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ФАКУЛЬТЕТ Информатика и системы управления

КАФЕДРА Системы обработки информации и управления

Лабораторная работа №3

По курсу «Методы машинного обучения в АСОИУ»

«Обработка признаков (часть 2).»

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Лабораторaня работа №3: Обработка признаков (часть 2).

In [3]:
```
#Датасет содержит данные о кредитах на покупку электроники, которые были
import pandas as pd
import numpy as np
#from sklearn.model_selection import train_test_split, GridSearchCV, Rand
#from sklearn.neighbors import KNeighborsClassifier
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import LinearRegression, Lasso
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustSca
from matplotlib import pyplot as plt
import seaborn as sns
#from sklearn.metrics import accuracy_score, precision_score, recall_scor
from warnings import simplefilter

simplefilter('ignore')
```

In [4]:
```
# записываем CSV-файл в объект DataFrame
data = pd.read_csv('credit_train.csv', encoding='cp1251', sep=';')
```

In [5]:
```
# смотрим на первые пять строк
data.head()
```

Out[5]:

	client_id	gender	age	marital_status	job_position	credit_sum	credit_month
0	1	M	NaN	NaN	UMN	59998,00	10
1	2	F	NaN	MAR	UMN	10889,00	6
2	3	M	32.0	MAR	SPC	10728,00	12
3	4	F	27.0	NaN	SPC	12009,09	12
4	5	M	45.0	NaN	SPC	NaN	10

1) Обработка пропусков в данных

In [6]:
```
#проверяем типы данных и заполненность столбцов
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 82356 entries, 0 to 82355
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   client_id             82356 non-null  int64  
 1   gender                82356 non-null  object 
 2   age                   82353 non-null  float64
 3   marital_status        82353 non-null  object 
 4   job_position          82356 non-null  object 
 5   credit_sum            82354 non-null  object 
 6   credit_month          82356 non-null  int64  
 7   tariff_id             82356 non-null  float64
 8   score_shk             82349 non-null  object 
 9   education             82350 non-null  object 
 10  living_region         82261 non-null  object 
 11  monthly_income        82350 non-null  float64
 12  credit_count          77921 non-null  float64
 13  overdue_credit_count  77921 non-null  float64
 14  open_account_flg      82355 non-null  float64
dtypes: float64(6), int64(2), object(7)
memory usage: 9.4+ MB
```

In [7]:
```
#удаляем столбец с номером клиента (так как он незначимый)
# и с регионом проживания (так как он нуждается в серьезной предобработке
data.drop(['client_id', 'living_region'], axis=1, inplace=True)
```

In [8]:
```
# анализируем столбец marital_status, смотрим, какое значение в нем являе
data['marital_status'].describe()
```

Out[8]:
```
count     82353
unique        5
top         MAR
freq      45350
Name: marital_status, dtype: object
```

In [9]:
```
# анализируем столбец education, смотрим, какое в нем самое частое значен
data['education'].describe()
```

Out[9]:
```
count     82350
unique        5
top         SCH
freq      42228
Name: education, dtype: object
```

In [10]:
```
# дозаполняем нечисловые столбцы с пропусками самыми часто встречающимися
data['marital_status'].fillna('MAR', inplace=True)
data['education'].fillna('SCH', inplace=True)
```

In [11]:
```
# дозаполняем числовые столбцы с пропусками медианными значениями
data['age'].fillna(data['age'].median(), inplace=True)
data['credit_count'].fillna(data['credit_count'].median(), inplace=True)
data['overdue_credit_count'].fillna(data['overdue_credit_count'].median()
```

In [12]:
```
#меняем в столбцах 'credit_sum', 'score_shk'  запятые на точки  и преобра
for i in ['credit_sum', 'score_shk']:
    data[i] = data[i].str.replace(',', '.').astype('float')
```

In [13]:
```
# дозаполняем ставшие теперь числовыми столбцы 'credit_sum', 'score_shk'
data['score_shk'].fillna(data['score_shk'].median(), inplace=True)
data['monthly_income'].fillna(data['monthly_income'].median(), inplace=Tr
data['credit_sum'].fillna(data['credit_sum'].median(), inplace=True)
```

In [14]:
```
# смотрим, что получилось
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 82356 entries, 0 to 82355
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   gender                82356 non-null  object 
 1   age                   82356 non-null  float64
 2   marital_status        82356 non-null  object 
 3   job_position          82356 non-null  object 
 4   credit_sum            82356 non-null  float64
 5   credit_month          82356 non-null  int64  
 6   tariff_id             82356 non-null  float64
 7   score_shk             82356 non-null  float64
 8   education             82356 non-null  object 
 9   monthly_income        82356 non-null  float64
 10  credit_count          82356 non-null  float64
 11  overdue_credit_count  82356 non-null  float64
 12  open_account_flg      82355 non-null  float64
dtypes: float64(8), int64(1), object(4)
memory usage: 8.2+ MB
```

2) Кодирование категориальных признаков

In [15]:
```
category_cols = ['gender', 'job_position', 'education', 'marital_status']
```

In [16]:
```
print("Количество уникальных значений\n")
for col in category_cols:
    print(f'{col}: {data[col].unique().size}')
```

```
Количество уникальных значений

gender: 2
job_position: 17
education: 5
marital_status: 5
```

In [17]:
```
# кодируем нечисловые столбцы методом дамми-кодирования
data = pd.concat([data,
                      pd.get_dummies(data['gender'], prefix="gender"),
                      pd.get_dummies(data['job_position'], prefix="job_po
                      pd.get_dummies(data['education'], prefix="education
                      pd.get_dummies(data['marital_status'], prefix="mari
                     axis=1)
```

