Как узнать свою аудиторию? Построение различных вариантов кластеризаций и интерпретация результатов.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mour
```

```
!pip install umap-learn
```

```
Requirement already satisfied: umap-learn in /usr/local/lib/python3.7/dist-packages (0.5
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.7/dist-packages (fro
Requirement already satisfied: numba>=0.49 in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: pynndescent>=0.5 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (fro
Requirement already satisfied: llvmlite<0.35,>=0.34.0.dev0 in /usr/local/lib/python3.7/d
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (f
```

Часть 1. EDA

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.graphics.gofplots import qqplot
from scipy.stats import shapiro
from scipy.stats import normaltest
from scipy.stats import norm
from tqdm import tqdm


import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering, DBSCAN
from sklearn.metrics import silhouette_score
from sklearn.neighbors import NearestNeighbors
from sklearn.decomposition import PCA
```

```
from scipy.cluster.hierarchy import dendrogram, linkage
import umap
from sklearn.manifold import TSNE

%matplotlib inline

plt.rcParams["figure.figsize"] = (12,8)
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning:
  import pandas.util.testing as tm
```

```
data = pd.read_csv('/content/drive/MyDrive/STUDY/otus/HW/4/german_credit_data.csv')
```

```
data.head()
```

	Unnamed: 0	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Pu
0	0	67	male	2	own	NaN	little	1169	6	ra
1	1	22	female	2	own	little	moderate	5951	48	ra
2	2	49	male	1	own	little	NaN	2096	12	edu
3	3	45	male	2	free	little	little	7882	42	furniture/equ
4	4	53	male	2	free	little	little	4870	24	

```
data.describe()
```

	Unnamed: 0	Age	Job	Credit amount	Duration
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	499.500000	35.546000	1.904000	3271.258000	20.903000
std	288.819436	11.375469	0.653614	2822.736876	12.058814
min	0.000000	19.000000	0.000000	250.000000	4.000000
25%	249.750000	27.000000	2.000000	1365.500000	12.000000
50%	499.500000	33.000000	2.000000	2319.500000	18.000000
75%	749.250000	42.000000	2.000000	3972.250000	24.000000
max	999.000000	75.000000	3.000000	18424.000000	72.000000

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
```

```
---  ------           --------------  -----
 0   Unnamed: 0       1000 non-null   int64
 1   Age              1000 non-null   int64
 2   Sex              1000 non-null   object
 3   Job              1000 non-null   int64
 4   Housing          1000 non-null   object
 5   Saving accounts  817 non-null    object
 6   Checking account 606 non-null    object
 7   Credit amount    1000 non-null   int64
 8   Duration         1000 non-null   int64
 9   Purpose          1000 non-null   object
dtypes: int64(5), object(5)
memory usage: 78.2+ KB
```

проверка на пропуски

```
data.isnull().sum()
```

```
Unnamed: 0            0
Age                   0
Sex                   0
Job                   0
Housing               0
Saving accounts     183
Checking account    394
Credit amount         0
Duration              0
Purpose               0
dtype: int64
```

Unnamed: 0

удалим неинформативный признак Unnamed: 0

```
del data['Unnamed: 0']
```

```
df = data.copy()
```

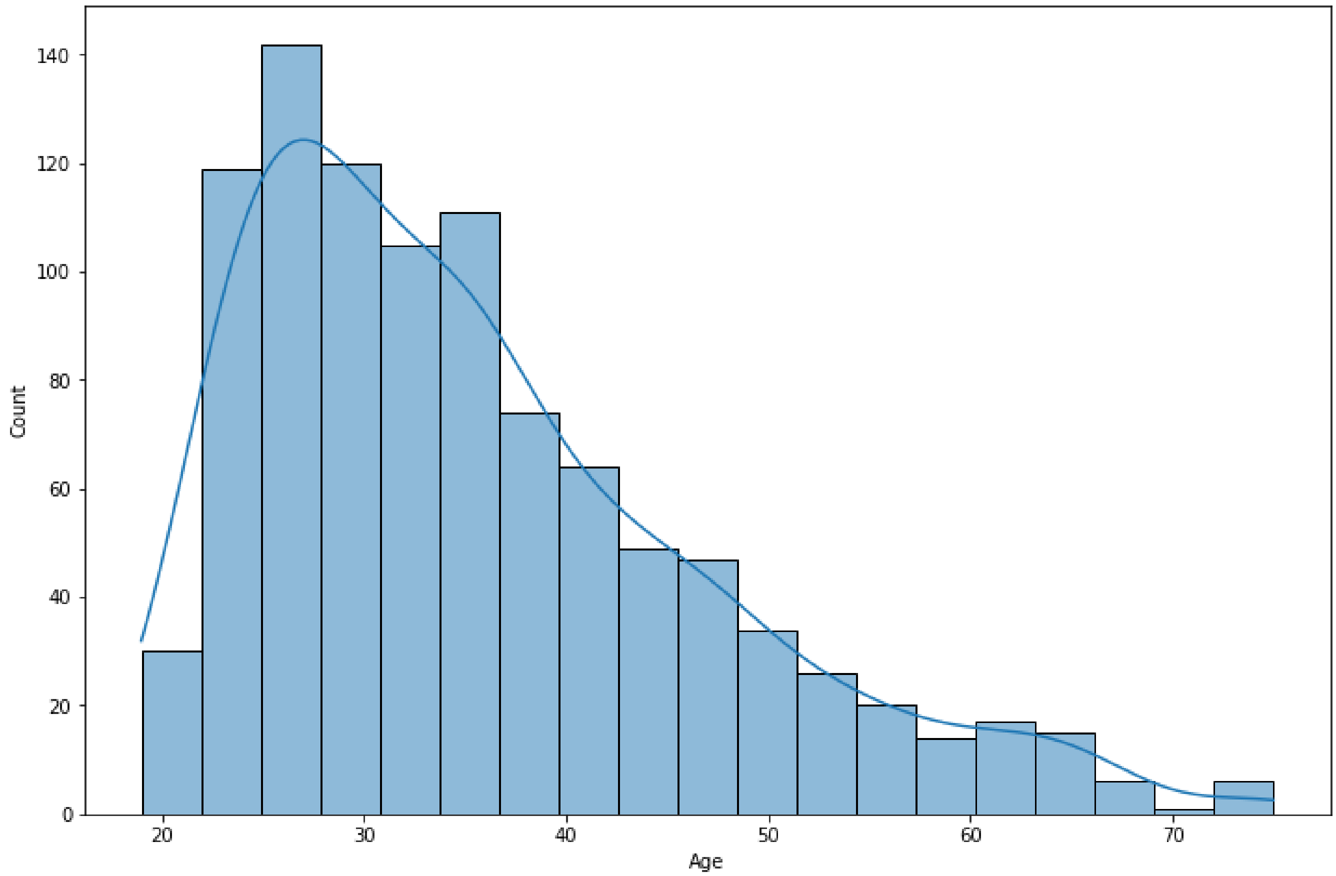
```
df.head()
```

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose
1	22	female	2	own	little	moderate	5951	48	radio/TV

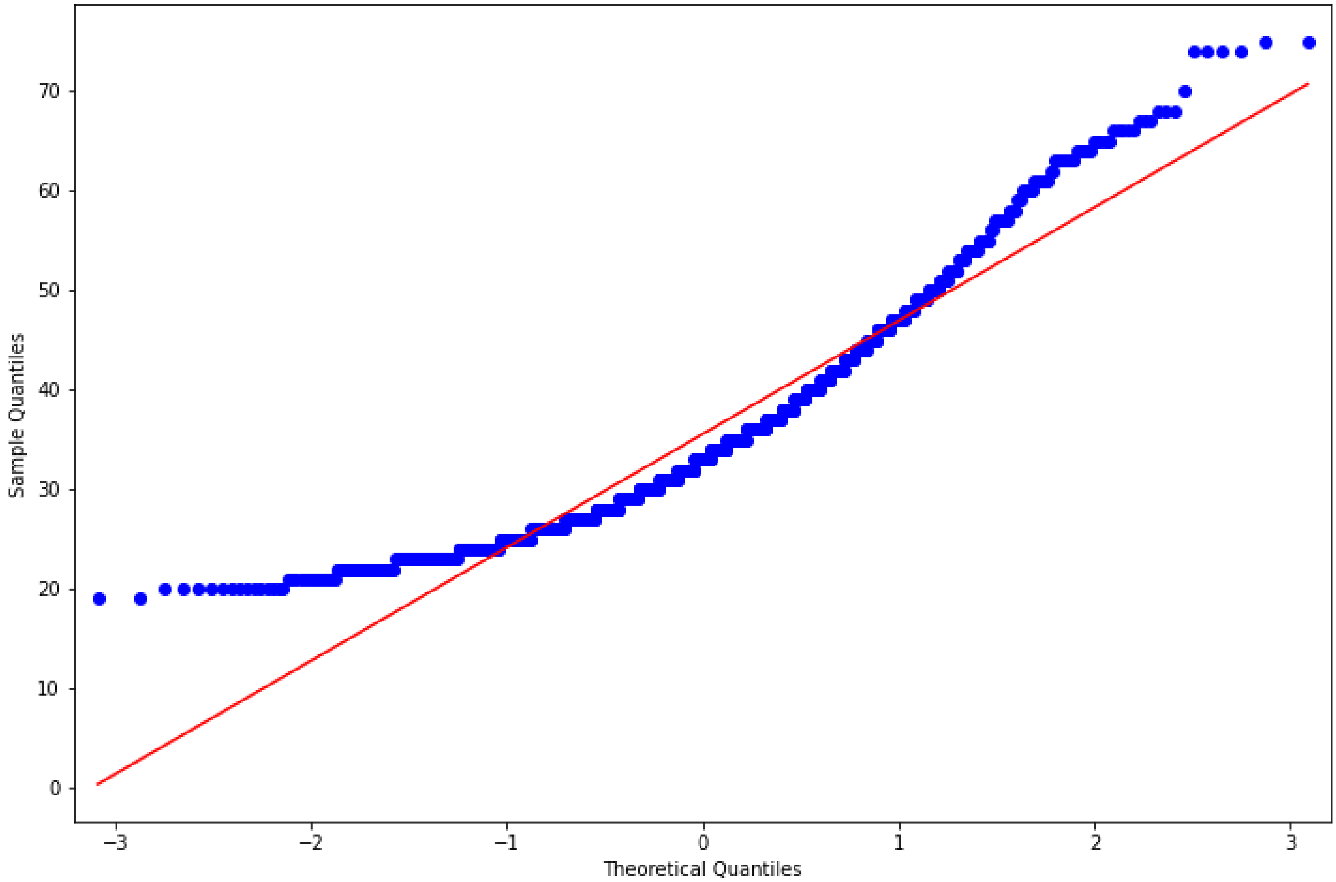
Age

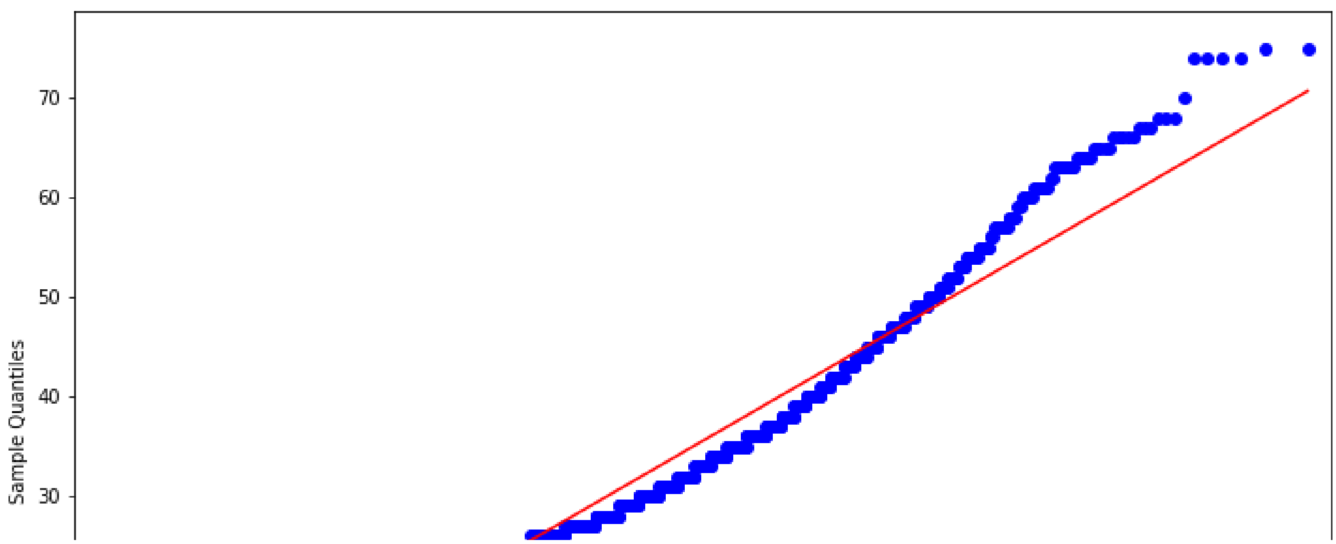
```
sns.histplot(data=df, x="Age", kde=True)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f980679c690>




```
qqplot(df.Age, line='s')
```





