Financial Programming Group3 assignment

1. Read the data in csv

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from scipy.stats.mstats import winsorize
from sklearn.preprocessing import MinMaxScaler
import os

import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
# Import banking data
# Note: This data was extracted on 1999

# Each record describes characteristics of a client
client = pd.read_csv('./data/data_berka/client.asc', sep=';')

# Each record describes static characteristics of an account
account = pd.read_csv('./data/data_berka/account.asc', sep=';')

# Each record describes a credit card issued to an account
card = pd.read_csv('./data/data_berka/card.asc', sep=';')

# Each record describes demographic characteristics of a district
district = pd.read_csv('./data/data_berka/district.asc', sep=';')

# Each record relates together a client with an account
# i.e. this relation describes the rights of clients to operate accounts
disp = pd.read_csv('./data/data_berka/disp.asc', sep=';')

# Each record describes characteristics of a payment order (debits only)
order = pd.read_csv('./data/data_berka/order.asc', sep=';')

# Each record describes one transaction on an account
trans = pd.read_csv('./data/data_berka/trans.asc', sep=';', low_memory=False)

# Each record describes a loan granted for a given account
loan = pd.read_csv('./data/data_berka/loan.asc', sep=';')
```

2. Create independent variables

2.1 Create the independent variable --- LOR

Select the accounts that openned before 1996 to have sufficient data for IV period

In [8]:
```
account.head()
account['year']= account['date'].astype(str).str[:2].astype(int) + 1900
df_independent = account[account['year'] < 1996].copy(deep=True)
df_independent.head()
```

Out[8]:

	account_id	district_id	frequency	date	year
0	576	55	POPLATEK MESICNE	930101	1993
1	3818	74	POPLATEK MESICNE	930101	1993
2	704	55	POPLATEK MESICNE	930101	1993
3	2378	16	POPLATEK MESICNE	930101	1993
4	2632	24	POPLATEK MESICNE	930102	1993

In [9]:
```
# Add length of relationship in year
df_independent['LOR'] = 1996 - df_independent['year']
df_independent.head()
```

Out[9]:

	account_id	district_id	frequency	date	year	LOR
0	576	55	POPLATEK MESICNE	930101	1993	3
1	3818	74	POPLATEK MESICNE	930101	1993	3
2	704	55	POPLATEK MESICNE	930101	1993	3
3	2378	16	POPLATEK MESICNE	930101	1993	3
4	2632	24	POPLATEK MESICNE	930102	1993	3

2.2 Create the independent variables --- Gender, age, age group

In [11]:
```
# Add information about account owner
df_independent = pd.merge(df_independent, disp[disp['type'] == 'OWNER'], how='left', on='account_id')
```

```python
df_independent = pd.merge(df_independent, client, how='left', on='client_id')
df_independent = df_independent.rename(columns={'district_id_x':'bank_district_id',
                        'district_id_y':'client_district_id'})
df_independent.head()
```

Out[11]:

	account_id	bank_district_id	frequency	date	year	LOR	disp_id	client_id	type	birth_number	client_district_id
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	74
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	1
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	22
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	16
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	24

In [12]:

```python
df_independent
```

Out[12]:

	account_id	bank_district_id	frequency	date	year	LOR	disp_id	client_id	type	birth_number	client_district_id
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	74
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	1
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	22
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	16
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	24
...	...	...	...	...	...	...	...	...	...	...	...
2234	4462	73	POPLATEK TYDNE	951227	1995	1	5384	5384	OWNER	350721	73
2235	3814	74	POPLATEK MESICNE	951227	1995	1	4596	4596	OWNER	735831	74
2236	2780	63	POPLATEK MESICNE	951229	1995	1	3357	3357	OWNER	545721	63
2237	3273	74	POPLATEK MESICNE	951229	1995	1	3962	3962	OWNER	521128	74
2238	3559	18	POPLATEK MESICNE	951230	1995	1	4295	4295	OWNER	600316	18

2239 rows × 11 columns

In [13]:

```python
# Transform the birth day into year
df_independent['birth_year'] = '19' + df_independent['birth_number'].astype(str).str[:2]
df_independent['birth_year'] = df_independent['birth_year'].astype(int)

# Transform the birth day to day
df_independent['birth_day'] = df_independent['birth_number'].astype(str).str[-2:].astype(int)

# Extract the birth month
df_independent['birth_month'] = df_independent['birth_number'].astype(str).str[2:4].astype(int)

# Extract and correct the gender
df_independent['gender'] = 'M'
df_independent.loc[df_independent['birth_month'] > 50, 'gender'] = 'F'

# Correct the birth month
df_independent.loc[df_independent['birth_month'] > 50, 'birth_month'] = df_independent.loc[df_independent['birth_month'] > 50, 'birth_month'] - 50
df_independent.head()
```

Out[13]:

	account_id	bank_district_id	frequency	date	year	LOR	disp_id	client_id	type	birth_number	client_district_id	birth_year	birth_day	birth_month	gende
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	74	1936	11	1	
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	1	1935	2	4	M
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	22	1945	14	1	M
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	16	1975	24	3	
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	24	1938	12	8	M

In [14]:

```python
# Age
df_independent['age'] = 1996 - df_independent['birth_year']

# Age group
df_independent['age_group'] = df_independent['age'] // 10 * 10
df_independent.head()
```

Out[14]:

	account_id	bank_district_id	frequency	date	year	LOR	disp_id	client_id	type	birth_number	client_district_id	birth_year	birth_day	birth_month	gende
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	74	1936	11	1	
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	1	1935	2	4	M
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	22	1945	14	1	M
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	16	1975	24	3	
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	24	1938	12	8	M

2.3 Create the independent variables--- (Recency, Frequency, Monetary)

In [16]:

```
#Merging table trans and account
transmerge = pd.merge(trans, account, on = 'account_id')
transmerge = transmerge.rename(columns= {'date_x': 'trans_date'})
transmerge = transmerge.rename(columns= {'date_y': 'dateacc'})

transmerge2 = pd.merge(transmerge, disp, on = 'account_id')
transmerge2 = transmerge2.rename(columns= {'type_y': 'type_client'})
transmerge2 = transmerge2.rename(columns= {'type_x': 'type_trans'})

transmerge2.head()
```

Out[16]:

	trans_id	account_id	trans_date	type_trans	operation	amount	balance	k_symbol	bank	account	district_id	frequency	dateacc	year	disp_id	client_id	typ
0	695247	2378	930101	PRIJEM	VKLAD	700.0	700.0	NaN	NaN	NaN	16	POPLATEK MESICNE	930101	1993	2873	2873	
1	171812	576	930101	PRIJEM	VKLAD	900.0	900.0	NaN	NaN	NaN	55	POPLATEK MESICNE	930101	1993	692	692	
2	171812	576	930101	PRIJEM	VKLAD	900.0	900.0	NaN	NaN	NaN	55	POPLATEK MESICNE	930101	1993	693	693	DISP
3	207264	704	930101	PRIJEM	VKLAD	1000.0	1000.0	NaN	NaN	NaN	55	POPLATEK MESICNE	930101	1993	844	844	
4	207264	704	930101	PRIJEM	VKLAD	1000.0	1000.0	NaN	NaN	NaN	55	POPLATEK MESICNE	930101	1993	845	845	DISP

In [17]:

```
# Select on transactions in and 1996
trans96 = transmerge2[transmerge2['trans_date'].astype(str).str[:2].isin(['96'])]
trans96.head()
```

Out[17]:

	trans_id	account_id	trans_date	type_trans	operation	amount	balance	k_symbol	bank	account	district_id	frequency	dateacc	year	disp_id	client_id
304624	732811	2504	960101	VYDAJ	VYBER KARTOU	900.0	38124.4	NaN	NaN	0.0	16	POPLATEK MESICNE	931209	1993	3023	3023
304625	800209	2729	960101	VYDAJ	VYBER	1920.0	34202.7	NaN	NaN	NaN	40	POPLATEK MESICNE	950116	1995	3295	3295
304626	803553	2738	960101	VYDAJ	VYBER	6500.0	25685.2	NaN	NaN	NaN	41	POPLATEK MESICNE	931112	1993	3305	3305
304627	1042686	3566	960101	VYDAJ	VYBER	1000.0	25919.7	NaN	NaN	NaN	21	POPLATEK MESICNE	930609	1993	4303	4303
304628	1042689	3566	960101	VYDAJ	VYBER	500.0	25419.7	NaN	NaN	NaN	21	POPLATEK MESICNE	930609	1993	4303	4303

2.3.1 Recency calculation

In [20]:

```
# Convert the 'date' column to datetime format
trans96['trans_date'] = pd.to_datetime(trans96['trans_date'], format='%y%m%d', errors='coerce')

