ADB HW1 Kambachekov Timur 201 var16

Part 1

In [ ]:
```
#import libraries
%matplotlib inline
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from pathlib import Path
import seaborn as sns
```

In [ ]:
```
#convert table to df
data_path = Path(Path.cwd()/'data', 'HW1_var_16.csv')
df = pd.read_csv(data_path, sep=';').drop(columns=['Номер варианта'])
df.head()
```

Out[ ]:

	ID	INCOME_BASE_TYPE	CREDIT_PURPOSE	INSURANCE_FLAG	DTI	SEX
0	1000016	2НДФЛ	Ремонт	1.0	0.26	мужской
1	1000036	Форма банка (без печати работодателя)	Обучение	1.0	0.45	мужской
2	1000056	Форма банка (без печати работодателя)	Покупка автомобиля	1.0	0.23	мужской
3	1000076	Свободная форма с печатью работодателя	Покупка недвижимости/ строительство	1.0	0.56	мужской
4	1000096	2НДФЛ	Ремонт	0.0	0.25	мужской

5 rows × 43 columns

In [ ]:
```
#export corrected table
df.to_csv(Path(Path.cwd()/'data/', 'HW1_var_16_corrected.csv'))
```

In [ ]:
```
#data shape
df.shape
```

Out[ ]:
```
(10242, 43)
```

In [ ]:
```
#data columns
for col in df.columns: print(col)
```

```
ID
INCOME_BASE_TYPE
CREDIT_PURPOSE
INSURANCE_FLAG
DTI
SEX
FULL_AGE_CHILD_NUMBER
DEPENDANT_NUMBER
EDUCATION
EMPL_TYPE
EMPL_SIZE
BANKACCOUNT_FLAG
Period_at_work
age
EMPL_PROPERTY
EMPL_FORM
FAMILY_STATUS
max90days
max60days
max30days
max21days
max14days
avg_num_delay
if_zalog
num_AccountActive180
num_AccountActive90
num_AccountActive60
Active_to_All_prc
numAccountActiveAll
numAccountClosed
sum_of_paym_months
all_credits
Active_not_cc
own_closed
min_MnthAfterLoan
max_MnthAfterLoan
dlq_exist
thirty_in_a_year
sixty_in_a_year
ninety_in_a_year
thirty_vintage
sixty_vintage
ninety_vintage
```

In [ ]:
```
numerical_cols = [
    'DTI',
    'FULL_AGE_CHILD_NUMBER',
    'DEPENDANT_NUMBER',
    'Period_at_work',
    'age',
    'max90days',
    'max60days',
    'max30days',
    'max21days',
    'max14days',
    'avg_num_delay',
    'num_AccountActive180',
    'num_AccountActive90',
    'num_AccountActive60',
    'Active_to_All_prc',
    'numAccountActiveAll',
    'numAccountClosed',
    'sum_of_paym_months',
    'all_credits',
    'Active_not_cc',
    'own_closed',
    'min_MnthAfterLoan',
    'max_MnthAfterLoan'
]

categorical_cols = [
    'ID',
    'INCOME_BASE_TYPE',
    'CREDIT_PURPOSE',
    'INSURANCE_FLAG',
    'SEX',
    'EDUCATION',
    'EMPL_TYPE',
    'EMPL_SIZE',
    'BANKACCOUNT_FLAG',
    'EMPL_PROPERTY',
    'EMPL_FORM',
    'FAMILY_STATUS',
    'if_zalog',
    'dlq_exist',
    'thirty_in_a_year',
    'sixty_in_a_year',
    'ninety_in_a_year',
    'thirty_vintage',
    'sixty_vintage',
    'ninety_vintage'
]
num_df = df[numerical_cols]
cat_df = df[categorical_cols]
```

In [ ]:
```
#get info about df
def col_data(df):
    t = []
    for col in df.columns:
        k_unique = df[col].nunique()
        k_nan = df[col].isna().sum()
        k_zeros = (df[col] == 0).sum()
        d_type = 'numerical' if (col in numerical_cols) else 'categorical

        t.append([col, k_unique, k_nan, k_zeros, d_type])

    col_info = pd.DataFrame(t, columns=['columns', 'unique', 'NaN', 'zero
    return col_info
col_data(df)
```

Out[ ]:

	columns	unique	NaN	zeros	d_type
0	ID	10242	0	0	categorical
1	INCOME_BASE_TYPE	4	65	0	categorical
2	CREDIT_PURPOSE	10	0	0	categorical
3	INSURANCE_FLAG	2	3	3960	categorical
4	DTI	58	118	0	numerical
5	SEX	2	0	0	categorical
6	FULL_AGE_CHILD_NUMBER	8	0	6110	numerical
7	DEPENDANT_NUMBER	5	0	10204	numerical
8	EDUCATION	9	1	0	categorical
9	EMPL_TYPE	9	8	0	categorical
10	EMPL_SIZE	8	115	0	categorical
11	BANKACCOUNT_FLAG	4	2327	6246	categorical
12	Period_at_work	357	2327	0	numerical
13	age	41	2327	0	numerical
14	EMPL_PROPERTY	12	2327	0	categorical
15	EMPL_FORM	6	6331	0	categorical
16	FAMILY_STATUS	6	6331	0	categorical
17	max90days	22	6388	1100	numerical
18	max60days	17	6388	1562	numerical
19	max30days	14	6388	1977	numerical
20	max21days	13	6388	2338	numerical
21	max14days	12	6388	2526	numerical
22	avg_num_delay	1134	6618	1504	numerical
23	if_zalog	2	6606	2392	categorical

24	num_AccountActive180	6	6606	2556	numerical
25	num_AccountActive90	4	6606	3134	numerical
26	num_AccountActive60	4	6606	3320	numerical
27	Active_to_All_prc	95	6606	473	numerical
28	numAccountActiveAll	15	6606	464	numerical
29	numAccountClosed	24	6606	441	numerical
30	sum_of_paym_months	327	6606	12	numerical
31	all_credits	30	6606	0	numerical
32	Active_not_cc	9	6606	1226	numerical
33	own_closed	9	6606	2079	numerical
34	min_MnthAfterLoan	94	6606	146	numerical
35	max_MnthAfterLoan	131	6606	5	numerical
36	dlq_exist	2	6606	1516	categorical
37	thirty_in_a_year	2	6606	3092	categorical
38	sixty_in_a_year	2	6606	3318	categorical
39	ninety_in_a_year	2	6606	3400	categorical
40	thirty_vintage	2	6606	3519	categorical
41	sixty_vintage	2	6606	3582	categorical
42	ninety_vintage	2	6606	3582	categorical