In [18]:
```
#удаляем старые нечисловые столбцы, вместо них уже появились новые числов
data.drop(['gender','job_position','education','marital_status'], axis=1,
```

In [19]:
```
data.head()
```

Out[19]:

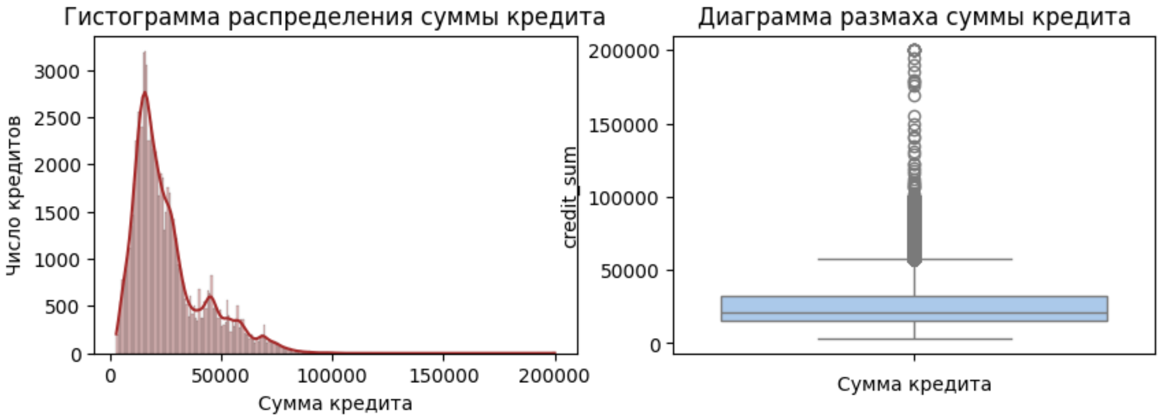
	age	credit_sum	credit_month	tariff_id	score_shk	monthly_income	credit_c
0	34.0	59998.00	10	1.6	0.461639	30000.0	
1	34.0	10889.00	6	1.1	0.461639	35000.0	
2	32.0	10728.00	12	1.1	0.461639	35000.0	
3	27.0	12009.09	12	1.1	0.461639	35000.0	
4	45.0	21197.50	10	1.1	0.421385	35000.0	

5 rows × 38 columns

3) Обработка выбросов для числовых признаков

Замена выбросов

In [20]:
```
fig = plt.figure(figsize=(10, 3))
axes = fig.subplots(1, 2)
sns.histplot(data['credit_sum'], kde=True, color='brown', alpha=0.3, ax=a
axes[0].title.set_text(f"Гистограмма распределения суммы кредита")
axes[0].set_xlabel('Сумма кредита')
axes[0].set_ylabel('Число кредитов')
sns.boxplot(data['credit_sum'], palette='pastel', ax=axes[1])
axes[1].title.set_text(f"Диаграмма размаха суммы кредита")
axes[1].set_xlabel('Сумма кредита')
plt.show();
```



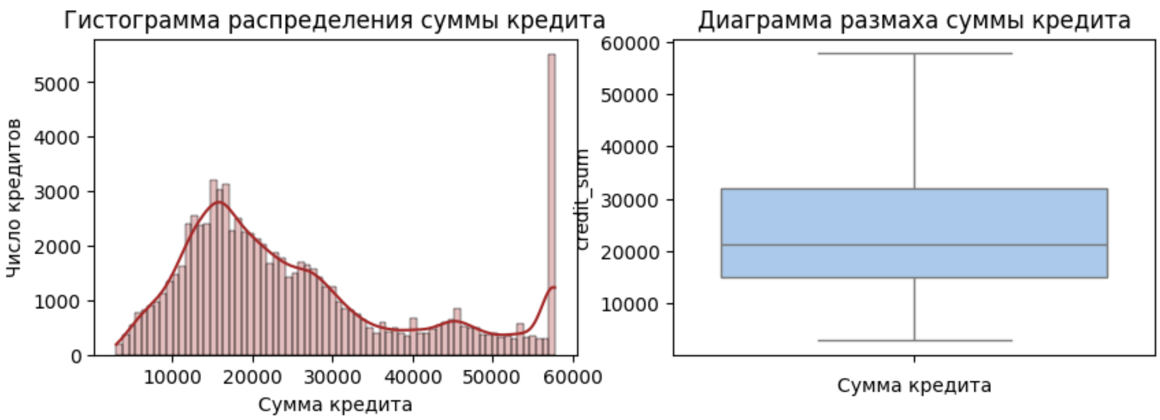
In [21]:
```
K = 1.5
col = 'credit_sum'
IQR = data[col].quantile(0.75) - data[col].quantile(0.25)
lower_boundary = data[col].quantile(0.25) - (K * IQR)
upper_boundary = data[col].quantile(0.75) + (K * IQR)
round(lower_boundary, 2), round(upper_boundary, 2)
```

Out[21]: (-10718.88, 57758.12)

In [22]:
```
data[col] = np.where(data[col] > upper_boundary, upper_boundary, np.where
```