# Subset of transaction data with only 'client_id' and 'trans_date'
purchase_date = trans96[['client_id', 'trans_date']]

# Group by 'client_id' and find the latest (maximum) purchase date for each client
last_purchase_date = purchase_date.groupby('client_id')['trans_date'].max().reset_index()

last_purchase_date['trans_date'].value_counts()
#checking the dates

last_purchase_date
```

Out[20]:

	client_id	trans_date
0	1	1996-12-31
1	2	1996-12-31
2	3	1996-12-31
3	6	1996-12-31
4	8	1996-12-31
...	...	...
4285	13955	1996-12-31
4286	13956	1996-12-31
4287	13968	1996-12-31
4288	13971	1996-12-31
4289	13998	1996-12-31

4290 rows × 2 columns

In [21]:
```
#setting a reference date
reference_date = pd.to_datetime('1996-12-31')

last_purchase_date['recency_days'] = (reference_date - last_purchase_date['trans_date']).dt.days

last_purchase_date.head()
```

Out[21]:

	client_id	trans_date	recency_days
0	1	1996-12-31	0
1	2	1996-12-31	0
2	3	1996-12-31	0
3	6	1996-12-31	0
4	8	1996-12-31	0

In [22]:
```
last_purchase_date = last_purchase_date.drop('trans_date', axis= 1)
last_purchase_date.head()
```

Out[22]:

	client_id	recency_days
0	1	0
1	2	0
2	3	0
3	6	0
4	8	0

In [23]:
```
#merging with the basetable
df_independent = pd.merge(df_independent, last_purchase_date, how= 'left', on= 'client_id')
```

2.3.2 Frequency - count of transactions per client

In [26]:
```
frequency_df = trans96.groupby('client_id').size().reset_index(name='frequency')

frequency_df.head()
```

Out[26]:

	client_id	frequency
0	1	74
1	2	85
2	3	85
3	6	39
4	8	63

In [27]:
```
#merge frequency with the basetable
df_independent = pd.merge(df_independent, frequency_df, how= 'left', on= 'client_id')
df_independent = df_independent.rename(columns= {'frequency_x': 'freq iss. stats'})
df_independent = df_independent.rename(columns= {'frequency_y': 'frequency'})
```

2.3.3 Monetary - the total amount of money a client has spent during 1996

In [30]:
```
# Calculate the total monetary value for each client
monetary_df = trans96.groupby('client_id')['amount'].sum().reset_index(name='monetary')
```

```
monetary_df
```

Out[30]:

	client_id	monetary
0	1	105645.2
1	2	563117.1
2	3	563117.1
3	6	88898.1
4	8	163310.9
...	...	...
4285	13955	1093960.3
4286	13956	1093960.3
4287	13968	704593.7
4288	13971	433577.6
4289	13998	837821.7

4290 rows × 2 columns

In [31]:

```
#merge monetary with the basetable
df_independent = pd.merge(df_independent, monetary_df, how= 'left', on= 'client_id')
```

2.4 Create the independent variables--- (Total credit per client, Total withdrawal per client, Credit and Withdrawal frequency per client)

2.4.1 Total credit per client

In [34]:

```
# Aggregate the total credit per account
trans_agg_credit = trans96[trans96['type_trans'].isin(['PRIJEM'])].groupby('client_id')['amount'].agg('sum')
trans_agg_credit = trans_agg_credit.reset_index()
trans_agg_credit = trans_agg_credit.rename(columns={'amount':'total_credit'})
trans_agg_credit.head()
```

Out[34]:

	client_id	total_credit
0	1	50066.0
1	2	288542.9
2	3	288542.9
3	6	56920.5
4	8	81507.7

2.4.2 Total withdrawal per client

In [36]:

```
# Aggregate the total withdrawal per account
trans_agg_withdrawal = trans96[trans96['type_trans'].isin(['VYDAJ','VYBER'])].groupby('client_id')['amount'].agg('sum')
trans_agg_withdrawal = trans_agg_withdrawal.reset_index()
trans_agg_withdrawal = trans_agg_withdrawal.rename(columns={'amount':'total_withdrawal'})
trans_agg_withdrawal.head()
```

Out[36]:

	client_id	total_withdrawal
0	1	55579.2
1	2	274574.2
2	3	274574.2
3	6	31977.6
4	8	81803.2

In [37]:

```
# Join with previous table
df_independent = pd.merge(df_independent, trans_agg_credit,how ='left', on='client_id')
df_independent = pd.merge(df_independent, trans_agg_withdrawal, how='left', on='client_id')
df_independent.head()
```

Out[37]:

	account_id	bank_district_id	freq iss. stats	date	year	LOR	disp_id	client_id	type	birth_number	...	birth_day	birth_month	gender	age	age_group	recen
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	...	11	1	F	60	60	
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	...	2	4	M	61	60	
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	...	14	1	M	51	50	
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	...	24	3	F	21	20	
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	...	12	8	M	58	50	

5 rows × 22 columns

2.4.3 Credit and withdrawal frequency per client

In [39]:
```
transaction_freq = trans96
```

In [40]:
```
transaction_freq['transaction_category'] = transaction_freq['type_trans'].replace({
    'PRIJEM': 'credit',
    'VYDAJ': 'withdrawal',
    'VYBER': 'withdrawal'
})
```

In [41]:
```
transaction_frequency = transaction_freq.groupby(['client_id', 'transaction_category']).size().unstack().reset_index()
transaction_frequency.columns = ['client_id', 'credit_frequency', 'withdrawal_frequency']
```

In [42]:
```
df_independent = pd.merge(df_independent, transaction_frequency, how='left', on='client_id')
df_independent.head()
```

Out[42]:

	account_id	bank_district_id	freq iss. stats	date	year	LOR	disp_id	client_id	type	birth_number	...	gender	age	age_group	recency_days	frequency	mor
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	...	F	60	60	0	62	146
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	...	M	61	60	0	98	458
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	...	M	51	50	0	84	447
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	...	F	21	20	0	83	1297
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	...	M	58	50	0	98	377

5 rows × 24 columns

2.5 Create other transaction related variables

2.5.1 The average and std of transaction amount in 1996 for each client -- avg_amount_trans_96, trans_std_96

The variable represents the Average amount per transaction per client for the year of 1996

In [46]:
```
# Find the average lifetime transaction amount for each client
avg_amount_trans_96 = trans96.groupby('client_id')['amount'].agg('mean')
avg_amount_trans_96 = avg_amount_trans_96.reset_index()
avg_amount_trans_96 = avg_amount_trans_96.rename(columns={'amount':'avg_amount_trans_96'})

# Join the previous basetable
df_independent = pd.merge(df_independent, avg_amount_trans_96, how='left', on='client_id')
```

In [47]:
```
transaction_std = trans96.groupby('client_id')['amount'].std().reset_index()
transaction_std.columns = ['client_id', 'transaction_std']
transaction_std.head()

# Join the previous basetable
df_independent = pd.merge(df_independent, transaction_std, how='left', on='client_id')
```

2.5.2 Average and std of account balances after all transactions in 1996 for each client -- avg_balance_96, std_balance_96

In [49]:
```
trans_data = trans96
trans_data = trans_data.sort_values(by=['client_id', 'trans_date'])

# Calculate the average balance for each client
avg_balance = trans_data.groupby('client_id')['balance'].mean().reset_index()

# Rename the balance column for clarity
avg_balance = avg_balance.rename(columns={'balance': 'avg_balance'})
```

In [50]:
```
balance_std = trans_data.groupby('client_id')['amount'].std().reset_index()
balance_std.columns = ['client_id', 'balance_std']
balance_std.head()
```

Out[50]:

	client_id	balance_std
0	1	1427.130533
1	2	7602.794537
2	3	7602.794537
3	6	2179.889656
4	8	2787.811379

In [51]:
```
# Join with previous table
df_independent = pd.merge(df_independent, avg_balance,how ='left', on='client_id')
df_independent = pd.merge(df_independent, balance_std, how='left', on='client_id')
df_independent.head()
```

Out[51]:

	account_id	bank_district_id	freq iss. stats	date	year	LOR	disp_id	client_id	type	birth_number	...	frequency	monetary	total_credit	total_withdrawal	cre
0	576	55	POPLATEK MESICNE	930101	1993	3	692	692	OWNER	365111	...	62	146516.5	76097.3	70419.2	
1	3818	74	POPLATEK MESICNE	930101	1993	3	4601	4601	OWNER	350402	...	98	458341.6	234806.4	223535.2	
2	704	55	POPLATEK MESICNE	930101	1993	3	844	844	OWNER	450114	...	84	447046.1	228514.9	218531.2	
3	2378	16	POPLATEK MESICNE	930101	1993	3	2873	2873	OWNER	755324	...	83	1297855.6	664545.4	633310.2	
4	2632	24	POPLATEK MESICNE	930102	1993	3	3177	3177	OWNER	380812	...	98	377730.1	186658.9	191071.2	

5 rows × 28 columns

Drop Non Necessary Columns

In [53]:
```
df_independent.columns
```

Out[53]:
```
Index(['account_id', 'bank_district_id', 'freq iss. stats', 'date', 'year',
       'LOR', 'disp_id', 'client_id', 'type', 'birth_number',
       'client_district_id', 'birth_year', 'birth_day', 'birth_month',
       'gender', 'age', 'age_group', 'recency_days', 'frequency', 'monetary',
       'total_credit', 'total_withdrawal', 'credit_frequency',
       'withdrawal_frequency', 'avg_amount_trans_96', 'transaction_std',
       'avg_balance', 'balance_std'],
      dtype='object')
```

In [54]:
```
needed_variables=['client_id','freq iss. stats','LOR','gender','age_group',
                 'total_credit', 'total_withdrawal', 'credit_frequency','withdrawal_frequency',
                 'avg_amount_trans_96', 'transaction_std','avg_balance', 'balance_std',
                 'recency_days', 'frequency', 'monetary', 'client_district_id']
```

In [55]:
```
df_independent=df_independent[needed_variables]
```

In [56]:
```
df_independent.head()
```

Out[56]:

	client_id	freq iss. stats	LOR	gender	age_group	total_credit	total_withdrawal	credit_frequency	withdrawal_frequency	avg_amount_trans_96	transaction_std	avg_
0	692	POPLATEK MESICNE	3	F	60	76097.3	70419.2	24.0	38.0	2363.169355	2469.018420	33263
1	4601	POPLATEK MESICNE	3	M	60	234806.4	223535.2	25.0	73.0	4676.955102	6125.480217	47088
2	844	POPLATEK MESICNE	3	M	50	228514.9	218531.2	24.0	60.0	5321.977381	7068.973119	26333
3	2873	POPLATEK MESICNE	3	F	20	664545.4	633310.2	34.0	49.0	15636.814458	15800.741309	71777
4	3177	POPLATEK MESICNE	3	M	50	186658.9	191071.2	24.0	74.0	3854.388776	5274.244269	25321

2.6 Create district related variables

In [58]:
```
df_dis = df_independent[['client_id','client_district_id']]
df_ds1 = pd.merge(df_dis, district, left_on='client_district_id', right_on='A1', how='left')
```

In [59]:
```
df_ds1 = df_ds1[['client_id', 'A10', 'A11', 'A13']]
df_ds1 = df_ds1.rename(columns={'A10':'urban_inhabitant_ratio', 'A11':'avg_dist_salary', 'A13':'dist_unemploy_rate'})
```

In [60]:
```python
df_independent = pd.merge(df_independent, df_ds1, how='left', on='client_id')
```

In [61]:
```python
df_independent = df_independent.drop(columns = 'client_district_id')
```

In [62]:
```python
df_independent.head()
```

Out[62]:

	client_id	freq iss. stats	LOR	gender	age_group	total_credit	total_withdrawal	credit_frequency	withdrawal_frequency	avg_amount_trans_96	transaction_std	avg_
0	692	POPLATEK MESICNE	3	F	60	76097.3	70419.2	24.0	38.0	2363.169355	2469.018420	33263
1	4601	POPLATEK MESICNE	3	M	60	234806.4	223535.2	25.0	73.0	4676.955102	6125.480217	47088
2	844	POPLATEK MESICNE	3	M	50	228514.9	218531.2	24.0	60.0	5321.977381	7068.973119	26333
3	2873	POPLATEK MESICNE	3	F	20	664545.4	633310.2	34.0	49.0	15636.814458	15800.741309	71777
4	3177	POPLATEK MESICNE	3	M	50	186658.9	191071.2	24.0	74.0	3854.388776	5274.244269	25321

3. Create dependent variable (or target variable)

Create target variable1: granted_loan and target variable2: card_issued

In [65]:
```python
# Select on transactions in 1997
loan_1997 = loan[loan['date'].astype(str).str[:2].isin(['97'])]
card_1997 = card[card['issued'].astype(str).str[:2].isin(['97'])]
print(loan_1997.head(5))
print(card_1997.head(5))
```

