

01_Exploration.ipynb

September 10, 2021

1 Initialisation

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

2 Exploration

```
[ ]: ! ls -lh 02_data/
```

```
total 2,5G
-rw-rw-r-- 1 adrien adrien 26M juin 26 2018 application_test.csv
-rw-rw-r-- 1 adrien adrien 159M juin 26 2018 application_train.csv
-rw-rw-r-- 1 adrien adrien 359M juin 26 2018 bureau_balance.csv
-rw-rw-r-- 1 adrien adrien 163M juin 26 2018 bureau.csv
-rw-rw-r-- 1 adrien adrien 405M juin 26 2018 credit_card_balance.csv
-rw-rw-r-- 1 adrien adrien 37K juin 26 2018
HomeCredit_columns_description.csv
-rw-rw-r-- 1 adrien adrien 690M juin 26 2018 installments_payments.csv
-rw-rw-r-- 1 adrien adrien 375M juin 26 2018 POS_CASH_balance.csv
-rw-rw-r-- 1 adrien adrien 387M juin 26 2018 previous_application.csv
-rw-rw-r-- 1 adrien adrien 524K juin 26 2018 sample_submission.csv
```

```
[ ]: col_desc = pd.read_csv('02_data/HomeCredit_columns_description.csv',
                           index_col=0)
col_desc
```

```
[ ]:
      Table                                     Row \
1    application_{train|test}.csv              SK_ID_CURR
2    application_{train|test}.csv              TARGET
5    application_{train|test}.csv      NAME_CONTRACT_TYPE
6    application_{train|test}.csv              CODE_GENDER
7    application_{train|test}.csv      FLAG_OWN_CAR
..
217  installments_payments.csv  NUM_INSTALLMENT_NUMBER
218  installments_payments.csv      DAYS_INSTALLMENT
```

```

219     installments_payments.csv      DAYS_ENTRY_PAYMENT
220     installments_payments.csv      AMT_INSTALMENT
221     installments_payments.csv      AMT_PAYMENT

```

```

                                     Description \
1                                     ID of loan in our sample
2     Target variable (1 - client with payment diffi...
5         Identification if loan is cash or revolving
6                                     Gender of the client
7         Flag if the client owns a car
..                                     ...
217        On which installment we observe payment
218 When the installment of previous credit was su...
219 When was the installments of previous credit p...
220 What was the prescribed installment amount of ...
221 What the client actually paid on previous cred...

```

```

                                     Special
1                                     NaN
2                                     NaN
5                                     NaN
6                                     NaN
7                                     NaN
..                                     ...
217        NaN
218 time only relative to the application
219 time only relative to the application
220        NaN
221        NaN

```

[219 rows x 4 columns]

2.1 Tables `application_{train|test}.csv`

Il y a plus de 200 colonnes pour 9 tables au format csv ! Avant d'aller plus loin dans l'exploration je vais me concentrer sur les tables principales : les tables `application_{train|test}.csv`.

Je vais d'abord regarder les plus grosses corrélations avec la variable `TARGET`

```

[ ]: app_train = pd.read_csv('02_data/application_train.csv')
      app_test = pd.read_csv('02_data/application_test.csv')
      app_train

```

```

[ ]:      SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
0          100002      1      Cash loans      M      N
1          100003      0      Cash loans      F      N
2          100004      0      Revolving loans      M      Y
3          100006      0      Cash loans      F      N

```

4	100007	0	Cash loans	M	N
...
307506	456251	0	Cash loans	M	N
307507	456252	0	Cash loans	F	N
307508	456253	0	Cash loans	F	N
307509	456254	1	Cash loans	F	N
307510	456255	0	Cash loans	F	N