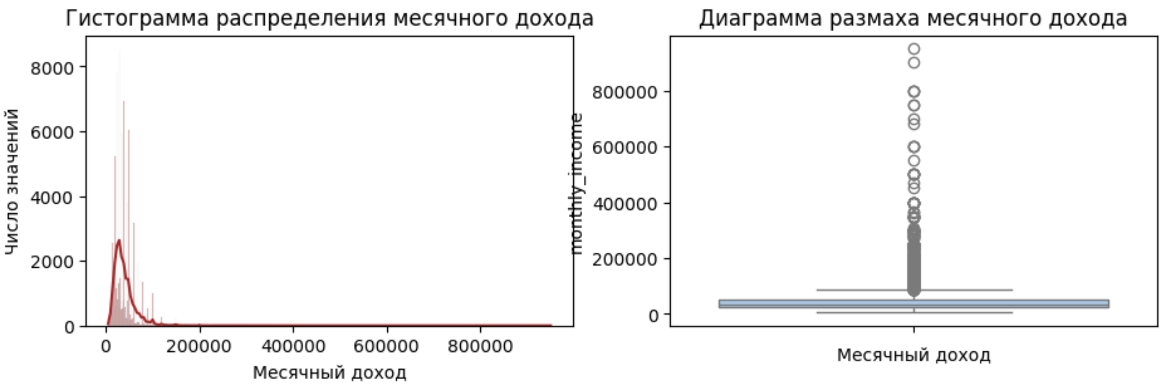
In [23]:
```
fig = plt.figure(figsize=(10, 3))
axes = fig.subplots(1, 2)
```

```
sns.histplot(data['credit_sum'], kde=True, color='brown', alpha=0.3, ax=a
axes[0].title.set_text(f"Гистограмма распределения суммы кредита")
axes[0].set_xlabel('Сумма кредита')
axes[0].set_ylabel('Число кредитов')
sns.boxplot(data['credit_sum'], palette='pastel', ax=axes[1])
axes[1].title.set_text(f"Диаграмма размаха суммы кредита")
axes[1].set_xlabel('Сумма кредита')
plt.show();
```



Удаление выбросов

In [24]:
```
fig = plt.figure(figsize=(11, 3))
axes = fig.subplots(1, 2)
sns.histplot(data['monthly_income'], kde=True, color='brown', alpha=0.3,
axes[0].title.set_text(f"Гистограмма распределения месячного дохода")
axes[0].set_xlabel('Месячный доход')
axes[0].set_ylabel('Число значений')
sns.boxplot(data['monthly_income'], palette='pastel', ax=axes[1])
axes[1].title.set_text(f"Диаграмма размаха месячного дохода")
axes[1].set_xlabel('Месячный доход')
plt.show();
```

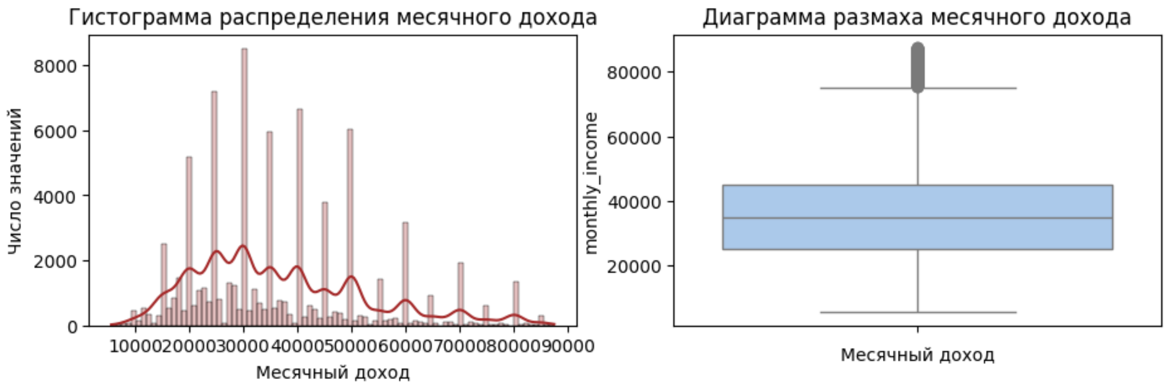


In [25]:
```
K = 1.5
col = 'monthly_income'
IQR = data[col].quantile(0.75) - data[col].quantile(0.25)
lower_boundary = data[col].quantile(0.25) - (K * IQR)
upper_boundary = data[col].quantile(0.75) + (K * IQR)
round(lower_boundary, 2), round(upper_boundary, 2)
```

Out[25]:
```
(-12500.0, 87500.0)
```

In [26]:
```
data = data[data['monthly_income'] < 87500.0]
```

In [27]:
```
fig = plt.figure(figsize=(11, 3))
axes = fig.subplots(1, 2)
sns.histplot(data['monthly_income'], kde=True, color='brown', alpha=0.3,
axes[0].title.set_text(f"Гистограмма распределения месячного дохода")
axes[0].set_xlabel('Месячный доход')
axes[0].set_ylabel('Число значений')
sns.boxplot(data['monthly_income'], palette='pastel', ax=axes[1])
axes[1].title.set_text(f"Диаграмма размаха месячного дохода")
axes[1].set_xlabel('Месячный доход')
plt.show();
```



4) Масштабирование данных

In [28]:
```
numeric_columns = [column for column in data.columns if data.dtypes[colum
```

In [29]:
```
numeric_columns
```

Out[29]:
```
['age',
 'credit_sum',
 'credit_month',
 'tariff_id',
 'score_shk',
 'monthly_income',
 'credit_count',
 'overdue_credit_count',
 'open_account_flg',
 'gender_F',
 'gender_M',
 'job_position_ATP',
 'job_position_BIS',
 'job_position_BIU',
 'job_position_DIR',
 'job_position_HSK',
 'job_position_INP',
 'job_position_INV',
 'job_position_NOR',
 'job_position_PNA',
 'job_position_PNI',
 'job_position_PNS',
 'job_position_PNV',
 'job_position_SPC',
 'job_position_UMN',
 'job_position_WOI',
 'job_position_WRK',
 'job_position_WRP',
 'education_ACD',
 'education_GRD',
 'education_PGR',
 'education_SCH',
 'education_UGR',
 'marital_status_CIV',
 'marital_status_DIV',
 'marital_status_MAR',
 'marital_status_UNM',
 'marital_status_WID']
```

