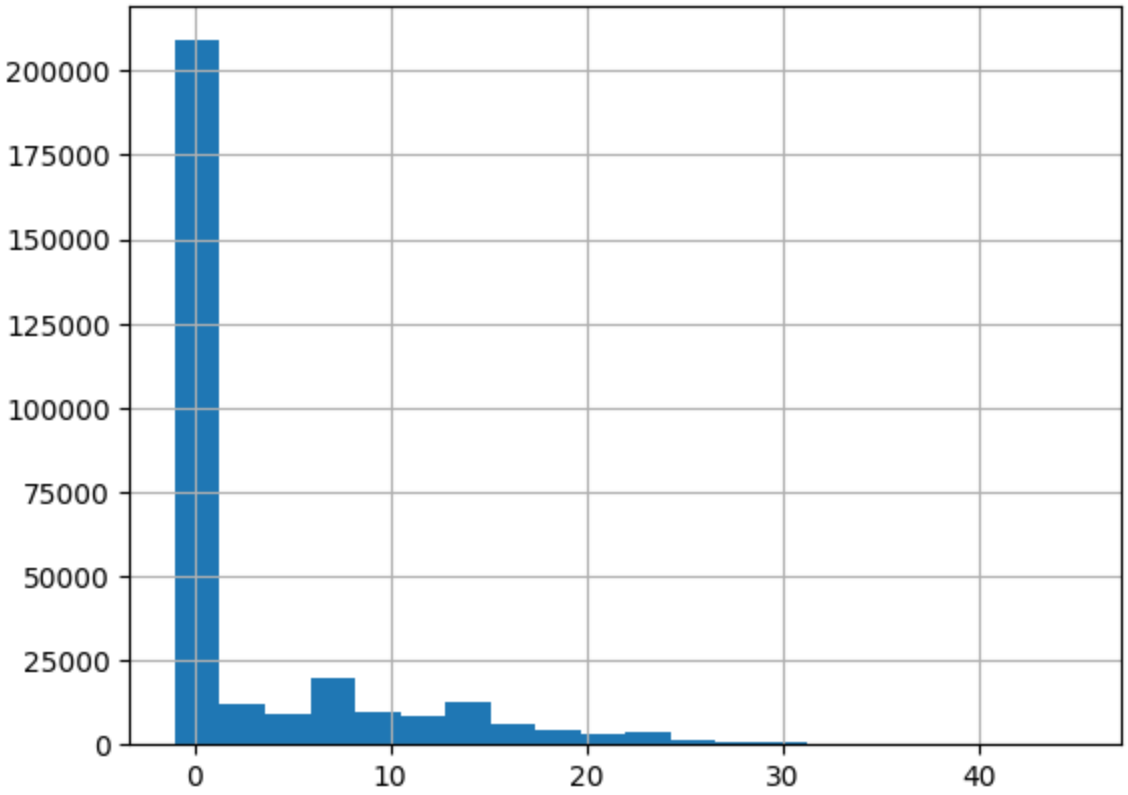

## 2. convert

In [85]:
```
# just rename to be consistent with other age columns
df = df.rename(columns={'OWN_CAR_AGE': 'AGE_CAR'})
df['AGE_CAR']
```

Out[85]:
```
0         -1.0
1         -1.0
2         26.0
3         -1.0
4         -1.0
          ...
307506    -1.0
307507    -1.0
307508    -1.0
307509    -1.0
307510    -1.0
Name: AGE_CAR, Length: 301996, dtype: float64
```

In [86]:
```
df['AGE_CAR'].hist(bins=20)
```

Out[86]:
```
<Axes: >
```




### 3. misc

In [87]:
```
# one tiny thing is there are some discrepancy
# between CAR_AGE == -1 and FLAG_OWN_CAR == 'N'

df[(df['AGE_CAR'] == -1) & (df['FLAG_OWN_CAR'] == 'Y')][['AGE_CAR', 'FLAG_OWN_CAR']]
```

Out[87]:

| | AGE_CAR | FLAG_OWN_CAR |
|---|---|---|
| **30897** | -1.0 | Y |
| **181231** | -1.0 | Y |
| **217549** | -1.0 | Y |
| **229867** | -1.0 | Y |
| **236868** | -1.0 | Y |

In [88]:
```
# drop them
df = df[~( (df['AGE_CAR'] == -1) & (df['FLAG_OWN_CAR'] == 'Y') ) ]
df
```

Out[88]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT |
|---|---|---|---|---|---|---|
| **0** | 100002 | Cash loans | M | N | Y | |
| **1** | 100003 | Cash loans | F | N | N | |
| **2** | 100004 | Revolving loans | M | Y | Y | |
| **3** | 100006 | Cash loans | F | N | Y | |
| **4** | 100007 | Cash loans | M | N | Y | |
| **...** | ... | ... | ... | ... | ... | |
| **307506** | 456251 | Cash loans | M | N | N | |
| **307507** | 456252 | Cash loans | F | N | Y | |
| **307508** | 456253 | Cash loans | F | N | Y | |
| **307509** | 456254 | Cash loans | F | N | Y | |
| **307510** | 456255 | Cash loans | F | N | N | |

301991 rows × 36 columns

In [89]:
```
# 301991 now, (307221)
```

## OCCUPATION_TYPE

In [90]:
```
# since it's str type, we cannot use the template from above
df['OCCUPATION_TYPE'].value_counts()
```

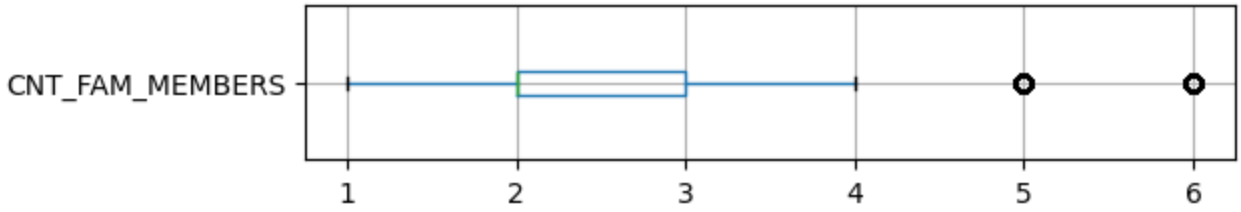
Out[90]:
```
OCCUPATION_TYPE
Unknown                 95059
Laborers                54231
Sales staff             31577
Core staff              27045
Managers                20538
Drivers                 18320
High skill tech staff   11128
Accountants              9603
Medicine staff           8374
Security staff           6610
Cooking staff            5860
Cleaning staff           4591
Private service staff    2594
Low-skill Laborers       2054
Waiters/barmen staff     1325
Secretaries              1282
Realty agents             740
HR staff                  553
IT staff                  507
Name: count, dtype: int64
```

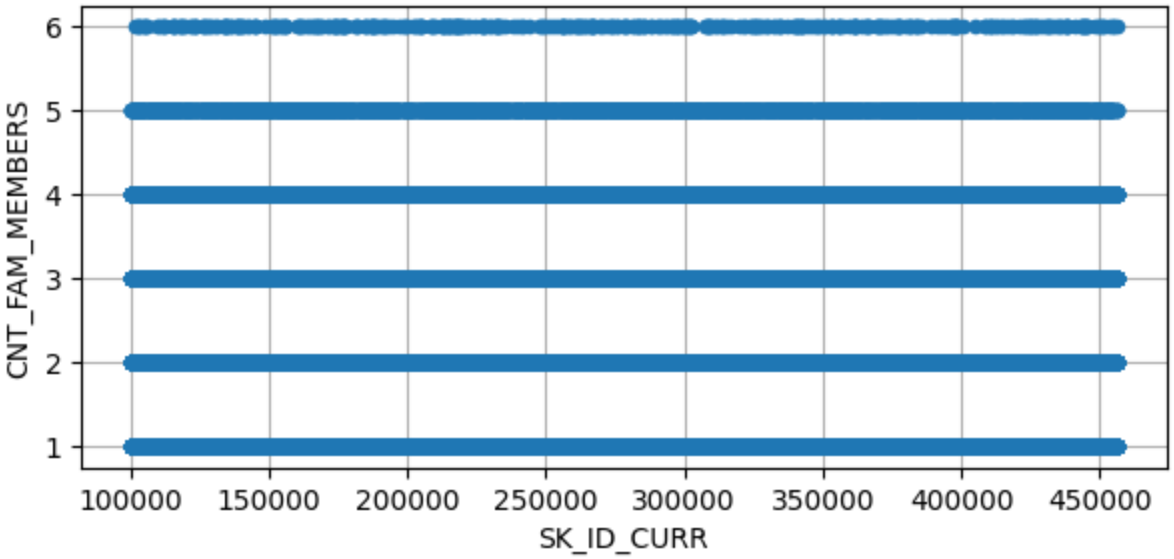
In [91]:
```
# seems ok, did not change so still the same len of df
# 301991 now, (307221)
```

## CNT_FAM_MEMBERS

In [92]:
```
# template:
# 1 chart
df.boxplot(column='CNT_FAM_MEMBERS', figsize=(6,1), vert=False)
df.plot.scatter(x='SK_ID_CURR', y='CNT_FAM_MEMBERS', figsize=(7,3), zorder=2, grid=True)

# 2 check outlier
find_outlier(df['CNT_FAM_MEMBERS'], 0.99)
find_outlier(df['CNT_FAM_MEMBERS'], 0.999)
```

```
Report:
1.5 IQR below is: 0.5, 1.5 IQR above is: 4.5
below count: 0, above count: 3804
q99.0 is: 5.0, count: 397, percent: 0.13%
total: 301991
Report:
1.5 IQR below is: 0.5, 1.5 IQR above is: 4.5
below count: 0, above count: 3804
q99.9 is: 6.0, count: 0, percent: 0.00%
total: 301991
```




In [93]:
```
# should be ok to leave as is
# if we adopted the 1.5 IQR method then 3804 records will be removed
# may be too many
# still 301991 now, (307221)
```

## ORGANIZATION_TYPE

In [94]:
```
# it's str type again
df['ORGANIZATION_TYPE'].value_counts()
```

Out[94]:

| ORGANIZATION_TYPE | |
|---|---|
| Business Entity Type 3 | 66504 |
| XNA | 54830 |
| Self-employed | 37785 |
| Other | 16354 |
| Medicine | 10963 |
| Business Entity Type 2 | 10290 |
| Government | 10227 |
| School | 8748 |
| Trade: type 7 | 7689 |
| Kindergarten | 6795 |
| Construction | 6597 |
| Business Entity Type 1 | 5845 |
| Transport: type 4 | 5300 |
| Trade: type 3 | 3435 |
| Industry: type 9 | 3304 |
| Industry: type 3 | 3222 |
| Security | 3185 |
| Housing | 2910 |
| Industry: type 11 | 2648 |
| Military | 2570 |
| Bank | 2438 |
| Agriculture | 2412 |
| Police | 2286 |
| Transport: type 2 | 2165 |
| Postal | 2127 |
| Security Ministries | 1925 |
| Trade: type 2 | 1854 |
| Restaurant | 1770 |
| Services | 1540 |
| University | 1293 |
| Industry: type 7 | 1269 |
| Transport: type 3 | 1175 |
| Industry: type 1 | 1023 |
| Hotel | 950 |
| Electricity | 930 |
| Industry: type 4 | 851 |
| Trade: type 6 | 612 |
| Industry: type 5 | 589 |
| Insurance | 576 |
| Telecom | 562 |
| Emergency | 555 |
| Industry: type 2 | 445 |
| Advertising | 418 |
| Realtor | 391 |
| Culture | 371 |
| Industry: type 12 | 365 |
| Trade: type 1 | 340 |
| Mobile | 312 |
| Legal Services | 297 |
| Cleaning | 257 |
| Transport: type 1 | 196 |
| Industry: type 6 | 108 |
| Industry: type 10 | 107 |
| Religion | 82 |
| Industry: type 13 | 64 |
| Trade: type 4 | 62 |
| Trade: type 5 | 49 |
| Industry: type 8 | 24 |

Name: count, dtype: int64

In [95]:
```
# seems ok
# 301991 now, (307221)
```

## Others

In [96]:
```
# check the str type and binary type columns to see if there are abnormalies
check_list = ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'NAME_TYPE_
              'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE
              'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FLAG_PHONE'
              'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_RI
              'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'TARG

for i in check_list:
    print(df[i].value_counts(), '\n')
```

```
NAME_CONTRACT_TYPE
Cash loans         273803
Revolving loans     28188
Name: count, dtype: int64

CODE_GENDER
F      199104
M      102883
XNA         4
Name: count, dtype: int64

FLAG_OWN_CAR
N    201666
Y    100325
Name: count, dtype: int64

FLAG_OWN_REALTY
Y    209408
N     92583
Name: count, dtype: int64

NAME_TYPE_SUITE
Unaccompanied      244213
Family              39505
Spouse, partner     11219
Children             3222
Other_B              1738
Unknown               985
Other_A               845
Group of people       264
Name: count, dtype: int64

NAME_INCOME_TYPE
Working                 155883
Commercial associate     69939
Pensioner                54818
State servant            21301
Unemployed                  21
Student                     18
Businessman                  6
Maternity leave              5
Name: count, dtype: int64

NAME_EDUCATION_TYPE
Secondary / secondary special    215474
Higher education                  72538
Incomplete higher                 10049
Lower secondary                    3771
Academic degree                     159
Name: count, dtype: int64

NAME_FAMILY_STATUS
Married                 193045
Single / not married     44282
Civil marriage           29366
Separated                19406
Widow                    15892
Name: count, dtype: int64

NAME_HOUSING_TYPE
House / apartment      268151
With parents            14525
```

```
Municipal apartment     11001
Rented apartment         4814
Office apartment         2557
Co-op apartment           943
Name: count, dtype: int64

FLAG_MOBIL
1    301990
0         1
Name: count, dtype: int64

FLAG_EMP_PHONE
1    247150
0     54841
Name: count, dtype: int64

FLAG_WORK_PHONE
0    241512
1     60479
Name: count, dtype: int64

FLAG_CONT_MOBILE
1    301439
0       552
Name: count, dtype: int64

FLAG_PHONE
0    217001
1     84990
Name: count, dtype: int64

FLAG_EMAIL
0    284978
1     17013
Name: count, dtype: int64

REG_REGION_NOT_LIVE_REGION
0    297453
1      4538
Name: count, dtype: int64

REG_REGION_NOT_WORK_REGION
0    286778
1     15213
Name: count, dtype: int64

LIVE_REGION_NOT_WORK_REGION
0    289821
1     12170
Name: count, dtype: int64

REG_CITY_NOT_LIVE_CITY
0    278373
1     23618
Name: count, dtype: int64

REG_CITY_NOT_WORK_CITY
0    232410
1     69581
Name: count, dtype: int64

LIVE_CITY_NOT_WORK_CITY
```

```
0    247766
1     54225
Name: count, dtype: int64

TARGET
0    277550
1     24441
Name: count, dtype: int64
```

In [97]:
```
# seems ok
```

## Export to csv

In [98]:
```
# we have done a tremendously lot.
# check the df now
df
```

Out[98]:

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT |
|---|---|---|---|---|---|---|
| **0** | 100002 | Cash loans | M | N | Y | |
| **1** | 100003 | Cash loans | F | N | N | |
| **2** | 100004 | Revolving loans | M | Y | Y | |
| **3** | 100006 | Cash loans | F | N | Y | |
| **4** | 100007 | Cash loans | M | N | Y | |
| **...** | ... | ... | ... | ... | ... | ... |
| **307506** | 456251 | Cash loans | M | N | N | |
| **307507** | 456252 | Cash loans | F | N | Y | |
| **307508** | 456253 | Cash loans | F | N | Y | |
| **307509** | 456254 | Cash loans | F | N | Y | |
| **307510** | 456255 | Cash loans | F | N | N | |