переменная в целом похожа на нормальное распределение, оставляем как есть

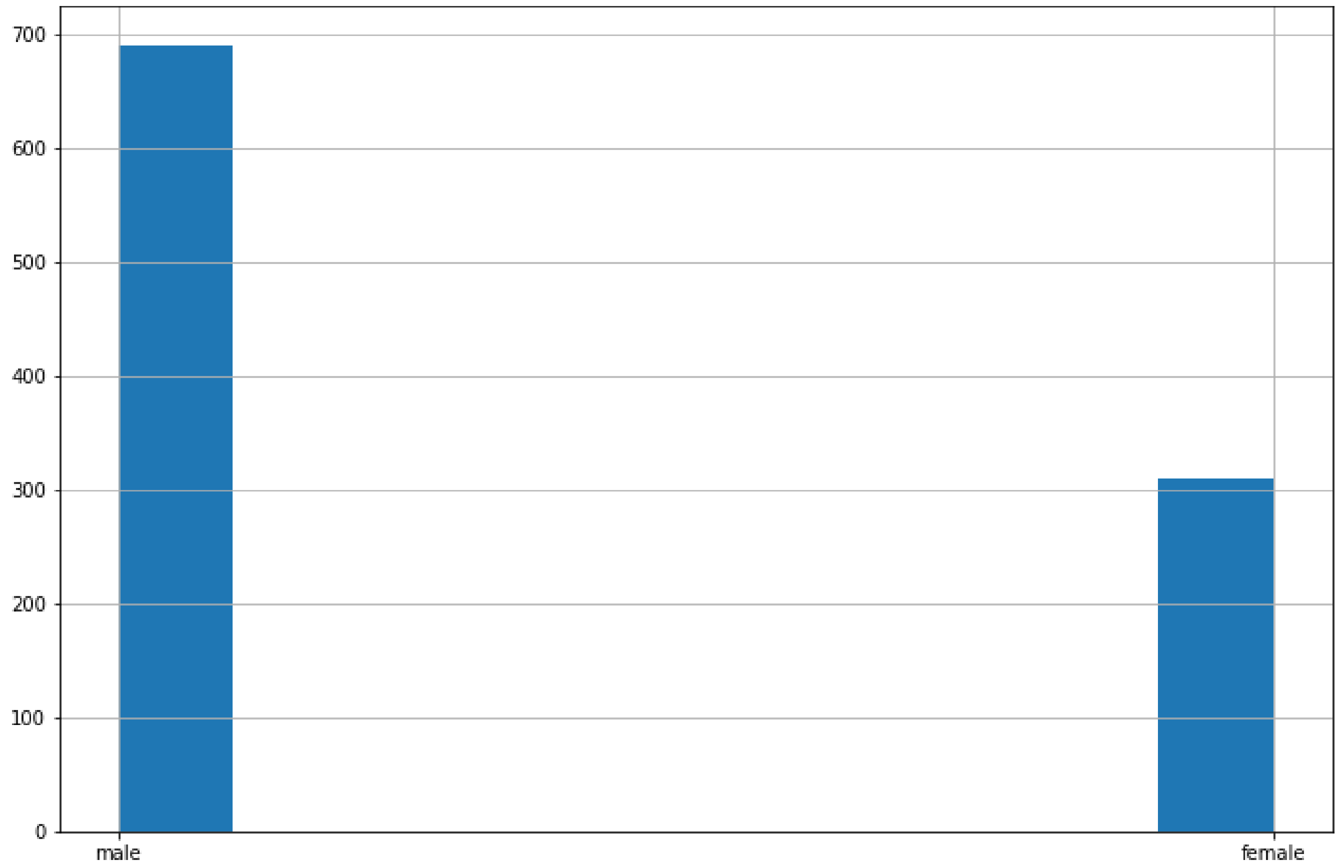
Sex

```
df.Sex.value_counts()
```

```
male      690
female    310
Name: Sex, dtype: int64
```

```
df.Sex.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98036d4490>
```



применим one-hot-encoding

```
df = pd.get_dummies(df, columns=['Sex'], drop_first=True)
```