```
     loan_id  account_id    date  amount  duration  payments status
328     5895        4473  970103   93960        60    1566.0      C
329     7122       10365  970104  260640        36    7240.0      D
330     6173        5724  970108  232560        48    4845.0      C
331     6142        5591  970121  221880        60    3698.0      C
332     5358        2018  970121   38520        12    3210.0      A
     card_id  disp_id     type           issued
201     1118    11393  classic  970102 00:00:00
202      175     1040  classic  970103 00:00:00
203      565     3601     gold  970106 00:00:00
204      714     4638  classic  970109 00:00:00
205      137      786   junior  970110 00:00:00
```

In [66]:
```python
df_dependent = account[account['year'] < 1996].copy(deep=True)
df_dependent = pd.merge(df_dependent, disp[disp['type'] == 'OWNER'], how='left', on='account_id')
df_dependent = pd.merge(df_dependent, client, how='left', on='client_id')
df_dependent.head()
```

Out[66]:

	account_id	district_id_x	frequency	date	year	disp_id	client_id	type	birth_number	district_id_y
0	576	55	POPLATEK MESICNE	930101	1993	692	692	OWNER	365111	74
1	3818	74	POPLATEK MESICNE	930101	1993	4601	4601	OWNER	350402	1
2	704	55	POPLATEK MESICNE	930101	1993	844	844	OWNER	450114	22
3	2378	16	POPLATEK MESICNE	930101	1993	2873	2873	OWNER	755324	16
4	2632	24	POPLATEK MESICNE	930102	1993	3177	3177	OWNER	380812	24

In [67]:
```python
df_dependent = pd.merge(df_dependent, loan_1997, how='left', on='account_id')
df_dependent = pd.merge(df_dependent, card_1997, how='left', on='disp_id')
df_dependent = df_dependent.drop(['date_y','amount','duration','payments','status', 'type_y', 'issued'], axis = 1)

#Target Variable 1
df_dependent['granted_loan'] = np.where(df_dependent['loan_id'].notna() & df_dependent['loan_id'].astype(bool), 1, 0)
#Target Variable 2
df_dependent['card_issued'] = np.where(df_dependent['card_id'].notna() & df_dependent['card_id'].astype(bool), 1, 0)
df_dependent.head()
```

Out[67]:

	account_id	district_id_x	frequency	date_x	year	disp_id	client_id	type_x	birth_number	district_id_y	loan_id	card_id	granted_loan	card_issued
0	576	55	POPLATEK MESICNE	930101	1993	692	692	OWNER	365111	74	NaN	NaN	0	0
1	3818	74	POPLATEK MESICNE	930101	1993	4601	4601	OWNER	350402	1	NaN	NaN	0	0
2	704	55	POPLATEK MESICNE	930101	1993	844	844	OWNER	450114	22	NaN	NaN	0	0
3	2378	16	POPLATEK MESICNE	930101	1993	2873	2873	OWNER	755324	16	NaN	NaN	0	0
4	2632	24	POPLATEK MESICNE	930102	1993	3177	3177	OWNER	380812	24	NaN	NaN	0	0

In [68]:
```python
df_dependent['granted_loan'].value_counts()
```

Out[68]:
```
granted_loan
0    2208
1      31
Name: count, dtype: int64
```

In [69]:
```
df_dependent['card_issued'].value_counts()
```

Out[69]:
```
card_issued
0    2119
1     120
Name: count, dtype: int64
```

In [70]:
```
df_dependent=df_dependent[['client_id', 'granted_loan','card_issued']]
```

In [71]:
```
df_dependent.head()
```

Out[71]:

	client_id	granted_loan	card_issued
0	692	0	0
1	4601	0	0
2	844	0	0
3	2873	0	0
4	3177	0	0

4. Data correction and Value transformation

4.1 Data correction

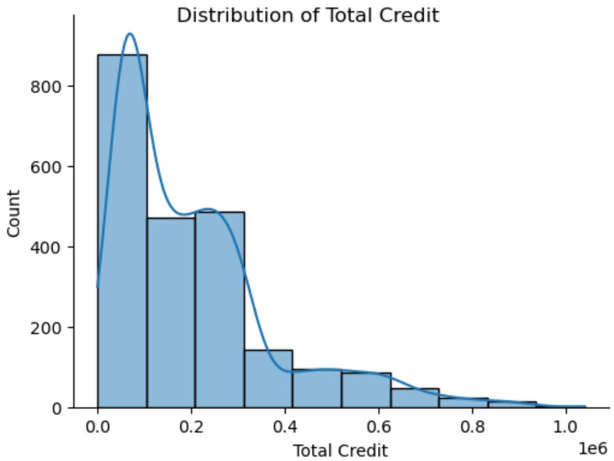
4.1.1 Missing values

In [75]:
```
df_independent.isna().sum()
```

Out[75]:
```
client_id                0
freq iss. stats          0
LOR                      0
gender                   0
age_group                0
total_credit             1
total_withdrawal         0
credit_frequency         1
withdrawal_frequency     0
avg_amount_trans_96      0
transaction_std          0
avg_balance              0
balance_std              0
recency_days             0
frequency                0
monetary                 0
urban_inhabitant_ratio   0
avg_dist_salary          0
dist_unemploy_rate       0
dtype: int64
```

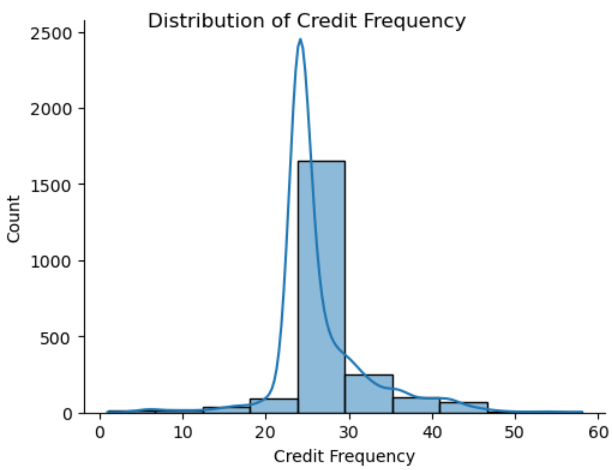
In [76]:
```
default_directory = './Plots/'
def save_plot(filename):
    save_path = os.path.join(default_directory, filename)
    plt.savefig(save_path)
```

In [77]:
```
displot = sns.displot(data=df_independent, x="total_credit", bins= 10, kde=True, height=4, aspect=1.33)
displot.set_axis_labels("Total Credit", "Count")
displot.fig.suptitle("Distribution of Total Credit")

save = os.path.join(default_directory, "Distribution of Total Credit.png")
displot.fig.savefig(save)
```



In [78]:
```
df_independent['total_credit']=df_independent['total_credit'].fillna(df_independent['total_credit'].median())
```

In [79]:
```
displot = sns.displot(data=df_independent, x="credit_frequency", bins= 10, kde=True, height=4, aspect=1.33)
displot.set_axis_labels("Credit Frequency", "Count")
displot.fig.suptitle("Distribution of Credit Frequency")

save1 = os.path.join(default_directory, "Distribution of Credit Frequency.png")
displot.fig.savefig(save1)
```



In [80]:
```
df_independent['credit_frequency']=df_independent['credit_frequency'].fillna(df_independent['credit_frequency'].median())
```

In [81]:
```
df_independent.isna().sum()
```

Out[81]:
```
client_id               0
freq iss. stats         0
LOR                     0
gender                  0
age_group               0
total_credit            0
total_withdrawal        0
credit_frequency        0
withdrawal_frequency    0
avg_amount_trans_96     0
transaction_std         0
avg_balance             0
balance_std             0
recency_days            0
frequency               0
monetary                0
urban_inhabitant_ratio  0
avg_dist_salary         0
dist_unemploy_rate      0
dtype: int64
```

4.1.2 Outlier

In [83]:
```
numerical_variables=df_independent.select_dtypes(include=['number']).columns
numerical_variables
```