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	\
0	Y	0	202500.0	406597.5	
1	N	0	270000.0	1293502.5	
2	Y	0	67500.0	135000.0	
3	Y	0	135000.0	312682.5	
4	Y	0	121500.0	513000.0	
...	
307506	N	0	157500.0	254700.0	
307507	Y	0	72000.0	269550.0	
307508	Y	0	153000.0	677664.0	
307509	Y	0	171000.0	370107.0	
307510	N	0	157500.0	675000.0	

	AMT_ANNUITY	...	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	\
0	24700.5	...	0	0	0	
1	35698.5	...	0	0	0	
2	6750.0	...	0	0	0	
3	29686.5	...	0	0	0	
4	21865.5	...	0	0	0	
...	
307506	27558.0	...	0	0	0	
307507	12001.5	...	0	0	0	
307508	29979.0	...	0	0	0	
307509	20205.0	...	0	0	0	
307510	49117.5	...	0	0	0	

	FLAG_DOCUMENT_21	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	\
0	0	0.0	0.0	
1	0	0.0	0.0	
2	0	0.0	0.0	
3	0	NaN	NaN	
4	0	0.0	0.0	
...	
307506	0	NaN	NaN	
307507	0	NaN	NaN	
307508	0	1.0	0.0	
307509	0	0.0	0.0	
307510	0	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0
...
307506	NaN	NaN
307507	NaN	NaN
307508	0.0	1.0
307509	0.0	0.0
307510	0.0	2.0

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
0	0.0	1.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0
...
307506	NaN	NaN
307507	NaN	NaN
307508	0.0	1.0
307509	0.0	0.0
307510	0.0	1.0

[307511 rows x 122 columns]

```
[ ]: assert len(app_train.SK_ID_CURR.unique()) == app_train.shape[0]
      assert len(app_test.SK_ID_CURR.unique()) == app_test.shape[0]

      app_train.set_index('SK_ID_CURR', inplace=True)
      app_test.set_index('SK_ID_CURR', inplace=True)
```

```
[ ]: app_train
```

```
[ ]: TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR \
      SK_ID_CURR
100002      1      Cash loans      M      N
100003      0      Cash loans      F      N
100004      0  Revolving loans      M      Y
100006      0      Cash loans      F      N
100007      0      Cash loans      M      N
...      ...      ...      ...      ...
456251      0      Cash loans      M      N
456252      0      Cash loans      F      N
456253      0      Cash loans      F      N
```

456254	1	Cash loans	F	N
456255	0	Cash loans	F	N

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	\
SK_ID_CURR					
100002	Y	0	202500.0	406597.5	
100003	N	0	270000.0	1293502.5	
100004	Y	0	67500.0	135000.0	
100006	Y	0	135000.0	312682.5	
100007	Y	0	121500.0	513000.0	
...	
456251	N	0	157500.0	254700.0	
456252	Y	0	72000.0	269550.0	
456253	Y	0	153000.0	677664.0	
456254	Y	0	171000.0	370107.0	
456255	N	0	157500.0	675000.0	

	AMT_ANNUITY	AMT_GOODS_PRICE	... FLAG_DOCUMENT_18	\
SK_ID_CURR			...	
100002	24700.5	351000.0	...	0
100003	35698.5	1129500.0	...	0
100004	6750.0	135000.0	...	0
100006	29686.5	297000.0	...	0
100007	21865.5	513000.0	...	0
...
456251	27558.0	225000.0	...	0
456252	12001.5	225000.0	...	0
456253	29979.0	585000.0	...	0
456254	20205.0	319500.0	...	0
456255	49117.5	675000.0	...	0

	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	\
SK_ID_CURR				
100002	0	0	0	
100003	0	0	0	
100004	0	0	0	
100006	0	0	0	
100007	0	0	0	
...	
456251	0	0	0	
456252	0	0	0	
456253	0	0	0	
456254	0	0	0	
456255	0	0	0	