In [30]:
```python
data1 = pd.DataFrame(StandardScaler().fit_transform(data[numeric_columns]
data1.head()
```

Out[30]:

	age	credit_sum	credit_month	tariff_id	score_shk	monthly_income	c
0	-0.231430	2.318766	-0.278885	1.167152	-0.079149	-0.423702	
1	-0.231430	-0.992644	-1.413550	-0.950709	-0.079149	-0.113102	
2	-0.419776	-1.004019	0.288447	-0.950709	-0.079149	-0.113102	
3	-0.890641	-0.913507	0.288447	-0.950709	-0.079149	-0.113102	
4	0.804473	-0.264325	-0.278885	-0.950709	-0.403861	-0.113102	

5 rows × 38 columns

In [31]:
```python
data1.describe()
```

Out[31]:

	age	credit_sum	credit_month	tariff_id	score_sh
count	7.903400e+04	7.903400e+04	7.903400e+04	7.903400e+04	7.903400e+0
mean	8.055347e-17	-6.715786e-16	3.955751e-18	-6.535080e-16	2.672829e-1
std	1.000006e+00	1.000006e+00	1.000006e+00	1.000006e+00	1.000006e+0
min	-1.738198e+00	-1.550020e+00	-2.264549e+00	-1.374281e+00	-3.802993e+0
25%	-7.964679e-01	-7.178068e-01	-2.788854e-01	-9.507088e-01	-7.262172e-0
50%	-2.314300e-01	-2.885943e-01	-2.788854e-01	-1.884996e-02	-6.432267e-0
75%	6.161268e-01	4.294978e-01	2.884469e-01	1.167152e+00	6.655166e-0
max	3.252970e+00	2.318766e+00	7.096435e+00	2.692012e+00	5.298447e+0

8 rows × 38 columns

In [32]:
```
data2 = pd.DataFrame(MinMaxScaler().fit_transform(data[numeric_columns]),
data2.head()
```

Out[32]:

	age	credit_sum	credit_month	tariff_id	score_shk	monthly_income	cr
0	0.301887	1.000000	0.212121	0.625000	0.409149	0.298289	
1	0.301887	0.144070	0.090909	0.104167	0.409149	0.359413	
2	0.264151	0.141130	0.272727	0.104167	0.409149	0.359413	
3	0.169811	0.164525	0.272727	0.104167	0.409149	0.359413	
4	0.509434	0.332325	0.212121	0.104167	0.373472	0.359413	

5 rows × 38 columns

In [33]:
```
data2.describe()
```

Out[33]:

	age	credit_sum	credit_month	tariff_id	score_shk
count	79034.000000	79034.000000	79034.000000	79034.000000	79034.000000
mean	0.348255	0.400648	0.241914	0.337969	0.417845
std	0.200355	0.258481	0.106827	0.245926	0.109873
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.188679	0.215110	0.212121	0.104167	0.338054
50%	0.301887	0.326052	0.212121	0.333333	0.410778
75%	0.471698	0.511664	0.272727	0.625000	0.490967
max	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 38 columns

In [34]:
```
data3 = pd.DataFrame(RobustScaler().fit_transform(data[numeric_columns]),
data3.head()
```

Out[34]:

	age	credit_sum	credit_month	tariff_id	score_shk	monthly_income	cre
0	0.000000	2.272596	0.0	0.56	-0.010653	-0.25	
1	0.000000	-0.613656	-2.0	-0.44	-0.010653	0.00	
2	-0.133333	-0.623570	1.0	-0.44	-0.010653	0.00	
3	-0.466667	-0.544679	1.0	-0.44	-0.010653	0.00	
4	0.733333	0.021153	0.0	-0.44	-0.243968	0.00	

5 rows × 38 columns

In [35]:
```
data3.describe()
```

Out[35]:

	age	credit_sum	credit_month	tariff_id	score_shk
count	79034.000000	79034.000000	79034.000000	79034.000000	79034.000000
mean	0.163833	0.251541	0.491573	0.008900	0.046218
std	0.707922	0.871614	1.762646	0.472178	0.718533
min	-1.066667	-1.099469	-3.500000	-0.640000	-2.686340
25%	-0.400000	-0.374105	0.000000	-0.440000	-0.475590
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.600000	0.625895	1.000000	0.560000	0.524410
max	2.466667	2.272596	13.000000	1.280000	3.853302

8 rows × 38 columns

5) Отбор признаков

Метод фильтрации

In [36]:
```
print(f'Всего записей: {data.shape[0]}')
print('--------------------')
for column in data.columns:
    print(f'{column}: {data[column].value_counts().count()} уникальных зн
```

```
Всего записей: 79034
--------------------
age: 54 уникальных значений

credit_sum: 25589 уникальных значений

credit_month: 27 уникальных значений

tariff_id: 30 уникальных значений

score_shk: 14365 уникальных значений

monthly_income: 941 уникальных значений

credit_count: 19 уникальных значений

overdue_credit_count: 4 уникальных значений

open_account_flg: 2 уникальных значений

gender_F: 2 уникальных значений

gender_M: 2 уникальных значений

job_position_ATP: 2 уникальных значений

job_position_BIS: 2 уникальных значений

job_position_BIU: 2 уникальных значений

job_position_DIR: 2 уникальных значений

job_position_HSK: 2 уникальных значений

job_position_INP: 2 уникальных значений

job_position_INV: 2 уникальных значений

job_position_NOR: 2 уникальных значений

job_position_PNA: 2 уникальных значений

job_position_PNI: 2 уникальных значений

job_position_PNS: 2 уникальных значений

job_position_PNV: 2 уникальных значений

job_position_SPC: 2 уникальных значений

job_position_UMN: 2 уникальных значений

job_position_WOI: 2 уникальных значений

job_position_WRK: 2 уникальных значений

job_position_WRP: 2 уникальных значений

education_ACD: 2 уникальных значений
```

```
education_GRD: 2 уникальных значений

education_PGR: 2 уникальных значений

education_SCH: 2 уникальных значений

education_UGR: 2 уникальных значений

marital_status_CIV: 2 уникальных значений

marital_status_DIV: 2 уникальных значений

marital_status_MAR: 2 уникальных значений

marital_status_UNM: 2 уникальных значений

marital_status_WID: 2 уникальных значений
```