```
Out[83]: Index(['client_id', 'LOR', 'age_group', 'total_credit', 'total_withdrawal',
       'credit_frequency', 'withdrawal_frequency', 'avg_amount_trans_96',
       'transaction_std', 'avg_balance', 'balance_std', 'recency_days',
       'frequency', 'monetary', 'urban_inhabitant_ratio', 'avg_dist_salary',
       'dist_unemploy_rate'],
      dtype='object')
```

```
In [84]: numerical_variables = numerical_variables.drop(['client_id','LOR','age_group'])
```

```
In [85]: for v in numerical_variables:
             print(f"Column: {v}, Data Type: {df_independent[v].dtypes}")
```

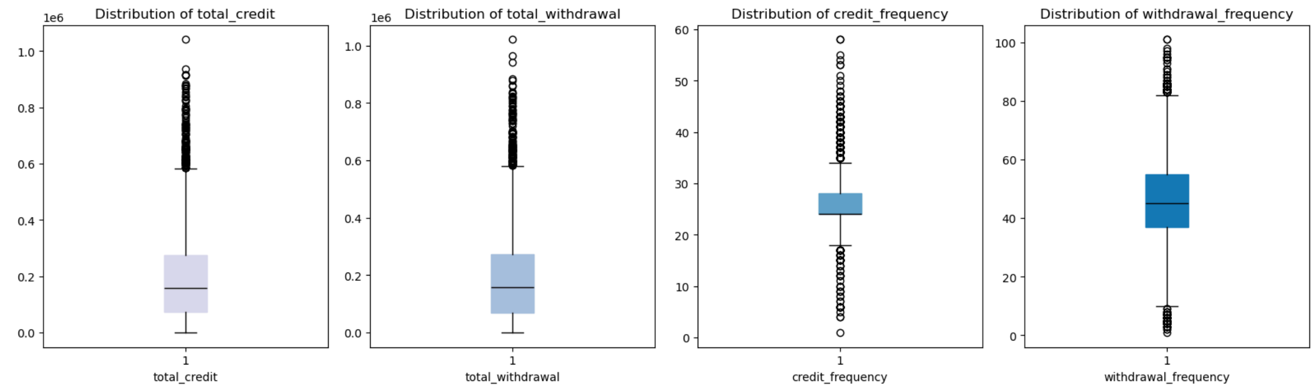
```
Column: total_credit, Data Type: float64
Column: total_withdrawal, Data Type: float64
Column: credit_frequency, Data Type: float64
Column: withdrawal_frequency, Data Type: float64
Column: avg_amount_trans_96, Data Type: float64
Column: transaction_std, Data Type: float64
Column: avg_balance, Data Type: float64
Column: balance_std, Data Type: float64
Column: recency_days, Data Type: int64
Column: frequency, Data Type: int64
Column: monetary, Data Type: float64
Column: urban_inhabitant_ratio, Data Type: float64
Column: avg_dist_salary, Data Type: int64
Column: dist_unemploy_rate, Data Type: float64
```

```
In [86]: for v in numerical_variables:

             # Calculate the lower and upper boundaries based on mean +/- 3*sd
             lower = df_independent[v].mean() - 3*df_independent[v].std()
             upper = df_independent[v].mean() + 3*df_independent[v].std()

             # Count the number of outliers
             cnt_outlier = sum((df_independent[v] < lower) | (df_independent[v] > upper))

             # Print out
             if cnt_outlier > 0:
                 print(v, '[', df_independent[v].dtype, ']', cnt_outlier, 'outlier(s)')
             else:
                     print(f"{v} [no outliers]")
```

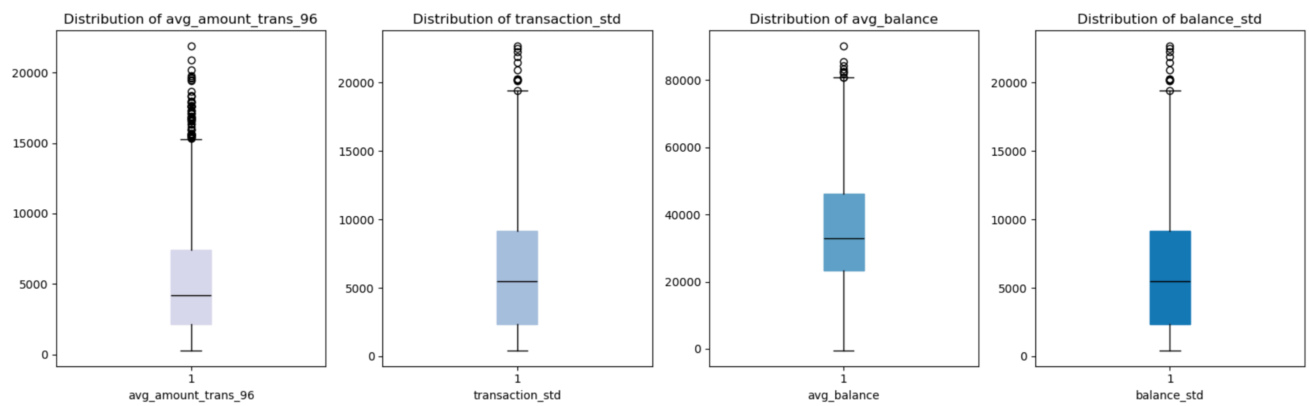
```
total_credit [ float64 ] 38 outlier(s)
total_withdrawal [ float64 ] 37 outlier(s)
credit_frequency [ float64 ] 50 outlier(s)
withdrawal_frequency [ float64 ] 12 outlier(s)
avg_amount_trans_96 [ float64 ] 25 outlier(s)
transaction_std [ float64 ] 7 outlier(s)
avg_balance [ float64 ] 4 outlier(s)
balance_std [ float64 ] 7 outlier(s)
recency_days [ int64 ] 17 outlier(s)
frequency [ int64 ] 30 outlier(s)
monetary [ float64 ] 38 outlier(s)
urban_inhabitant_ratio [no outliers]
avg_dist_salary [no outliers]
dist_unemploy_rate [no outliers]
```

```
In [87]: outlier_variables1 = ['total_credit', 'total_withdrawal','credit_frequency', 'withdrawal_frequency']
         outlier_variables2 = ['avg_amount_trans_96','transaction_std', 'avg_balance', 'balance_std']
         outlier_variables3 = ['recency_days','frequency', 'monetary']
```

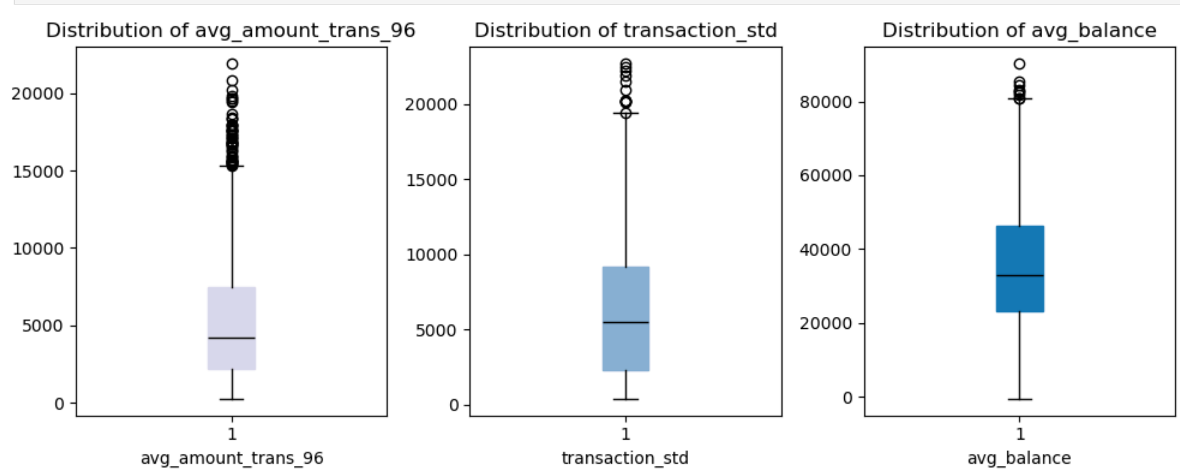
```
In [88]: fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(16, 5))
         colors = plt.cm.PuBu(np.linspace(0.2, 0.7, len(outlier_variables1)))

         for i, var in enumerate(outlier_variables1[:4]):
             axes[i].boxplot(df_independent[var], patch_artist=True,
                             boxprops=dict(facecolor=colors[i], color=colors[i]),
                             medianprops=dict(color='black'))
             axes[i].set_title(f'Distribution of {var}')
             axes[i].set_xlabel(var)

         plt.tight_layout()
         save_plot('Boxplot of numeric variables1.png')

         plt.show()
```



In [89]:
```python
fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(16, 5))
colors = plt.cm.PuBu(np.linspace(0.2, 0.7, len(outlier_variables2)))

for i, var in enumerate(outlier_variables2[:4]):
    axes[i].boxplot(df_independent[var], patch_artist=True,
                    boxprops=dict(facecolor=colors[i], color=colors[i]),
                    medianprops=dict(color='black'))
    axes[i].set_title(f'Distribution of {var}')
    axes[i].set_xlabel(var)

plt.tight_layout()
save_plot('Boxplot of numeric variables2.png')

plt.show()
```



In [90]:
```python
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(10, 4))
colors = plt.cm.PuBu(np.linspace(0.2, 0.7, len(outlier_variables3)))

for i, var in enumerate(outlier_variables2[:3]):
    axes[i].boxplot(df_independent[var], patch_artist=True,
                    boxprops=dict(facecolor=colors[i], color=colors[i]),
                    medianprops=dict(color='black'))
    axes[i].set_title(f'Distribution of {var}')
    axes[i].set_xlabel(var)

plt.tight_layout()
save_plot('Boxplot of numeric variables3.png')

plt.show()
```



In [91]:
```
for v in numerical_variables:

    # Calculate the lower and upper boundaries based on +/- 3*sd
    lower =df_independent[v].mean() - 3*df_independent[v].std()
    upper = df_independent[v].mean() + 3*df_independent[v].std()

    # Count the number of outliers
    cnt_outlier = sum((df_independent[v] < lower) | (df_independent[v] > upper))

    if cnt_outlier > 0:

        # Replace the outliers < lower boudary
        df_independent.loc[df_independent[v] < lower, v] = lower

        # Replace the outliers > upper boudary
        df_independent.loc[df_independent[v] > upper, v] = upper
```

In [92]:
```
df_independent.head()
```

Out[92]:

	client_id	freq iss. stats	LOR	gender	age_group	total_credit	total_withdrawal	credit_frequency	withdrawal_frequency	avg_amount_trans_96	transaction_std	avg_
0	692	POPLATEK MESICNE	3	F	60	76097.3	70419.2	24.0	38.0	2363.169355	2469.018420	33263
1	4601	POPLATEK MESICNE	3	M	60	234806.4	223535.2	25.0	73.0	4676.955102	6125.480217	47088
2	844	POPLATEK MESICNE	3	M	50	228514.9	218531.2	24.0	60.0	5321.977381	7068.973119	26333
3	2873	POPLATEK MESICNE	3	F	20	664545.4	633310.2	34.0	49.0	15636.814458	15800.741309	71777
4	3177	POPLATEK MESICNE	3	M	50	186658.9	191071.2	24.0	74.0	3854.388776	5274.244269	25321

4.2 Value transformation

4.2.1 Discretization

In [95]:
```
# Sample DataFrame with Recency, Frequency, and Monetary values
# Step 1: Assign scores to Recency, Frequency, and Monetary using quantiles
df_independent['R_Score'] = pd.cut(df_independent['recency_days'], 4, labels=[4, 3, 2, 1])
#For Recency, a lower value is better (more recent), so we reverse the labels ([4, 3, 2, 1]).
df_independent['F_Score'] = pd.cut(df_independent['frequency'], 4, labels=[1, 2, 3, 4])
df_independent['M_Score'] = pd.cut(df_independent['monetary'], 4, labels=[1, 2, 3, 4])
#For Frequency and Monetary, a higher value is better, so we use labels in ascending order ([1, 2, 3, 4]).

# Step 2: Combine R, F, M scores into a single RFM score
df_independent['RFM_Score'] = df_independent['R_Score'].astype(int)+ df_independent['F_Score'].astype(int) + df_independent['M_Score'].astype(int)

df_independent['Credit_F_Score'] = pd.cut(df_independent['credit_frequency'], 4, labels=[1, 2, 3, 4])
df_independent['Withdrawal_F_Score'] = pd.cut(df_independent['withdrawal_frequency'], 4, labels=[1, 2, 3, 4])
#For credit_frequency and withdrawal_frequency, a higher value is better, so we use labels in ascending order ([1, 2, 3, 4]).

df_independent.head()
```

Out[95]:

	client_id	freq iss. stats	LOR	gender	age_group	total_credit	total_withdrawal	credit_frequency	withdrawal_frequency	avg_amount_trans_96	...	monetary	urban_i
0	692	POPLATEK MESICNE	3	F	60	76097.3	70419.2	24.0	38.0	2363.169355	...	146516.5	
1	4601	POPLATEK MESICNE	3	M	60	234806.4	223535.2	25.0	73.0	4676.955102	...	458341.6	
2	844	POPLATEK MESICNE	3	M	50	228514.9	218531.2	24.0	60.0	5321.977381	...	447046.1	
3	2873	POPLATEK MESICNE	3	F	20	664545.4	633310.2	34.0	49.0	15636.814458	...	1297855.6	
4	3177	POPLATEK MESICNE	3	M	50	186658.9	191071.2	24.0	74.0	3854.388776	...	377730.1	

5 rows × 25 columns

In [96]:
```
df_independent = df_independent.drop(['monetary', 'frequency', 'recency_days', 'credit_frequency', 'withdrawal_frequency'], axis= 1)
```

In [97]:
```
df_independent['dist_salary_avg'] = pd.cut(df_independent['avg_dist_salary'], 3, labels=['Low salary', 'Medium salary', 'High salary'])
```

In [98]:
```
df_independent = df_independent.drop(['avg_dist_salary'], axis= 1)
df_independent.head()
```

Out[98]:

	client_id	freq iss. stats	LOR	gender	age_group	total_credit	total_withdrawal	avg_amount_trans_96	transaction_std	avg_balance	balance_std	urban_inhabitant_
0	692	POPLATEK MESICNE	3	F	60	76097.3	70419.2	2363.169355	2469.018420	33263.845161	2469.018420	
1	4601	POPLATEK MESICNE	3	M	60	234806.4	223535.2	4676.955102	6125.480217	47088.326531	6125.480217	
2	844	POPLATEK MESICNE	3	M	50	228514.9	218531.2	5321.977381	7068.973119	26333.983333	7068.973119	
3	2873	POPLATEK MESICNE	3	F	20	664545.4	633310.2	15636.814458	15800.741309	71777.087952	15800.741309	
4	3177	POPLATEK MESICNE	3	M	50	186658.9	191071.2	3854.388776	5274.244269	25321.784694	5274.244269	

4.2.2 Dummy coding

In [100…
```
freq_iss_encoded = pd.get_dummies(df_independent['freq iss. stats'], drop_first= True)
```

In [101…
```
df_independent = pd.concat([df_independent, freq_iss_encoded], axis= 1)
```

In [102…
```
df_independent = df_independent.drop('freq iss. stats', axis=1)
```

In [103…
```
df_independent.head()
```

Out[103…

	client_id	LOR	gender	age_group	total_credit	total_withdrawal	avg_amount_trans_96	transaction_std	avg_balance	balance_std	...	dist_unemploy_rate	R_Sc
0	692	3	F	60	76097.3	70419.2	2363.169355	2469.018420	33263.845161	2469.018420	...	5.44	
1	4601	3	M	60	234806.4	223535.2	4676.955102	6125.480217	47088.326531	6125.480217	...	0.43	
2	844	3	M	50	228514.9	218531.2	5321.977381	7068.973119	26333.983333	7068.973119	...	1.25	
3	2873	3	F	20	664545.4	633310.2	15636.814458	15800.741309	71777.087952	15800.741309	...	1.54	
4	3177	3	M	50	186658.9	191071.2	3854.388776	5274.244269	25321.784694	5274.244269	...	2.01	

5 rows × 21 columns

In [104…
```
#Renaming the account statement frequency variable; if it is false for both, then it is a monthly issuance
#POPLATEK PO OBRATU:stat_issued_after_trans
#POPLATEK TYDNE: stat_issued_weekly
df_independent = df_independent.rename(columns={'POPLATEK PO OBRATU':'stat_issued_after_trans',
                                                'POPLATEK TYDNE': 'stat_issued_weekly'})
```

4.2.3 Log transformation

In [106…
```
df_independent.describe()
```

Out[106…

	client_id	LOR	age_group	total_credit	total_withdrawal	avg_amount_trans_96	transaction_std	avg_balance	balance_std	urban_inhabitant_
count	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.000000	2239.00
mean	3413.595802	2.213488	37.405092	202845.810414	200815.812138	5286.732774	6377.519411	35855.979766	6377.519411	69.21
std	2880.044705	0.871029	17.354316	167936.533641	166247.063448	3900.383938	4597.435184	15762.092602	4597.435184	19.76
min	1.000000	1.000000	10.000000	295.600000	900.000000	281.410714	414.728827	-525.731250	414.728827	33.90
25%	1393.000000	1.000000	20.000000	71643.600000	69750.100000	2180.818831	2333.321193	23265.855272	2333.321193	52.70
50%	2874.000000	3.000000	40.000000	158249.100000	157826.000000	4189.183019	5486.702425	32808.267164	5486.702425	63.10
75%	4349.500000	3.000000	50.000000	275681.600000	274053.300000	7438.187478	9165.479285	46241.108710	9165.479285	85.50
max	13998.000000	3.000000	70.000000	724634.918893	715924.577785	17159.117423	20218.717624	83191.376731	20218.717624	100.00

In [107…
```
transform_col = ['total_credit', 'total_withdrawal', 'avg_amount_trans_96', 'transaction_std', 'avg_balance', 'balance_std']
```

In [108…
```
for col in transform_col:
    df_independent[f'log_{col}'] = np.log(df_independent[col])

# Check the result
df_independent.head()
```

Out[108…

	client_id	LOR	gender	age_group	total_credit	total_withdrawal	avg_amount_trans_96	transaction_std	avg_balance	balance_std	...	Withdrawal_F_Score	dist_
0	692	3	F	60	76097.3	70419.2	2363.169355	2469.018420	33263.845161	2469.018420	...	2	Me
1	4601	3	M	60	234806.4	223535.2	4676.955102	6125.480217	47088.326531	6125.480217	...	4	
2	844	3	M	50	228514.9	218531.2	5321.977381	7068.973119	26333.983333	7068.973119	...	3	
3	2873	3	F	20	664545.4	633310.2	15636.814458	15800.741309	71777.087952	15800.741309	...	3	
4	3177	3	M	50	186658.9	191071.2	3854.388776	5274.244269	25321.784694	5274.244269	...	4	

5 rows × 27 columns

In [109…