301991 rows × 36 columns

In [99]:
```
df.describe()
```

Out[99]:

| | SK_ID_CURR | CNT_CHILDREN | AMT_INCOME_TOTAL | AMT_CREDIT | AMT_ANNUITY | AMT_GOODS_ |
|---|---|---|---|---|---|---|
| **count** | 301991.000000 | 301991.000000 | 301991.000000 | 3.019910e+05 | 301991.000000 | 3.019910 |
| **mean** | 278159.322635 | 0.413496 | 165820.171490 | 5.954274e+05 | 26952.516194 | 5.347469 |
| **std** | 102793.025755 | 0.710710 | 85299.541881 | 3.940471e+05 | 13997.221054 | 3.613969 |
| **min** | 100002.000000 | 0.000000 | 25650.000000 | 4.500000e+04 | 1615.500000 | 4.050000 |
| **25%** | 189120.500000 | 0.000000 | 112500.000000 | 2.700000e+05 | 16524.000000 | 2.385000 |
| **50%** | 278193.000000 | 0.000000 | 144000.000000 | 5.124465e+05 | 24867.000000 | 4.500000 |
| **75%** | 367121.500000 | 1.000000 | 202500.000000 | 8.086500e+05 | 34573.500000 | 6.795000 |
| **max** | 456255.000000 | 4.000000 | 699750.000000 | 2.479860e+06 | 124893.000000 | 2.250000 |

8 rows × 25 columns

In [100…

```
df.isna().sum()
```

Out[100…

```
SK_ID_CURR                    0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
FLAG_OWN_REALTY               0
CNT_CHILDREN                  0
AMT_INCOME_TOTAL              0
AMT_CREDIT                    0
AMT_ANNUITY                   0
AMT_GOODS_PRICE               0
NAME_TYPE_SUITE               0
NAME_INCOME_TYPE              0
NAME_EDUCATION_TYPE           0
NAME_FAMILY_STATUS            0
NAME_HOUSING_TYPE             0
AGE                           0
AGE_EMPLOYED                  0
AGE_REGISTRATION              0
AGE_ID                        0
AGE_CAR                       0
FLAG_MOBIL                    0
FLAG_EMP_PHONE                0
FLAG_WORK_PHONE               0
FLAG_CONT_MOBILE              0
FLAG_PHONE                    0
FLAG_EMAIL                    0
OCCUPATION_TYPE               0
CNT_FAM_MEMBERS               0
REG_REGION_NOT_LIVE_REGION    0
REG_REGION_NOT_WORK_REGION    0
LIVE_REGION_NOT_WORK_REGION   0
REG_CITY_NOT_LIVE_CITY        0
REG_CITY_NOT_WORK_CITY        0
LIVE_CITY_NOT_WORK_CITY       0
ORGANIZATION_TYPE             0
TARGET                        0
dtype: int64
```

In [101…

```
df.nunique()
```

Out[101…

```
SK_ID_CURR                   301991
NAME_CONTRACT_TYPE                2
CODE_GENDER                       3
FLAG_OWN_CAR                      2
FLAG_OWN_REALTY                   2
CNT_CHILDREN                      5
AMT_INCOME_TOTAL               2395
AMT_CREDIT                     5511
AMT_ANNUITY                   13469
AMT_GOODS_PRICE                 977
NAME_TYPE_SUITE                   8
NAME_INCOME_TYPE                  8
NAME_EDUCATION_TYPE               5
NAME_FAMILY_STATUS                5
NAME_HOUSING_TYPE                 6
AGE                           17453
AGE_EMPLOYED                  12386
AGE_REGISTRATION              15383
AGE_ID                         6139
AGE_CAR                          47
FLAG_MOBIL                        2
FLAG_EMP_PHONE                    2
FLAG_WORK_PHONE                   2
FLAG_CONT_MOBILE                  2
FLAG_PHONE                        2
FLAG_EMAIL                        2
OCCUPATION_TYPE                  19
CNT_FAM_MEMBERS                   6
REG_REGION_NOT_LIVE_REGION        2
REG_REGION_NOT_WORK_REGION        2
LIVE_REGION_NOT_WORK_REGION       2
REG_CITY_NOT_LIVE_CITY            2
REG_CITY_NOT_WORK_CITY            2
LIVE_CITY_NOT_WORK_CITY           2
ORGANIZATION_TYPE                58
TARGET                            2
dtype: int64
```

In [102…

```
# might be useful to save all the work up to this point to a new csv
# we will read the new csv from later sections

# only need to run this export once
# since we may need to re-run the codes when re-opening the notebook
# set some safeguard

import os

if not os.path.exists('application_train_clean.csv'):
    df.to_csv('application_train_clean.csv', index=False)
```

# 4. Analysis

## Reload the df

In [103…

```
# add ',' for thousands and round to 0.1
pd.options.display.float_format = '{:,.1f}'.format
df = pd.read_csv('application_train_clean.csv')
```

```
df.head()
```

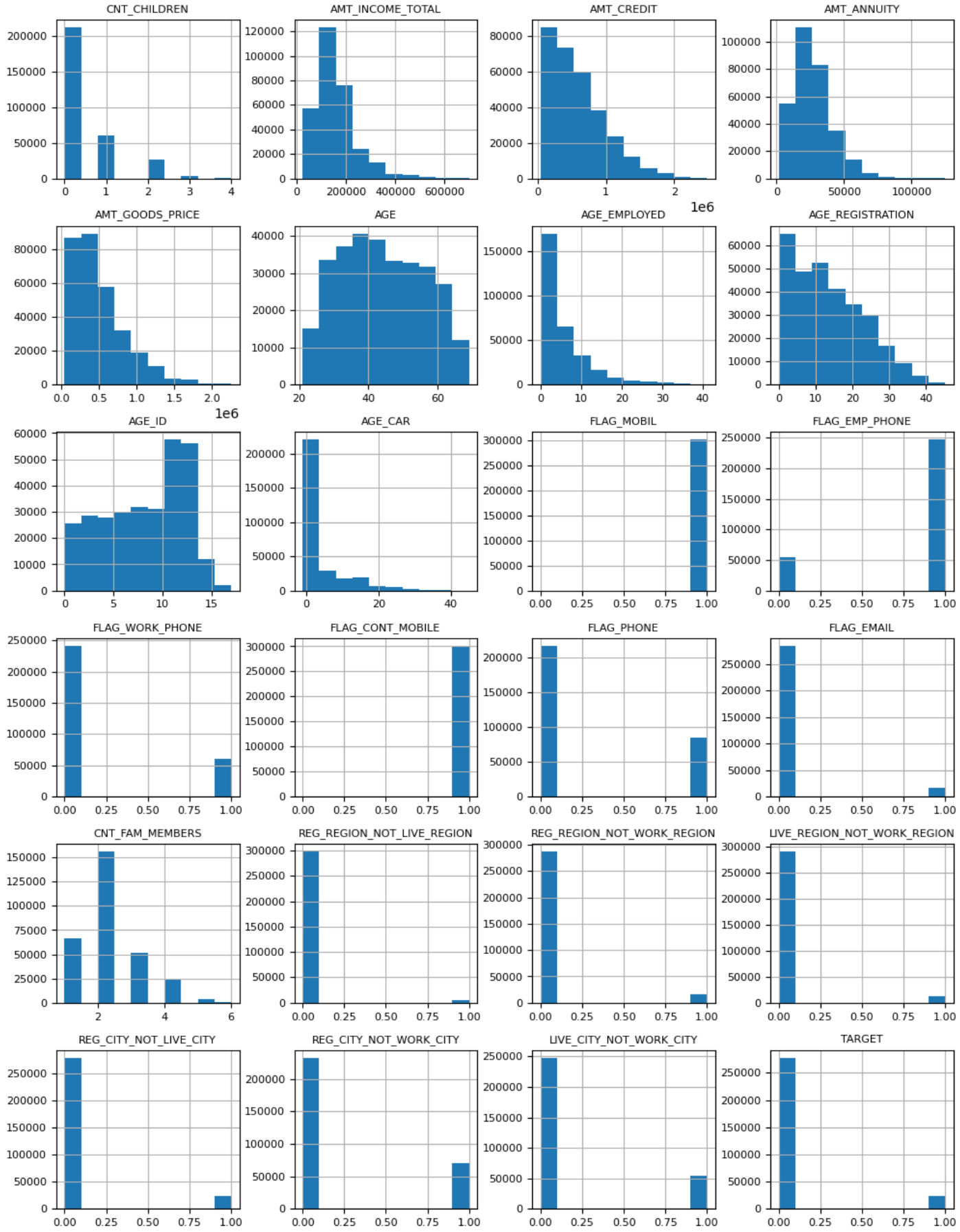
Out[103…

| | SK_ID_CURR | NAME_CONTRACT_TYPE | CODE_GENDER | FLAG_OWN_CAR | FLAG_OWN_REALTY | CNT_CHILI |
|---|---|---|---|---|---|---|
| **0** | 100002 | Cash loans | M | N | Y | |
| **1** | 100003 | Cash loans | F | N | N | |
| **2** | 100004 | Revolving loans | M | Y | Y | |
| **3** | 100006 | Cash loans | F | N | Y | |
| **4** | 100007 | Cash loans | M | N | Y | |

5 rows × 36 columns

In [104…

```
fig = df.loc[:, 'CNT_CHILDREN':].hist(layout=(6,4), figsize=(12,16))
for x in fig:
    for j in x:
        j.title.set_size(8)
        j.tick_params(axis='both', labelsize=8)
```




## General analysis

In [105…

```
# How much (total) do they have out in loans?
loan_sum = df['AMT_CREDIT'].sum()
f'${loan_sum:,}'
```

Out[105… '$179,813,705,827.5'

In [106…
```
# How much are in default/late?
# Target variable: 1 - client with payment difficulties
target_count = df.groupby('TARGET', as_index=False)['SK_ID_CURR'].count()

# How much are in default/late?
target_amt = df.groupby('TARGET', as_index=False)['AMT_CREDIT'].sum()

target_count, target_amt
```

Out[106…
```
(   TARGET  SK_ID_CURR
 0       0      277550
 1       1       24441,
    TARGET        AMT_CREDIT
 0       0 166,218,071,859.0
 1       1  13,595,633,968.5)
```

In [107…
```
# What percentage of the business are default and late?
# percent_count = target_count[1] / (target_count[0] + target_count[1]) * 100
percent_count = (target_count['SK_ID_CURR'][1] /
                 (target_count['SK_ID_CURR'][0] + target_count['SK_ID_CURR'][1]) * 100)
f'{percent_count:.2f} % is in trouble by count'
```

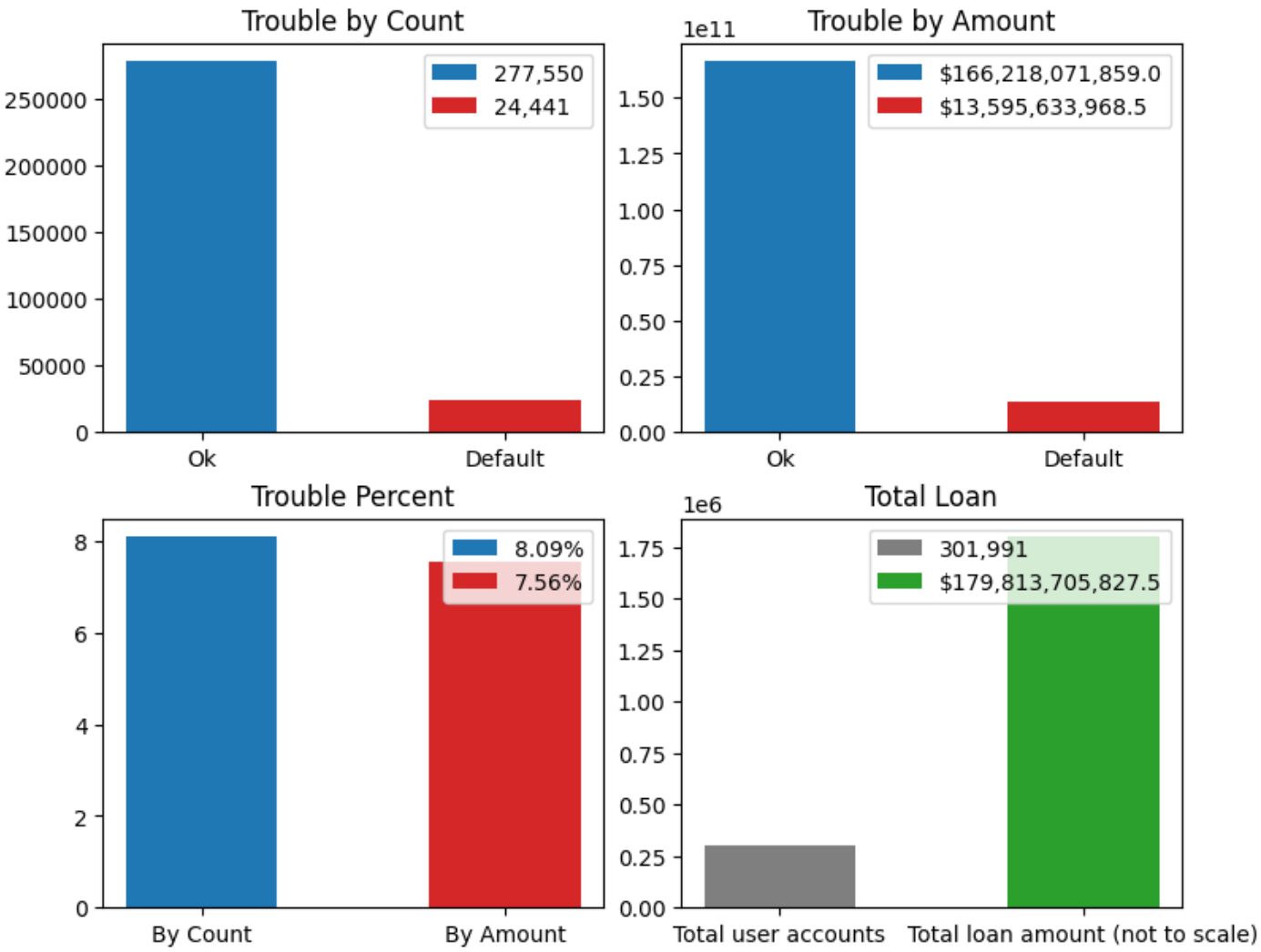
Out[107… '8.09 % is in trouble by count'

In [108…
```
# What percentage of the business are default and late?
percent_amt = (target_amt['AMT_CREDIT'][1] /
                 (target_amt['AMT_CREDIT'][0] + target_amt['AMT_CREDIT'][1]) * 100)
f'{percent_amt:.2f} % is in trouble by amount'
```

Out[108… '7.56 % is in trouble by amount'

In [109…
```
# putting it altogether so we have a graphic report
fig, axs = plt.subplots(2, 2, figsize=(8,6), layout='constrained')

axs[0, 0].bar(target_count['TARGET'], target_count['SK_ID_CURR'],
              label=[f'{target_count["SK_ID_CURR"][0]:,}', f'{target_count["SK_ID_CURR"][1]:,}'],
              width=0.5, color=['tab:blue', 'tab:red'])
axs[0, 0].set_title('Trouble by Count')
axs[0, 0].set_xticks(target_count['TARGET'], labels=['Ok', 'Default'])

axs[0, 1].bar(target_amt['TARGET'], target_amt['AMT_CREDIT'],
              label=[f'${target_amt["AMT_CREDIT"][0]:,}', f'${target_amt["AMT_CREDIT"][1]:,}'],
              width=0.5, color=['tab:blue', 'tab:red'])
axs[0, 1].set_title('Trouble by Amount')
axs[0, 1].set_xticks(target_amt['TARGET'], labels=['Ok', 'Default'])

axs[1, 0].bar([0,1], [percent_count, percent_amt],
              label=[f'{percent_count:.2f}%', f'{percent_amt:.2f}%'],
              width=0.5, color=['tab:blue', 'tab:red'])
axs[1, 0].set_title('Trouble Percent')
axs[1, 0].set_xticks([0,1], labels=['By Count', 'By Amount'])

axs[1, 1].bar([0,1], [len(df), loan_sum/100000],
              label=[f'{len(df):,}', f'${loan_sum:,}'],
              width=0.5, color=['tab:grey', 'tab:green'])
axs[1, 1].set_title('Total Loan')
axs[1, 1].set_xticks([0,1], labels=['Total user accounts',
                                    'Total loan amount (not to scale)'])
```

```
# show legends
for i in axs:
    for j in i:
        j.legend(loc=1)
```