In [37]:

```
data.corr()
```

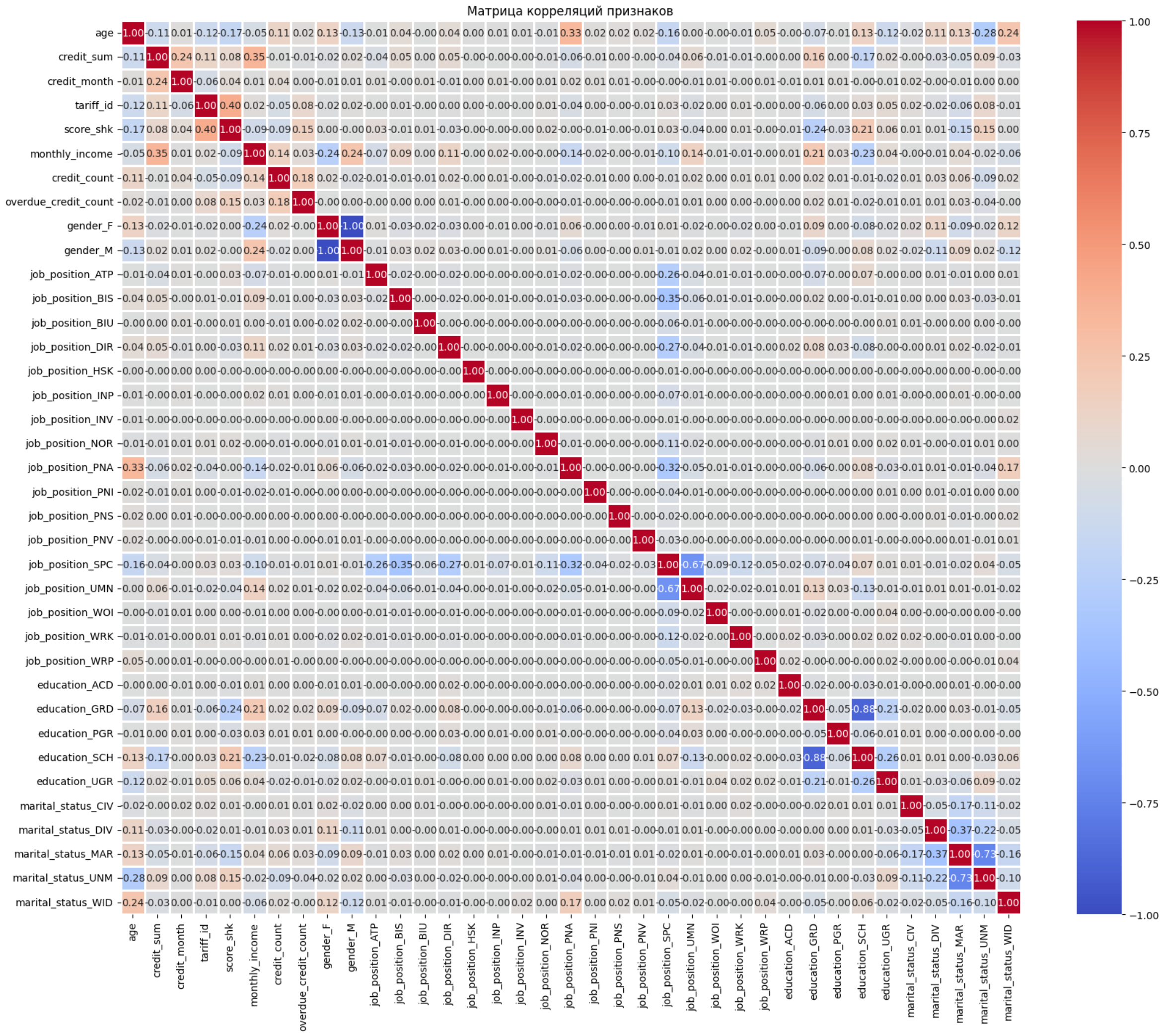
Out[37]:

	age	credit_sum	credit_month	tariff_id	score_shk
age	1.000000	-0.112618	0.011200	-0.116458	-0.167398
credit_sum	-0.112618	1.000000	0.239466	0.106084	0.079267
credit_month	0.011200	0.239466	1.000000	-0.056082	0.039668
tariff_id	-0.116458	0.106084	-0.056082	1.000000	0.401538
score_shk	-0.167398	0.079267	0.039668	0.401538	1.000000
monthly_income	-0.048194	0.346088	0.006920	0.020132	-0.087018
credit_count	0.112318	-0.006833	0.044137	-0.054323	-0.086355
overdue_credit_count	0.017269	-0.011576	0.002195	0.081571	0.153771
open_account_flg	-0.033687	-0.073936	0.028312	-0.070104	0.053183
gender_F	0.129520	-0.015916	-0.005237	-0.015206	0.004258
gender_M	-0.129520	0.015916	0.005237	0.015206	-0.004258
job_position_ATP	-0.005078	-0.043034	0.008983	-0.001685	0.033050
job_position_BIS	0.043827	0.049635	-0.001930	0.005126	-0.006734
job_position_BIU	-0.004995	0.004297	0.013466	-0.002117	0.005011
job_position_DIR	0.039958	0.054784	-0.012414	0.003820	-0.028895
job_position_HSK	0.000182	-0.001393	0.001026	0.001138	-0.000624
job_position_INP	0.006148	-0.001274	0.012969	-0.002989	-0.003902
job_position_INV	0.005876	-0.000289	-0.000992	-0.000067	-0.002574
job_position_NOR	-0.014000	-0.012277	0.007582	0.011938	0.016941
job_position_PNA	0.331209	-0.061549	0.021457	-0.041930	-0.000418
job_position_PNI	0.015394	-0.008852	0.014596	0.000655	-0.005162
job_position_PNS	0.018833	0.002159	0.005904	-0.000824	-0.000149
job_position_PNV	0.023257	-0.003685	-0.001193	-0.006183	-0.005385
job_position_SPC	-0.160989	-0.039569	-0.004370	0.029063	0.031066
job_position_UMN	0.001233	0.058358	-0.008549	-0.024391	-0.044078
job_position_WOI	-0.003148	-0.007868	0.006021	0.003982	0.000687
job_position_WRK	-0.010322	-0.014556	-0.003054	0.008473	0.013920
job_position_WRP	0.048280	-0.004955	0.007184	-0.001783	-0.001845
education_ACD	-0.002077	0.002727	-0.005603	0.003796	-0.009754
education_GRD	-0.068802	0.163202	0.005776	-0.056521	-0.240199
education_PGR	-0.006519	0.004471	0.008601	0.002316	-0.032425
education_SCH	0.126504	-0.172471	-0.003522	0.032755	0.214188
education_UGR	-0.123728	0.023435	-0.006069	0.048180	0.056879
marital_status_CIV	-0.021917	-0.003650	0.015562	0.017026	0.008971

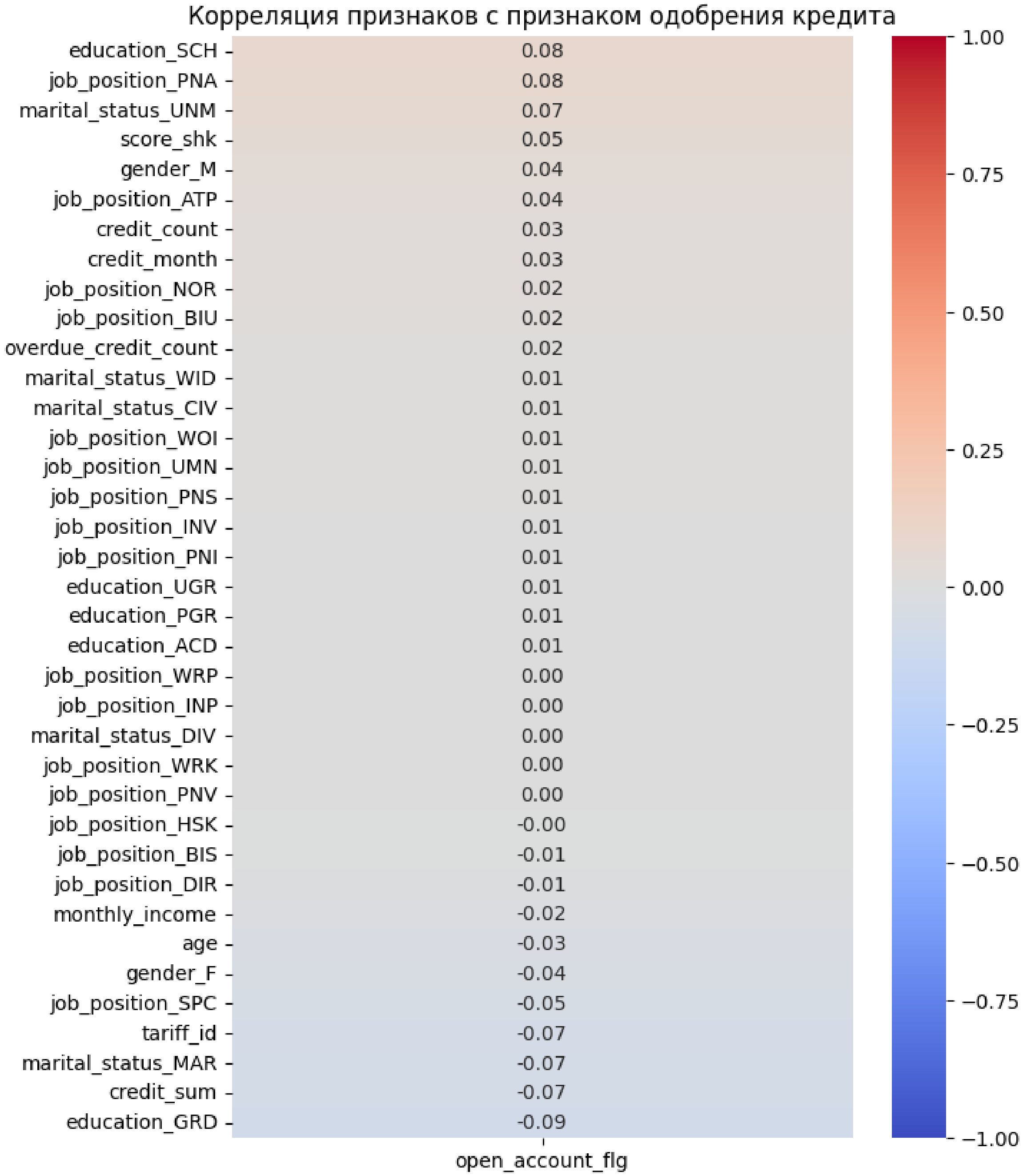
	age	credit_sum	credit_month	tariff_id	score_shk
marital_status_DIV	0.111030	-0.032855	-0.003432	-0.017804	0.006348
marital_status_MAR	0.128837	-0.049328	-0.006206	-0.063324	-0.146677
marital_status_UNM	-0.278682	0.085035	0.002828	0.078418	0.149492
marital_status_WID	0.240181	-0.029645	0.002721	-0.013794	0.004779