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	\
SK_ID_CURR			

100002	0.0	0.0
100003	0.0	0.0
100004	0.0	0.0
100006	NaN	NaN
100007	0.0	0.0
...
456251	NaN	NaN
456252	NaN	NaN
456253	1.0	0.0
456254	0.0	0.0
456255	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON \
SK_ID_CURR		
100002	0.0	0.0
100003	0.0	0.0
100004	0.0	0.0
100006	NaN	NaN
100007	0.0	0.0
...
456251	NaN	NaN
456252	NaN	NaN
456253	0.0	1.0
456254	0.0	0.0
456255	0.0	2.0

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
SK_ID_CURR		
100002	0.0	1.0
100003	0.0	0.0
100004	0.0	0.0
100006	NaN	NaN
100007	0.0	0.0
...
456251	NaN	NaN
456252	NaN	NaN
456253	0.0	1.0
456254	0.0	0.0
456255	0.0	1.0

[307511 rows x 121 columns]

2.1.1 Encodage des colonnes textuelles

```
[ ]: app_train.dtypes.value_counts()
```

```
[ ]: float64    65
      int64     40
      object    16
      dtype: int64
```

```
[ ]: app_train.select_dtypes('object').apply(pd.Series.nunique, axis=0)
```

```
[ ]: NAME_CONTRACT_TYPE          2
      CODE_GENDER                3
      FLAG_OWN_CAR              2
      FLAG_OWN_REALTY           2
      NAME_TYPE_SUITE            7
      NAME_INCOME_TYPE           8
      NAME_EDUCATION_TYPE        5
      NAME_FAMILY_STATUS        6
      NAME_HOUSING_TYPE          6
      OCCUPATION_TYPE           18
      WEEKDAY_APPR_PROCESS_START  7
      ORGANIZATION_TYPE         58
      FONDKAPREMONT_MODE         4
      HOUSETYPE_MODE             3
      WALLSMATERIAL_MODE         7
      EMERGENCYSTATE_MODE        2
      dtype: int64
```

```
[ ]: categorical_labels = app_train.select_dtypes('object').columns.tolist()
```

```
[ ]: for col in categorical_labels:
      null_count = app_train[col].isna().sum()
      null_perct = null_count / app_train[col].isna().count()
      if null_count != 0:
          print(col, null_count, round(null_perct, 4))
```

```
NAME_TYPE_SUITE 1292 0.0042
OCCUPATION_TYPE 96391 0.3135
FONDKAPREMONT_MODE 210295 0.6839
HOUSETYPE_MODE 154297 0.5018
WALLSMATERIAL_MODE 156341 0.5084
EMERGENCYSTATE_MODE 145755 0.474
```

```
[ ]: app_train.OCCUPATION_TYPE.unique()
```

```
[ ]: array(['Laborers', 'Core staff', 'Accountants', 'Managers', nan,
           'Drivers', 'Sales staff', 'Cleaning staff', 'Cooking staff',
           'Private service staff', 'Medicine staff', 'Security staff',
           'High skill tech staff', 'Waiters/barmen staff',
           'Low-skill Laborers', 'Realty agents', 'Secretaries', 'IT staff',
```

```

        'HR staff'], dtype=object)

[ ]: col_desc.loc[col_desc.Table.eq('application_{train|test}.csv')
        & col_desc.Row.eq('OCCUPATION_TYPE')].Description.tolist()

[ ]: ['What kind of occupation does the client have']

[ ]: app_train.OCCUPATION_TYPE.fillna('Unknown', inplace=True)

[ ]: app_train.dropna(subset=['NAME_TYPE_SUITE'], inplace=True)

[ ]: app_train.drop(columns=['FONDKAPREMONT_MODE',
                            'HOUSETYPE_MODE',
                            'WALLSMATERIAL_MODE',
                            'EMERGENCYSTATE_MODE'], inplace=True)

[ ]: from sklearn.preprocessing import OrdinalEncoder
      from sklearn.preprocessing import OneHotEncoder
      from sklearn.compose import make_column_transformer

[ ]: app_train.WEEKDAY_APPR_PROCESS_START.unique()

weekday_codes = {
    'MONDAY': 0,
    'TUESDAY': 1,
    'WEDNESDAY': 2,
    'THURSDAY': 3,
    'FRIDAY': 4,
    'SATURDAY': 5,
    'SUNDAY': 6
}

app_train.WEEKDAY_APPR_PROCESS_START = \
    app_train.WEEKDAY_APPR_PROCESS_START.map(weekday_codes)

[ ]: len(categorical_labels)

[ ]: 11

[ ]: categorical_labels = app_train.select_dtypes('object').columns.tolist()
      preprocessor = make_column_transformer(
          (OrdinalEncoder(), categorical_labels), remainder='passthrough'
      )

      app_train_encoded = preprocessor.fit_transform(app_train)

[ ]: app_train_encoded