```
df_independent.columns
```

Out[109…

```
Index(['client_id', 'LOR', 'gender', 'age_group', 'total_credit',
       'total_withdrawal', 'avg_amount_trans_96', 'transaction_std',
       'avg_balance', 'balance_std', 'urban_inhabitant_ratio',
       'dist_unemploy_rate', 'R_Score', 'F_Score', 'M_Score', 'RFM_Score',
       'Credit_F_Score', 'Withdrawal_F_Score', 'dist_salary_avg',
       'stat_issued_after_trans', 'stat_issued_weekly', 'log_total_credit',
       'log_total_withdrawal', 'log_avg_amount_trans_96',
       'log_transaction_std', 'log_avg_balance', 'log_balance_std'],
      dtype='object')
```

In [110…

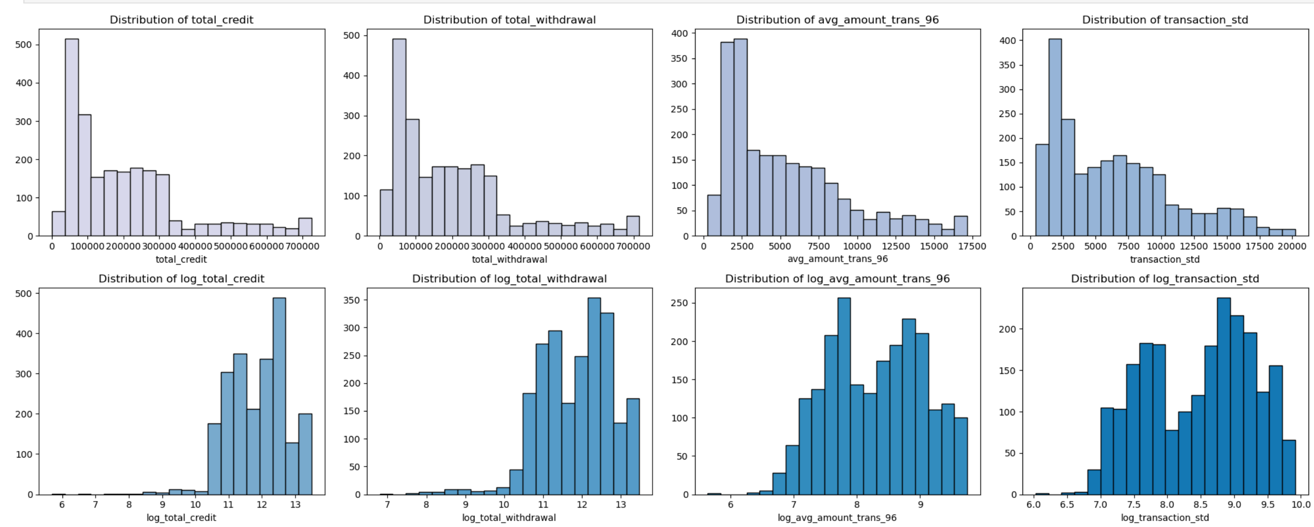
```
hist_col1 = ['total_credit', 'total_withdrawal', 'avg_amount_trans_96', 'transaction_std',
             'log_total_credit', 'log_total_withdrawal', 'log_avg_amount_trans_96', 'log_transaction_std']
```

In [111…

```
hist_col2 = ['avg_balance', 'balance_std', 'log_avg_balance','log_balance_std']
```

In [112…

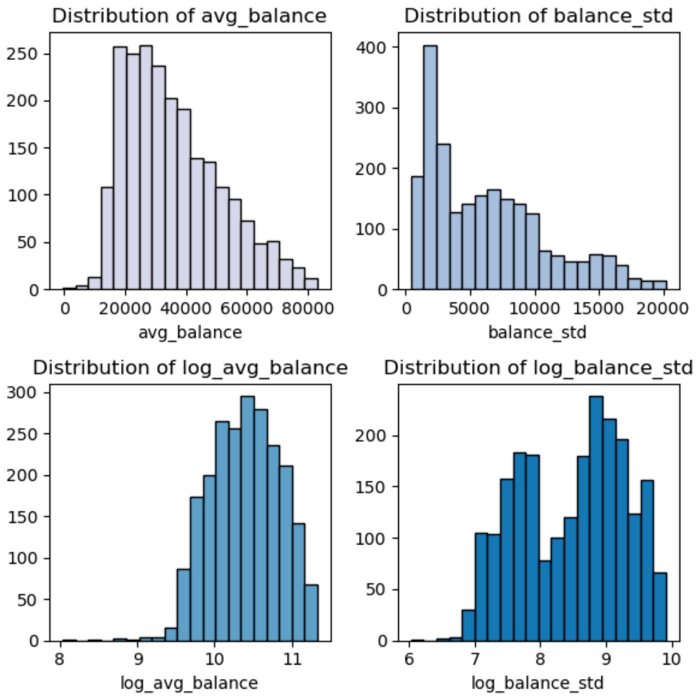
```
fig, axes = plt.subplots(nrows=2, ncols=4, figsize=(20, 8))

# Generate colors using a colormap
colors = plt.cm.PuBu(np.linspace(0.2, 0.7, len(hist_col1)))

# Loop through the list of variables
for i, var in enumerate(hist_col1):
    row, col = divmod(i, 4)

    axes[row, col].hist(df_independent[var], bins=20, color=colors[i], edgecolor='black')
    axes[row, col].set_title(f'Distribution of {var}')
    axes[row, col].set_xlabel(var)

plt.tight_layout()
save_plot('Histograms of log transform variables1.png')

# Show the plot
plt.show()
```



In [113…

```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(6, 6))

# Generate colors using a colormap
colors = plt.cm.PuBu(np.linspace(0.2, 0.7, len(hist_col2)))

# Loop through the list of variables
for i, var in enumerate(hist_col2):
    row, col = divmod(i, 2)

    axes[row, col].hist(df_independent[var], bins=20, color=colors[i], edgecolor='black')
    axes[row, col].set_title(f'Distribution of {var}')
    axes[row, col].set_xlabel(var)

plt.tight_layout()
save_plot('Histograms of log transform variables2.png')
```

```
# Show the plot
plt.show()
```



In [114…

```
df_independent = df_independent.drop(['total_credit', 'total_withdrawal', 'avg_amount_trans_96', 'transaction_std',
                                      'avg_balance', 'balance_std'], axis =1)
```

In [115…

```
df_independent
```

Out[115…

	client_id	LOR	gender	age_group	urban_inhabitant_ratio	dist_unemploy_rate	R_Score	F_Score	M_Score	RFM_Score	...	Withdrawal_F_Score	dist_salary_avg
0	692	3	F	60	100.0	5.44	4	2	1	7	...	2	Medium salary
1	4601	3	M	60	100.0	0.43	4	3	2	9	...	4	High salary
2	844	3	M	50	52.4	1.25	4	3	2	9	...	3	Low salary
3	2873	3	F	20	56.9	1.54	4	3	4	11	...	3	Low salary
4	3177	3	M	50	80.0	2.01	4	3	2	9	...	4	Low salary
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2234	5384	1	M	60	56.4	3.74	4	2	2	8	...	2	Low salary
2235	4596	1	F	20	100.0	5.44	2	1	1	4	...	1	Medium salary
2236	3357	1	F	40	50.5	4.52	4	2	1	7	...	2	Low salary
2237	3962	1	M	40	100.0	5.44	4	2	4	10	...	2	Medium salary
2238	4295	1	M	30	65.3	3.35	4	2	1	7	...	2	Low salary

2239 rows × 21 columns

4.2.4 Normalization

In [117…

```
normalize_var = ['urban_inhabitant_ratio', 'dist_unemploy_rate']

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the selected columns
df_independent[normalize_var] = scaler.fit_transform(df_independent[normalize_var])
```

4.3 Creating the Basetable

In [119…

```
basetable=df_independent.merge(df_dependent, how='left', on='client_id')
```

In [120…

```
basetable.head()
```

Out[120...

	client_id	LOR	gender	age_group	urban_inhabitant_ratio	dist_unemploy_rate	R_Score	F_Score	M_Score	RFM_Score	...	stat_issued_after_trans	stat_issued_wee
0	692	3	F	60	1.000000	0.558528	4	2	1	7	...	False	Fa
1	4601	3	M	60	1.000000	0.000000	4	3	2	9	...	False	Fa
2	844	3	M	50	0.279879	0.091416	4	3	2	9	...	False	Fa
3	2873	3	F	20	0.347958	0.123746	4	3	4	11	...	False	Fa
4	3177	3	M	50	0.697428	0.176143	4	3	2	9	...	False	Fa

5 rows × 23 columns

In [121...

```
#save the basetable
basetable.to_csv('./basetable.csv', index=False)
```

5. Variable description and visualization

5.1 LOR and client demographics

In [124...

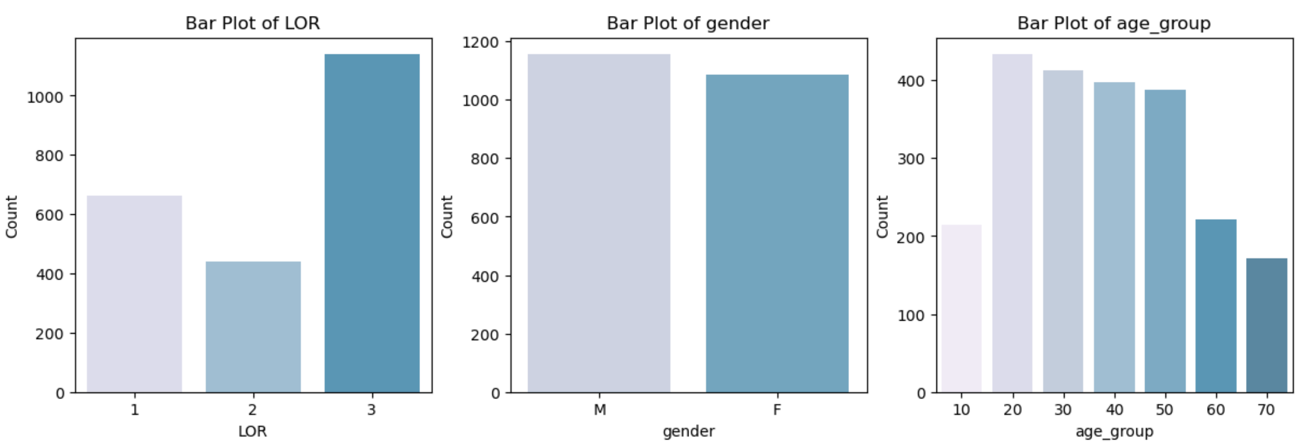
```
basetable.columns
```

Out[124...