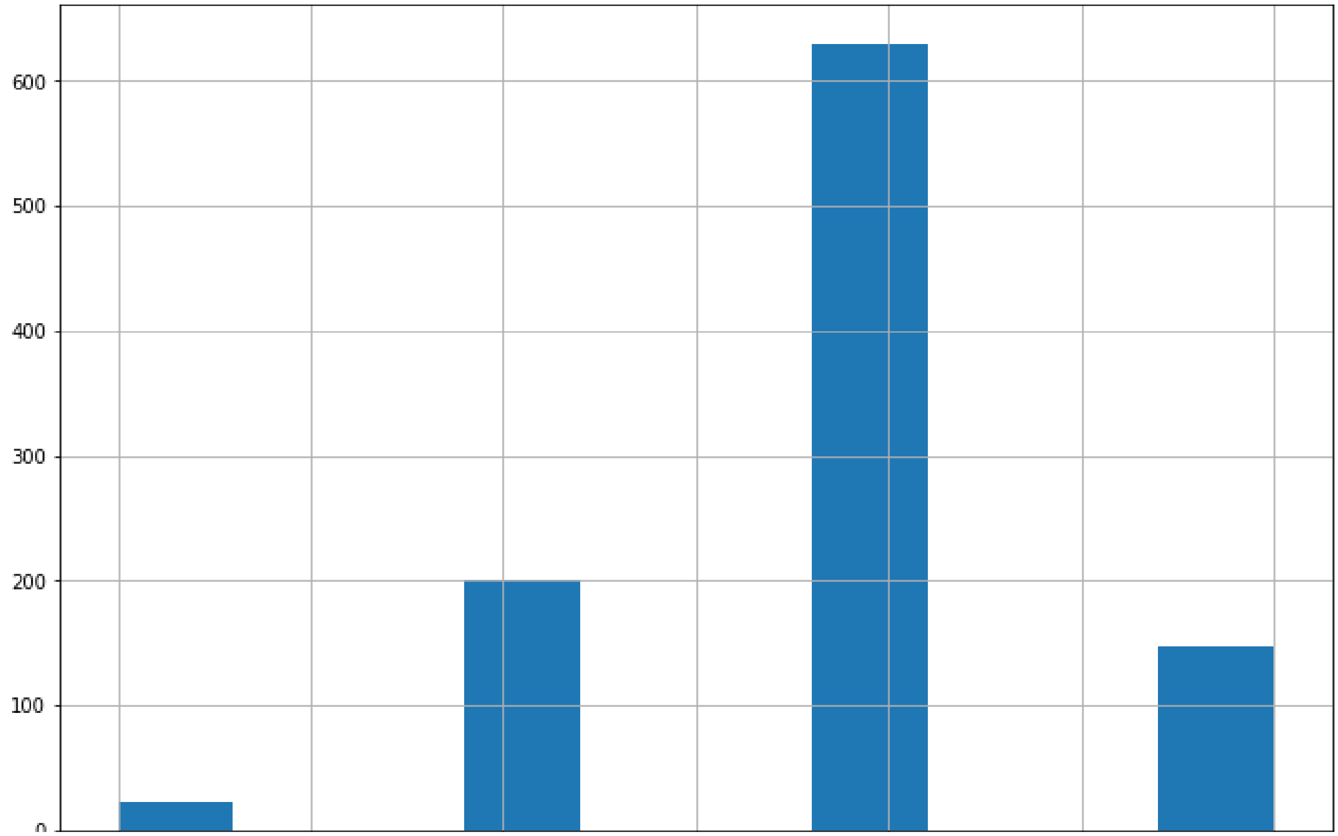
Job

```
df.Job.value_counts()
```

```
2    630
1    200
3    148
0     22
Name: Job, dtype: int64
```

```
df.Job.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f980365f410>
```



оставим данную переменную как есть,т.к. Job = 3 вроде как означает highlyskilled, 0 - unskilled and non-resident по информации из kaggle ноутбуков

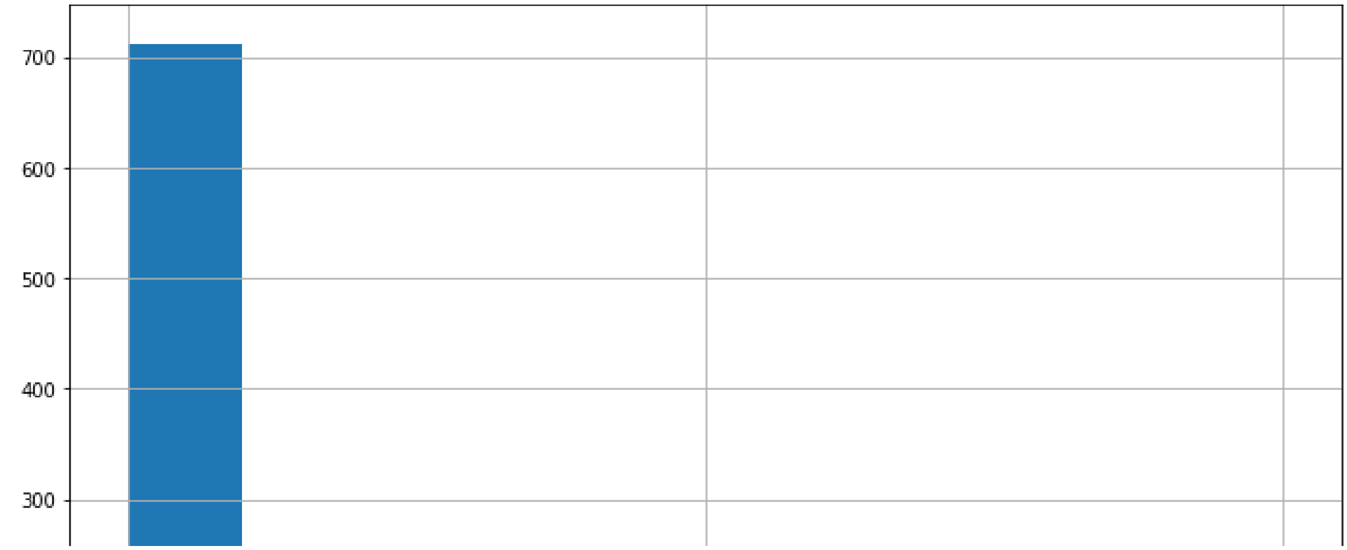
Housing

```
df.Housing.value_counts()
```

```
own     713
rent    179
free    108
Name: Housing, dtype: int64
```

```
df.Housing.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98036cfd10>
```



применим ohe

```
df = pd.get_dummies(df, columns=['Housing'], drop_first=True)
```

```
df.head()
```

	Age	Job	Saving accounts	Checking account	Credit amount	Duration	Purpose	Sex_male	Housing_c
0	67	2	NaN	little	1169	6	radio/TV	1	
1	22	2	little	moderate	5951	48	radio/TV	0	
2	49	1	little	NaN	2096	12	education	1	
3	45	2	little	little	7882	42	furniture/equipment	1	
4	53	2	little	little	4870	24	car	1	

Saving accounts

```
df['Saving accounts'].value_counts()
```

```
little        603
moderate      103
quite rich     63
rich           48
Name: Saving accounts, dtype: int64
```

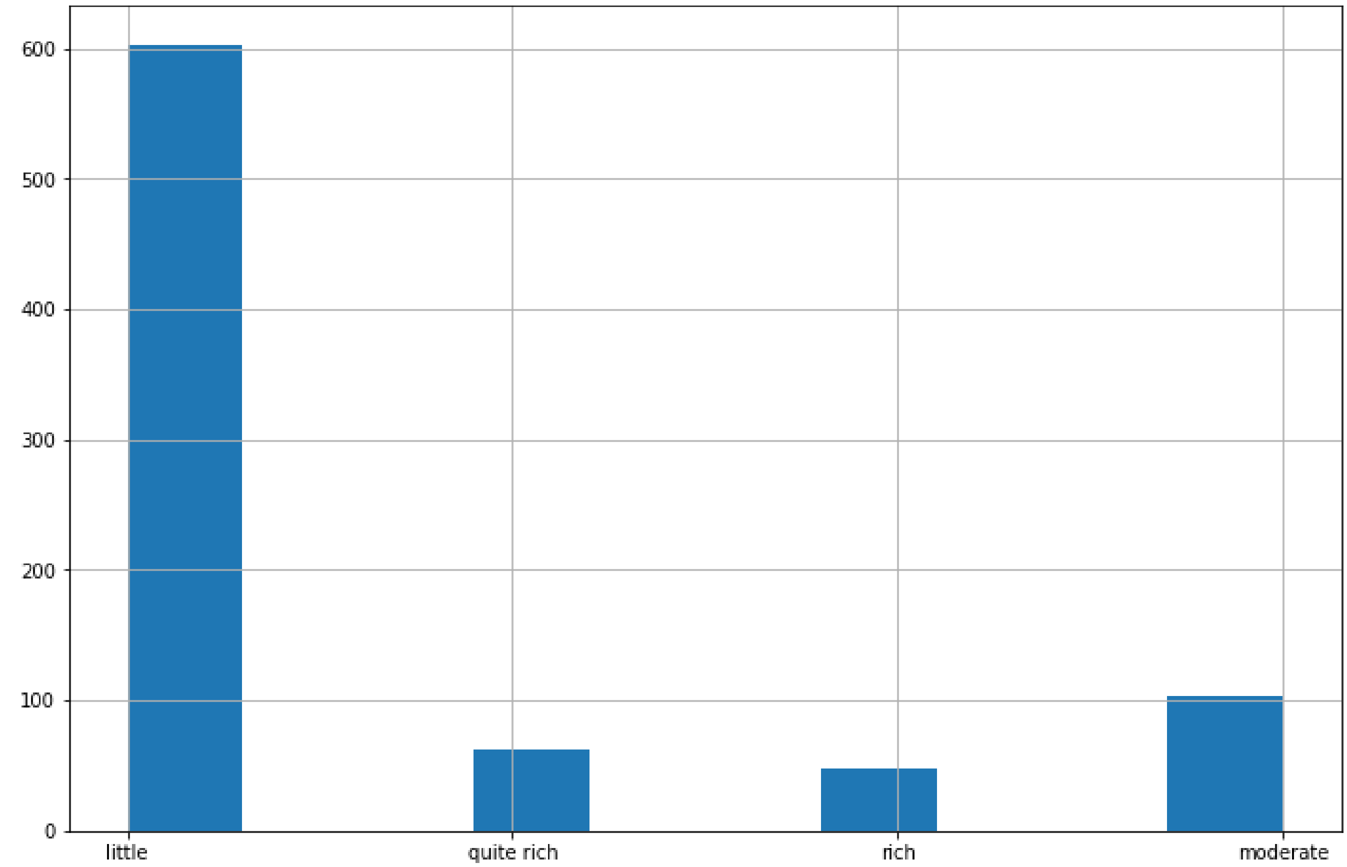
```
df['Saving accounts'].isnull().sum()
```

```
183
```

```
df['Saving accounts'].hist()
```

```
df['Saving accounts'].hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f980360ccd0>
```