38 rows × 38 columns

In [38]:
```
plt.figure(figsize=(20, 16))
sns.heatmap(data1.drop('open_account_flg', axis=1).corr(), vmin=-1, vmax=
plt.title('Матрица корреляций признаков');
```



In [39]:
```
plt.figure(figsize=(7, 10))
sns.heatmap(pd.DataFrame(data.corr()['open_account_flg'].sort_values(asce
plt.title('Корреляция признаков с признаком одобрения кредита');
```



Метод обертывания

In [50]:
```
!pip install gmdh
from gmdh import Multi
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell` automatically in the future. Please pass the result to `transformed_cell` argument and any exception that happen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
Requirement already satisfied: gmdh in /usr/local/lib/python3.10/dist-packages (1.0.3)
Requirement already satisfied: docstring-inheritance in /usr/local/lib/python3.10/dist-packages (from gmdh) (2.1.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from gmdh) (1.25.2)
```

In [46]:
```
data = data[data['open_account_flg'].notna()]
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell` automatically in the future. Please pass the result to `transformed_cell` argument and any exception that happen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

In [47]:

```python
data.isna().sum()
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell` automatically in the future. Please pass the result to `transformed_cell` argument and any exception that happen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

Out[47]:

```
age                     0
credit_sum              0
credit_month            0
tariff_id               0
score_shk               0
monthly_income          0
credit_count            0
overdue_credit_count    0
open_account_flg        0
gender_F                0
gender_M                0
job_position_ATP        0
job_position_BIS        0
job_position_BIU        0
job_position_DIR        0
job_position_HSK        0
job_position_INP        0
job_position_INV        0
job_position_NOR        0
job_position_PNA        0
job_position_PNI        0
job_position_PNS        0
job_position_PNV        0
job_position_SPC        0
job_position_UMN        0
job_position_WOI        0
job_position_WRK        0
job_position_WRP        0
education_ACD           0
education_GRD           0
education_PGR           0
education_SCH           0
education_UGR           0
marital_status_CIV      0
marital_status_DIV      0
marital_status_MAR      0
marital_status_UNM      0
marital_status_WID      0
dtype: int64
```

In [55]:

```python
Multi().fit(np.array(data[numeric_columns].drop('open_account_flg', axis=
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell` automatically in the future. Please pass the result to `transformed_cell` argument and any exception that happen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:1641: DeprecationWarning: np.find_common_type is deprecated.  Please use `np.result_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs for more information.  (Deprecated NumPy 1.25)
  return np.find_common_type(types, [])
LEVEL 1  [========================] 100% [00m:00s] (37 combinations) error=5733.556645
LEVEL 2  [========================] 100% [00m:00s] (36 combinations) error=5703.75954
LEVEL 3  [========================] 100% [00m:00s] (35 combinations) error=5673.079493
LEVEL 4  [========================] 100% [00m:00s] (34 combinations) error=5644.188026
LEVEL 5  [========================] 100% [00m:00s] (33 combinations) error=5621.783416
LEVEL 6  [========================] 100% [00m:00s] (32 combinations) error=5602.845014
LEVEL 7  [========================] 100% [00m:00s] (31 combinations) error=5585.934086
LEVEL 8  [========================] 100% [00m:00s] (30 combinations) error=5574.048604
LEVEL 9  [========================] 100% [00m:00s] (29 combinations) error=5562.467126
LEVEL 10 [========================] 100% [00m:00s] (28 combinations) error=5555.536065
```

Out[55]:
```
'y = - 0.0023*x1 - 1.83876e-06*x2 - 0.1648*x4 + 0.198*x5 + 0.0092*x7 + 0.1834*x19 - 0.0395*x23 - 0.0525*x29 + 0.0477*x36 + 0.4452'
```