```



```
[ ]: array([[0., 1., 0., ..., 0., 0., 1.],
          [0., 0., 0., ..., 0., 0., 0.],
          [1., 1., 1., ..., 0., 0., 0.],
          ...,
          [0., 0., 0., ..., 1., 0., 1.],
          [0., 0., 0., ..., 0., 0., 0.],
          [0., 0., 0., ..., 2., 0., 1.]])
```

2.2 Autres tables

```
[ ]: col_desc.loc[col_desc.Table == 'bureau_balance.csv'].Description.values
```

```
[ ]: array(['Recoded ID of Credit Bureau credit (unique coding for each application)
- use this to join to CREDIT_BUREAU table ',
          'Month of balance relative to application date (-1 means the freshest
balance date)',
          'Status of Credit Bureau loan during the month (active, closed, DPD0-30,
[C means closed, X means status unknown, 0 means no DPD, 1 means maximal did
during month between 1-30, 2 means DPD 31-60, 5 means DPD 120+ or sold or
written off ] )'],
          dtype=object)
```

```
[ ]: bureau = pd.read_csv('02_data/bureau.csv')
bureau_balance = pd.read_csv('02_data/bureau_balance.csv')
```

```
[ ]: bureau_balance.shape
```

```
[ ]: (27299925, 3)
```

```
[ ]: bureau_balance.shape[0] / 10 ** 3
```

```
[ ]: 27299.925
```

```
[ ]: bureau_balance.columns
```

```
[ ]: Index(['SK_ID_BUREAU', 'MONTHS_BALANCE', 'STATUS'], dtype='object')
```

```
[ ]: bureau.shape
```

```
[ ]: (1716428, 17)
```

```
[ ]: app_train.NAME_FAMILY_STATUS.value_counts()
```

```
[ ]: Married          196432
Single / not married  45444
Civil marriage        29775
Separated             19770
```

```
Widow          16088
Unknown         2
Name: NAME_FAMILY_STATUS, dtype: int64
```

```
[ ]: app_train.NAME_EDUCATION_TYPE.value_counts()
```

```
[ ]: Secondary / secondary special    218391
Higher education                     74863
Incomplete higher                     10277
Lower secondary                      3816
Academic degree                      164
Name: NAME_EDUCATION_TYPE, dtype: int64
```

```
[ ]: app_train.NAME_TYPE_SUITE.value_counts()
```

```
[ ]: Unaccompanied    248526
Family               40149
Spouse, partner      11370
Children             3267
Other_B              1770
Other_A               866
Group of people       271
Name: NAME_TYPE_SUITE, dtype: int64
```

```
[ ]: app_train['AGE'] = round(app_train['DAYS_BIRTH'] / - 365, 0).astype('int')
```

```
[ ]: app_train.AGE
```

```
[ ]: 0         26
1         46
2         52
3         52
4         55
..
307506    26
307507    57
307508    41
307509    33
307510    46
Name: AGE, Length: 307511, dtype: int64
```

```
[ ]: educ_type_dict = {
    'Lower secondary' : 0,
    'Secondary / secondary special': 1,
    'Incomplete higher': 2,
    'Higher education': 3,
    'Academic degree': 4
```

```
}
app_train.NAME_EDUCATION_TYPE.map(educ_type_dict)
```

```
[ ]: 0      1
      1      3
      2      1
      3      1
      4      1
      ..
307506  1
307507  1
307508  3
307509  1
307510  3
Name: NAME_EDUCATION_TYPE, Length: 307511, dtype: int64
```

```
[ ]: app_train.corr()['TARGET'].sort_values()
```

```
[ ]: EXT_SOURCE_3      -0.178919
EXT_SOURCE_2      -0.160472
EXT_SOURCE_1      -0.155317
AGE              -0.078263
DAYS_EMPLOYED     -0.044932
...
DAYS_LAST_PHONE_CHANGE  0.055218
REGION_RATING_CLIENT    0.058899
REGION_RATING_CLIENT_W_CITY  0.060893
DAYS_BIRTH            0.078239
TARGET                1.000000
Name: TARGET, Length: 107, dtype: float64
```

```
[ ]: print(app_train.CODE_GENDER.unique())
print(app_train.CODE_GENDER.value_counts(normalize=True))
```

```
['M' 'F' 'XNA']
F      0.658344
M      0.341643
XNA     0.000013
Name: CODE_GENDER, dtype: float64
```

```
[ ]: str_cols = [col for col in app_train.columns if app_train[col].dtype ==
↳ 'object']
```

```
[ ]: from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
```

```

for col in str_cols:
    app_train[col] = le.fit_transform(app_train[col])
app_train