In [ ]:
```
#Check value eligibility in each categorical feature
for col in cat_df.columns: print(col, cat_df[col].unique(), '\n')
```

```
ID [1000016 1000036 1000056 ... 1204796 1204816 1204836]

INCOME_BASE_TYPE ['2НДФЛ' 'Форма банка (без печати работодателя)'
 'Свободная форма с печатью работодателя' 'Поступление зарплаты на счет'
 nan]

CREDIT_PURPOSE ['Ремонт' 'Обучение' 'Покупка автомобиля'
 'Покупка недвижимости/ строительство' 'Отпуск' 'Другое' 'Покупка мебели'
 'Лечение' 'Покупка бытовой техники' 'Покупка земли']

INSURANCE_FLAG [ 1.  0. nan]

SEX ['мужской' 'женский']

EDUCATION ['Высшее/Второе высшее/Ученая степень' 'высшее' 'второе высшее'
 'среднее-специальное' 'среднее' 'незаконченное высшее' '*n.a.*'
 'ученая степень' 'Неполное среднее' nan]

EMPL_TYPE ['специалист' 'менеджер высшего звена' 'вспомогательный персона
л'
```

```
 'менеджер среднего звена' 'рабочий' 'торговый представитель'
 'менеджер по продажам' 'другое' nan 'страховой агент']

EMPL_SIZE ['>250' '< 50' '>100' '>=150' '>=50' '>=100' '>=200' nan '*n.a.
*']

BANKACCOUNT_FLAG [ 0. nan  3.  1.  4.]

EMPL_PROPERTY ['Транспорт' 'Торговля' nan 'Государственная служба' 'Друго
е'
 'Строительство' 'Производство' 'Информационные технологии' 'Финансы'
 'Наука' 'Туризм' 'Сельское и лесное хозяйство' 'Юридические услуги']

EMPL_FORM [nan 'ООО' 'ОАО' 'Иная форма' 'ЗАО' 'Индивидуальный предпринима
тель'
 'Государственное предприятие']

FAMILY_STATUS [nan 'холост / не замужем' 'женат / замужем' 'разведен / ра
зведена'
 'гражданский брак' 'повторный брак' 'вдовец / вдова']

if_zalog [nan  1.  0.]

dlq_exist [nan  1.  0.]

thirty_in_a_year [nan  0.  1.]

sixty_in_a_year [nan  0.  1.]

ninety_in_a_year [nan  0.  1.]

thirty_vintage [nan  0.  1.]

sixty_vintage [nan  0.  1.]

ninety_vintage [nan  0.  1.]
```

We should replace manually filled in nan values with actual nan's in order to eliminate confusion between these 2 identical values in each feature.

In [ ]:
```
clean_df = df.replace('*n.a.*', np.nan)
```

Also, we should replace education values like below to avoid ambiguity and allow for future ordinal encoding

In [ ]:
```
education_map = {
    'Высшее/Второе высшее/Ученая степень' : 'Высшее/Второе высшее/Ученая
    'высшее' : 'Высшее/Второе высшее/Ученая степень',
    'второе высшее' : 'Высшее/Второе высшее/Ученая степень',
    'ученая степень' : 'Высшее/Второе высшее/Ученая степень',
    # 'среднее-специальное' : 'среднее-специальное',
    # 'незаконченное высшее' : 'незаконченное высшее',
    # 'среднее' : 'среднее',
    # 'Неполное среднее' : 'Неполное среднее'
}

clean_df['EDUCATION'] = clean_df['EDUCATION'].replace(education_map)
```

In [ ]:
```
clean_df['EMPL_SIZE'] = clean_df['EMPL_SIZE'].replace('>100', '>=100')
```

We should drop the features below because they are missing almost a half of observations, that means that however we fill in those values, the most likely income would be that these features would not be anymore representative of their distribution.

In [ ]:
```
cols_to_drop = [
    #numerical
    'max90days',
    'max60days',
    'max30days',
    'max21days',
    'max14days',
    'avg_num_delay',
    'num_AccountActive180',
    'num_AccountActive90',
    'num_AccountActive60',
    'Active_to_All_prc',
    'numAccountActiveAll',
    'numAccountClosed',
    'sum_of_paym_months',
    'all_credits',
    'Active_not_cc',
    'own_closed',
    'min_MnthAfterLoan',
    'max_MnthAfterLoan',
    #categorical
    'EMPL_FORM',
    'FAMILY_STATUS',
    'if_zalog',
    'dlq_exist',
    'thirty_in_a_year',
    'sixty_in_a_year',
    'ninety_in_a_year',
    'thirty_vintage',
    'sixty_vintage',
    'ninety_vintage'
]

clean_df = clean_df.drop(columns=cols_to_drop)
col_data_clean_df = col_data(clean_df)
numerical_cols = col_data_clean_df.loc[col_data(clean_df)['d_type'] == 'n
categorical_cols = col_data_clean_df.loc[col_data(clean_df)['d_type'] ==
col_data(clean_df)
```

Out[ ]:

	columns	unique	NaN	zeros	d_type
0	ID	10242	0	0	categorical
1	INCOME_BASE_TYPE	4	65	0	categorical
2	CREDIT_PURPOSE	10	0	0	categorical
3	INSURANCE_FLAG	2	3	3960	categorical
4	DTI	58	118	0	numerical
5	SEX	2	0	0	categorical
6	FULL_AGE_CHILD_NUMBER	8	0	6110	numerical
7	DEPENDANT_NUMBER	5	0	10204	numerical
8	EDUCATION	5	38	0	categorical
9	EMPL_TYPE	9	8	0	categorical
10	EMPL_SIZE	6	118	0	categorical
11	BANKACCOUNT_FLAG	4	2327	6246	categorical
12	Period_at_work	357	2327	0	numerical
13	age	41	2327	0	numerical
14	EMPL_PROPERTY	12	2327	0	categorical

It is hard to restore 2327 categorical observations and keep the same distribution so we would be better off removing those features.

In [ ]:

```
cols_to_drop = ['BANKACCOUNT_FLAG', 'EMPL_PROPERTY']
clean_df = clean_df.drop(columns=cols_to_drop)
col_data(clean_df)
```

Out[ ]:

	columns	unique	NaN	zeros	d_type
0	ID	10242	0	0	categorical
1	INCOME_BASE_TYPE	4	65	0	categorical
2	CREDIT_PURPOSE	10	0	0	categorical
3	INSURANCE_FLAG	2	3	3960	categorical
4	DTI	58	118	0	numerical
5	SEX	2	0	0	categorical
6	FULL_AGE_CHILD_NUMBER	8	0	6110	numerical
7	DEPENDANT_NUMBER	5	0	10204	numerical
8	EDUCATION	5	38	0	categorical
9	EMPL_TYPE	9	8	0	categorical
10	EMPL_SIZE	6	118	0	categorical
11	Period_at_work	357	2327	0	numerical
12	age	41	2327	0	numerical

In order not to lose other features we can remove categorical nan obesrvations from the dataset, since there are not relatively many of them (maximum 118 of 10242). This way we will not distort the sample too much.

In [ ]:

```
clean_df = clean_df.dropna(subset=['INCOME_BASE_TYPE', 'INSURANCE_FLAG',
col_data(clean_df)
```

Out[ ]:

	columns	unique	NaN	zeros	d_type
0	ID	10084	0	0	categorical
1	INCOME_BASE_TYPE	4	0	0	categorical
2	CREDIT_PURPOSE	10	0	0	categorical
3	INSURANCE_FLAG	2	0	3842	categorical
4	DTI	58	2	0	numerical
5	SEX	2	0	0	categorical
6	FULL_AGE_CHILD_NUMBER	8	0	6006	numerical
7	DEPENDANT_NUMBER	5	0	10047	numerical
8	EDUCATION	5	0	0	categorical
9	EMPL_TYPE	9	0	0	categorical
10	EMPL_SIZE	6	0	0	categorical
11	Period_at_work	357	2320	0	numerical
12	age	41	2320	0	numerical

Now, we need to restore missing observations from numerical features. For that we will replace nans with mean.