In [56]:
```
columns2 = [numeric_columns[i-1] for i in [1, 2, 4, 5, 7, 19, 23, 29, 36]]
columns2
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell` automatically in the future. Please pass the result to `transformed_cell` argument and any exception that happen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

Out[56]:
```
['age',
 'credit_sum',
 'tariff_id',
 'score_shk',
 'credit_count',
 'job_position_NOR',
 'job_position_PNV',
 'education_ACD',
 'marital_status_MAR']
```

Метод вложений

In [58]:
```
numeric_columns.remove('open_account_flg')
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Depreca
tionWarning: `should_run_async` will not call `transform_cell` automatical
ly in the future. Please pass the result to `transformed_cell` argument an
d any exception that happen during thetransform in `preprocessing_exc_tupl
e` in IPython 7.17 and above.
  and should_run_async(code)
```

In [59]:
```python
e_ls1 = Lasso(random_state=1)
e_ls1.fit(data[numeric_columns], data['open_account_flg'])
list(zip(numeric_columns, e_ls1.coef_))
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Depreca
tionWarning: `should_run_async` will not call `transform_cell` automatical
ly in the future. Please pass the result to `transformed_cell` argument an
d any exception that happen during thetransform in `preprocessing_exc_tupl
e` in IPython 7.17 and above.
  and should_run_async(code)
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:1641: D
eprecationWarning: np.find_common_type is deprecated.  Please use `np.resu
lt_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs for m
ore information.  (Deprecated NumPy 1.25)
  return np.find_common_type(types, [])
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:1641: D
eprecationWarning: np.find_common_type is deprecated.  Please use `np.resu
lt_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs for m
ore information.  (Deprecated NumPy 1.25)
  return np.find_common_type(types, [])
```

Out[59]:
```
[('age', -0.0),
 ('credit_sum', -2.008029186524592e-06),
 ('credit_month', 0.0),
 ('tariff_id', -0.0),
 ('score_shk', 0.0),
 ('monthly_income', 5.255957933062646e-08),
 ('credit_count', 0.0),
 ('overdue_credit_count', 0.0),
 ('gender_F', -0.0),
 ('gender_M', 0.0),
 ('job_position_ATP', 0.0),
 ('job_position_BIS', -0.0),
 ('job_position_BIU', 0.0),
 ('job_position_DIR', -0.0),
 ('job_position_HSK', -0.0),
 ('job_position_INP', 0.0),
 ('job_position_INV', 0.0),
 ('job_position_NOR', 0.0),
 ('job_position_PNA', 0.0),
 ('job_position_PNI', 0.0),
 ('job_position_PNS', 0.0),
 ('job_position_PNV', 0.0),
 ('job_position_SPC', -0.0),
 ('job_position_UMN', 0.0),
 ('job_position_WOI', 0.0),
 ('job_position_WRK', 0.0),
 ('job_position_WRP', 0.0),
 ('education_ACD', 0.0),
 ('education_GRD', -0.0),
 ('education_PGR', 0.0),
 ('education_SCH', 0.0),
 ('education_UGR', 0.0),
 ('marital_status_CIV', 0.0),
 ('marital_status_DIV', 0.0),
 ('marital_status_MAR', -0.0),
 ('marital_status_UNM', 0.0),
 ('marital_status_WID', 0.0)]
```

In [60]:
```python
sel_e_ls1 = SelectFromModel(e_ls1)
sel_e_ls1.fit(data[numeric_columns], data['open_account_flg'])
list(zip(numeric_columns, sel_e_ls1.get_support()))
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Depreca
tionWarning: `should_run_async` will not call `transform_cell` automatical
ly in the future. Please pass the result to `transformed_cell` argument an
d any exception that happen during thetransform in `preprocessing_exc_tupl
e` in IPython 7.17 and above.
  and should_run_async(code)
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:1641: D
eprecationWarning: np.find_common_type is deprecated.  Please use `np.resu
lt_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs for m
ore information.  (Deprecated NumPy 1.25)
  return np.find_common_type(types, [])
/usr/local/lib/python3.10/dist-packages/pandas/core/dtypes/cast.py:1641: D
eprecationWarning: np.find_common_type is deprecated.  Please use `np.resu
lt_type` or `np.promote_types`.
See https://numpy.org/devdocs/release/1.25.0-notes.html and the docs for m
ore information.  (Deprecated NumPy 1.25)
  return np.find_common_type(types, [])
```

Out[60]:
```
[('age', False),
 ('credit_sum', False),
 ('credit_month', False),
 ('tariff_id', False),
 ('score_shk', False),
 ('monthly_income', False),
 ('credit_count', False),
 ('overdue_credit_count', False),
 ('gender_F', False),
 ('gender_M', False),
 ('job_position_ATP', False),
 ('job_position_BIS', False),
 ('job_position_BIU', False),
 ('job_position_DIR', False),
 ('job_position_HSK', False),
 ('job_position_INP', False),
 ('job_position_INV', False),
 ('job_position_NOR', False),
 ('job_position_PNA', False),
 ('job_position_PNI', False),
 ('job_position_PNS', False),
 ('job_position_PNV', False),
 ('job_position_SPC', False),
 ('job_position_UMN', False),
 ('job_position_WOI', False),
 ('job_position_WRK', False),
 ('job_position_WRP', False),
 ('education_ACD', False),
 ('education_GRD', False),
 ('education_PGR', False),
 ('education_SCH', False),
 ('education_UGR', False),
 ('marital_status_CIV', False),
 ('marital_status_DIV', False),
 ('marital_status_MAR', False),
 ('marital_status_UNM', False),
 ('marital_status_WID', False)]
```

In [61]:
```
columns3 = numeric_columns
columns3
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: Depreca
tionWarning: `should_run_async` will not call `transform_cell` automatical
ly in the future. Please pass the result to `transformed_cell` argument an
d any exception that happen during thetransform in `preprocessing_exc_tupl
e` in IPython 7.17 and above.
  and should_run_async(code)
```

```
Out[61]: ['age',
 'credit_sum',
 'credit_month',
 'tariff_id',
 'score_shk',
 'monthly_income',
 'credit_count',
 'overdue_credit_count',
 'gender_F',
 'gender_M',
 'job_position_ATP',
 'job_position_BIS',
 'job_position_BIU',
 'job_position_DIR',
 'job_position_HSK',
 'job_position_INP',
 'job_position_INV',
 'job_position_NOR',
 'job_position_PNA',
 'job_position_PNI',
 'job_position_PNS',
 'job_position_PNV',
 'job_position_SPC',
 'job_position_UMN',
 'job_position_WOI',
 'job_position_WRK',
 'job_position_WRP',
 'education_ACD',
 'education_GRD',
 'education_PGR',
 'education_SCH',
 'education_UGR',
 'marital_status_CIV',
 'marital_status_DIV',
 'marital_status_MAR',
 'marital_status_UNM',
 'marital_status_WID']
```