## Demographic analysis

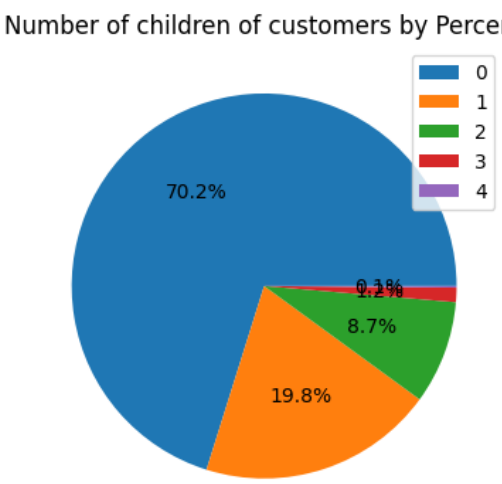
### 1. Pie

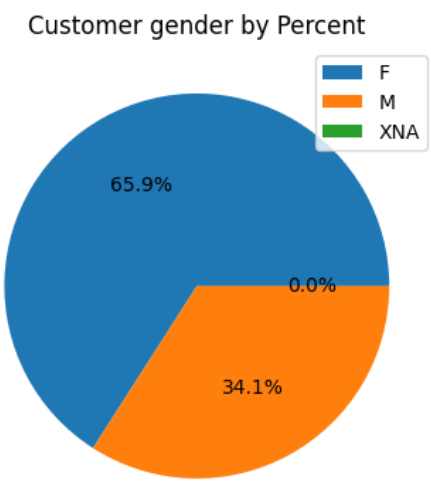
In [110…

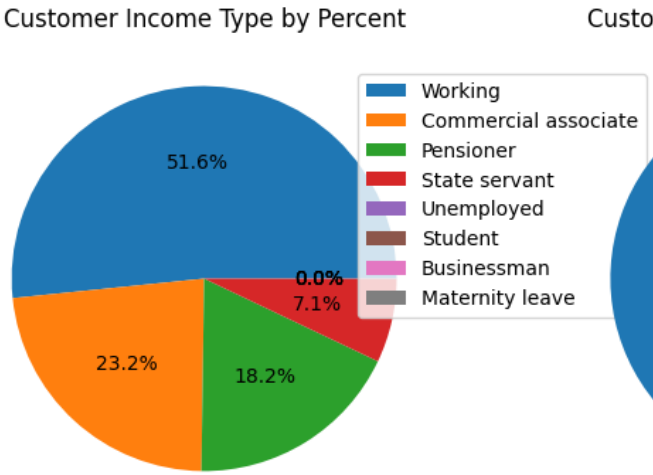
```
# demographics of the customers
# age, education, income, marital status
# employment, family structure, gender, occupation etc

sr_children = df['CNT_CHILDREN'].value_counts()
sr_gender = df['CODE_GENDER'].value_counts()
sr_income_type = df['NAME_INCOME_TYPE'].value_counts()
sr_education_type = df['NAME_EDUCATION_TYPE'].value_counts()
sr_family = df['NAME_FAMILY_STATUS'].value_counts()
sr_housing = df['NAME_HOUSING_TYPE'].value_counts()

# the pie report
fig, axs = plt.subplots(3, 2, figsize=(10,15))

axs[0,0].pie(sr_children, labels=sr_children.index.values, labeldistance=None, autopct='%1.1f%%'
axs[0,0].set_title('Number of children of customers by Percent')
axs[0,0].legend()
```

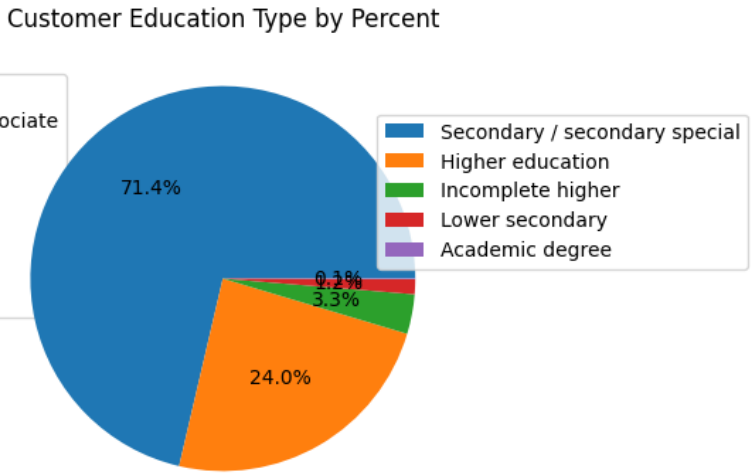
```
axs[0,1].pie(sr_gender, labels=sr_gender.index.values, labeldistance=None, autopct='%1.1f%%')
axs[0,1].set_title('Customer gender by Percent')
axs[0,1].legend()

axs[1,0].pie(sr_income_type, labels=sr_income_type.index.values, labeldistance=None, autopct='%1
axs[1,0].set_title('Customer Income Type by Percent')
axs[1,0].legend(loc='lower left', bbox_to_anchor=(0.8, 0.4, 0.1, 0.1))

axs[1,1].pie(sr_education_type, labels=sr_education_type.index.values, labeldistance=None, autop
axs[1,1].set_title('Customer Education Type by Percent')
axs[1,1].legend(loc='lower left', bbox_to_anchor=(0.8, 0.5, 0.1, 0.1))

axs[2,0].pie(sr_family, labels=sr_family.index.values, labeldistance=None, autopct='%1.1f%%')
axs[2,0].set_title('Customer Family Status by Percent')
axs[2,0].legend(loc='lower left', bbox_to_anchor=(0.8, 0.5, 0.1, 0.1))

axs[2,1].pie(sr_housing, labels=sr_housing.index.values, labeldistance=None, autopct='%1.1f%%')
axs[2,1].set_title('Customer Housing Type by Percent')
axs[2,1].legend(loc='lower left', bbox_to_anchor=(0.8, 0.5, 0.1, 0.1))
```

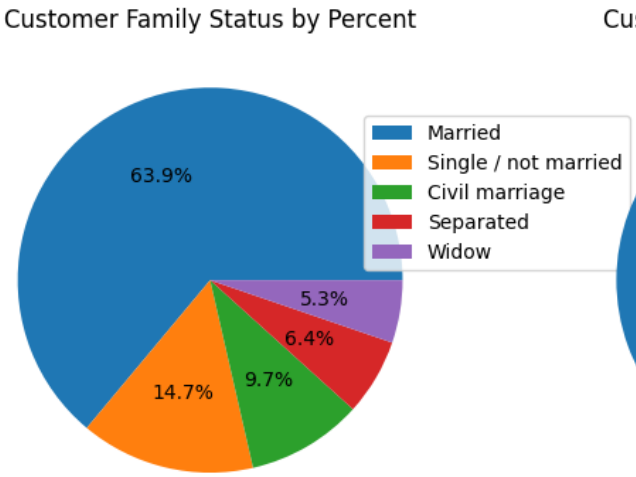
Out[110… `<matplotlib.legend.Legend at 0x1742cb9ffe0>`

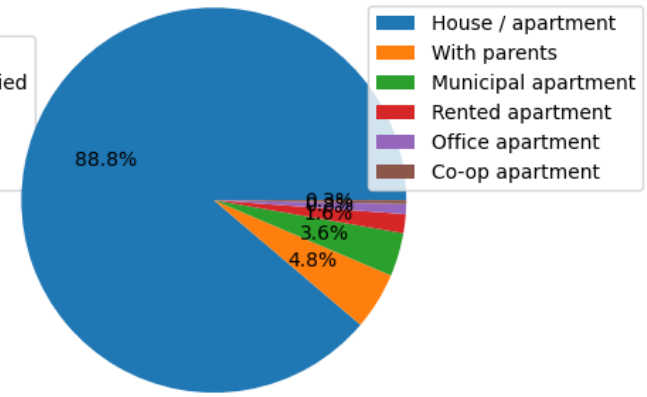


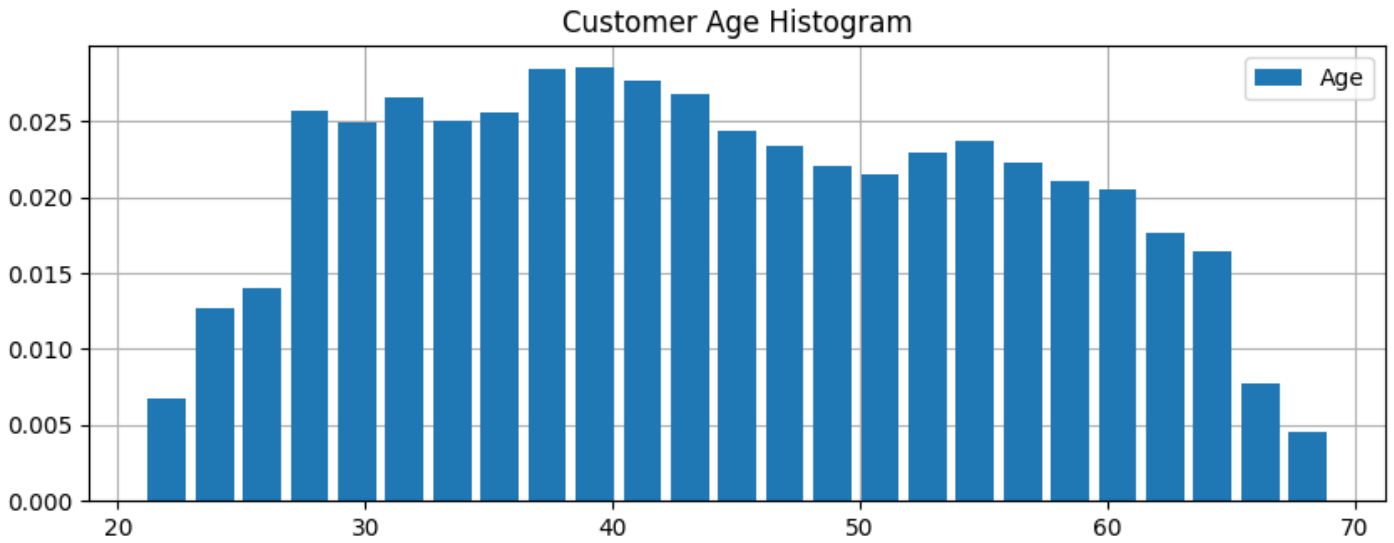

## 2. Histogram

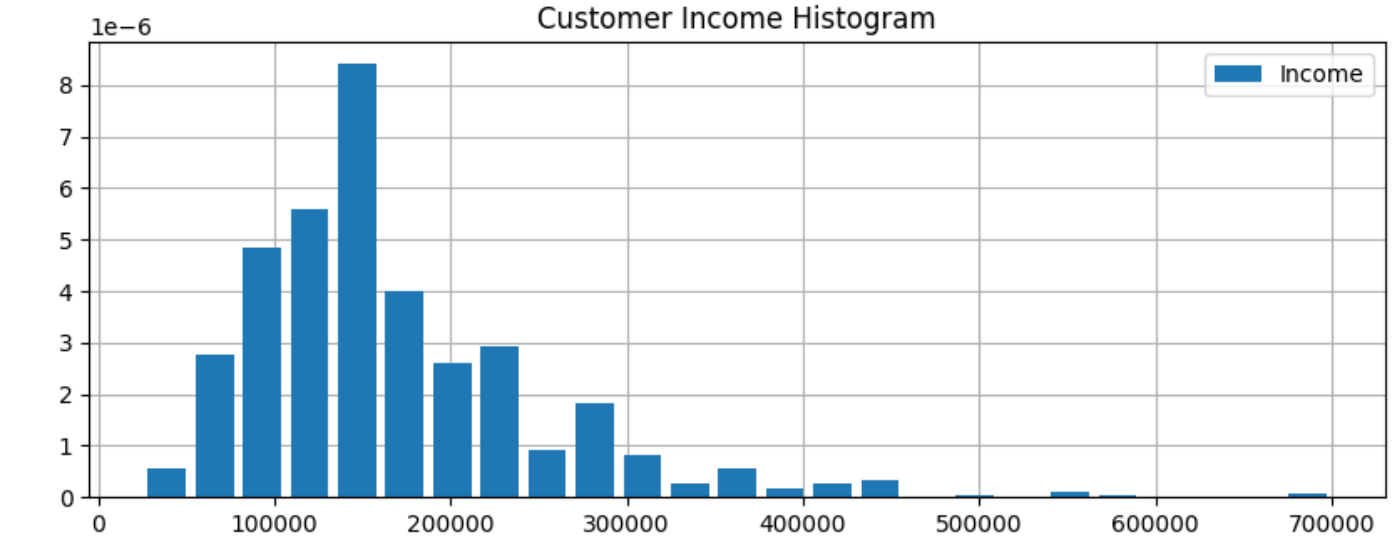
In [111…

```
sr_age = df['AGE']
sr_employed = df['AGE_EMPLOYED']
sr_income = df['AMT_INCOME_TOTAL']

# hist report
fig1, axs1 = plt.subplots(3, 1, figsize=(10,12))

# sr_age.plot.hist(ax=axs1[0], bins=25, rwidth=0.8, density=True)
```

```
axs1[0].hist(sr_age, bins=25, rwidth=0.8, density=True, zorder=2)
axs1[0].grid(True)
axs1[0].set_title('Customer Age Histogram')
axs1[0].legend(labels=['Age'])

axs1[1].hist(sr_income, bins=25, rwidth=0.8, density=True, zorder=2)
axs1[1].grid(True)
axs1[1].set_title('Customer Income Histogram')
axs1[1].legend(labels=['Income'])

axs1[2].hist(sr_employed, bins=25, rwidth=0.8, density=True, zorder=2)
axs1[2].grid(True)
axs1[2].set_title('Customer Employed Years Histogram')
axs1[2].legend(labels=['Employed Years'])
```

Out[111… <matplotlib.legend.Legend at 0x17410eb3b60>





### 3. Bin

In [112…

```
df['AGEBIN'] = pd.cut(df['AGE'], bins=[20, 30, 40, 50, 60, 80],
                      labels=['20-30','30-40','40-50','50-60','60+'])

df_edu_age_income = df.groupby(['NAME_EDUCATION_TYPE', 'AGEBIN'], as_index=False, observed=True)
df_edu_age_income
```