In [ ]:
```
clean_df = clean_df.fillna(df.mean(numeric_only=True))
col_data_clean_df = col_data(clean_df)
col_data_clean_df
```

Out[ ]:

	columns	unique	NaN	zeros	d_type
0	ID	10084	0	0	categorical
1	INCOME_BASE_TYPE	4	0	0	categorical
2	CREDIT_PURPOSE	10	0	0	categorical
3	INSURANCE_FLAG	2	0	3842	categorical
4	DTI	59	0	0	numerical
5	SEX	2	0	0	categorical
6	FULL_AGE_CHILD_NUMBER	8	0	6006	numerical
7	DEPENDANT_NUMBER	5	0	10047	numerical
8	EDUCATION	5	0	0	categorical
9	EMPL_TYPE	9	0	0	categorical
10	EMPL_SIZE	6	0	0	categorical
11	Period_at_work	358	0	0	numerical
12	age	42	0	0	numerical

In [ ]:

```
numerical_cols = col_data_clean_df.loc[col_data_clean_df['d_type'] == 'nu
categorical_cols = col_data_clean_df.loc[col_data_clean_df['d_type'] == '
```

In [ ]:

```
for col in clean_df[categorical_cols].columns: print(col, clean_df[col].u
```

```
ID [1000016 1000036 1000056 ... 1204796 1204816 1204836]

INCOME_BASE_TYPE ['2НДФЛ' 'Форма банка (без печати работодателя)'
 'Свободная форма с печатью работодателя' 'Поступление зарплаты на счет']


CREDIT_PURPOSE ['Ремонт' 'Обучение' 'Покупка автомобиля'
 'Покупка недвижимости/ строительство' 'Отпуск' 'Другое' 'Покупка мебели'
 'Лечение' 'Покупка бытовой техники' 'Покупка земли']

INSURANCE_FLAG [1. 0.]

SEX ['мужской' 'женский']

EDUCATION ['Высшее/Второе высшее/Ученая степень' 'среднее-специальное' 'с
реднее'
 'незаконченное высшее' 'Неполное среднее']

EMPL_TYPE ['специалист' 'менеджер высшего звена' 'вспомогательный персона
л'
 'менеджер среднего звена' 'рабочий' 'торговый представитель'
 'менеджер по продажам' 'другое' 'страховой агент']

EMPL_SIZE ['>250' '< 50' '>=100' '>=150' '>=50' '>=200']
```

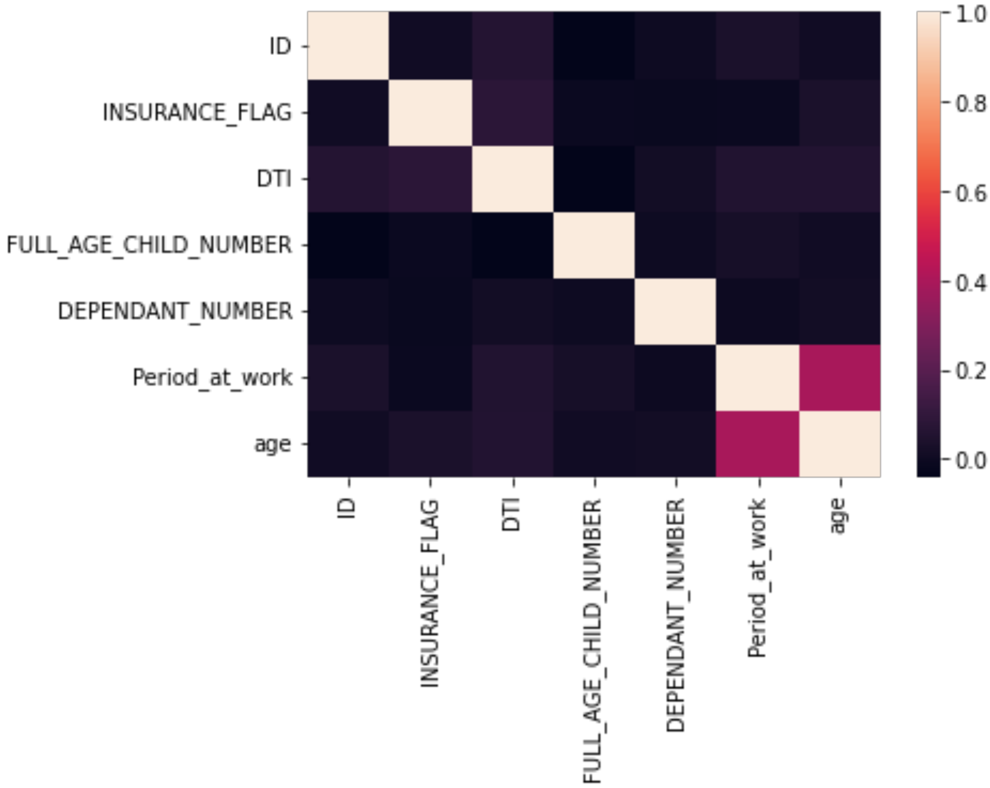
Voila! Now we have a clean dataset to start segmentation

In [ ]:
```
clean_df[numerical_cols].describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75'
DTI	10084.0	0.385694	0.136622	0.02	0.28	0.400000	0.4
FULL_AGE_CHILD_NUMBER	10084.0	0.555534	0.781233	0.00	0.00	0.000000	1.0
DEPENDANT_NUMBER	10084.0	0.005653	0.130105	0.00	0.00	0.000000	0.0
Period_at_work	10084.0	66.406678	58.108735	5.00	27.00	66.267214	73.0
age	10084.0	36.331596	7.627587	23.00	31.00	36.289577	40.0

In [ ]:
```
corr_matrix = clean_df.corr()