```
Index(['client_id', 'LOR', 'gender', 'age_group', 'urban_inhabitant_ratio',
       'dist_unemploy_rate', 'R_Score', 'F_Score', 'M_Score', 'RFM_Score',
       'Credit_F_Score', 'Withdrawal_F_Score', 'dist_salary_avg',
       'stat_issued_after_trans', 'stat_issued_weekly', 'log_total_credit',
       'log_total_withdrawal', 'log_avg_amount_trans_96',
       'log_transaction_std', 'log_avg_balance', 'log_balance_std',
       'granted_loan', 'card_issued'],
      dtype='object')
```

In [125...

```
# Create the subplots
variables = ['LOR', 'gender', 'age_group']

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(12, 4), constrained_layout=True)
ax = ax.flatten()


for i, var in enumerate(variables):
        sns.barplot(x=basetable[var].value_counts().index, y=basetable[var].value_counts(), ax=ax[i], palette="PuBu",
                    alpha=0.7)
        ax[i].set_title(f'Bar Plot of {var}')
        ax[i].set_xlabel(var)
        ax[i].set_ylabel('Count')

save_plot("Bar plots of three variables.png")
# Display the plots
plt.show()
```



In [126...

```
for var in variables:
    print (basetable[var].value_counts())
    print("")
```

```
LOR
3    1139
1     661
2     439
Name: count, dtype: int64

gender
M    1155
F    1084
Name: count, dtype: int64

age_group
20    433
30    413
40    398
50    388
60    221
10    215
70    171
Name: count, dtype: int64
```

In [127…

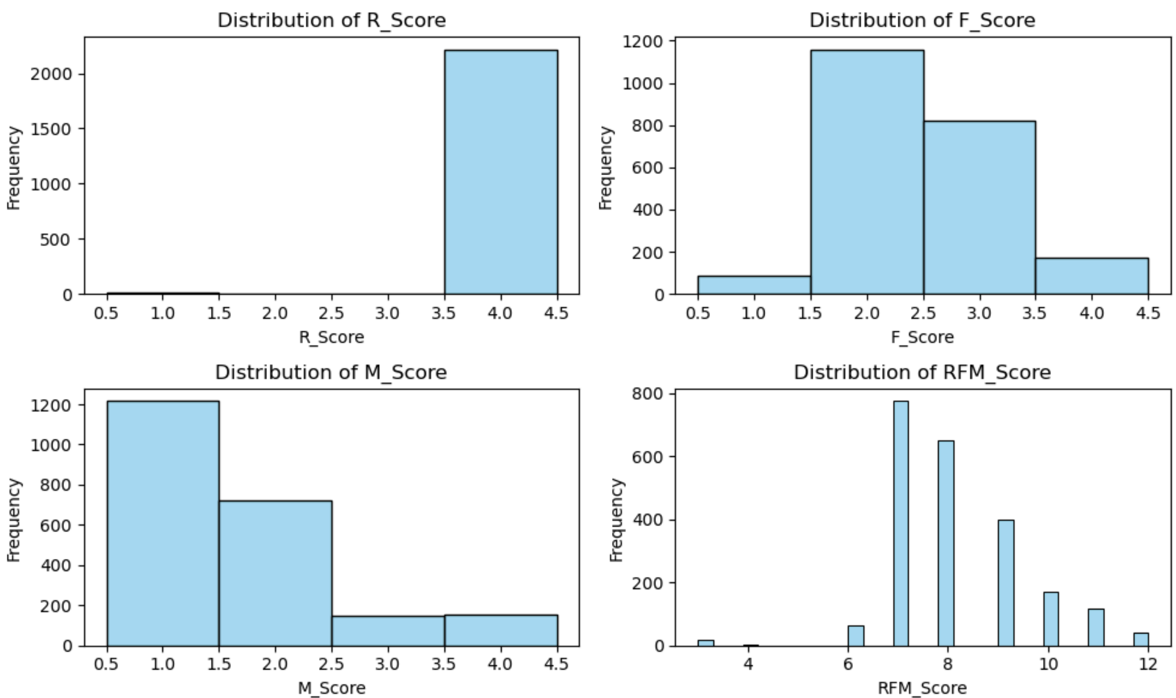
```
for var in variables:
    print(var + " description and key numbers: ")
    print (basetable[var].describe())
    print("")
```

```
LOR description and key numbers:
count    2239.000000
mean        2.213488
std         0.871029
min         1.000000
25%         1.000000
50%         3.000000
75%         3.000000
max         3.000000
Name: LOR, dtype: float64

gender description and key numbers:
count      2239
unique        2
top           M
freq       1155
Name: gender, dtype: object

age_group description and key numbers:
count    2239.000000
mean       37.405092
std        17.354316
min        10.000000
25%        20.000000
50%        40.000000
75%        50.000000
max        70.000000
Name: age_group, dtype: float64
```

5.2 R Score, F Score, M Score and RFM Score

In [129…

```
rfm_data = basetable[['R_Score', 'F_Score', 'M_Score', 'RFM_Score']]

fig, ax = plt.subplots(2, 2, figsize=(10,6))
ax = ax.flatten()

# Plot histograms
for i, score in enumerate(rfm_data.columns):
    sns.histplot(rfm_data[score], ax=ax[i], color='skyblue')
    ax[i].set_title(f'Distribution of {score}')
    ax[i].set_xlabel(score)
    ax[i].set_ylabel('Frequency')

plt.tight_layout()
save_plot("Distribution of four scores.png")
plt.show()
```



In [130…

```python
for var in rfm_data:
    print(basetable[var].value_counts())
    print("")
```

```
R_Score
4    2218
1      18
2       3
3       0
Name: count, dtype: int64

F_Score
2    1160
3     823
4     170
1      86
Name: count, dtype: int64

M_Score
1    1218
2     720
4     154
3     147
Name: count, dtype: int64

RFM_Score
7     777
8     650
9     398
10    170
11    119
6      63
12     41
3      18
4       3
Name: count, dtype: int64
```

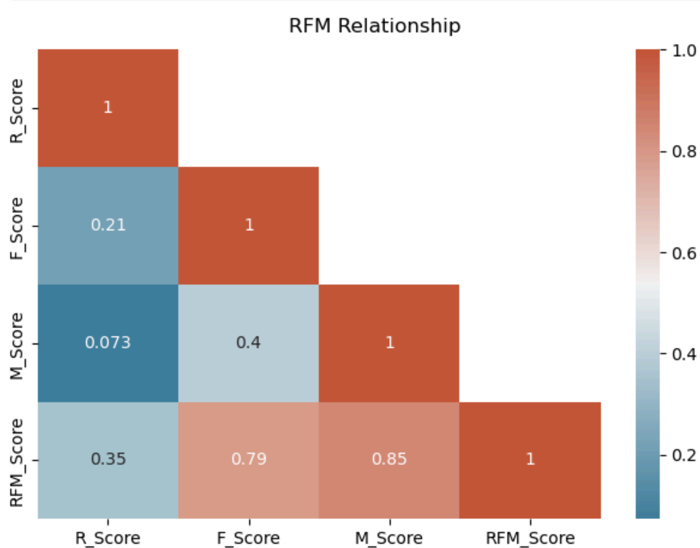
In [131…

```python
for var in rfm_data:
    print(var + " description and key numbers: ")
    print (basetable[var].describe())
    print("")
```

```
R_Score description and key numbers:
count     2239
unique       3
top          4
freq      2218
Name: R_Score, dtype: int64

F_Score description and key numbers:
count     2239
unique       4
top          2
freq      1160
Name: F_Score, dtype: int64

M_Score description and key numbers:
count     2239
unique       4
top          1
freq      1218
Name: M_Score, dtype: int64

RFM_Score description and key numbers:
count    2239.000000
mean        8.113444
std         1.386644
min         3.000000
25%         7.000000
50%         8.000000
75%         9.000000
max        12.000000
Name: RFM_Score, dtype: float64
```

In [132…

```
corr_matrix = rfm_data.corr()
mask = np.triu(np.ones_like(corr_matrix, dtype=bool), k=1)
cmap = sns.diverging_palette(230, 20, as_cmap = True)

sns.heatmap(corr_matrix, mask=mask, annot=True, cmap=cmap)
plt.suptitle("RFM Relationship", y=0.95)
plt.tight_layout()
save_plot('Heatmap of RFM scores')
plt.show()
```



5.3 Other independent variables

In [134…

```
print(basetable[['stat_issued_after_trans', 'stat_issued_weekly']].value_counts())
```

```
stat_issued_after_trans  stat_issued_weekly
False                    False                 2069
                         True                   122
True                     False                   48
Name: count, dtype: int64
```

In [135…

```
print(basetable['dist_salary_avg'].value_counts())
```

```
dist_salary_avg
Low salary       1436
Medium salary     497
High salary       306
Name: count, dtype: int64
```

In [136…