Out[112…

| | NAME_EDUCATION_TYPE | AGEBIN | AMT_INCOME_TOTAL |
|---|---|---|---|
| **0** | Academic degree | 20-30 | 201,000.0 |
| **1** | Academic degree | 30-40 | 248,062.5 |
| **2** | Academic degree | 40-50 | 245,736.7 |
| **3** | Academic degree | 50-60 | 208,950.0 |
| **4** | Academic degree | 60+ | 160,464.7 |
| **5** | Higher education | 20-30 | 178,944.1 |
| **6** | Higher education | 30-40 | 205,996.8 |
| **7** | Higher education | 40-50 | 217,725.2 |
| **8** | Higher education | 50-60 | 209,060.8 |
| **9** | Higher education | 60+ | 173,822.5 |
| **10** | Incomplete higher | 20-30 | 163,589.6 |
| **11** | Incomplete higher | 30-40 | 192,331.0 |
| **12** | Incomplete higher | 40-50 | 204,095.0 |
| **13** | Incomplete higher | 50-60 | 179,066.9 |
| **14** | Incomplete higher | 60+ | 150,927.8 |
| **15** | Lower secondary | 20-30 | 137,583.8 |
| **16** | Lower secondary | 30-40 | 145,078.2 |
| **17** | Lower secondary | 40-50 | 146,737.8 |
| **18** | Lower secondary | 50-60 | 122,566.5 |
| **19** | Lower secondary | 60+ | 106,550.3 |
| **20** | Secondary / secondary special | 20-30 | 146,291.1 |
| **21** | Secondary / secondary special | 30-40 | 159,973.5 |
| **22** | Secondary / secondary special | 40-50 | 164,263.6 |
| **23** | Secondary / secondary special | 50-60 | 151,700.9 |
| **24** | Secondary / secondary special | 60+ | 131,184.3 |

In [113…

```
df_fam_age_income = df.groupby(['NAME_FAMILY_STATUS', 'AGEBIN'], as_index=False, observed=True)[
df_fam_age_income
```

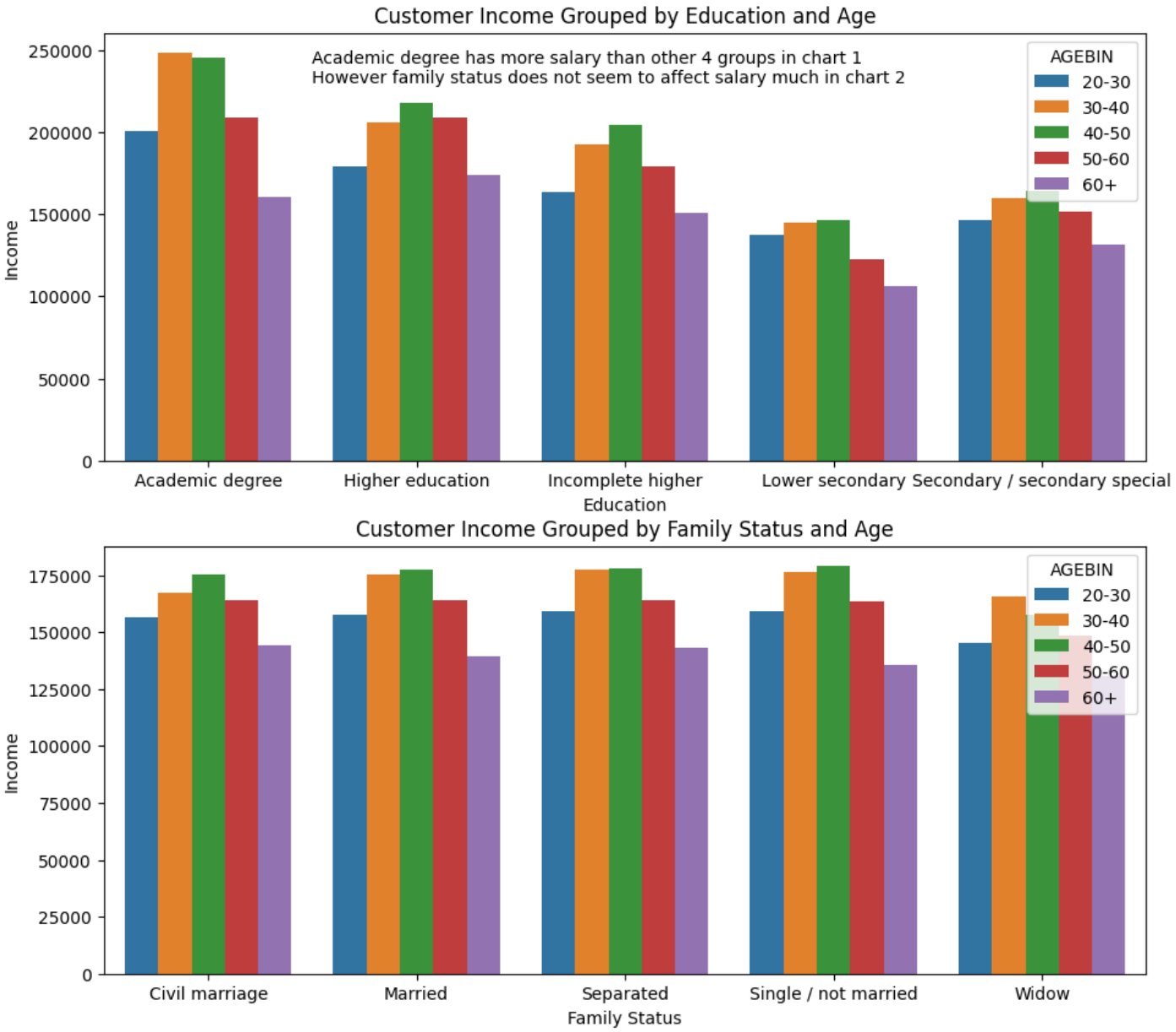
Out[113…

| | NAME_FAMILY_STATUS | AGEBIN | AMT_INCOME_TOTAL |
|---|---|---|---|
| **0** | Civil marriage | 20-30 | 156,753.2 |
| **1** | Civil marriage | 30-40 | 167,490.7 |
| **2** | Civil marriage | 40-50 | 175,424.0 |
| **3** | Civil marriage | 50-60 | 164,290.0 |
| **4** | Civil marriage | 60+ | 144,260.0 |
| **5** | Married | 20-30 | 157,438.9 |
| **6** | Married | 30-40 | 175,076.9 |
| **7** | Married | 40-50 | 177,680.6 |
| **8** | Married | 50-60 | 163,888.9 |
| **9** | Married | 60+ | 139,521.4 |
| **10** | Separated | 20-30 | 159,004.0 |
| **11** | Separated | 30-40 | 177,657.2 |
| **12** | Separated | 40-50 | 178,158.5 |
| **13** | Separated | 50-60 | 164,089.8 |
| **14** | Separated | 60+ | 143,029.8 |
| **15** | Single / not married | 20-30 | 159,005.9 |
| **16** | Single / not married | 30-40 | 176,447.5 |
| **17** | Single / not married | 40-50 | 178,843.8 |
| **18** | Single / not married | 50-60 | 163,739.0 |
| **19** | Single / not married | 60+ | 135,811.4 |
| **20** | Widow | 20-30 | 145,230.0 |
| **21** | Widow | 30-40 | 165,800.0 |
| **22** | Widow | 40-50 | 157,730.7 |
| **23** | Widow | 50-60 | 148,659.9 |
| **24** | Widow | 60+ | 130,806.0 |

In [114…

```
fig2, axs2 = plt.subplots(2, 1, figsize=(11,10))

sns.barplot(ax=axs2[0], data=df_edu_age_income, x='NAME_EDUCATION_TYPE', y='AMT_INCOME_TOTAL', hu
axs2[0].set_title('Customer Income Grouped by Education and Age')
axs2[0].set_xlabel('Education')
axs2[0].set_ylabel('Income')
axs2[0].text(0.5, 230000, ('Academic degree has more salary than other 4 groups in chart 1\n'
                           'However family status does not seem to affect salary much in chart 2'))

sns.barplot(ax=axs2[1], data=df_fam_age_income, x='NAME_FAMILY_STATUS', y='AMT_INCOME_TOTAL', hue
axs2[1].set_title('Customer Income Grouped by Family Status and Age')
axs2[1].set_xlabel('Family Status')
axs2[1].set_ylabel('Income')
```

Out[114… Text(0, 0.5, 'Income')




# Analysis about who defaults

## 1. gender vs trouble

In [115…

```
# Who defaults or has problems replaying loans?

# we can probably drop the 4 counts of XNA since it's too small a sample
df = df[df['CODE_GENDER'] != 'XNA']
target_gender_count = df.groupby(['TARGET','CODE_GENDER'], as_index=False)['SK_ID_CURR'].count()
target_gender_count
```

Out[115…

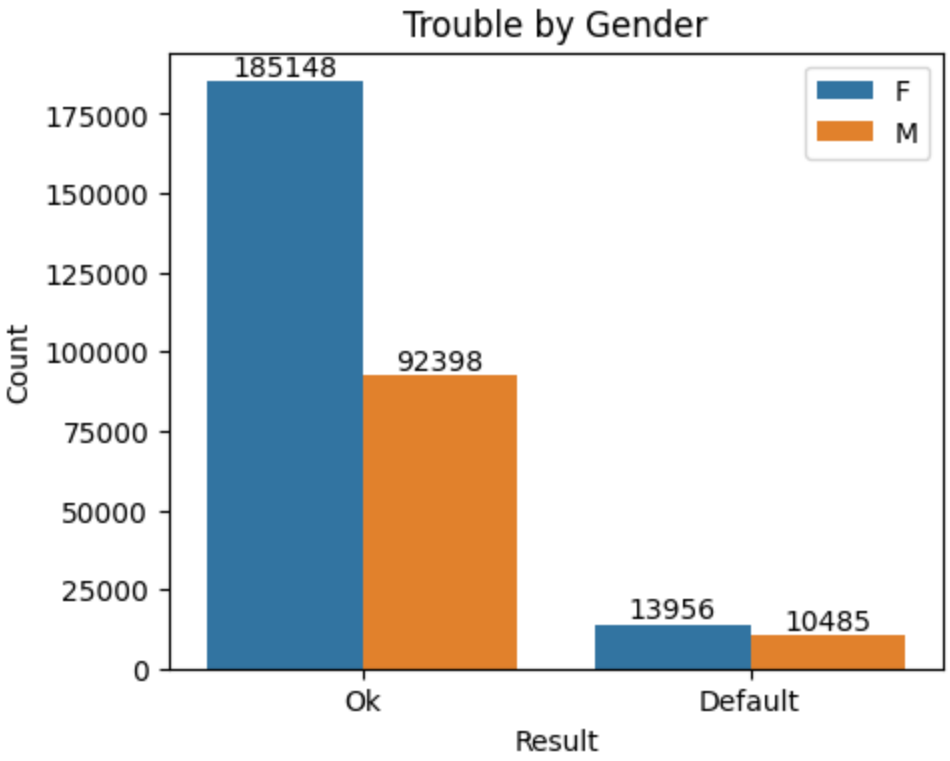
| | TARGET | CODE_GENDER | SK_ID_CURR |
|---|---|---|---|
| **0** | 0 | F | 185148 |
| **1** | 0 | M | 92398 |
| **2** | 1 | F | 13956 |
| **3** | 1 | M | 10485 |

In [116…

```
# in case we need to deal with single plot
# these can set figsize
# plt.rcParams['figure.figsize']=(10,10)
plt.figure(figsize=(5,4))

ax = sns.barplot(target_gender_count, x='TARGET', y='SK_ID_CURR', hue='CODE_GENDER')
ax.set_title('Trouble by Gender')
ax.set_xticks([0,1], labels=['Ok', 'Default'])
ax.set_xlabel('Result')
ax.set_ylabel('Count')
ax.bar_label(ax.containers[0], fontsize=10)
ax.bar_label(ax.containers[1], fontsize=10)
ax.legend(title=None)
```

Out[116…

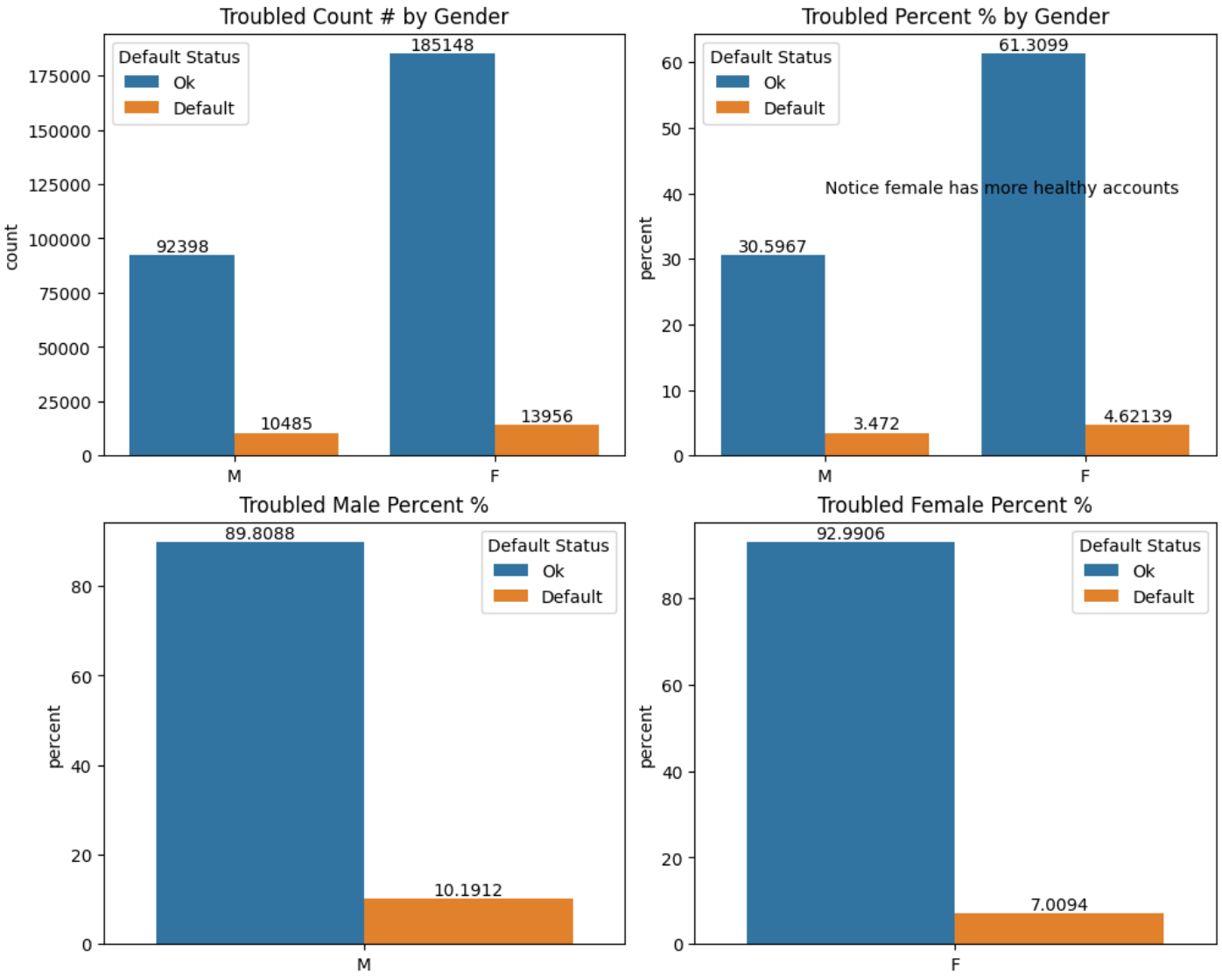
```
<matplotlib.legend.Legend at 0x17410cb2b40>
```