sns.heatmap(corr_matrix)
plt.show()
```

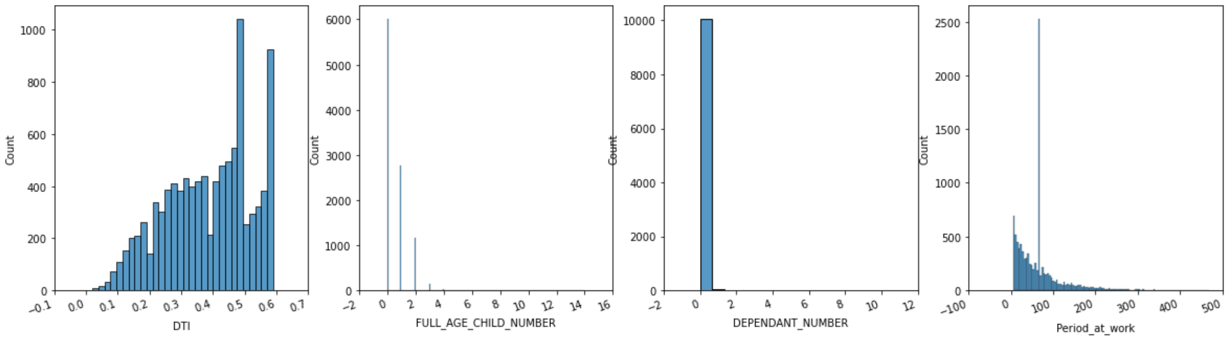


Numerical features almost do not correlate in the sample which means that the feature selection is likely to not experience indpendent variable colinearity.

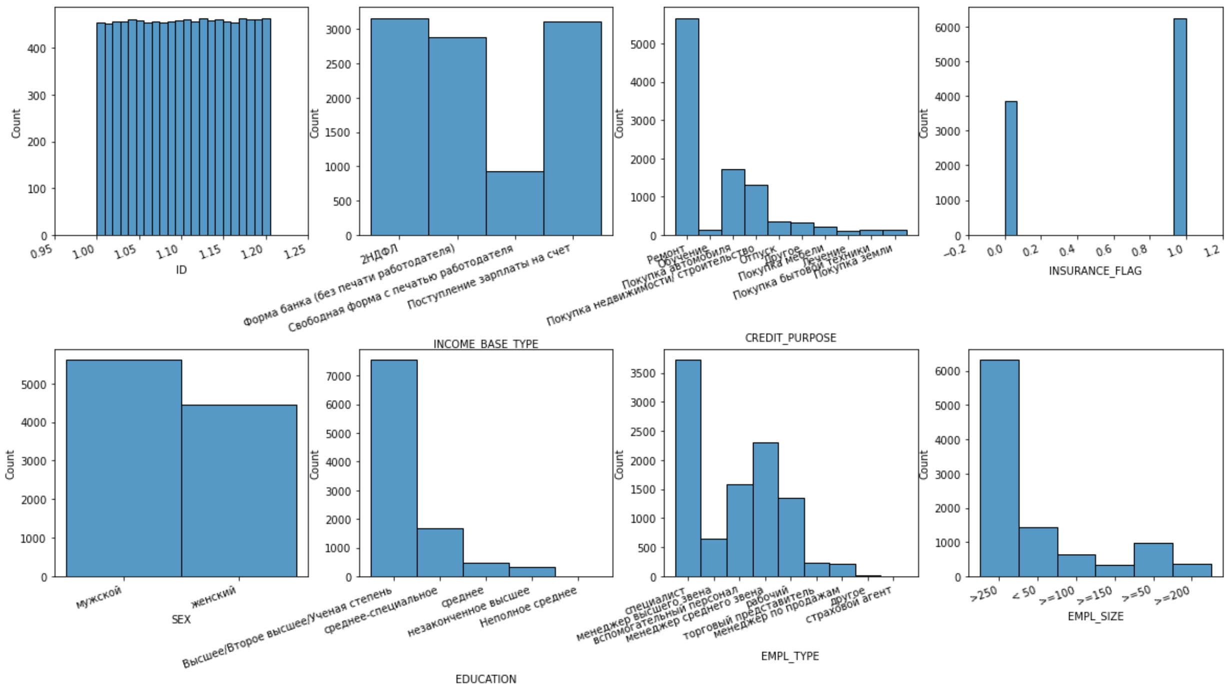
Now, we plot histograms to see distributions of features

In [ ]:
```python
def feature_relationship(df):
    cols = df.columns
    n = df.shape[1]

    fig, axes = plt.subplots(n // 4, 4)
    for i, ax in enumerate(axes.flat):
        ax.set_xlabel(cols[i])
        sns.histplot(df[cols[i]], ax=ax)
        plt.draw()
        ax.set_xticks(ax.get_xticks())
        ax.set_xticklabels(ax.get_xticklabels(), rotation=20, ha='right')

    plt.subplots_adjust(hspace=0.5)
    plt.show()
```

In [ ]:
```python
plt.rcParams["figure.figsize"] = (20,5)
feature_relationship(clean_df[numerical_cols])
```



In [ ]:
```python
plt.rcParams["figure.figsize"] = (20,10)
feature_relationship(clean_df[categorical_cols])
```



Part 2

Method 1: K-Means

In this task, K-Means seems to be a great solution since:

- it has successully been used for market segmentation, which also applies to data on loans
- provides a framework which allows to separate clients in such a way that the difference between the clusters would be maximal, and difference within the cluster would be minimal

In [ ]:
```
#import necessary libraries
from sklearn.cluster import KMeans
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
```

In [ ]:
```
# Drop id column since it provides no relevant info and simply acts as an
x = clean_df
categorical_cols.pop(0)
x.drop(columns=['ID'])
```

Out[ ]:

	INCOME_BASE_TYPE	CREDIT_PURPOSE	INSURANCE_FLAG	DTI	SEX	FULL
0	2НДФЛ	Ремонт	1.0	0.26	мужской	
1	Форма банка (без печати работодателя)	Обучение	1.0	0.45	мужской	
2	Форма банка (без печати работодателя)	Покупка автомобиля	1.0	0.23	мужской	
3	Свободная форма с печатью работодателя	Покупка недвижимости/ строительство	1.0	0.56	мужской	
4	2НДФЛ	Ремонт	0.0	0.25	мужской	
...	...	...	...	...	...	
10237	Свободная форма с печатью работодателя	Ремонт	0.0	0.48	женский	
10238	Свободная форма с печатью работодателя	Ремонт	1.0	0.59	женский	
10239	2НДФЛ	Ремонт	1.0	0.24	женский	
10240	Поступление зарплаты на счет	Ремонт	0.0	0.49	женский	
10241	2НДФЛ	Отпуск	1.0	0.32	мужской	

10084 rows × 12 columns

In [ ]:
```
x = x.drop(columns=['ID'])
```

In [ ]:
```
#One-hot encoding
dummy_cols = ['INCOME_BASE_TYPE', 'CREDIT_PURPOSE', 'EMPL_TYPE']
x = pd.get_dummies(x, columns=dummy_cols, drop_first=True)