переведем строку в цифры, в данном случае rich = 4, little = 1 учитывает порядок, поэтому обойдемся без ohe

```
#data = pd.get_dummies(data, columns=['Saving accounts'], drop_first=True)
d = {'little': 0, 'moderate':1, 'quite rich': 2 , 'rich': 3}
df['Saving accounts'] = df['Saving accounts'].map(d)
```

```
df.head()
```

	Age	Job	Saving accounts	Checking account	Credit amount	Duration	Purpose	Sex_male	Housing_c
0	67	2	NaN	little	1169	6	radio/TV	1	
1	22	2	0.0	moderate	5951	48	radio/TV	0	
2	49	1	0.0	NaN	2096	12	education	1	
3	45	2	0.0	little	7882	42	furniture/equipment	1	
4	53	2	0.0	little	4870	24	car	1	

```
df['Saving accounts'].isnull().median()
```

```
0.0
```

заменим Nan на median()

```
df['Saving accounts'] = df['Saving accounts'].fillna(df['Saving accounts'].isnull().median())
```

Checking account

```
df['Checking account'].value_counts()
```

```
little      274
moderate    269
rich         63
Name: Checking account, dtype: int64
```

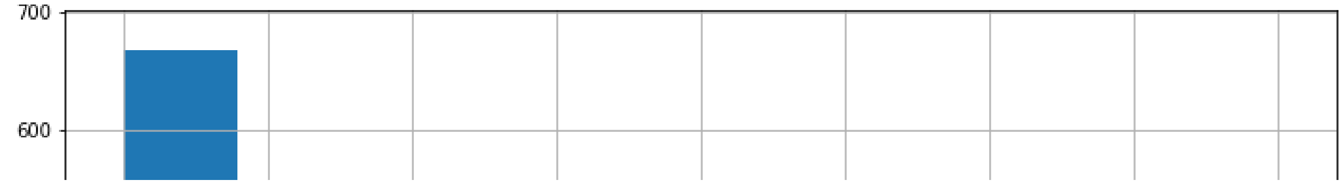
поступим аналогично Saving accounts

```
d = {'little': 0, 'moderate':1, 'rich': 2}
df['Checking account'] = df['Checking account'].map(d)
```

```
df['Checking account'] = df['Checking account'].fillna(df['Checking account'].isnull().median
```

```
df['Checking account'].hist()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f98034f6dd0>



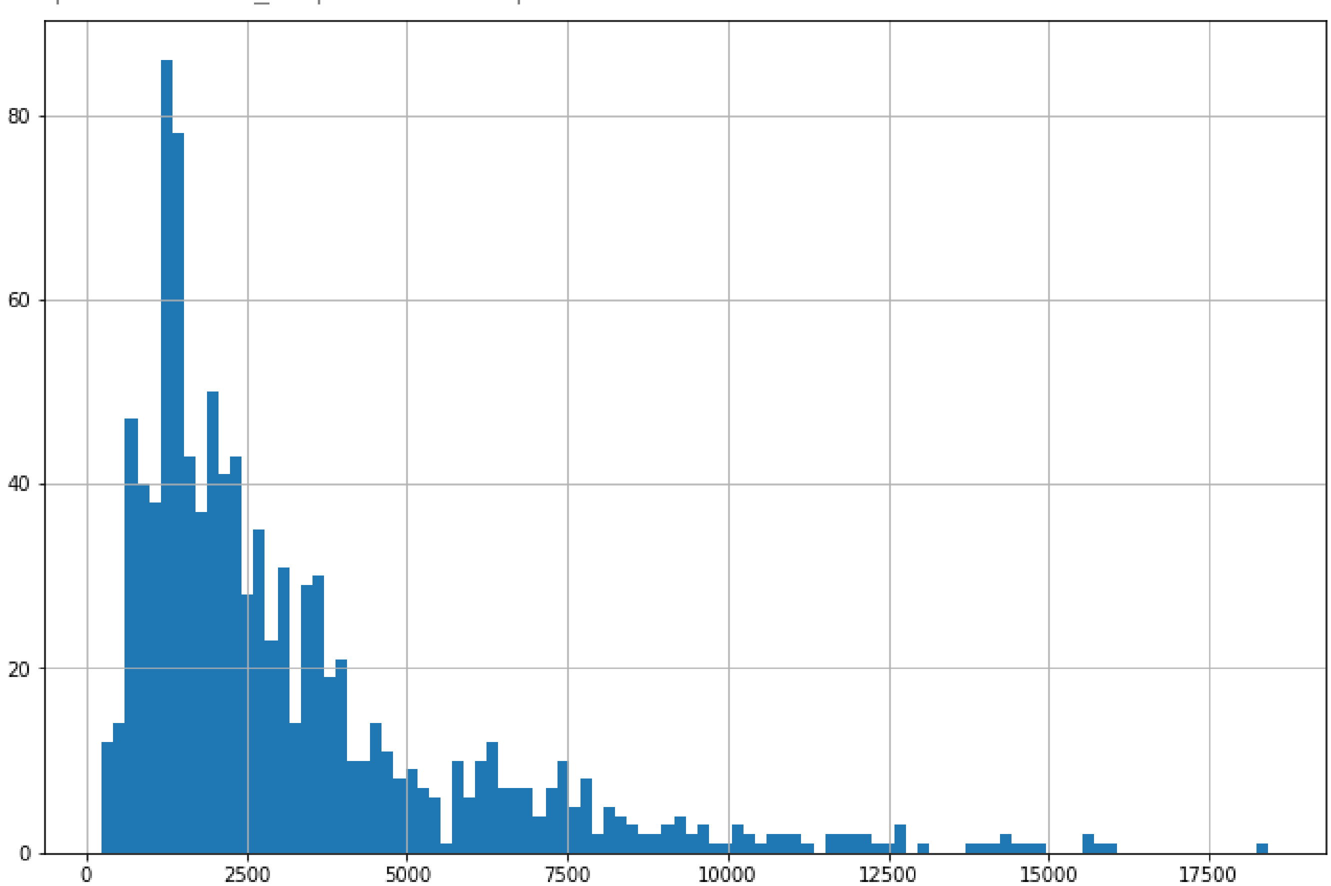

```
df.head()
```

	Age	Job	Saving accounts	Checking account	Credit amount	Duration	Purpose	Sex_male	Housing_c
0	67	2	0.0	0.0	1169	6	radio/TV	1	
1	22	2	0.0	1.0	5951	48	radio/TV	0	
2	49	1	0.0	0.0	2096	12	education	1	
3	45	2	0.0	0.0	7882	42	furniture/equipment	1	
4	53	2	0.0	0.0	4870	24	car	1	

Credit amount