In [117…

```
# actually we do not need to get a sub df first
# seaborn as a countplot that can count and group at the same time
# using the 'hue' parameter

# multi/sub plots
# for our report
fig, axs = plt.subplots(2, 2, figsize=(10,8), layout='constrained')

# each gender's user counts grouped by 'target'
sns.countplot(ax=axs[0,0], data=df, x='CODE_GENDER', hue='TARGET')
axs[0,0].set_title('Troubled Count # by Gender')

# each gender's user counts grouped by 'target', in percent
sns.countplot(ax=axs[0,1], data=df, x='CODE_GENDER', hue='TARGET', stat='percent')
axs[0,1].set_title('Troubled Percent % by Gender')
axs[0,1].text(0, 40, 'Notice female has more healthy accounts')

# male analysis
sns.countplot(ax=axs[1,0], data=df[df['CODE_GENDER'] == 'M'],
              x='CODE_GENDER', hue='TARGET', stat='percent')
axs[1,0].set_title('Troubled Male Percent %')
```

```
# female analysis
sns.countplot(ax=axs[1,1], data=df[df['CODE_GENDER'] == 'F'],
              x='CODE_GENDER', hue='TARGET', stat='percent')
axs[1,1].set_title('Troubled Female Percent %')

# this small loop adds value in text to top of bars
# also get ride of the x labels
# the M/F tick is clear enough
# touch up the legends as well for a complete report
for i in axs:
    for j in i:
        j.set_xlabel('')
        j.legend(title='Default Status', labels=['Ok', 'Default'])

        for o in j.containers:
            j.bar_label(o)
```



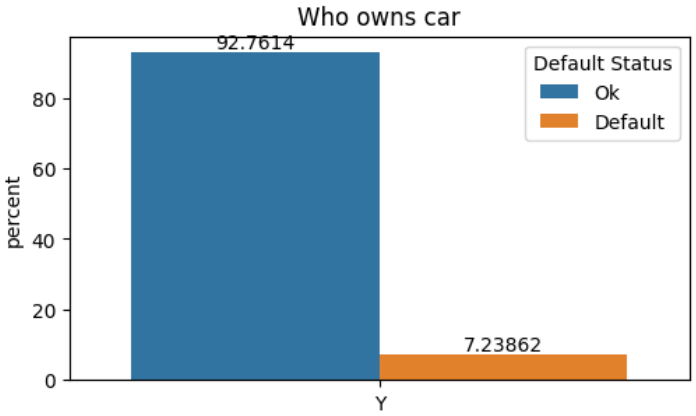

## 2. car, realty, children vs trouble

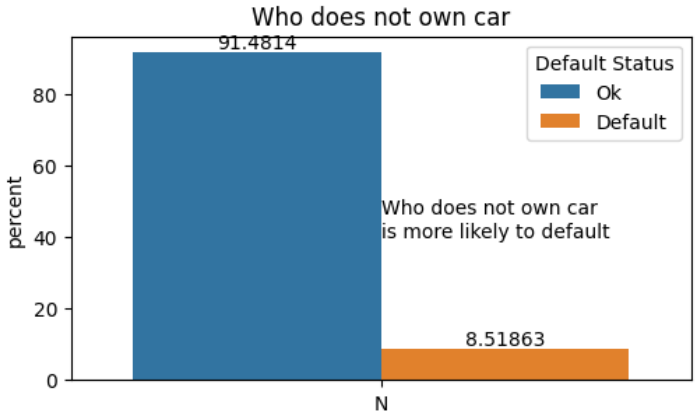
In [118…

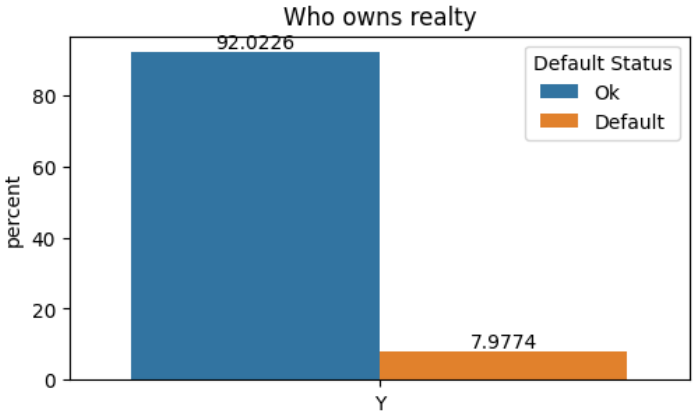
```
# 1. multi plots again
fig, axs = plt.subplots(2, 2, figsize=(10,6), layout='constrained')

# people who own car
sns.countplot(ax=axs[0,0], data=df[df['FLAG_OWN_CAR'] == 'Y'],
              x='FLAG_OWN_CAR', hue='TARGET', stat='percent')
axs[0,0].set_title('Who owns car')
```

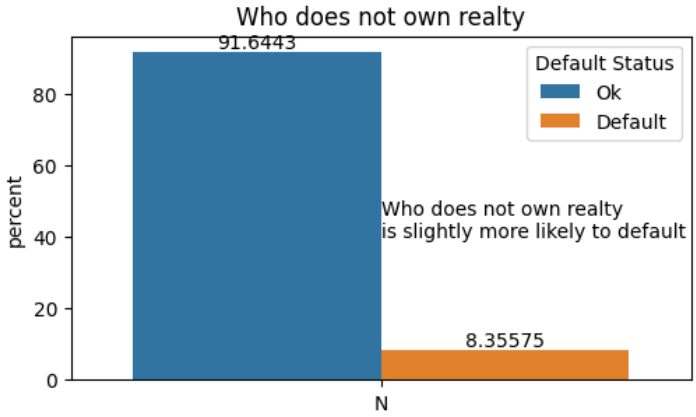
```
# people who do not own car
sns.countplot(ax=axs[0,1], data=df[df['FLAG_OWN_CAR'] == 'N'],
              x='FLAG_OWN_CAR', hue='TARGET', stat='percent')
axs[0,1].set_title('Who does not own car')
axs[0,1].text(0, 40, 'Who does not own car\nis more likely to default')

# people who own realty
sns.countplot(ax=axs[1,0], data=df[df['FLAG_OWN_REALTY'] == 'Y'],
              x='FLAG_OWN_REALTY', hue='TARGET', stat='percent')
axs[1,0].set_title('Who owns realty')

# people who do not own realty
sns.countplot(ax=axs[1,1], data=df[df['FLAG_OWN_REALTY'] == 'N'],
              x='FLAG_OWN_REALTY', hue='TARGET', stat='percent')
axs[1,1].set_title('Who does not own realty')
axs[1,1].text(0, 40, 'Who does not own realty\nis slightly more likely to default')

# 2. second multi plots
# keep things organized
fig1, axs1 = plt.subplots(3, 2, figsize=(10,9), layout='constrained')

# does number of children have effect
sns.countplot(ax=axs1[0,0], data=df[df['CNT_CHILDREN'] == 0],
              x='CNT_CHILDREN', hue='TARGET', stat='percent')
axs1[0,0].set_title('Who has 0 child')

sns.countplot(ax=axs1[0,1], data=df[df['CNT_CHILDREN'] == 1],
              x='CNT_CHILDREN', hue='TARGET', stat='percent')
axs1[0,1].set_title('Who has 1 child')

sns.countplot(ax=axs1[1,0], data=df[df['CNT_CHILDREN'] == 2],
              x='CNT_CHILDREN', hue='TARGET', stat='percent')
axs1[1,0].set_title('Who has 2 children')

sns.countplot(ax=axs1[1,1], data=df[df['CNT_CHILDREN'] == 3],
              x='CNT_CHILDREN', hue='TARGET', stat='percent')
axs1[1,1].set_title('Who has 3 children')

sns.countplot(ax=axs1[2,0], data=df[df['CNT_CHILDREN'] == 4],
              x='CNT_CHILDREN', hue='TARGET', stat='percent')
axs1[2,0].set_title('Who has 4 children')
axs1[2,0].text(0, 40, 'In our dataset, people who\nhave 4 children has\nhighest default percenta

sns.countplot(ax=axs1[2,1], data=df[df['CNT_CHILDREN'] == 5],
              x='CNT_CHILDREN', hue='TARGET', stat='percent')
axs1[2,1].set_title('Who has 5 children')

for i in axs:
    for j in i:
        j.set_xlabel('')
        j.legend(title='Default Status', labels=['Ok', 'Default'])

        for o in j.containers:
            j.bar_label(o)

for i in axs1:
    for j in i:
        j.set_xlabel('')
        j.legend(title='Default Status', labels=['Ok', 'Default'])
```

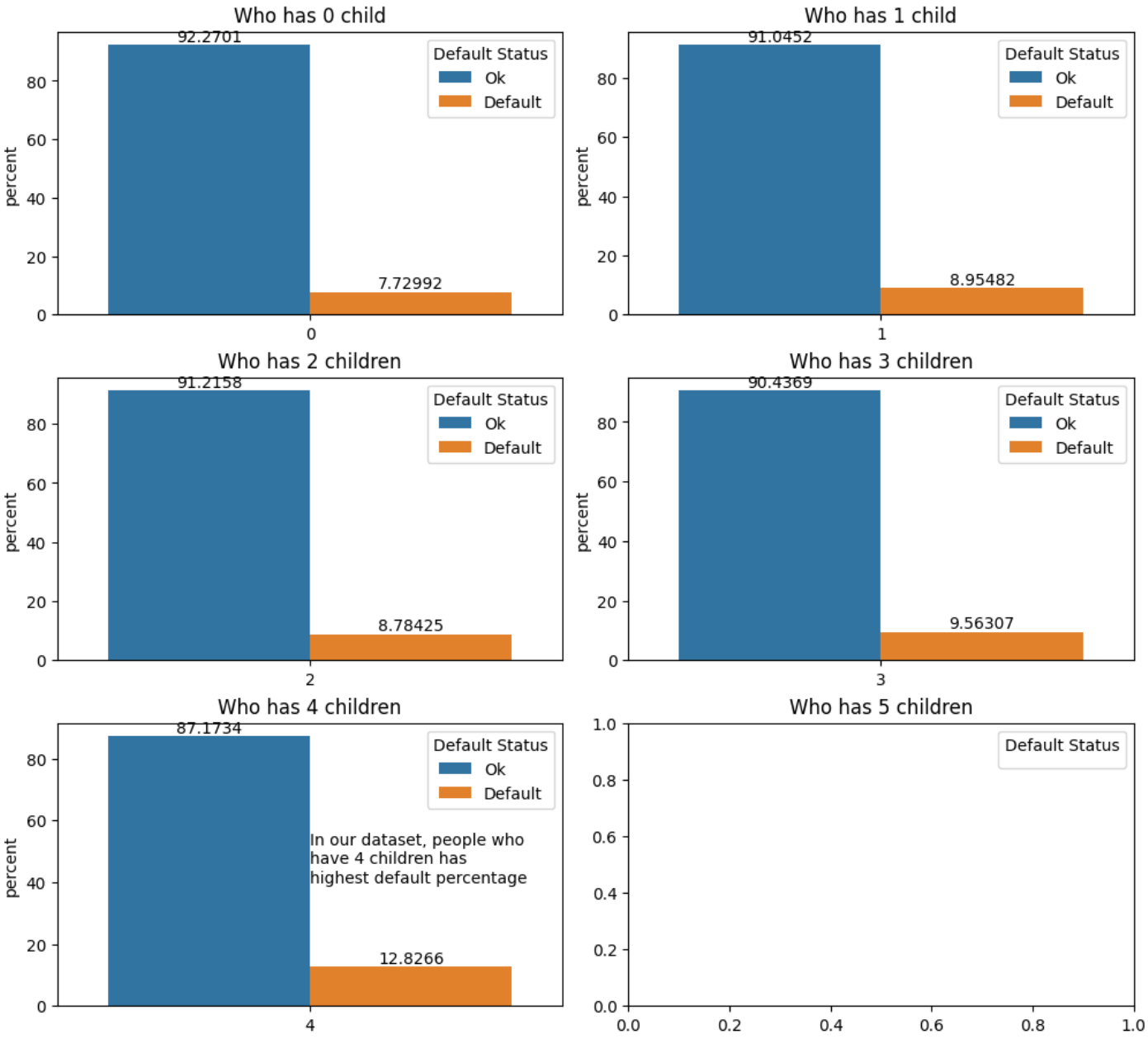
```
        for o in j.containers:
            j.bar_label(o)
```