#Ordinal encoding with custom objective order.
oe = OrdinalEncoder()
categories = [
    [0, 1],
    ['женский', 'мужской'],
    ['Неполное среднее', 'среднее', 'незаконченное высшее', 'среднее-спец
    ['< 50', '>=50', '>100', '>250', '>=100', '>=150', '>=200'],
]
cols = [i for i in categorical_cols if i not in dummy_cols]
x[cols] = oe.fit_transform(x[cols])
x
```

Out[ ]:

	INSURANCE_FLAG	DTI	SEX	FULL_AGE_CHILD_NUMBER	DEPENDANT_NUMBER
0	1.0	0.26	1.0	0	0
1	1.0	0.45	1.0	1	0
2	1.0	0.23	1.0	0	0
3	1.0	0.56	1.0	2	0
4	0.0	0.25	1.0	1	0
...	...	...	...	...	...
10237	0.0	0.48	0.0	1	0
10238	1.0	0.59	0.0	0	0
10239	1.0	0.24	0.0	0	0
10240	0.0	0.49	0.0	0	0
10241	1.0	0.32	1.0	0	0

10084 rows × 29 columns

In [ ]:
```
x
```

Out[ ]:

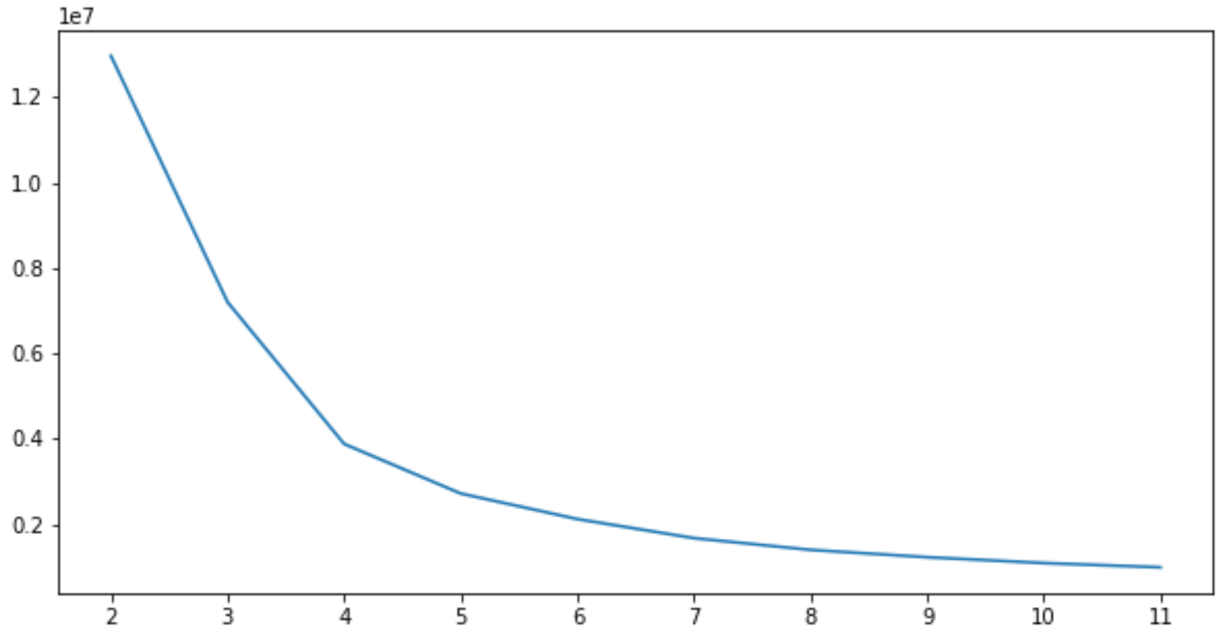
	INSURANCE_FLAG	DTI	SEX	FULL_AGE_CHILD_NUMBER	DEPENDANT_NUMBER
0	1.0	0.26	1.0	0	0
1	1.0	0.45	1.0	1	0
2	1.0	0.23	1.0	0	0
3	1.0	0.56	1.0	2	0
4	0.0	0.25	1.0	1	0
...	...	...	...	...	...
10237	0.0	0.48	0.0	1	0
10238	1.0	0.59	0.0	0	0
10239	1.0	0.24	0.0	0	0
10240	0.0	0.49	0.0	0	0
10241	1.0	0.32	1.0	0	0

10084 rows × 29 columns

Next, we apply the Elbow method to see the optimal number of cluster, that is, K in K-Means.

In [ ]:

```
ess = []
for k in range(2, 12):
    kmeans = KMeans(n_clusters=k, random_state=0, max_iter=100)
    kmeans.fit(x)
    ess.append(kmeans.inertia_)

plt.rcParams["figure.figsize"] = (10,5)
plt.plot(range(2, 12), ess)
plt.xticks(range(2, 12))
plt.show()
```



The curve seems to bend fairly smoothly, however it really starts to flatten after the 4th k, so the optimal choice according to the elbow rule is $k = 4$

In [ ]:
```
k = 4
kmeans = KMeans(n_clusters=k, random_state=0)
y = kmeans.fit_predict(x)
x
```

Out[ ]:

	INSURANCE_FLAG	DTI	SEX	FULL_AGE_CHILD_NUMBER	DEPENDANT_NUMBER
0	1.0	0.26	1.0	0	0
1	1.0	0.45	1.0	1	0
2	1.0	0.23	1.0	0	0
3	1.0	0.56	1.0	2	0
4	0.0	0.25	1.0	1	0
...	...	...	...	...	...
10237	0.0	0.48	0.0	1	0
10238	1.0	0.59	0.0	0	0
10239	1.0	0.24	0.0	0	0
10240	0.0	0.49	0.0	0	0
10241	1.0	0.32	1.0	0	0

10084 rows × 29 columns

In [ ]:
```
y
```

Out[ ]:
```
array([2, 0, 0, ..., 2, 2, 2], dtype=int32)
```

In [ ]:
```
df_kmeans = clean_df
df_kmeans['cluster'] = y
df_kmeans
```

Out[ ]:

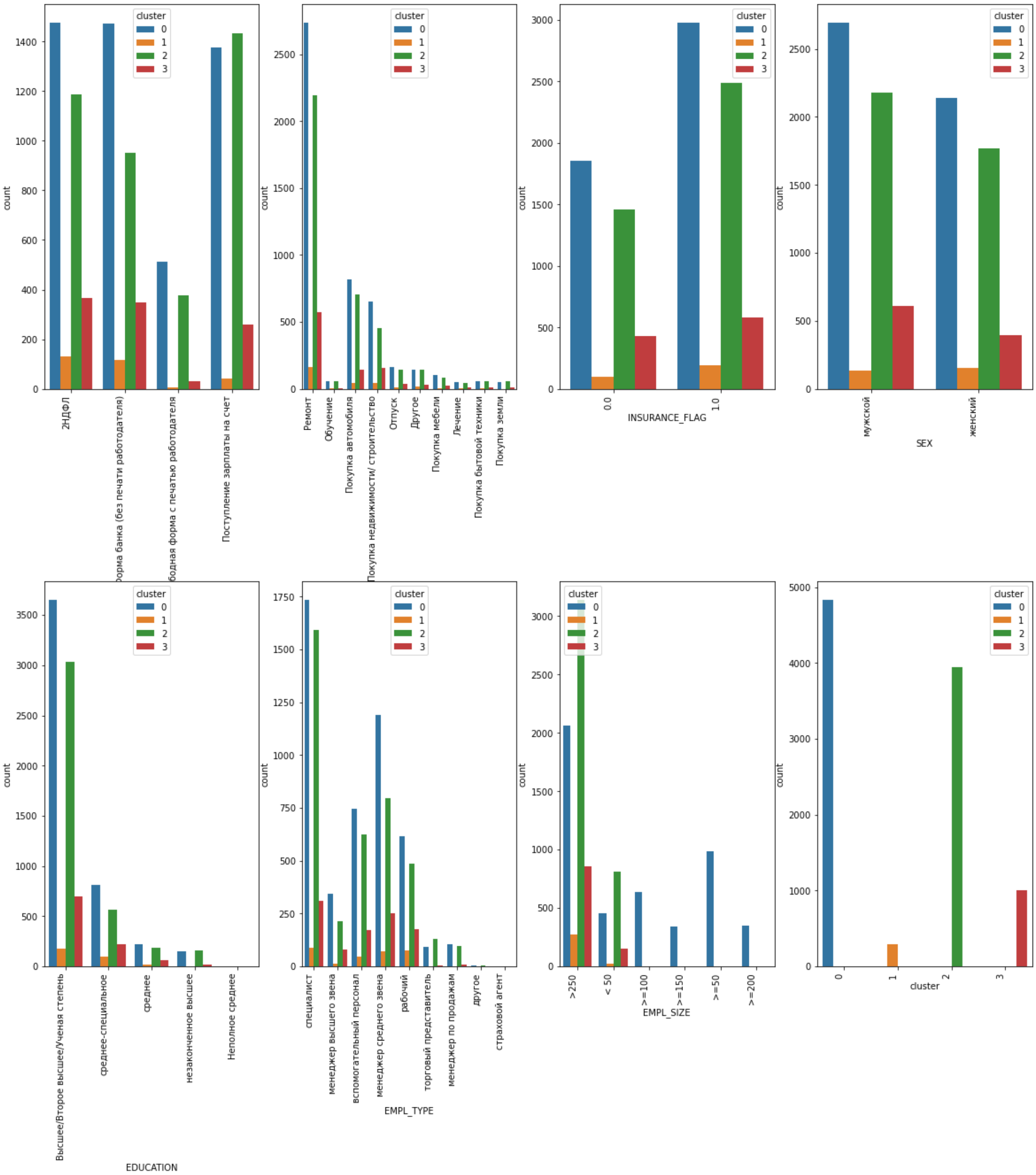
	ID	INCOME_BASE_TYPE	CREDIT_PURPOSE	INSURANCE_FLAG	DTI	S
0	1000016	2НДФЛ	Ремонт	1.0	0.26	мужс
1	1000036	Форма банка (без печати работодателя)	Обучение	1.0	0.45	мужс
2	1000056	Форма банка (без печати работодателя)	Покупка автомобиля	1.0	0.23	мужс
3	1000076	Свободная форма с печатью работодателя	Покупка недвижимости/ строительство	1.0	0.56	мужс
4	1000096	2НДФЛ	Ремонт	0.0	0.25	мужс
...	...	...	...	...	...	
10237	1204756	Свободная форма с печатью работодателя	Ремонт	0.0	0.48	женс
10238	1204776	Свободная форма с печатью работодателя	Ремонт	1.0	0.59	женс
10239	1204796	2НДФЛ	Ремонт	1.0	0.24	женс
10240	1204816	Поступление зарплаты на счет	Ремонт	0.0	0.49	женс
10241	1204836	2НДФЛ	Отпуск	1.0	0.32	мужс

10084 rows × 14 columns

In [ ]:
```
# Each cluster's fraction of the dataset
cluster_counts = np.array(df_kmeans['cluster'].value_counts().sort_index(
cluster_frac = cluster_counts/np.sum(cluster_counts)
cluster_frac
```

Out[ ]:
```
array([0.4795716 , 0.02905593, 0.39151131, 0.09986117])
```

In [ ]:
```
#Plot categorical data with separation by clusters
plt.rcParams["figure.figsize"] = (20,20)