```
df['Credit amount'].hist(bins = 100)
```

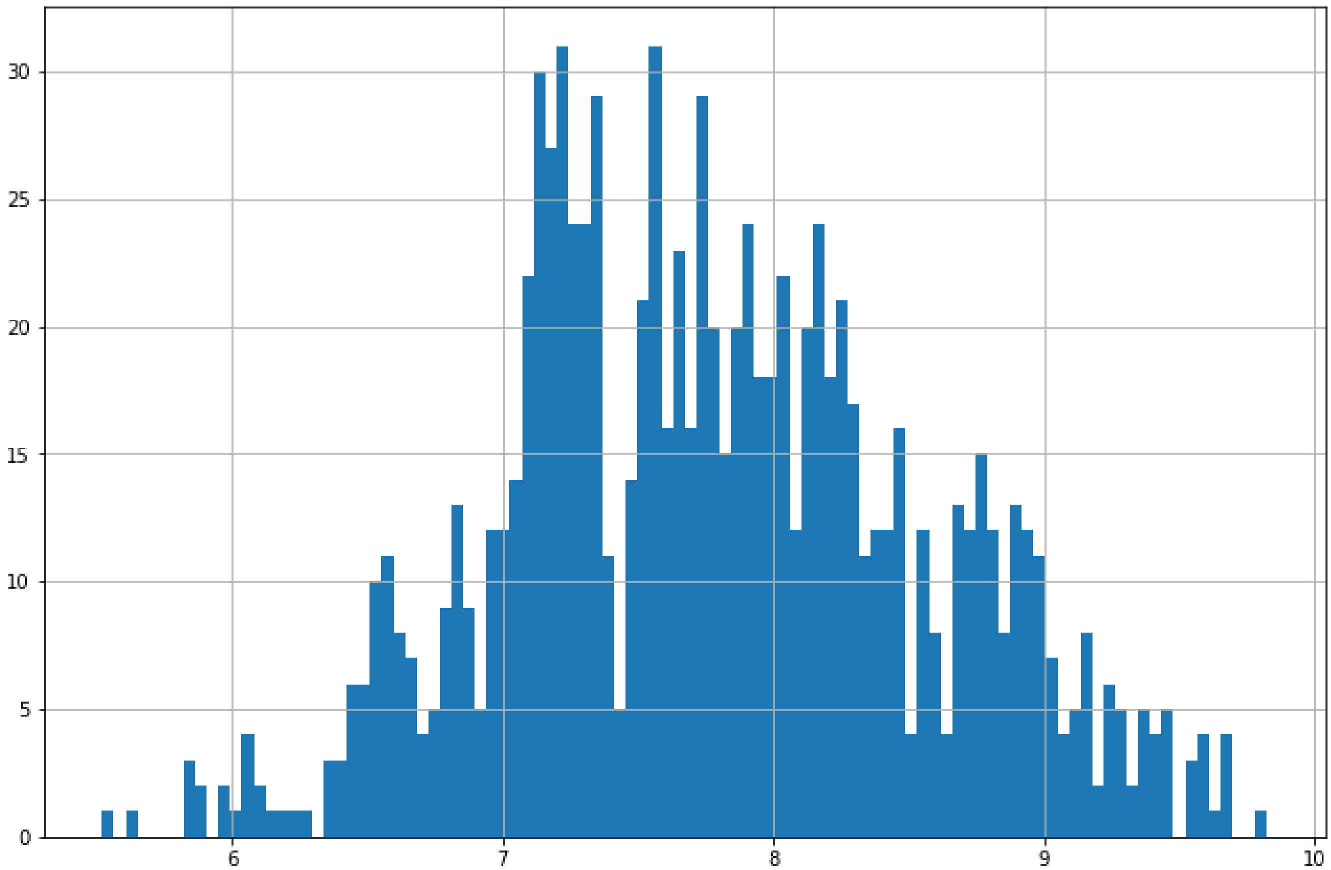
<matplotlib.axes._subplots.AxesSubplot at 0x7f98034ff3d0>



смещено влево, попробуем пролагорифмировать, чтобы сделать нормальным

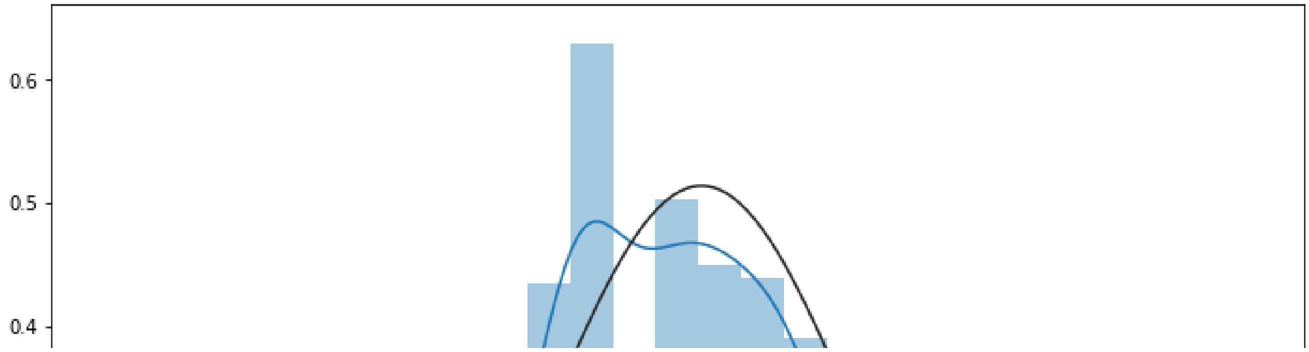
```
np.log(df['Credit amount']).hist(bins = 100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f98032994d0>
```

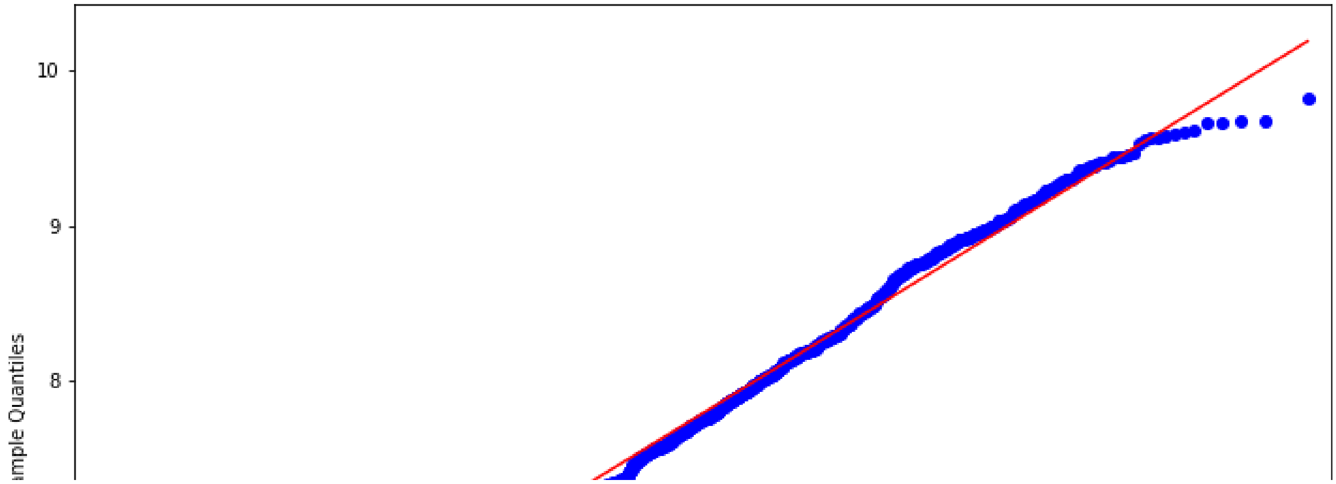



```
sns.distplot(np.log(df['Credit amount']), fit=norm)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9803213450>
```




```
qqplot(np.log(df['Credit amount']), line='s')
```



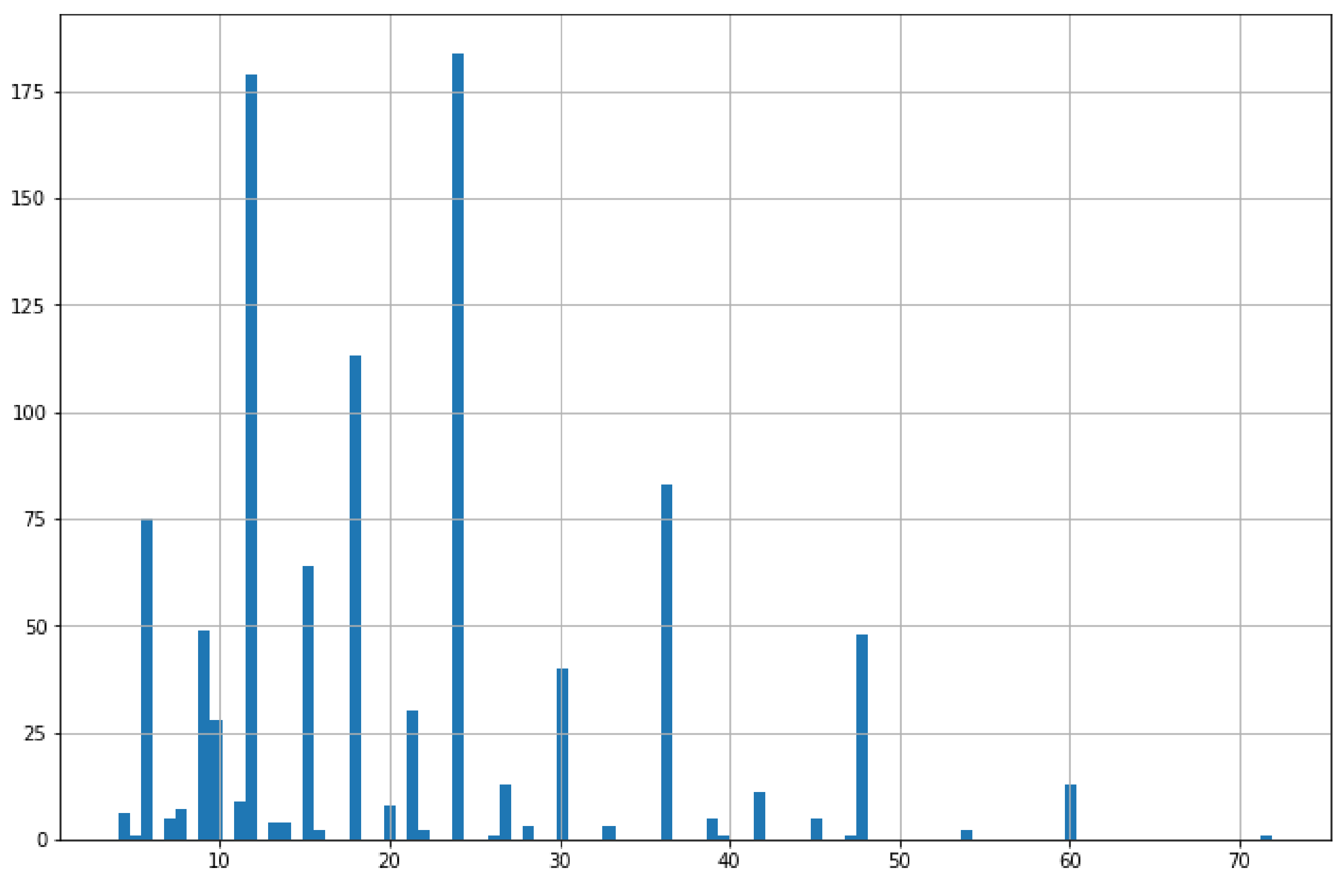
ок, логарифмируем