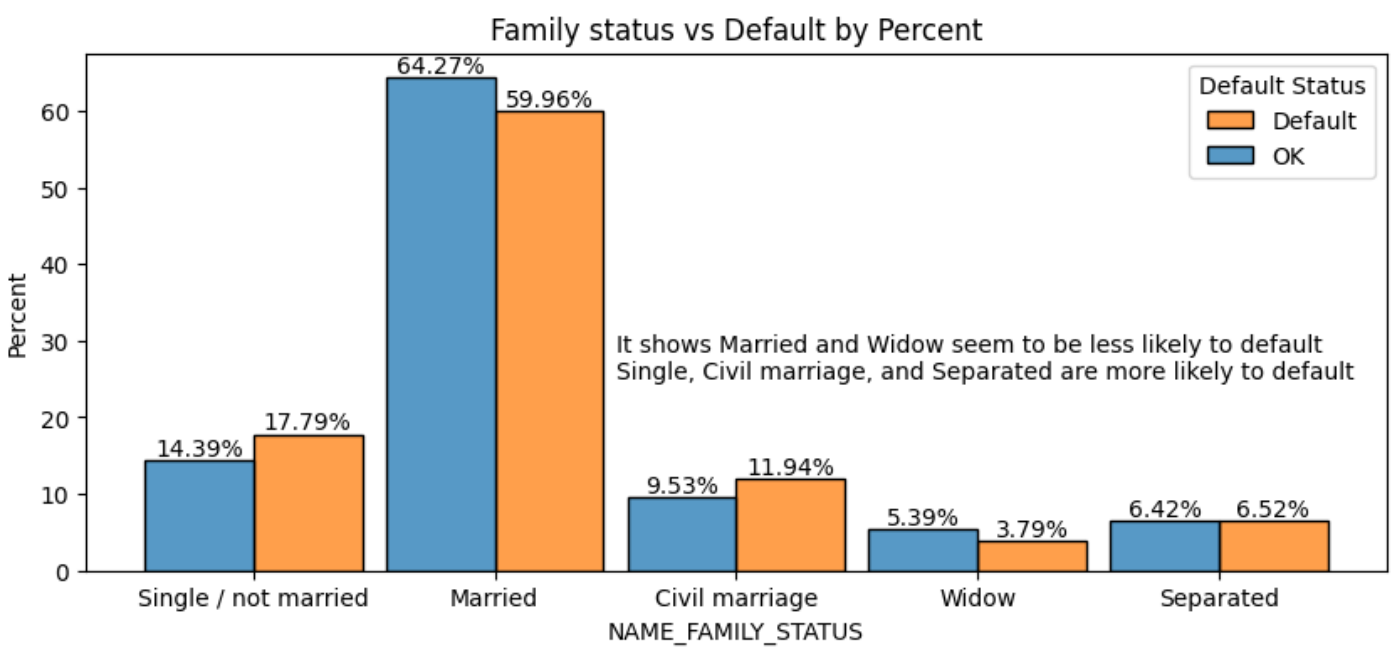






## 3. family status vs trouble

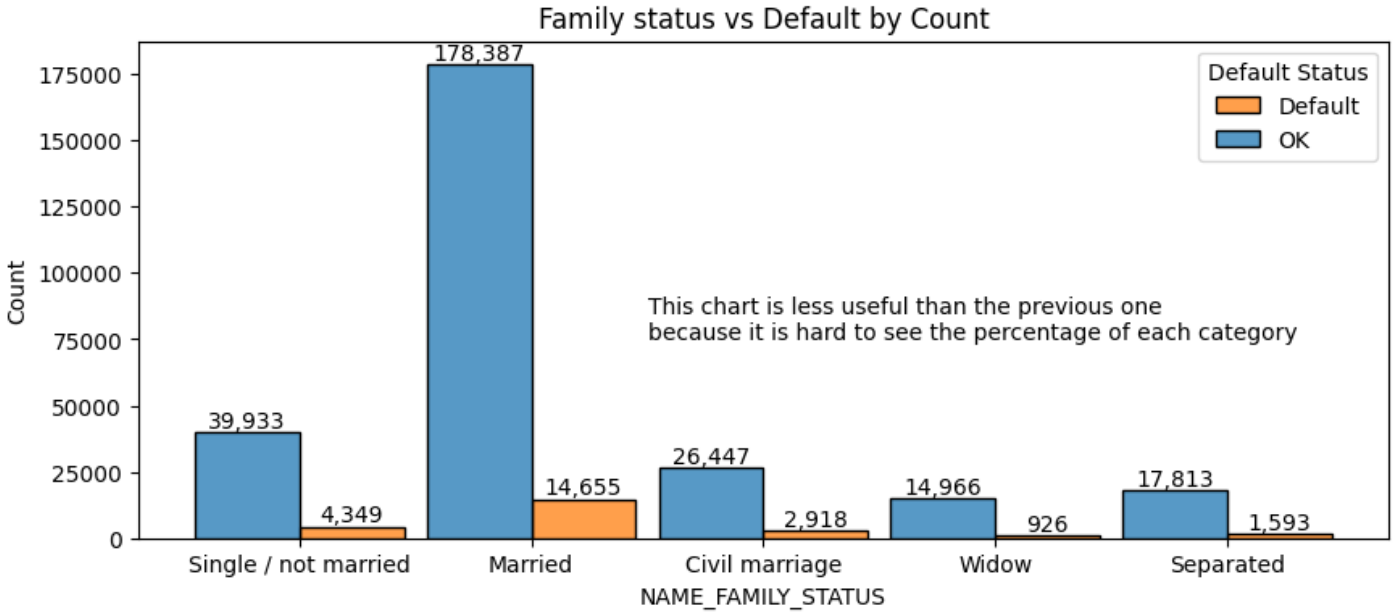
In [119…

```
# always learning new things
# it turns out we can combine all those children plots into one
# more compact, maybe harder to see all the numbers
# but it is good everything is in the same place
# we only need 1 chart

plt.rcParams['figure.figsize'] = (10,4)

h = sns.histplot(data=df, x='NAME_FAMILY_STATUS', hue='TARGET',
                 stat='percent', multiple='dodge', common_norm=False, shrink=0.9)
h.set_title('Family status vs Default by Percent')
# notice the reverse order of the labels than the countplot in above section
h.legend(title='Default Status', labels=['Default', 'OK'])
h.text(1.5, 25, ('It shows Married and Widow seem to be less likely to default\n'
                 'Single, Civil marriage, and Separated are more likely to default'))

for o in h.containers:
    h.bar_label(o, fmt='%.2f%%')
```




In [120…

```
plt.rcParams['figure.figsize'] = (10,4)

h = sns.histplot(data=df, x='NAME_FAMILY_STATUS', hue='TARGET',
                 multiple='dodge', common_norm=False, shrink=0.9)
h.set_title('Family status vs Default by Count')
h.legend(title='Default Status', labels=['Default', 'OK'])
h.text(1.5, 75000, ('This chart is less useful than the previous one\n'
                    'because it is hard to see the percentage of each category'))

for o in h.containers:
    h.bar_label(o, fmt='{:,.0f}')
```

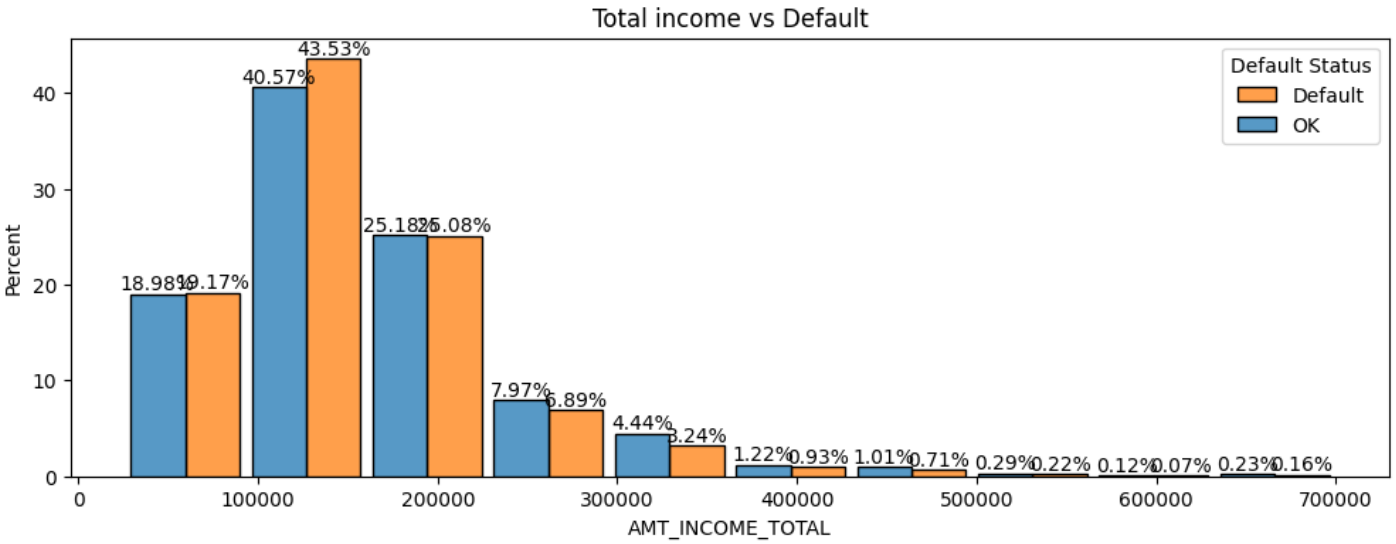



## 4. income vs trouble

In [121…

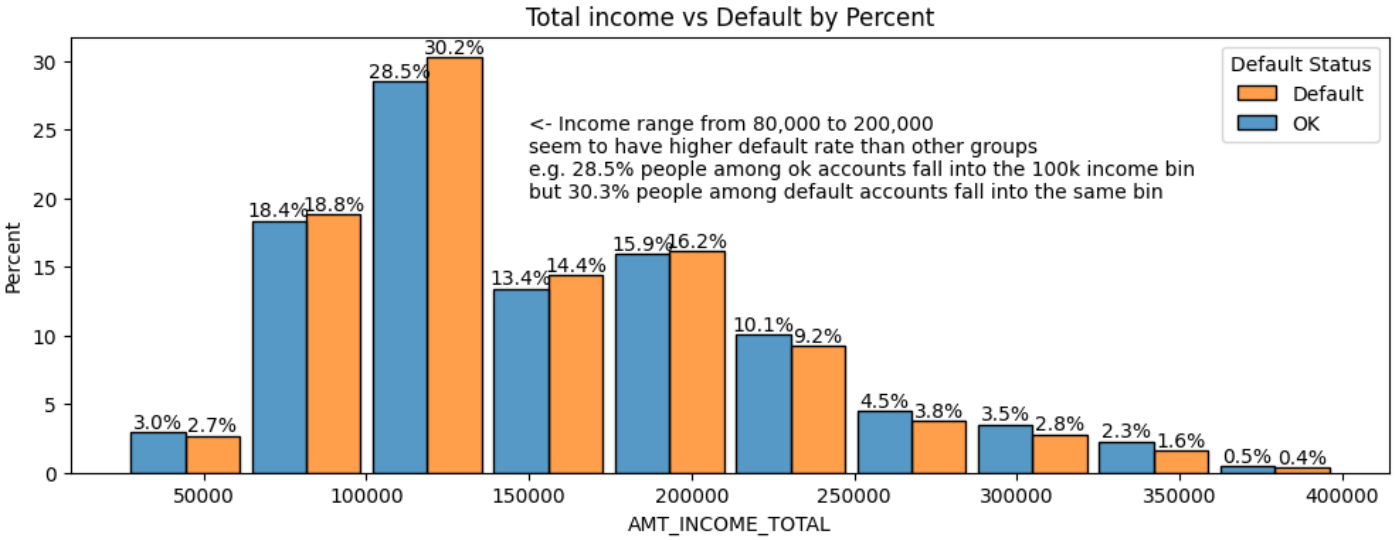
```
plt.rcParams['figure.figsize'] = (12,4)

h2 = sns.histplot(data=df, x='AMT_INCOME_TOTAL', hue='TARGET', bins=10,
                  stat='percent', multiple='dodge', common_norm=False, shrink=0.9)

h2.set_title('Total income vs Default')
h2.legend(title='Default Status', labels=['Default', 'OK'])
```

```
for o in h2.containers:
    h2.bar_label(o, fmt='{:.2f}%')
```




In [122…

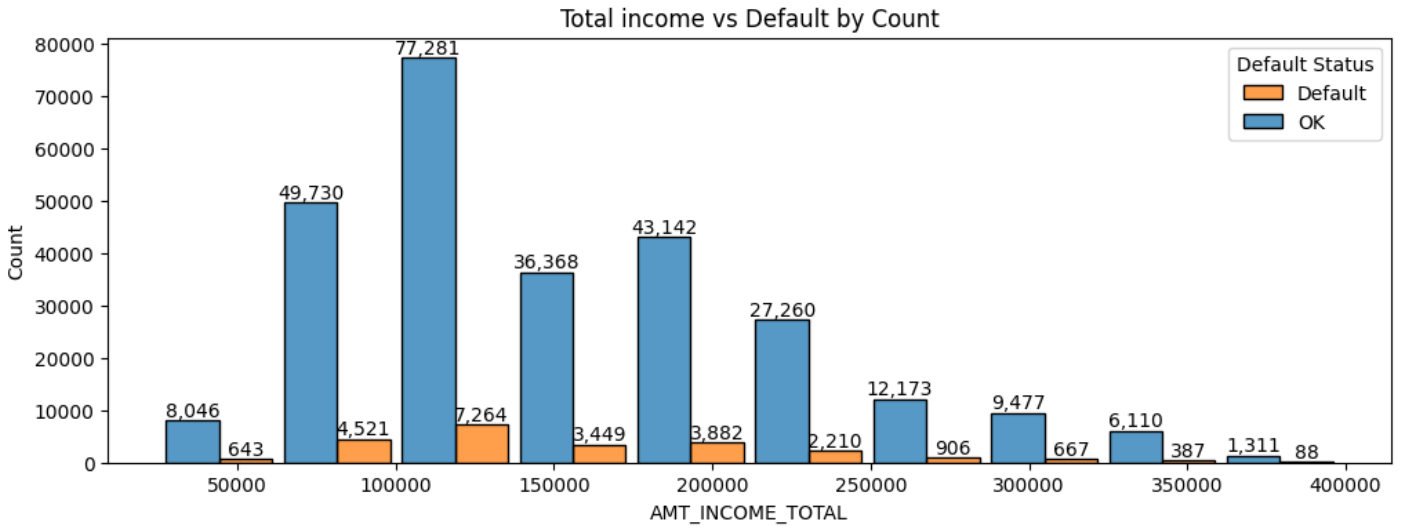
```
# the high income groups - 0.4 * 1e6 and above - are hard to see
# let's focus on the lower values

plt.rcParams['figure.figsize'] = (12,4)

h2 = sns.histplot(data=df[df['AMT_INCOME_TOTAL'] < 400000], x='AMT_INCOME_TOTAL', hue='TARGET', l
                  stat='percent', multiple='dodge', common_norm=False, shrink=0.9)

h2.set_title('Total income vs Default by Percent')
h2.legend(title='Default Status', labels=['Default', 'OK'])
h2.text(150000, 20, ('<- Income range from 80,000 to 200,000\n'
                     'seem to have higher default rate than other groups\n'
                     'e.g. 28.5% people among ok accounts fall into the 100k income bin\n'
                     'but 30.3% people among default accounts fall into the same bin'))

for o in h2.containers:
    h2.bar_label(o, fmt='{:.1f}%')
```




In [123…

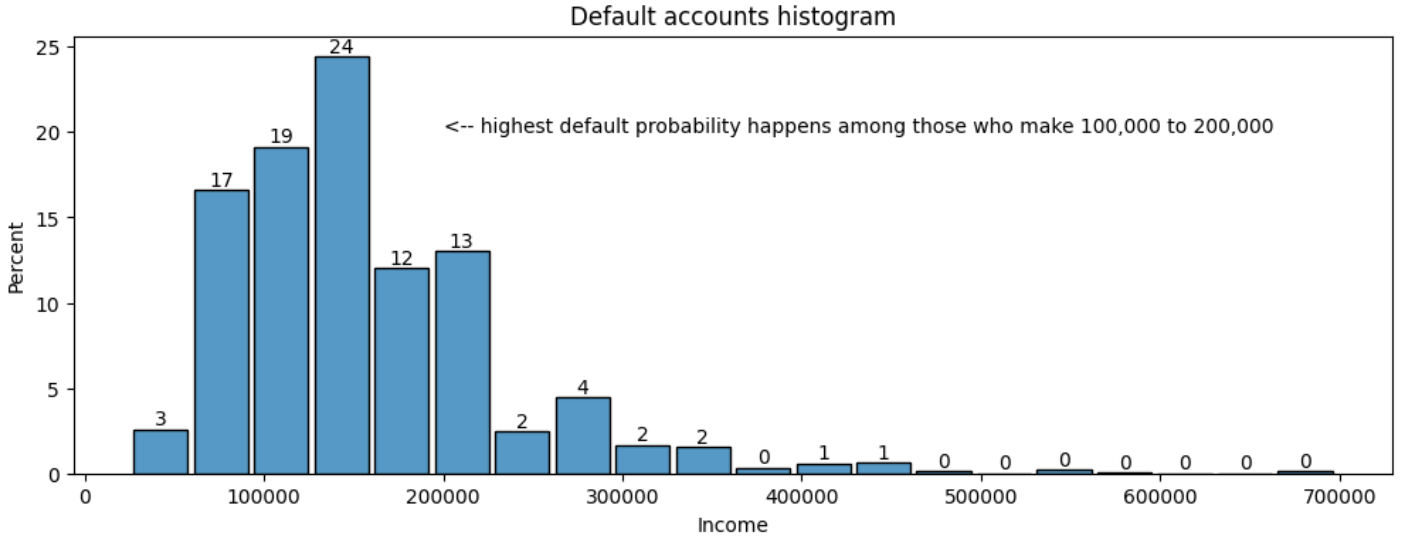
```
# check the counts

plt.rcParams['figure.figsize'] = (12,4)

h2 = sns.histplot(data=df[df['AMT_INCOME_TOTAL'] < 400000], x='AMT_INCOME_TOTAL', hue='TARGET', l
```

```
                multiple='dodge', shrink=0.9)

h2.set_title('Total income vs Default by Count')
h2.legend(title='Default Status', labels=['Default', 'OK'])

for o in h2.containers:
    h2.bar_label(o, fmt='{:,.0f}')
```




In [124…

```
# show histogram of all the default accounts

plt.rcParams['figure.figsize'] = (12,4)

h2 = sns.histplot(data=df[df['TARGET'] == 1], x='AMT_INCOME_TOTAL', stat='percent', bins=20, shr

h2.set_title('Default accounts histogram')
h2.set_xlabel('Income')
h2.text(200000, 20, '<-- highest default probability happens among those who make 100,000 to 200,

for o in h2.containers:
    h2.bar_label(o, fmt='{:,.0f}')
```




# 5. Regression

## Logistic Regression

## 1. data

In [125…
```
# reload
df = pd.read_csv('application_train_clean.csv')

# focus on a few columns
df_sub = df.loc[:, ['CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT',
                    'AMT_ANNUITY',
                    'AGE', 'AGE_EMPLOYED', 'AGE_REGISTRATION', 'AGE_ID',
                    'AGE_CAR', 'CNT_FAM_MEMBERS']]
y = df.loc[:, 'TARGET']

len(df_sub)
```