t = df_kmeans[categorical_cols+['cluster']]
cols = t.columns
n = t.shape[1]
fig, axes = plt.subplots(n // 4, 4)
for i, ax in enumerate(axes.flat):
    ax.set_xlabel(cols[i])
    sns.countplot(data=t, x=cols[i], hue='cluster', ax=ax)
    plt.draw()
    ax.set_xticks(ax.get_xticks())
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90, ha='right')

plt.subplots_adjust(hspace=0.5)
plt.show()
```

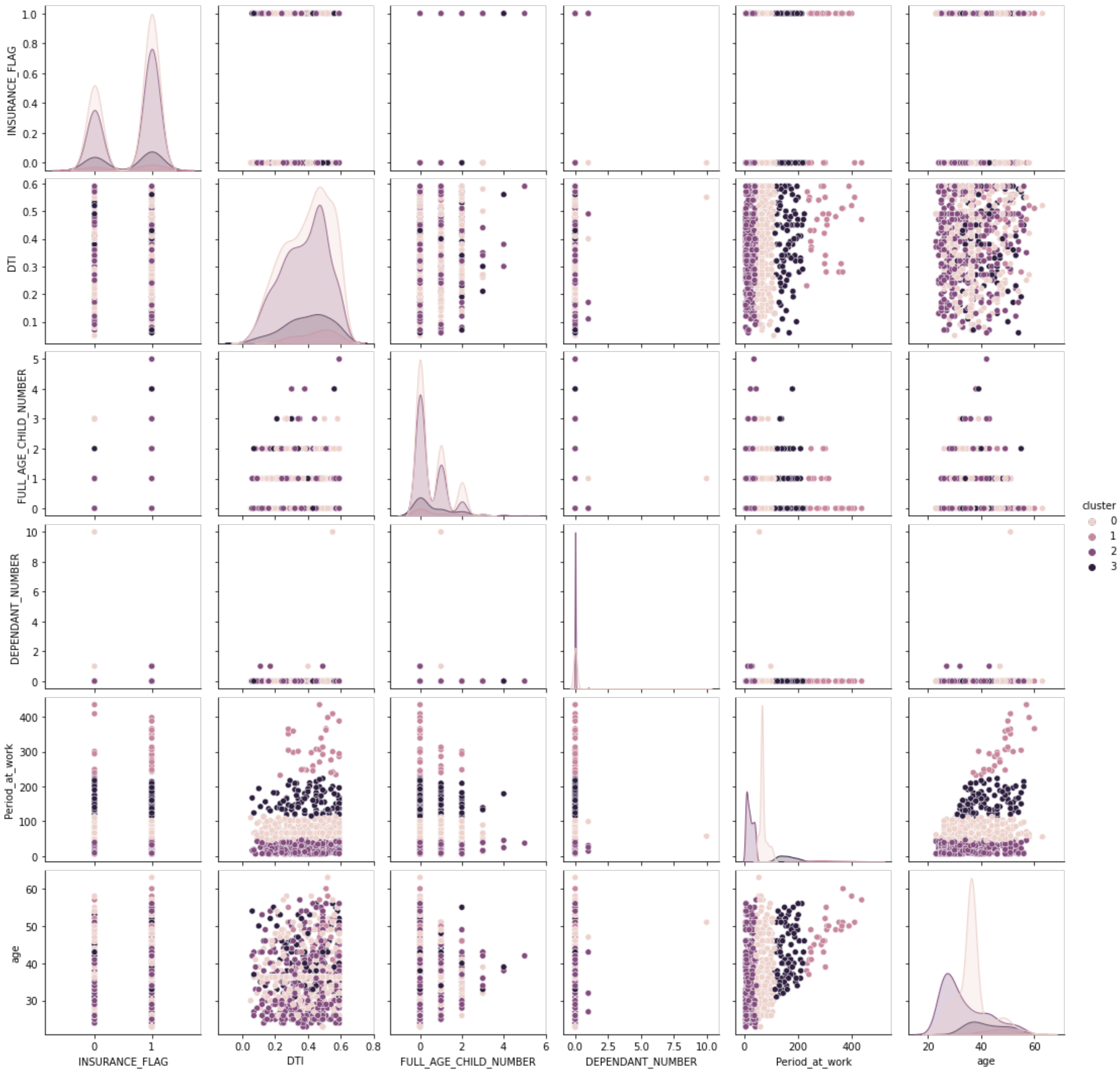


In [ ]:

```
#Plot numerical data to notice any anomalies acounting for clusters
sns.pairplot(df_kmeans.sample(1000).drop(columns=['ID']), hue='cluster',
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7f9231a11e80>
```



From above studies, we are ready to separate our clients into segments:

Cluster 0

- Cluster 0 represents the main volume of clients, accumulating to 48% of the clients.
- They represent average clients which have close to average statistics in almost every feature, rarely standing out among other clients. Clients from this cluster are present in almost every categorical segment.

Cluster 1

- Cluster 1 represents our hard workers approaching a wealthy retirement.
- They are academically highly educated: Most of them have one or more academic degrees, and some of them have secondary professional education. Nearly none of them have fewer than that.
- Unlike in other categories, there are more women then men.
- They are generally older and have been working at their position for a long time

- They are high-earners, a dominant majority earn a salary above 250k/month and have the best DTI's

Cluster 2

- Cluster 2 represents our young adults.
- Second cluster in terms of volume, 39% of the clients
- They represent the youngest client group
- They are likely frequently changing jobs as they have the least working days since appointment
- Either high earners or extremly poor: this clusters contains the most <50k/month and >250k/month earners.
- Take the most student loans.

Cluster 4

- Cluster 3 represent established workers.
- Most of the clients are middle-aged and some are a bit older
- Their career growth have slowed down, approaching the peak:
    - Most of them have settled at their job position
    - They earn more than Cluster 2 clients, but still do not match Cluster 1 clients' wealth

Overall, this segmentation has split the clients into some sort of a life cycle, cluster 2 representing a younger client-base at the start of their career in the stage of rapid developement, cluster 4 represent middle-aged clients slowing down their rise in job-position pyramid, and cluster 1 represent elderly workers who have alrealy achieved their peak position and have settled. Cluster 0 depicts people who can not necessarily could be represented by any other cluster, providing average statistics.

Method 2: RFM

For this task RFM is a great solution because:

- it is fairly simple to implement on any dataset, where you can pick out recency, frequency, monetary metrics, and in our case we can
- easy to interpret
- we know what we looking for in our segmentation: who are our new clients, frequent clients, best value clients.

In order to conduct RFM segmentation, we will pick out min_MnthAfterLoan as a recency metric, all_credits as a frequency metric, and sum_of_paym_months as monetary metric.

In [ ]:
```
rfm_df = df[['ID', 'min_MnthAfterLoan', 'all_credits', 'sum_of_paym_month
```

In [ ]:
```
rfm_df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	
ID	3636.0	1.097197e+06	59890.821857	1000036.0	1045326.0	1092
min_MnthAfterLoan	3636.0	1.397442e+01	15.142411	-1.0	4.0	
all_credits	3636.0	5.728548e+00	4.062140	1.0	3.0	
sum_of_paym_months	3636.0	8.117547e+01	70.477991	0.0	31.0	

For each R-F-M metric we split our clients into 5 tiers: 5, 4, 3, 2, 1 (the more, the better). Let us rank our clients in each metric

In [ ]:
```
tiers = ['5', '4', '3', '2', '1']

rfm_df['R'] = pd.qcut(rfm_df['min_MnthAfterLoan'], 5, labels=tiers)
rfm_df['F'] = pd.qcut(rfm_df['all_credits'], 5, labels=tiers[::-1])
rfm_df['M'] = pd.qcut(rfm_df['sum_of_paym_months'], 5, labels=tiers[::-1]
rfm_df['score'] = rfm_df['R'].astype(str) + rfm_df['F'].astype(str) + rfm
rfm_df
```

Out[ ]:

	ID	min_MnthAfterLoan	all_credits	sum_of_paym_months	R	F	M	score
1	1000036	2.0	12.0	268.0	5	5	5	555
5	1000116	4.0	5.0	48.0	4	3	2	432
6	1000136	33.0	3.0	46.0	1	2	2	122
8	1000176	16.0	3.0	35.0	2	2	2	222
9	1000196	3.0	3.0	15.0	5	2	1	521
...	...	...	...	...	...	...	...	...
10230	1204616	10.0	4.0	26.0	3	2	2	322
10235	1204716	38.0	3.0	91.0	1	2	4	124
10238	1204776	5.0	9.0	145.0	4	4	5	445
10240	1204816	1.0	7.0	93.0	5	4	4	544
10241	1204836	7.0	1.0	1.0	4	1	1	411

3636 rows × 8 columns

Let us map our segments the following way:

In [ ]:
```
seg_map = {
    r'[1-2][1-2].': 'hibernating',
    r'[1-2][3-4].': 'at risk',
    r'[1-2]5.': 'can\'t loose',
    r'3[1-2].': 'about to sleep',
    r'33.': 'need attention',
    r'[3-4][4-5].': 'loyal',
    r'41.': 'promising',
    r'51.': 'new',
    r'[4-5][2-3].': 'potentially loyal',
    r'5[4-5].': 'top'
}
```

In [ ]:
```
rfm_df['segment'] = rfm_df['score'].replace(seg_map, regex=True)
rfm_df
```

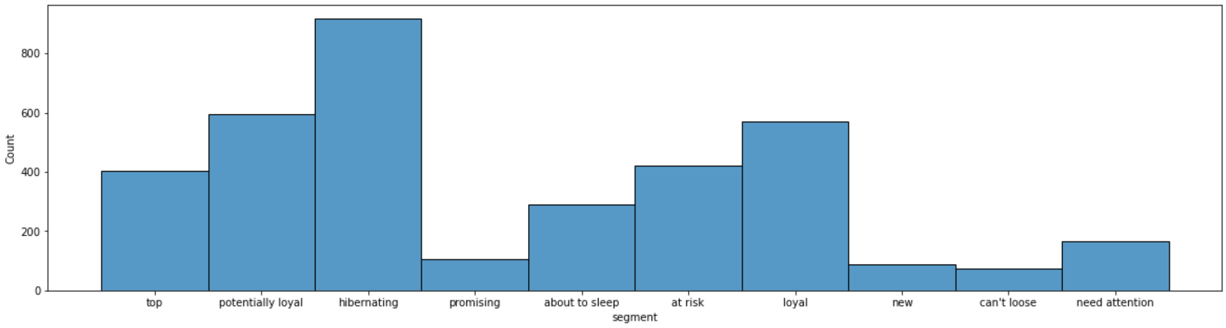
Out[ ]:

	ID	min_MnthAfterLoan	all_credits	sum_of_paym_months	R	F	M	score
1	1000036	2.0	12.0	268.0	5	5	5	555
5	1000116	4.0	5.0	48.0	4	3	2	432
6	1000136	33.0	3.0	46.0	1	2	2	122
8	1000176	16.0	3.0	35.0	2	2	2	222
9	1000196	3.0	3.0	15.0	5	2	1	521
...	...	...	...	...	...	...	...	..
10230	1204616	10.0	4.0	26.0	3	2	2	322
10235	1204716	38.0	3.0	91.0	1	2	4	124
10238	1204776	5.0	9.0	145.0	4	4	5	445
10240	1204816	1.0	7.0	93.0	5	4	4	544
10241	1204836	7.0	1.0	1.0	4	1	1	411

3636 rows × 9 columns

In [ ]:
```
#histogram to see how many cleints of each segment we have
plt.rcParams["figure.figsize"] = (20,5)
sns.histplot(rfm_df['segment'])
```