```
df['Credit amount'] = np.log(df['Credit amount'])
```

Duration

```
df.Duration.hist(bins = 100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9802f888d0>
```



```
df.Duration.value_counts()
```

```
24    184
12    179
18    113
36     83
6      75
15     64
9      49
48     48
30     40
21     30
10     28
27     13
60     13
42     11
11      9
20      8
8       7
4       6
39      5
45      5
7       5
14      4
13      4
33      3
28      3
22      2
16      2
54      2
26      1
40      1
47      1
5       1
72      1
Name: Duration, dtype: int64
```

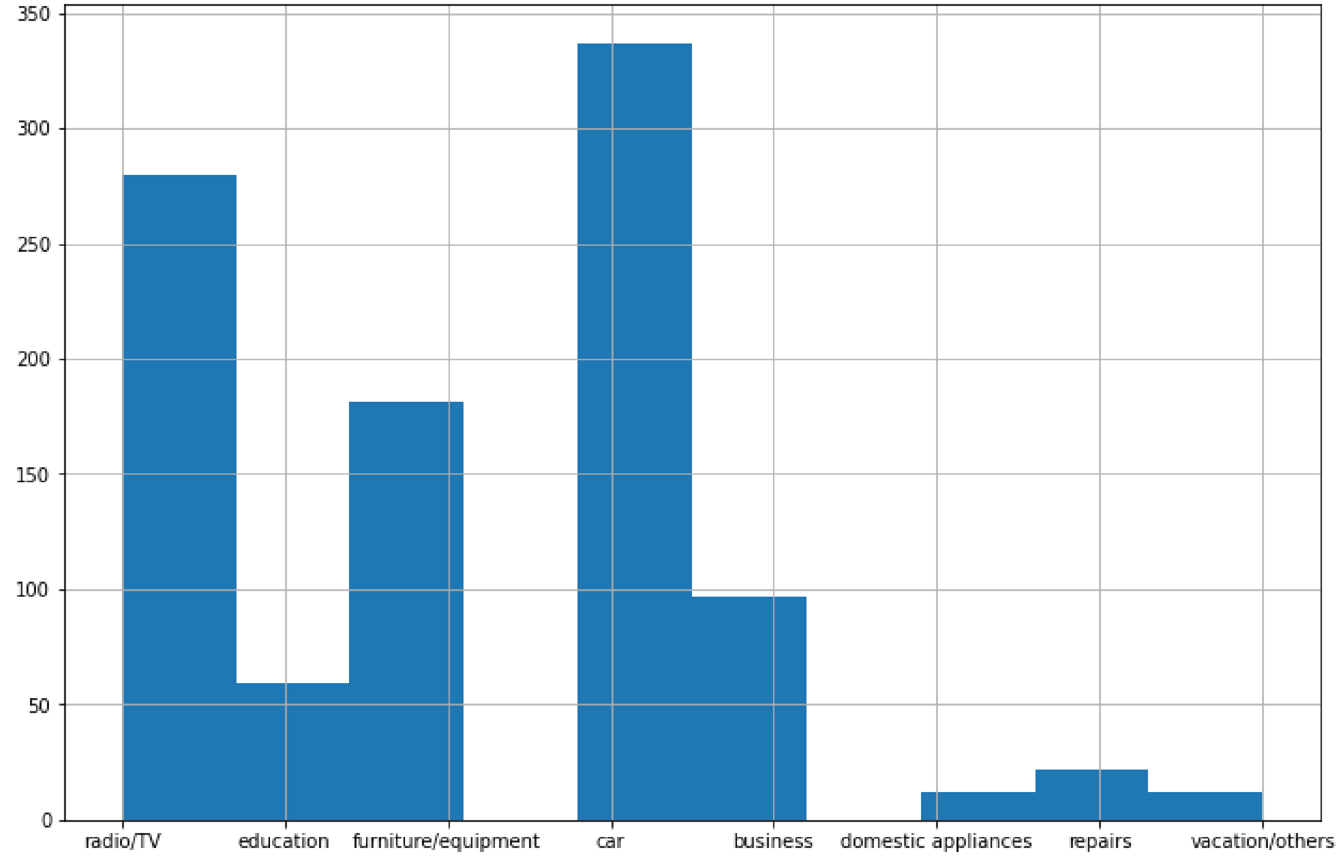
Purpose

```
df.Purpose.value_counts()
```

```
car                    337
radio/TV               280
furniture/equipment    181
business                97
education               59
repairs                 22
domestic appliances     12
vacation/others         12
Name: Purpose, dtype: int64
```

```
df.Purpose.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9802e79790>
```



применим частотное кодирование

```
df['Purpose'] = df['Purpose'].map(df['Purpose'].value_counts(normalize=True))
```

```
df.head()
```

	Age	Job	Saving accounts	Checking account	Credit amount	Duration	Purpose	Sex_male	Housing_own	Hou
0	67	2	0.0	0.0	7.063904	6	0.280	1	1	
1	22	2	0.0	1.0	8.691315	48	0.280	0	1	
2	49	1	0.0	0.0	7.647786	12	0.059	1	1	
3	45	2	0.0	0.0	8.972337	42	0.181	1	0	
4	53	2	0.0	0.0	8.490849	24	0.337	1	0	

Scalling

шкалирование нам необходимо чтобы модель воспринимала данные в одном масштабе, и

```
continuous_vars = [
  'Age',
  'Job',
  'Credit amount',
 'Duration',
]
```

```
scaler = StandardScaler()
df[continuous_vars] = scaler.fit_transform(df[continuous_vars])
```