Out[125…
```
301991
```

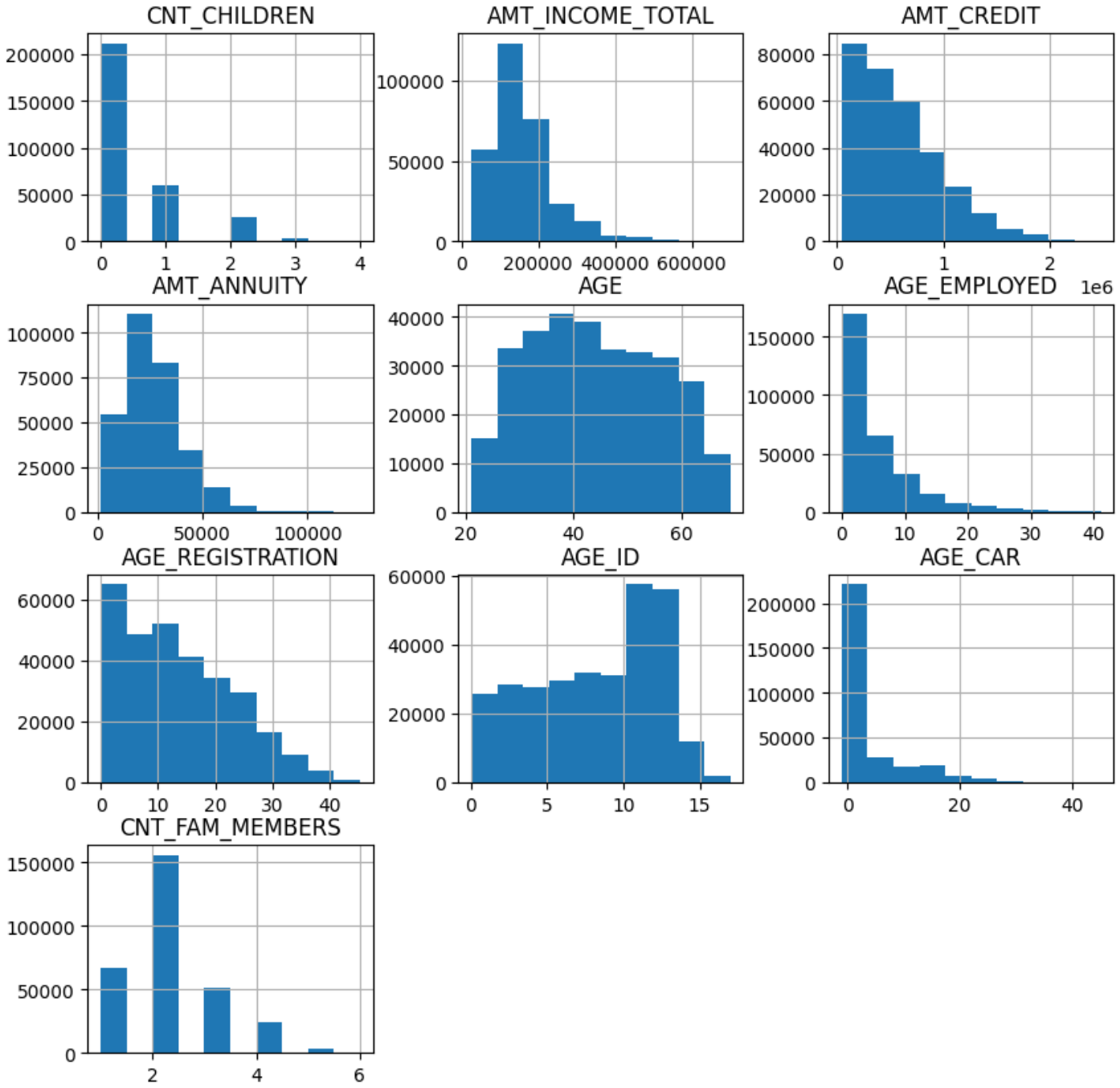
In [126…
```
df_sub.head()
```

Out[126…

| | CNT_CHILDREN | AMT_INCOME_TOTAL | AMT_CREDIT | AMT_ANNUITY | AGE | AGE_EMPLOYED | AGE_REGIS |
|---|---|---|---|---|---|---|---|
| **0** | 0 | 202,500.0 | 406,597.5 | 24,700.5 | 25.9 | 1.7 | |
| **1** | 0 | 270,000.0 | 1,293,502.5 | 35,698.5 | 45.9 | 3.3 | |
| **2** | 0 | 67,500.0 | 135,000.0 | 6,750.0 | 52.2 | 0.6 | |
| **3** | 0 | 135,000.0 | 312,682.5 | 29,686.5 | 52.1 | 8.3 | |
| **4** | 0 | 121,500.0 | 513,000.0 | 21,865.5 | 54.6 | 8.3 | |

In [127…
```
df_sub.hist(figsize=(10,10))
```

Out[127…
```
array([[<Axes: title={'center': 'CNT_CHILDREN'}>,
        <Axes: title={'center': 'AMT_INCOME_TOTAL'}>,
        <Axes: title={'center': 'AMT_CREDIT'}>],
       [<Axes: title={'center': 'AMT_ANNUITY'}>,
        <Axes: title={'center': 'AGE'}>,
        <Axes: title={'center': 'AGE_EMPLOYED'}>],
       [<Axes: title={'center': 'AGE_REGISTRATION'}>,
        <Axes: title={'center': 'AGE_ID'}>,
        <Axes: title={'center': 'AGE_CAR'}>],
       [<Axes: title={'center': 'CNT_FAM_MEMBERS'}>, <Axes: >, <Axes: >]],
      dtype=object)
```




In [128…
```
# fit LogisticRegression without feature names
# easier for later prediction part
# no warnings
df_sub_values = df_sub.values
df_sub_values.shape
```

Out[128…
```
(301991, 10)
```

In [129…
```
len(y)
```

Out[129…
```
301991
```

In [130…
```
y.head()
```

Out[130…
```
0    1
1    0
2    0
3    0
4    0
Name: TARGET, dtype: int64
```

In [131…
```
y.shape
```

Out[131…
```
(301991,)
```

In [132…
```
lr = LogisticRegression(class_weight='balanced')

lr.fit(df_sub_values, y)
```

Out[132…

LogisticRegression

```
LogisticRegression(class_weight='balanced')
```

## 2. scoring and confusion matrix

In [133…
```
lr.score(df_sub_values, y)
```

Out[133…
```
0.7086800600017882
```

In [134…
```
predict_test = lr.predict(df_sub_values)

np.unique(predict_test, return_counts=True)
```

Out[134…
```
(array([0, 1], dtype=int64), array([221954,  80037], dtype=int64))
```

In [135…
```
y.value_counts()
```

Out[135…
```
TARGET
0    277550
1     24441
Name: count, dtype: int64
```

In [136…
```
from sklearn.metrics import confusion_matrix

df_cm = pd.DataFrame(confusion_matrix(y, predict_test))

df_cm = df_cm.rename(columns={0: 'pred no', 1: 'pred yes'},
                     index={0: 'actual no', 1: 'actual yes'}
                    )
df_cm
```

Out[136…

| | pred no | pred yes |
|---|---|---|
| **actual no** | 205764 | 71786 |
| **actual yes** | 16190 | 8251 |

## 3. predict

In [137…
```
# lr was trained by 301991 records
# score 0.7086800600017882
```

```
# try to predict with some made-up independent varaible
# this is the template

X = pd.DataFrame([[0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]],
                 columns=['CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT',
                          'AMT_ANNUITY',
                          'AGE', 'AGE_EMPLOYED', 'AGE_REGISTRATION', 'AGE_ID',
                          'AGE_CAR', 'CNT_FAM_MEMBERS']
                )

# this is from the head of the training dataset
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]
b = np.array(a).reshape(1, -1)

lr.predict_proba(b)
```

Out[137…

```
array([[0.55818112, 0.44181888]])
```

In [138…

```
# this one actualy predicts correctly
# 55.8% probability points to 0
y[2]
```

Out[138…

```
0
```

In [139…

```
# now let's check each independent variable
# CNT_CHILDREN
# no effect
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(7):
    a[0] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.55818112 0.44181888]]
[0] [[0.55814823 0.44185177]]
[0] [[0.55811533 0.44188467]]
[0] [[0.55808243 0.44191757]]
[0] [[0.55804953 0.44195047]]
[0] [[0.55801663 0.44198337]]
[0] [[0.55798372 0.44201628]]
```

In [140…

```
# AMT_INCOME_TOTAL
# more income, more likely to default
# ?? not common sense
# just slightly though
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 500000, 50000):
    a[1] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.56061684 0.43938316]]
[0] [[0.55881288 0.44118712]]
[0] [[0.55700737 0.44299263]]
[0] [[0.55520035 0.44479965]]
[0] [[0.55339187 0.44660813]]
[0] [[0.55158198 0.44841802]]
[0] [[0.54977071 0.45022929]]
[0] [[0.54795813 0.45204187]]
[0] [[0.54614428 0.45385572]]
[0] [[0.5443292 0.4556708]]
```

In [141…

```python
# AMT_CREDIT
# more credit, less likely to default
# don't know
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 1500000, 100000):
    a[2] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.54186499 0.45813501]]
[0] [[0.55396162 0.44603838]]
[0] [[0.56599467 0.43400533]]
[0] [[0.57795042 0.42204958]]
[0] [[0.5898155 0.4101845]]
[0] [[0.60157697 0.39842303]]
[0] [[0.61322235 0.38677765]]
[0] [[0.62473967 0.37526033]]
[0] [[0.63611755 0.36388245]]
[0] [[0.64734518 0.35265482]]
[0] [[0.65841241 0.34158759]]
[0] [[0.66930975 0.33069025]]
[0] [[0.68002839 0.31997161]]
[0] [[0.69056022 0.30943978]]
[0] [[0.70089788 0.29910212]]
```

In [142…

```python
# AMT_ANNUITY
# more annuity, more likely to default
# sounds about right
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 50000, 5000):
    a[3] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.58624847 0.41375153]]
[0] [[0.56550117 0.43449883]]
[0] [[0.54452181 0.45547819]]
[0] [[0.52338323 0.47661677]]
[0] [[0.50216055 0.49783945]]
[1] [[0.48093008 0.51906992]]
[1] [[0.45976825 0.54023175]]
[1] [[0.4387505 0.5612495]]
[1] [[0.41795023 0.58204977]]
[1] [[0.39743778 0.60256222]]
```

In [143…

```python
# AGE
# older, less likely to default
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 70, 5):
```

```
    a[4] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[1] [[0.49391628 0.50608372]]
[0] [[0.50009701 0.49990299]]
[0] [[0.5062777 0.4937223]]
[0] [[0.51245648 0.48754352]]
[0] [[0.51863145 0.48136855]]
[0] [[0.52480073 0.47519927]]
[0] [[0.53096246 0.46903754]]
[0] [[0.53711476 0.46288524]]
[0] [[0.54325577 0.45674423]]
[0] [[0.54938367 0.45061633]]
[0] [[0.55549663 0.44450337]]
[0] [[0.56159283 0.43840717]]
[0] [[0.56767049 0.43232951]]
[0] [[0.57372785 0.42627215]]
```

In [144…

```
# AGE_EMPLOYED
# not much difference
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 40, 5):
    a[5] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.55788722 0.44211278]]
[0] [[0.56033515 0.43966485]]
[0] [[0.56278016 0.43721984]]
[0] [[0.56522211 0.43477789]]
[0] [[0.5676609 0.4323391]]
[0] [[0.57009642 0.42990358]]
[0] [[0.57252855 0.42747145]]
[0] [[0.57495718 0.42504282]]
```

In [145…

```
# AGE_REGISTRATION
# not much effect
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 40, 5):
    a[6] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.55090057 0.44909943]]
[0] [[0.55401477 0.44598523]]
[0] [[0.55712474 0.44287526]]
[0] [[0.56023024 0.43976976]]
[0] [[0.56333103 0.43666897]]
[0] [[0.56642687 0.43357313]]
[0] [[0.56951754 0.43048246]]
[0] [[0.57260281 0.42739719]]
```

In [146…

```
# AGE_CAR
# no effect
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 50, 5):
    a[7] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.55600536 0.44399464]]
[0] [[0.55758222 0.44241778]]
[0] [[0.55915792 0.44084208]]
[0] [[0.56073243 0.43926757]]
[0] [[0.56230572 0.43769428]]
[0] [[0.56387775 0.43612225]]
[0] [[0.56544851 0.43455149]]
[0] [[0.56701795 0.43298205]]
[0] [[0.56858604 0.43141396]]
[0] [[0.57015276 0.42984724]]
```

In [147…

```python
# CNT_FAM_MEMBERS
# no effect
a = [0, 67500, 135000, 6750, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(8):
    a[8] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[0] [[0.5593935 0.4406065]]
[0] [[0.55934688 0.44065312]]
[0] [[0.55930027 0.44069973]]
[0] [[0.55925365 0.44074635]]
[0] [[0.55920703 0.44079297]]
[0] [[0.55916041 0.44083959]]
[0] [[0.55911378 0.44088622]]
[0] [[0.55906716 0.44093284]]
```

In [148…

```python
# the first try has a good score of 0.71
# however it is not satisfactory
# because most of the age columns do not seem to matter
# or has an effect that is too small to change the final outcome from 0 to 1
# which is big
# let's try again
```

## Logistic Regression second version

### 1. second version

In [149…

```python
# focus on fewer columns
# we suspect the money ones have too wide a range
# and the age ones has too narrow a range
# 0-70 is nothing compared to 0-1million

df_less = df_sub.drop(columns=['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY'])

y = df['TARGET']

df_less, y
```