```

```

[ ]:      SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
0          100002        1             0          1          0
1          100003        0             0          0          0
2          100004        0             1          1          1
3          100006        0             0          0          0
4          100007        0             0          1          0
...          ...      ...             ...          ...          ...
307506     456251        0             0          1          0
307507     456252        0             0          0          0
307508     456253        0             0          0          0
307509     456254        1             0          0          0
307510     456255        0             0          0          0

```

```

      FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
0                   1             0        202500.0    406597.5
1                   0             0        270000.0   1293502.5
2                   1             0         67500.0    135000.0
3                   1             0        135000.0    312682.5
4                   1             0        121500.0    513000.0
...          ...      ...             ...          ...
307506              0             0        157500.0    254700.0
307507              1             0         72000.0    269550.0
307508              1             0        153000.0    677664.0
307509              1             0        171000.0    370107.0
307510              0             0        157500.0    675000.0

```

```

      AMT_ANNUITY  ...  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
0        24700.5  ...             0             0
1        35698.5  ...             0             0
2         6750.0  ...             0             0
3        29686.5  ...             0             0
4        21865.5  ...             0             0
...          ...  ...             ...             ...
307506     27558.0  ...             0             0
307507     12001.5  ...             0             0
307508     29979.0  ...             0             0
307509     20205.0  ...             0             0
307510     49117.5  ...             0             0

```

```

      FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
0                   0             0              0.0
1                   0             0              0.0
2                   0             0              0.0

```

3	0	0	NaN
4	0	0	0.0
...
307506	0	0	NaN
307507	0	0	NaN
307508	0	0	1.0
307509	0	0	0.0
307510	0	0	0.0

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0
...
307506	NaN	NaN
307507	NaN	NaN
307508	0.0	0.0
307509	0.0	0.0
307510	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0
...
307506	NaN	NaN
307507	NaN	NaN
307508	1.0	0.0
307509	0.0	0.0
307510	2.0	0.0