```
df.head()
```

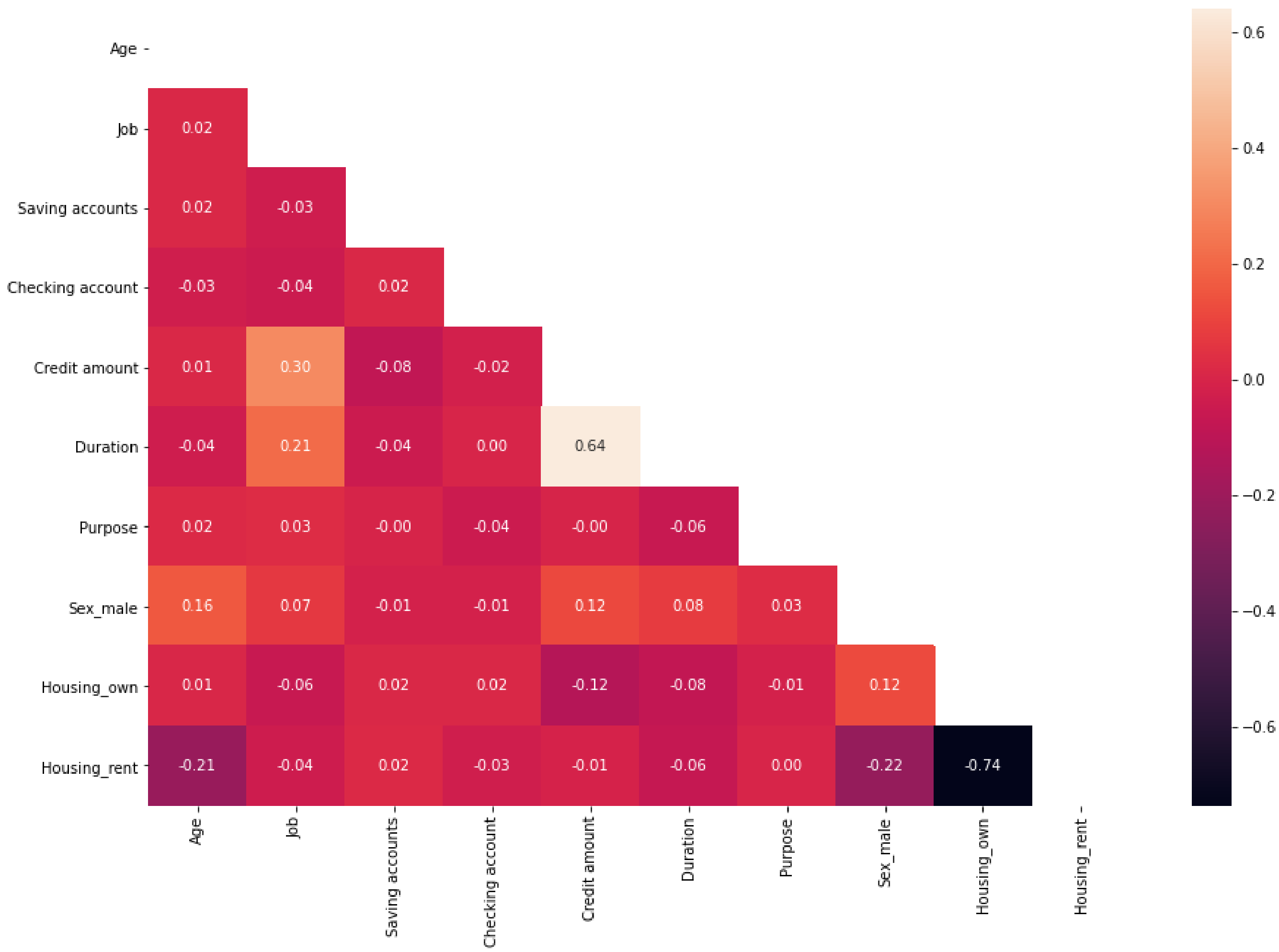
	Age	Job	Saving accounts	Checking account	Credit amount	Duration	Purpose	Sex_male	Housi
0	2.766456	0.146949	0.0	0.0	-0.933901	-1.236478	0.280	1	
1	-1.191404	0.146949	0.0	1.0	1.163046	2.248194	0.280	0	
2	1.183312	-1.383771	0.0	0.0	-0.181559	-0.738668	0.059	1	
3	0.831502	0.146949	0.0	0.0	1.525148	1.750384	0.181	1	
4	1.535122	0.146949	0.0	0.0	0.904743	0.256953	0.337	1	

распредделения

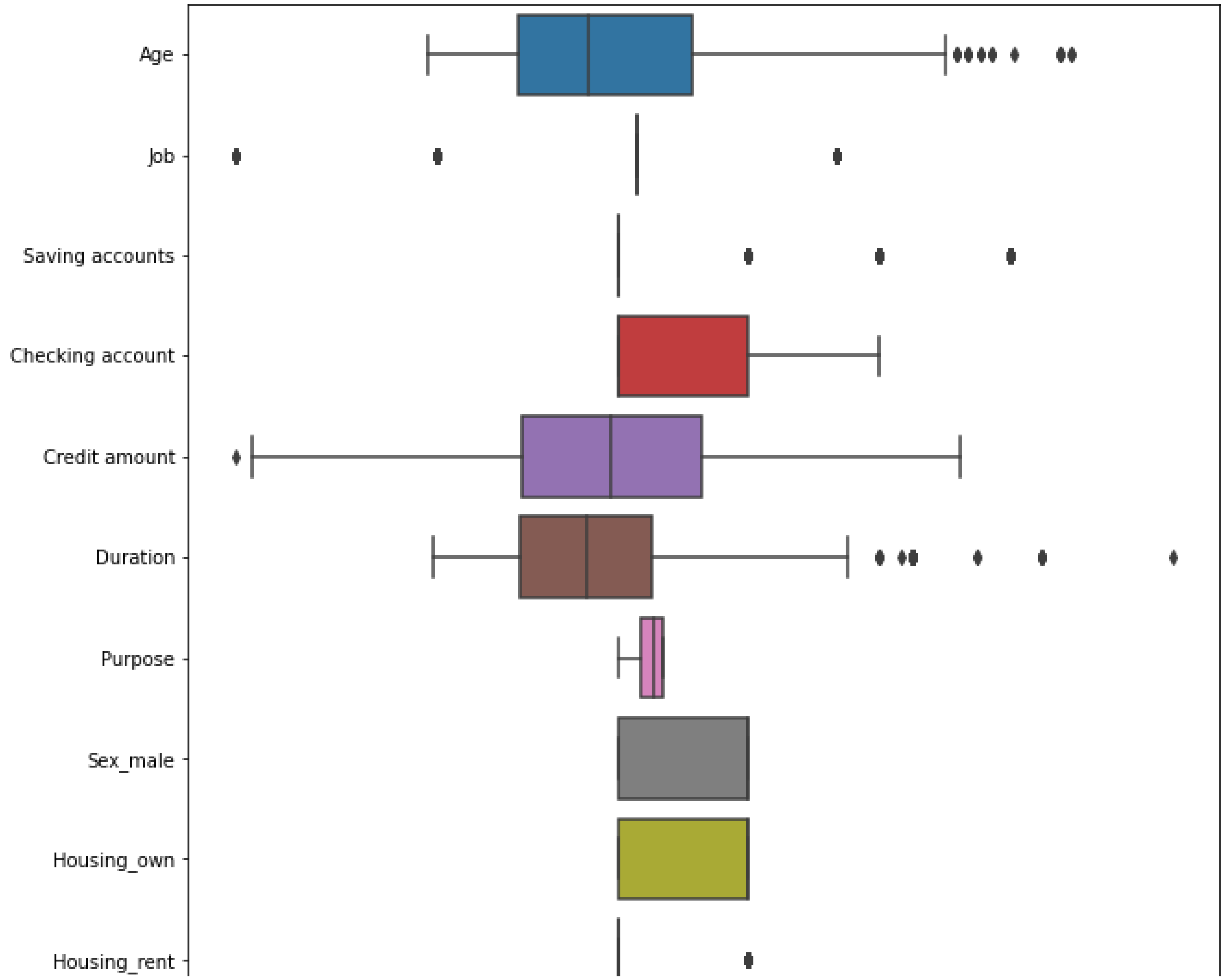
```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7f9802daaa90>
```

```
corr = df.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
plt.figure(figsize=(15,10))
sns.heatmap(corr, mask=mask, annot=True, fmt='.2f');
```




```
plt.figure(figsize=(10,10))
sns.boxplot(data=df, orient='h');
```




```
df.tail()
```

	Age	Job	Saving accounts	Checking account	Credit amount	Duration	Purpose	Sex_male	Hou
995	-0.399832	-1.383771	0.0	0.0	-0.424376	-0.738668	0.181	0	
996	0.391740	1.677670	0.0	0.0	0.604255	0.754763	0.337	1	
997	0.215835	0.146949	0.0	0.0	-1.416199	-0.738668	0.280	1	
998	-1.103451	0.146949	0.0	0.0	-0.345911	1.999289	0.280	1	
999	0.751642	0.146949	1.0	1.0	0.824508	1.999289	0.337	1	

Часть 2 Моделирование

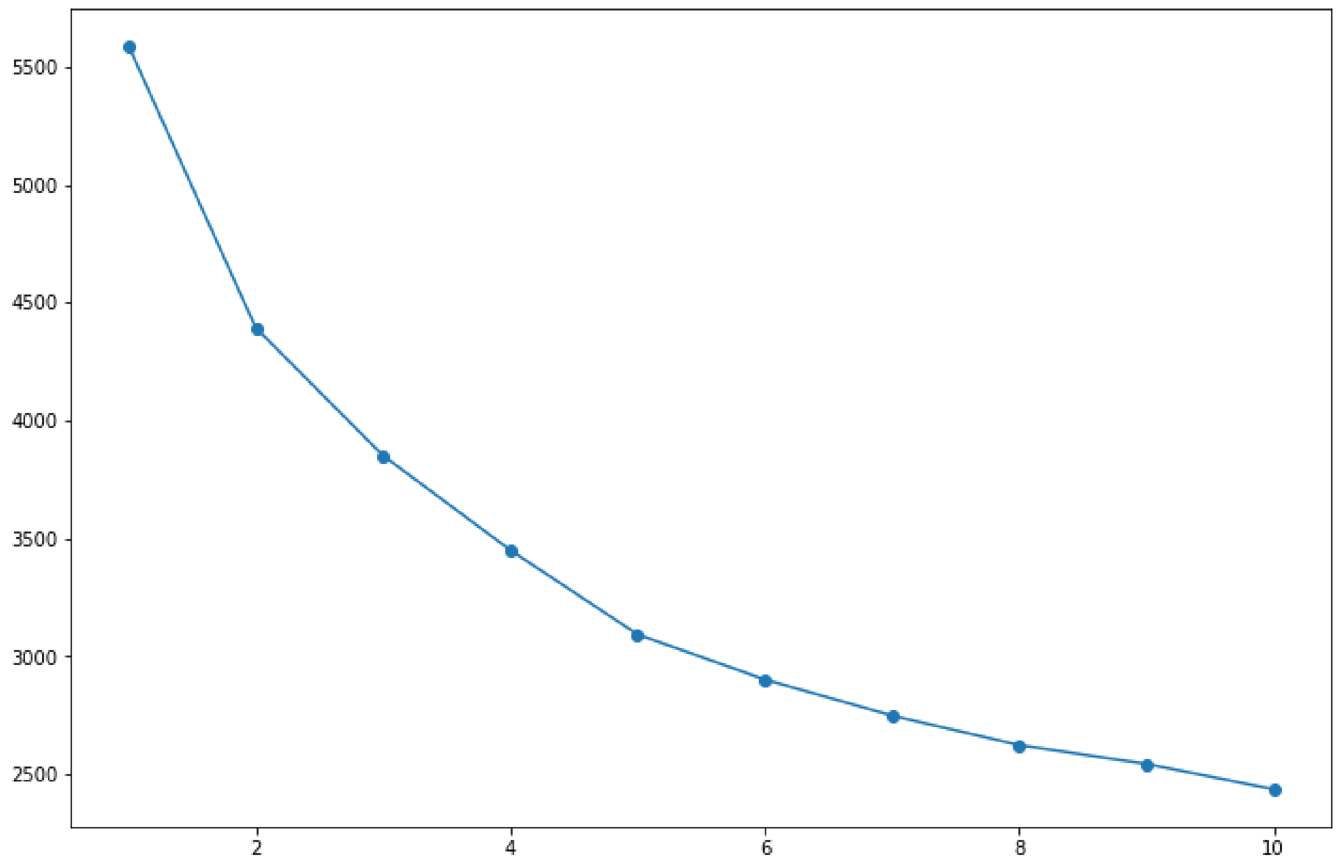
k-means