```
pd.crosstab(basetable['Credit_F_Score'], basetable['Withdrawal_F_Score'])
```

Out[136...

Withdrawal_F_Score	1	2	3	4
Credit_F_Score				
1	48	6	3	0
2	22	814	545	131
3	5	231	188	37
4	1	90	97	21

5.4 Dependent variables: granted_loan, card_issued

5.4.1 Basic statistics and distribution

In [139...

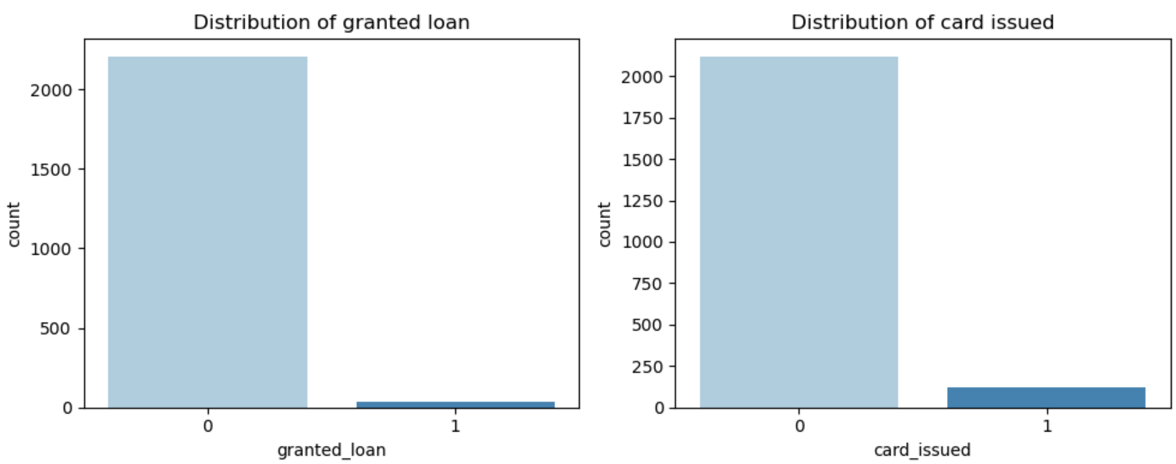
```
pd.crosstab(basetable['granted_loan'], basetable['card_issued'])
```

Out[139...

card_issued	0	1
granted_loan		
0	2093	115
1	26	5

In [140...

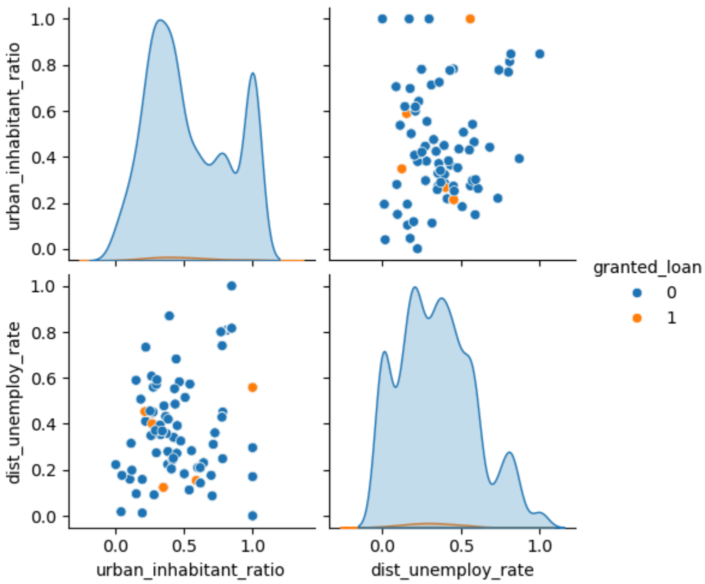
```
fig, ax = plt.subplots(1, 2, figsize=(10, 4))

sns.countplot(x='granted_loan', data=basetable, ax=ax[0], palette = 'Blues', hue = 'granted_loan', legend=False)
ax[0].set_title('Distribution of granted loan')

sns.countplot(x='card_issued', data=basetable, ax=ax[1], palette = 'Blues', hue = 'card_issued', legend=False)
ax[1].set_title('Distribution of card issued')

plt.tight_layout()
save_plot("Distribution of dependent variables.png")
plt.show()
```



5.4.2 Relationship between independent variables and target variables

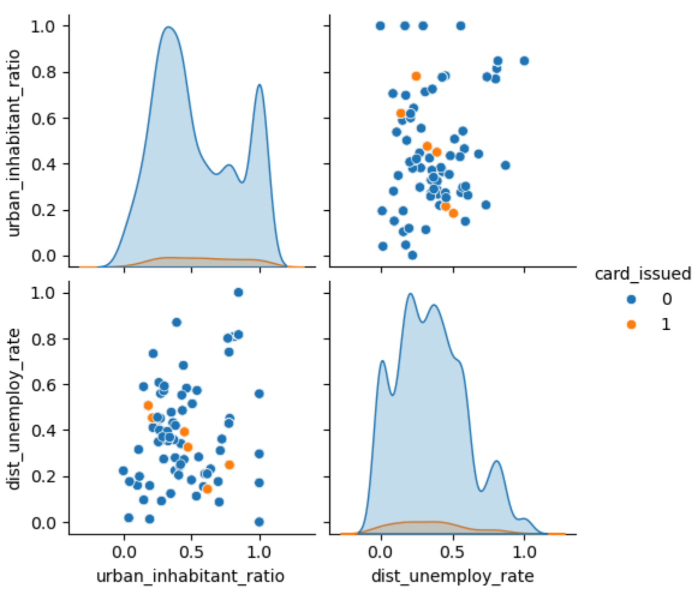
In [142...

```
pairplot = sns.pairplot(basetable, hue='granted_loan', vars=['urban_inhabitant_ratio', 'dist_unemploy_rate'])
save_plot("Relationships between two independent variables and granted loan.png")
```



In [143…

```
sns.pairplot(basetable, hue='card_issued', vars=['urban_inhabitant_ratio', 'dist_unemploy_rate'])
save_plot("Relationships between two independent variables and card issued.png")
```



In [144…

```
basetable_corr=basetable

# Create a dummy variable for gender: 1 for female ('F') and 0 for male ('M')
basetable_corr['is_female']=basetable['gender'].map({'F': 1, 'M': 0})
# Convert 'stat_issued_after_trans' and 'stat_issued_weekly' to binary variables: 1 for True, 0 for False
basetable_corr['stat_issued_after_trans']=basetable['stat_issued_after_trans'].map({False: 0, True: 1})
basetable_corr['stat_issued_weekly']=basetable['stat_issued_weekly'].map({False: 0, True: 1})

basetable_corr=basetable.drop(['client_id', 'gender'], axis=1)
```

In [145…

```
# Convert 'dist_salary_avg' into dummy variables
dist_salary_avg_encoded = pd.get_dummies(basetable_corr['dist_salary_avg'], drop_first= True)
basetable_corr = pd.concat([basetable_corr, dist_salary_avg_encoded], axis= 1)
basetable_corr = basetable_corr.drop('dist_salary_avg', axis=1)

# Convert the 'Medium salary' and 'High salary' dummy variables to binary: 1 for True, 0 for False
basetable_corr['Medium salary']=basetable_corr['Medium salary'].map({False: 0, True: 1})
basetable_corr['High salary']=basetable_corr['High salary'].map({False: 0, True: 1})
basetable_corr.head()
```

Out[145…

	LOR	age_group	urban_inhabitant_ratio	dist_unemploy_rate	R_Score	F_Score	M_Score	RFM_Score	Credit_F_Score	Withdrawal_F_Score	...	log_total_withdrawal
0	3	60	1.000000	0.558528	4	2	1	7	2	2	...	11.162221
1	3	60	1.000000	0.000000	4	3	2	9	2	4	...	12.317324
2	3	50	0.279879	0.091416	4	3	2	9	2	3	...	12.294684
3	3	20	0.347958	0.123746	4	3	4	11	3	3	...	13.358716
4	3	50	0.697428	0.176143	4	3	2	9	2	4	...	12.160401

5 rows × 23 columns

In [146…

```
basetable_corr.columns
```

Out[146…

```
Index(['LOR', 'age_group', 'urban_inhabitant_ratio', 'dist_unemploy_rate',
       'R_Score', 'F_Score', 'M_Score', 'RFM_Score', 'Credit_F_Score',
       'Withdrawal_F_Score', 'stat_issued_after_trans', 'stat_issued_weekly',
       'log_total_credit', 'log_total_withdrawal', 'log_avg_amount_trans_96',
       'log_transaction_std', 'log_avg_balance', 'log_balance_std',
       'granted_loan', 'card_issued', 'is_female', 'Medium salary',
       'High salary'],
      dtype='object')
```

In [147…

```
#change sequence
basetable_ = basetable_corr[['LOR', 'age_group', 'urban_inhabitant_ratio', 'dist_unemploy_rate',
       'R_Score', 'F_Score', 'M_Score', 'RFM_Score', 'Credit_F_Score',
       'Withdrawal_F_Score', 'stat_issued_after_trans', 'stat_issued_weekly',
       'log_total_credit', 'log_total_withdrawal', 'log_avg_amount_trans_96',
       'log_transaction_std', 'log_avg_balance', 'log_balance_std',
        'is_female', 'Medium salary','High salary',
        'granted_loan', 'card_issued']]
```

In [148…

```
corr_matrix = basetable_corr.corr()
cmap = sns.diverging_palette(230, 20, as_cmap=True)

plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, cmap=cmap,
            xticklabels=corr_matrix.columns, yticklabels=corr_matrix.index, square=True)

# Set the title and show the plot
plt.tight_layout()
plt.title("Correlation Matrix")
plt.xticks(rotation=90)
plt.yticks(rotation=0)
save_plot('Correlation matrix')
plt.show()
```