	AMT_REQ_CREDIT_BUREAU_YEAR
0	1.0
1	0.0
2	0.0
3	NaN
4	0.0
...	...
307506	NaN
307507	NaN
307508	1.0
307509	0.0
307510	1.0

[307511 rows x 122 columns]

```
[ ]: app_train.CODE_GENDER.value_counts()
```

```
[ ]: 0    202448
      1    105059
      2         4
      Name: CODE_GENDER, dtype: int64
```

```
[ ]: bureau = pd.read_csv('02_data/bureau.csv')
      bureau
```

```
[ ]:      SK_ID_CURR  SK_ID_BUREAU  CREDIT_ACTIVE  CREDIT_CURRENCY  DAYS_CREDIT  \
0          215354      5714462         Closed      currency 1         -497
1          215354      5714463         Active      currency 1         -208
2          215354      5714464         Active      currency 1         -203
3          215354      5714465         Active      currency 1         -203
4          215354      5714466         Active      currency 1         -629
...          ...          ...          ...          ...          ...
1716423      259355      5057750         Active      currency 1          -44
1716424      100044      5057754         Closed      currency 1        -2648
1716425      100044      5057762         Closed      currency 1        -1809
1716426      246829      5057770         Closed      currency 1        -1878
1716427      246829      5057778         Closed      currency 1         -463
```

```
      CREDIT_DAY_OVERDUE  DAYS_CREDIT_ENDDATE  DAYS_ENDDATE_FACT  \
0              0          -153.0          -153.0
1              0          1075.0             NaN
2              0           528.0             NaN
3              0             NaN             NaN
4              0          1197.0             NaN
...          ...          ...          ...
1716423          0          -30.0             NaN
1716424          0         -2433.0        -2493.0
1716425          0         -1628.0         -970.0
1716426          0         -1513.0        -1513.0
1716427          0             NaN        -387.0
```

```
      AMT_CREDIT_MAX_OVERDUE  CNT_CREDIT_PROLONG  AMT_CREDIT_SUM  \
0              NaN              0          91323.00
1              NaN              0         225000.00
2              NaN              0        464323.50
3              NaN              0          90000.00
4          77674.5              0       2700000.00
...          ...          ...          ...
1716423          0.0              0          11250.00
```

1716424	5476.5	0	38130.84
1716425	NaN	0	15570.00
1716426	NaN	0	36000.00
1716427	NaN	0	22500.00

	AMT_CREDIT_SUM_DEBT	AMT_CREDIT_SUM_LIMIT	AMT_CREDIT_SUM_OVERDUE	\
0	0.0	NaN	0.0	
1	171342.0	NaN	0.0	
2	NaN	NaN	0.0	
3	NaN	NaN	0.0	
4	NaN	NaN	0.0	
...	
1716423	11250.0	0.0	0.0	
1716424	0.0	0.0	0.0	
1716425	NaN	NaN	0.0	
1716426	0.0	0.0	0.0	
1716427	0.0	NaN	0.0	

	CREDIT_TYPE	DAYS_CREDIT_UPDATE	AMT_ANNUITY
0	Consumer credit	-131	NaN
1	Credit card	-20	NaN
2	Consumer credit	-16	NaN
3	Credit card	-16	NaN
4	Consumer credit	-21	NaN
...
1716423	Microloan	-19	NaN
1716424	Consumer credit	-2493	NaN
1716425	Consumer credit	-967	NaN
1716426	Consumer credit	-1508	NaN
1716427	Microloan	-387	NaN