Out[ ]:
```
<AxesSubplot:xlabel='segment', ylabel='Count'>
```



In [ ]:
```
#Merge segmentation results with original data
df_seg = df.dropna(subset=['ID', 'min_MnthAfterLoan', 'all_credits', 'sum
df_seg = pd.merge(df_seg, rfm_df, on=['ID', 'min_MnthAfterLoan', 'all_cre
```

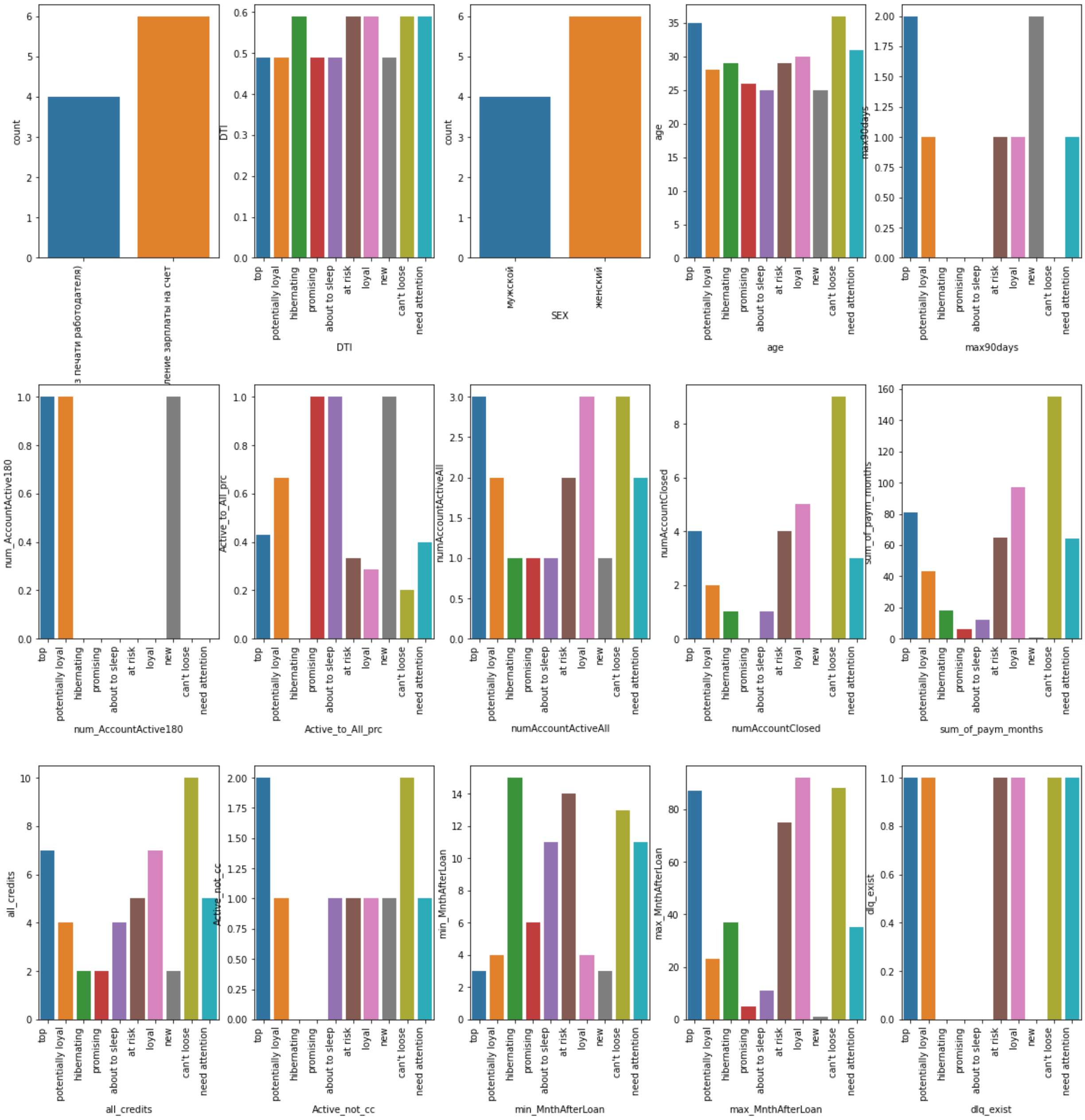
In [ ]:
```
#Show mode profiles of each segment
segments = df_seg['segment'].unique().tolist()
profiles = []

for client in segments:
    profiles.append([df_seg.loc[df_seg['segment'] == client][col].mode()[

profiles = pd.DataFrame(profiles, columns=df.columns, index=segments)

useful_cols_dfm = ['INCOME_BASE_TYPE', 'DTI', 'SEX', 'age', 'max90days','
       'Active_to_All_prc', 'numAccountActiveAll', 'numAccountClosed',
       'sum_of_paym_months', 'all_credits', 'Active_not_cc',
       'min_MnthAfterLoan', 'max_MnthAfterLoan', 'dlq_exist']
profiles = profiles[useful_cols_dfm]
profiles
```

Out[ ]:

	INCOME_BASE_TYPE	DTI	SEX	age	max90days	num_AccountActive1
top	Форма банка (без печати работодателя)	0.49	мужской	35.0	2.0	
potentially loyal	Поступление зарплаты на счет	0.49	женский	28.0	1.0	
hibernating	Поступление зарплаты на счет	0.59	мужской	29.0	0.0	
promising	Поступление зарплаты на счет	0.49	женский	26.0	0.0	
about to sleep	Поступление зарплаты на счет	0.49	женский	25.0	0.0	
at risk	Форма банка (без печати работодателя)	0.59	мужской	29.0	1.0	
loyal	Форма банка (без печати работодателя)	0.59	женский	30.0	1.0	
new	Поступление зарплаты на счет	0.49	женский	25.0	2.0	
can't loose	Форма банка (без печати работодателя)	0.59	мужской	36.0	0.0	
need attention	Поступление зарплаты на счет	0.59	женский	31.0	1.0	

In [ ]:

```
plt.rcParams["figure.figsize"] = (20,20)

cols = profiles.columns
n = profiles.shape[1]
fig, axes = plt.subplots(n // 4, 5)
for i, ax in enumerate(axes.flat):
    ax.set_xlabel(cols[i])
    if(np.issubdtype(profiles[cols[i]].dtype, np.number)):
        sns.barplot(y=profiles[cols[i]], x=profiles.index, ax=ax)
    else:
        sns.countplot(data=profiles, x=cols[i], ax=ax)
    plt.draw()
    ax.set_xticks(ax.get_xticks())
    ax.set_xticklabels(ax.get_xticklabels(), rotation=90, ha='right')

plt.subplots_adjust(hspace=0.5)
plt.show()
```


count
з печати работодателя)
ление зарплаты на счет
DTI
SEX
мужской
женский
age
max90days
num_AccountActive180
Active_to_All_prc
numAccountActiveAll
numAccountClosed
sum_of_paym_months
all_credits
Active_not_cc
min_MnthAfterLoan
max_MnthAfterLoan
dlq_exist
top
potentially loyal
hibernating
promising
about to sleep
at risk
loyal
new
can't loose
need attention