Out[149…

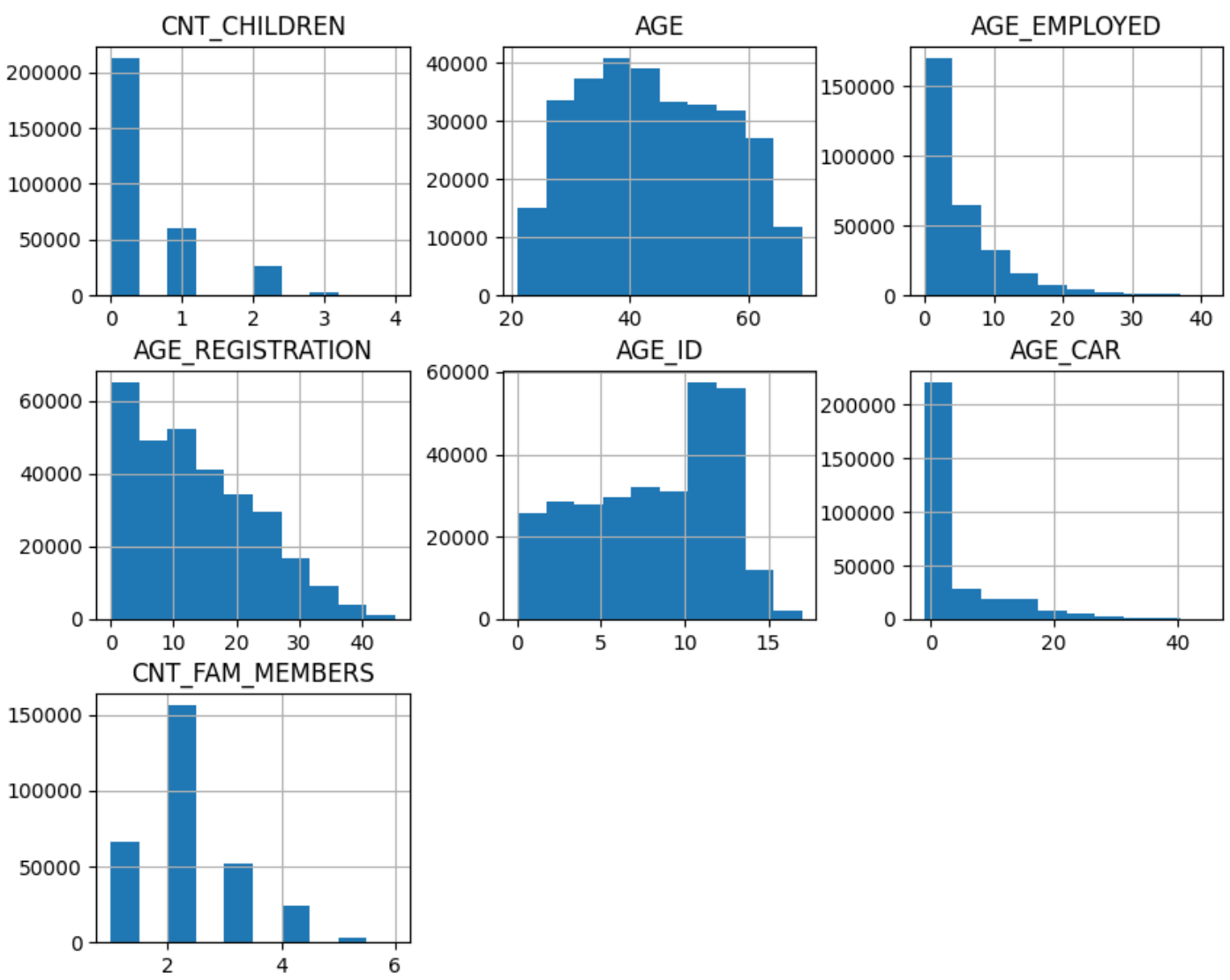
```
(        CNT_CHILDREN  AGE  AGE_EMPLOYED  AGE_REGISTRATION  AGE_ID  AGE_CAR  \
0                  0 25.9           1.7              10.0     5.8     -1.0
1                  0 45.9           3.3               3.2     0.8     -1.0
2                  0 52.2           0.6              11.7     6.9     26.0
3                  0 52.1           8.3              26.9     6.7     -1.0
4                  0 54.6           8.3              11.8     9.5     -1.0
...              ...  ...           ...               ...     ...      ...
301986             0 25.6           0.6              23.2     5.4     -1.0
301987             0 56.9          -0.0              12.0    11.2     -1.0
301988             0 41.0          21.7              18.5    14.1     -1.0
301989             0 32.8          13.1               7.0     2.6     -1.0
301990             0 46.2           3.5              14.0     1.1     -1.0

        CNT_FAM_MEMBERS
0                   1.0
1                   2.0
2                   1.0
3                   2.0
4                   1.0
...                 ...
301986              1.0
301987              1.0
301988              1.0
301989              2.0
301990              2.0

[301991 rows x 7 columns],
0         1
1         0
2         0
3         0
4         0
         ..
301986    0
301987    0
301988    0
301989    1
301990    0
Name: TARGET, Length: 301991, dtype: int64)
```

In [150…

```
df_less.hist(figsize=(10,8))
```

Out[150…

```
array([[<Axes: title={'center': 'CNT_CHILDREN'}>,
        <Axes: title={'center': 'AGE'}>,
        <Axes: title={'center': 'AGE_EMPLOYED'}>],
       [<Axes: title={'center': 'AGE_REGISTRATION'}>,
        <Axes: title={'center': 'AGE_ID'}>,
        <Axes: title={'center': 'AGE_CAR'}>],
       [<Axes: title={'center': 'CNT_FAM_MEMBERS'}>, <Axes: >, <Axes: >]],
      dtype=object)
```




In [151…
```
lr = LogisticRegression(class_weight='balanced')

lr.fit(df_less.values, y)

lr.score(df_less.values, y)
```

Out[151…
```
0.5742224106016405
```

In [152…
```
test = lr.predict(df_less.values)

np.unique(test, return_counts=True)
```

Out[152…
```
(array([0, 1], dtype=int64), array([169163, 132828], dtype=int64))
```

## 2. predict

In [153…
```
# lr was trained by 301991 records
# score 0.5742224106016405

# this is the template of input

X = pd.DataFrame([[0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]],
                 columns=['CNT_CHILDREN', 'AGE', 'AGE_EMPLOYED',
                          'AGE_REGISTRATION', 'AGE_ID',
                          'AGE_CAR', 'CNT_FAM_MEMBERS']
                )
```

```
# this is from the head of the training dataset
a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]
b = np.array(a).reshape(1, -1)

lr.predict_proba(b)
```

Out[153…
```
array([[0.4946436, 0.5053564]])
```

In [154…
```
# CNT_CHILDREN
# here we go
# looks like we guessed the right thing by dropping the money columns
# now we can see the differences of outcomes if we change CNT_CHILDREN
# more children, more likely to default
a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(8):
    a[0] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[1] [[0.4946436 0.5053564]]
[1] [[0.47304373 0.52695627]]
[1] [[0.45154429 0.54845571]]
[1] [[0.43022422 0.56977578]]
[1] [[0.40915982 0.59084018]]
[1] [[0.38842368 0.61157632]]
[1] [[0.36808375 0.63191625]]
[1] [[0.3482025 0.6517975]]
```

In [155…
```
# AGE
# better than first version as now we can see the difference among age groups
# older, less likely to default
a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 77, 5):
    a[1] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[1] [[0.252991 0.747009]]
[1] [[0.27268021 0.72731979]]
[1] [[0.29330011 0.70669989]]
[1] [[0.31480438 0.68519562]]
[1] [[0.33713316 0.66286684]]
[1] [[0.3602131 0.6397869]]
[1] [[0.38395786 0.61604214]]
[1] [[0.40826902 0.59173098]]
[1] [[0.43303746 0.56696254]]
[1] [[0.45814513 0.54185487]]
[1] [[0.48346718 0.51653282]]
[0] [[0.50887442 0.49112558]]
[0] [[0.53423589 0.46576411]]
[0] [[0.5594216 0.4405784]]
[0] [[0.58430512 0.41569488]]
[0] [[0.60876611 0.39123389]]
```

In [156…
```
# AGE_EMPLOYED
# slight increase in account's realiability as holder's work age increase
a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(0, 40, 5):
```

```
    a[3] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[1] [[0.47371657 0.52628343]]
[1] [[0.48265274 0.51734726]]
[1] [[0.49160001 0.50839999]]
[0] [[0.50055267 0.49944733]]
[0] [[0.50950498 0.49049502]]
[0] [[0.51845119 0.48154881]]
[0] [[0.52738559 0.47261441]]
[0] [[0.53630248 0.46369752]]
```

In [157…

```
# CNT_FAM_MEMBERS
# more family members, less likely to default
a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]

for i in range(8):
    a[6] = i
    b = np.array(a).reshape(1, -1)
    print(lr.predict(b), lr.predict_proba(b))
```

```
[1] [[0.47362801 0.52637199]]
[1] [[0.4946436 0.5053564]]
[0] [[0.51567814 0.48432186]]
[0] [[0.53665727 0.46334273]]
[0] [[0.55750743 0.44249257]]
[0] [[0.57815686 0.42184314]]
[0] [[0.59853658 0.40146342]]
[0] [[0.61858126 0.38141874]]
```

In [158…

```
# conclusion
# the second version is not complete because it omits those money columns
# like income, amount of credit etc
# however it is very useful for us to see the difference of outcome
# from changing those age columns
```

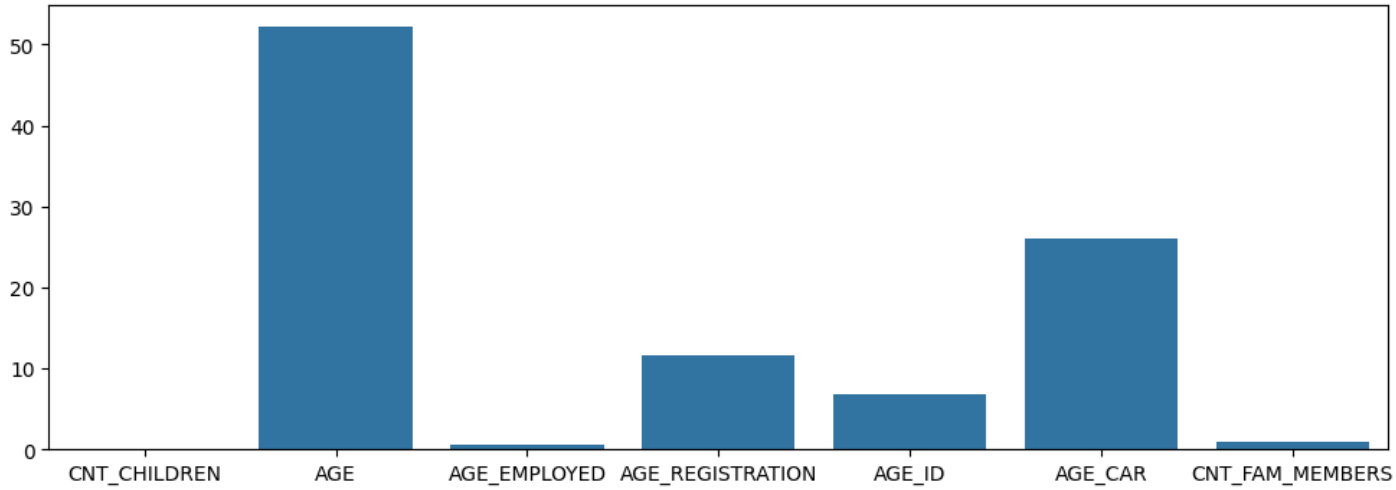
## 3. plot

In [159…

```
# finally some plot to show the prediction visually

# this is our average person Joe
# [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]
# 0 children
# 52.2 years old
# 0.6 years of being employed
# 11.7 years of latest registration
# 6.9 years of latest ID
# with a car of 26 years old
# and a family member of 1

sns.barplot(x=['CNT_CHILDREN', 'AGE', 'AGE_EMPLOYED',
               'AGE_REGISTRATION', 'AGE_ID',
               'AGE_CAR', 'CNT_FAM_MEMBERS'],
            y=[0, 52.2, 0.6, 11.7, 6.9, 26.0, 1])
```

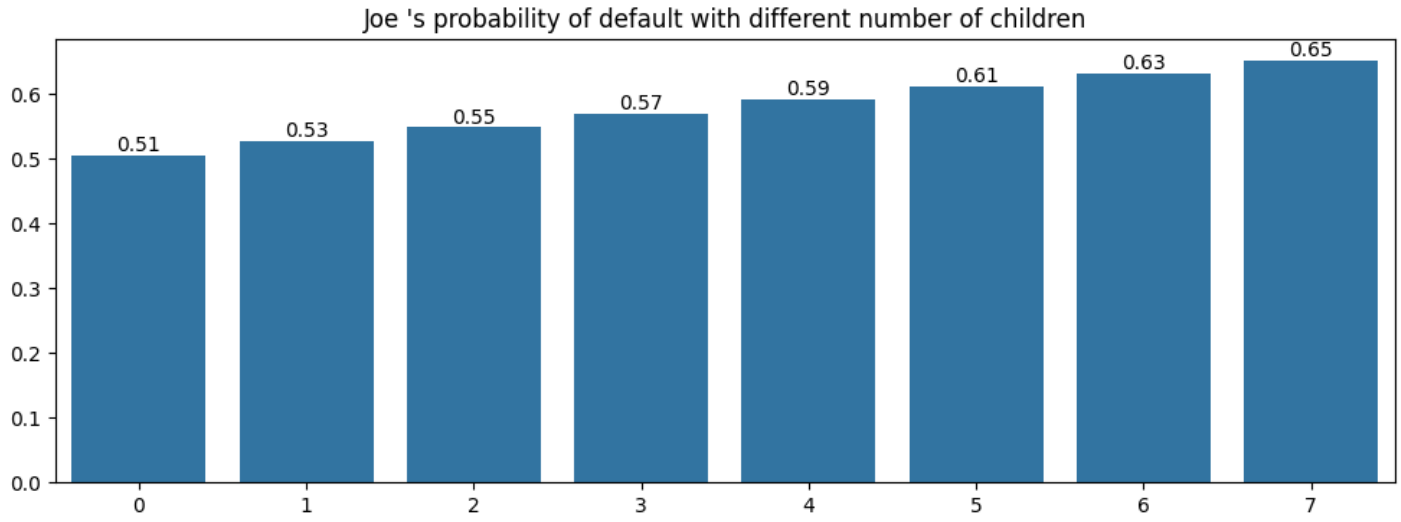
Out[159…

```
<Axes: >
```




In [160…

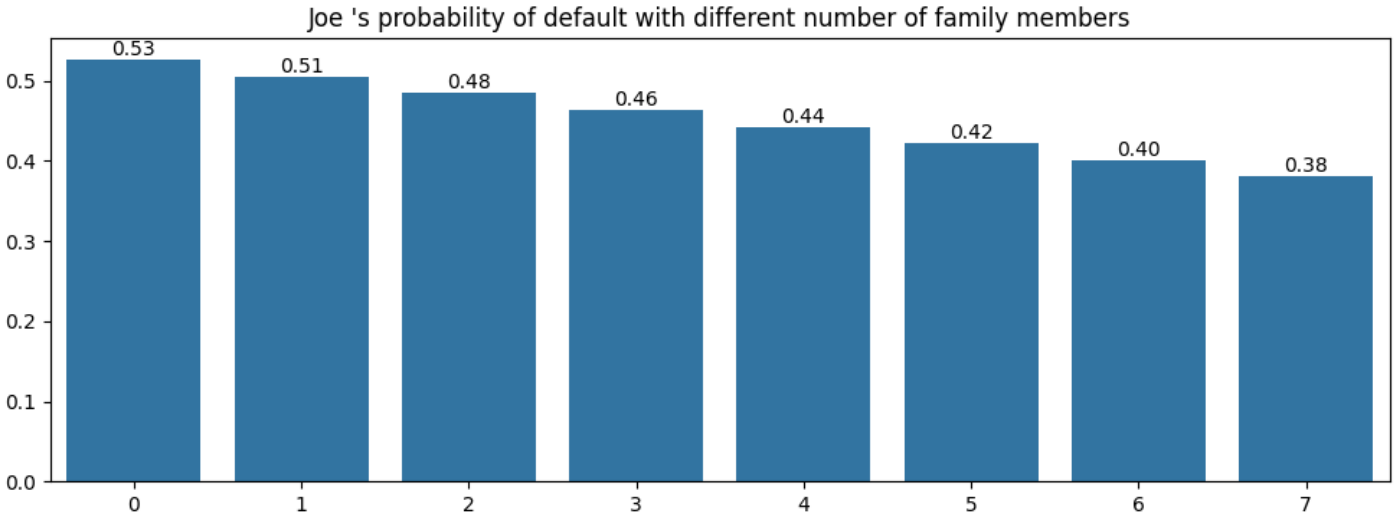
```
# what if we change some of the inputs?

a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]
x_list = []
y_list = []

for i in range(8):
    a[0] = i
    b = np.array(a).reshape(1, -1)

    x_list.append(i)
    y_list.append(lr.predict_proba(b)[0][1])

ax = sns.barplot(x=x_list, y=y_list)
ax.set_title('Joe \'s probability of default with different number of children')
for o in ax.containers:
    ax.bar_label(o, fmt='%.2f')
```




In [161…

```
a = [0, 52.2, 0.6, 11.7, 6.9, 26.0, 1]
x_list = []
y_list = []

for i in range(8):
    a[6] = i
    b = np.array(a).reshape(1, -1)

    x_list.append(i)
    y_list.append(lr.predict_proba(b)[0][1])
```

```
ax = sns.barplot(x=x_list, y=y_list, errorbar=None)
ax.set_title('Joe \'s probability of default with different number of family members')
for o in ax.containers:
    ax.bar_label(o, fmt='%.2f')
```




In [162…

```
# end of project
```