[1716428 rows x 17 columns]

```
[ ]: app_train.columns
```

```
[ ]: Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
          'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
          'AMT_CREDIT', 'AMT_ANNUITY',
          ...,
          'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
          'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
          'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
          'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
          'AMT_REQ_CREDIT_BUREAU_YEAR'],
          dtype='object', length=122)
```

```
[ ]: bureau.columns
```

```
[ ]: Index(['SK_ID_CURR', 'SK_ID_BUREAU', 'CREDIT_ACTIVE', 'CREDIT_CURRENCY',
          'DAYS_CREDIT', 'CREDIT_DAY_OVERDUE', 'DAYS_CREDIT_ENDDATE',
          'DAYS_ENDDATE_FACT', 'AMT_CREDIT_MAX_OVERDUE', 'CNT_CREDIT_PROLONG',
          'AMT_CREDIT_SUM', 'AMT_CREDIT_SUM_DEBT', 'AMT_CREDIT_SUM_LIMIT',
          'AMT_CREDIT_SUM_OVERDUE', 'CREDIT_TYPE', 'DAYS_CREDIT_UPDATE',
          'AMT_ANNUITY'],
          dtype='object')
```

```
[ ]: col_desc.loc[col_desc.Row.eq('SK_ID_CURR') & col_desc.Table.eq('bureau.csv')].
      ↳Description.values
```

```
[ ]: array(['ID of loan in our sample - one loan in our sample can have 0,1,2 or more
          related previous credits in credit bureau '],
          dtype=object)
```

```
[ ]: bureau.shape
```

```
[ ]: (1716428, 17)
```

```
[ ]: len(bureau.SK_ID_BUREAU.unique())
```

```
[ ]: 1716428
```

```
[ ]: len(bureau.SK_ID_CURR.unique())
```

```
[ ]: 305811
```

```
[ ]: bureau[bureau.duplicated(subset=['SK_ID_CURR']) == True]
```

```
[ ]:
```

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	\
1	215354	5714463	Active	currency 1	-208	
2	215354	5714464	Active	currency 1	-203	
3	215354	5714465	Active	currency 1	-203	
4	215354	5714466	Active	currency 1	-629	
5	215354	5714467	Active	currency 1	-273	
...	
1716423	259355	5057750	Active	currency 1	-44	
1716424	100044	5057754	Closed	currency 1	-2648	
1716425	100044	5057762	Closed	currency 1	-1809	
1716426	246829	5057770	Closed	currency 1	-1878	
1716427	246829	5057778	Closed	currency 1	-463	

	CREDIT_DAY_OVERDUE	DAYS_CREDIT_ENDDATE	DAYS_ENDDATE_FACT	\
1	0	1075.0	NaN	
2	0	528.0	NaN	
3	0	NaN	NaN	
4	0	1197.0	NaN	

5	0	27460.0	NaN
...
1716423	0	-30.0	NaN
1716424	0	-2433.0	-2493.0
1716425	0	-1628.0	-970.0
1716426	0	-1513.0	-1513.0
1716427	0	NaN	-387.0

	AMT_CREDIT_MAX_OVERDUE	CNT_CREDIT_PROLONG	AMT_CREDIT_SUM	\
1	NaN	0	225000.00	
2	NaN	0	464323.50	
3	NaN	0	90000.00	
4	77674.5	0	2700000.00	
5	0.0	0	180000.00	
...	
1716423	0.0	0	11250.00	
1716424	5476.5	0	38130.84	
1716425	NaN	0	15570.00	
1716426	NaN	0	36000.00	
1716427	NaN	0	22500.00	

	AMT_CREDIT_SUM_DEBT	AMT_CREDIT_SUM_LIMIT	AMT_CREDIT_SUM_OVERDUE	\
1	171342.00	NaN	0.0	
2	NaN	NaN	0.0	
3	NaN	NaN	0.0	
4	NaN	NaN	0.0	
5	71017.38	108982.62	0.0	
...	
1716423	11250.00	0.00	0.0	
1716424	0.00	0.00	0.0	
1716425	NaN	NaN	0.0	
1716426	0.00	0.00	0.0	
1716427	0.00	NaN	0.0	

	CREDIT_TYPE	DAYS_CREDIT_UPDATE	AMT_ANNUITY
1	Credit card	-20	NaN
2	Consumer credit	-16	NaN
3	Credit card	-16	NaN
4	Consumer credit	-21	NaN
5	Credit card	-31	NaN
...
1716423	Microloan	-19	NaN
1716424	Consumer credit	-2493	NaN
1716425	Consumer credit	-967	NaN
1716426	Consumer credit	-1508	NaN
1716427	Microloan	-387	NaN

[1410617 rows x 17 columns]