```
inertia = []
for i in range(1,11):
```

```
for i in range(1,11):
    kmeans = KMeans(n_clusters=i, random_state=2021, n_jobs=-1).fit(df)
    labels_k = kmeans.labels_
    inertia_i = kmeans.inertia_
    inertia.append(inertia_i)
```

Elbow method

```
plt.plot(range(1,11), inertia, marker='o');
```

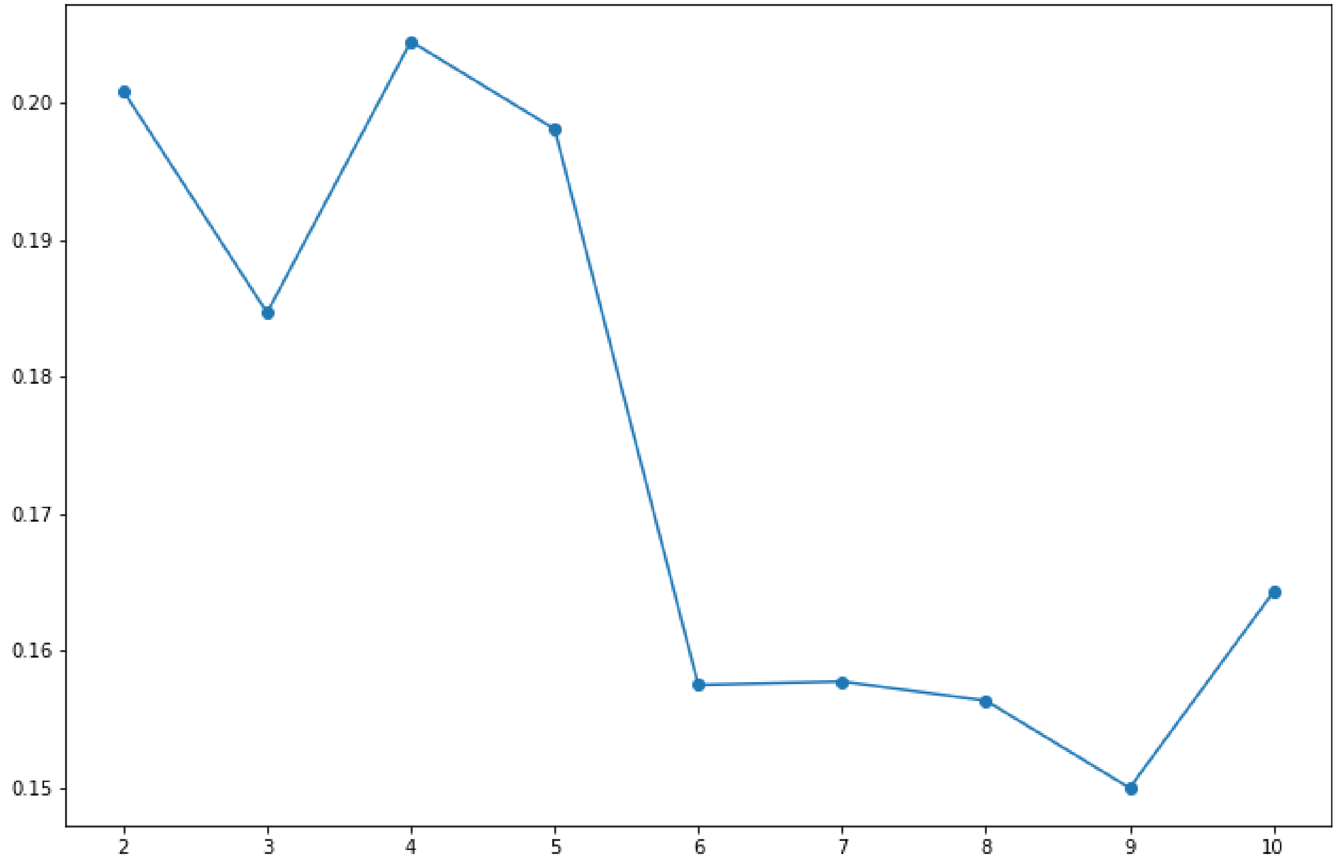


Silhouette plot

```
silhouette = []
for i in tqdm(range(2,11)):
    agg = KMeans(n_clusters=i, random_state=2021, n_jobs=-1).fit(df)
    labels_k = agg.labels_
    score = silhouette_score(df, labels_k)
    silhouette.append(score)
```

```
 100%|██████████| 9/9 [00:01<00:00,  5.61it/s]
```

```
plt.plot(range(2,11), silhouette, marker='o');
```



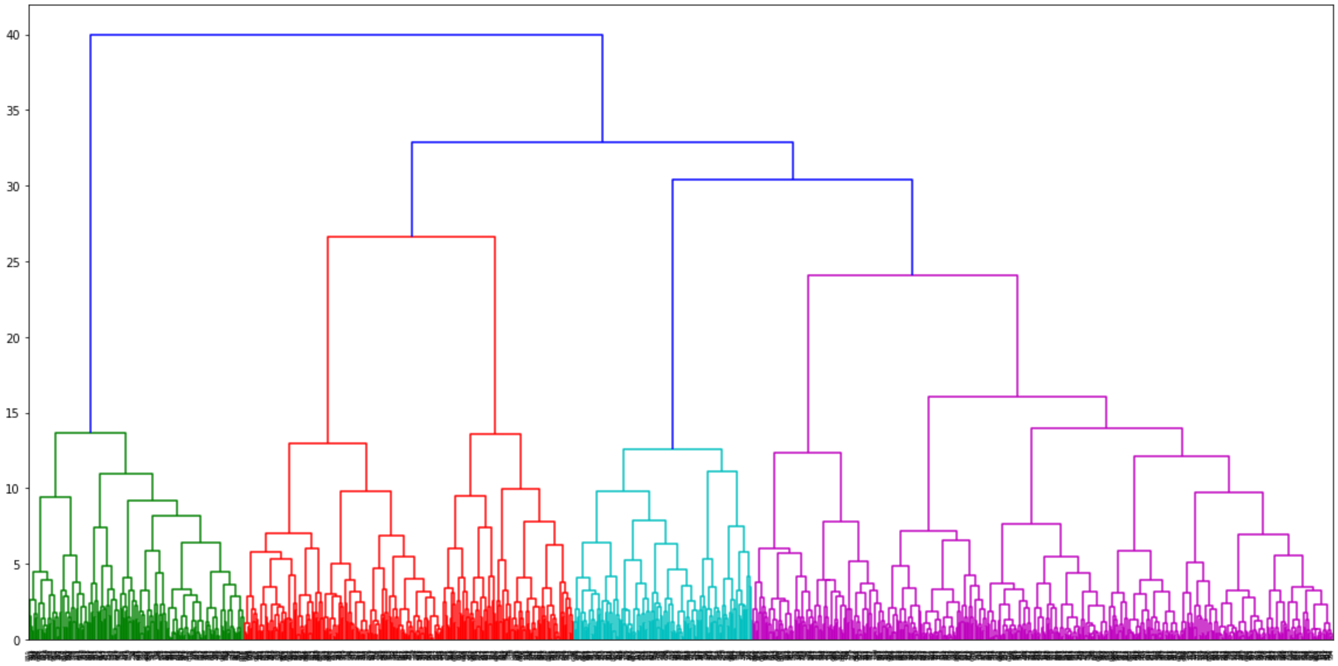
k-means говорит о 4 кластерах

```
kmeans = KMeans(n_clusters=4, random_state=2021, n_jobs=-1).fit(df)
labels_k = kmeans.labels_
```

hierarhical clustering (AgglomerativeClustering)

dendrogram метод определения кластеров

```
plt.figure(figsize=(20,10))
linkage_ = linkage(df, method='ward')
dendrogram_ = dendrogram(linkage_)
```

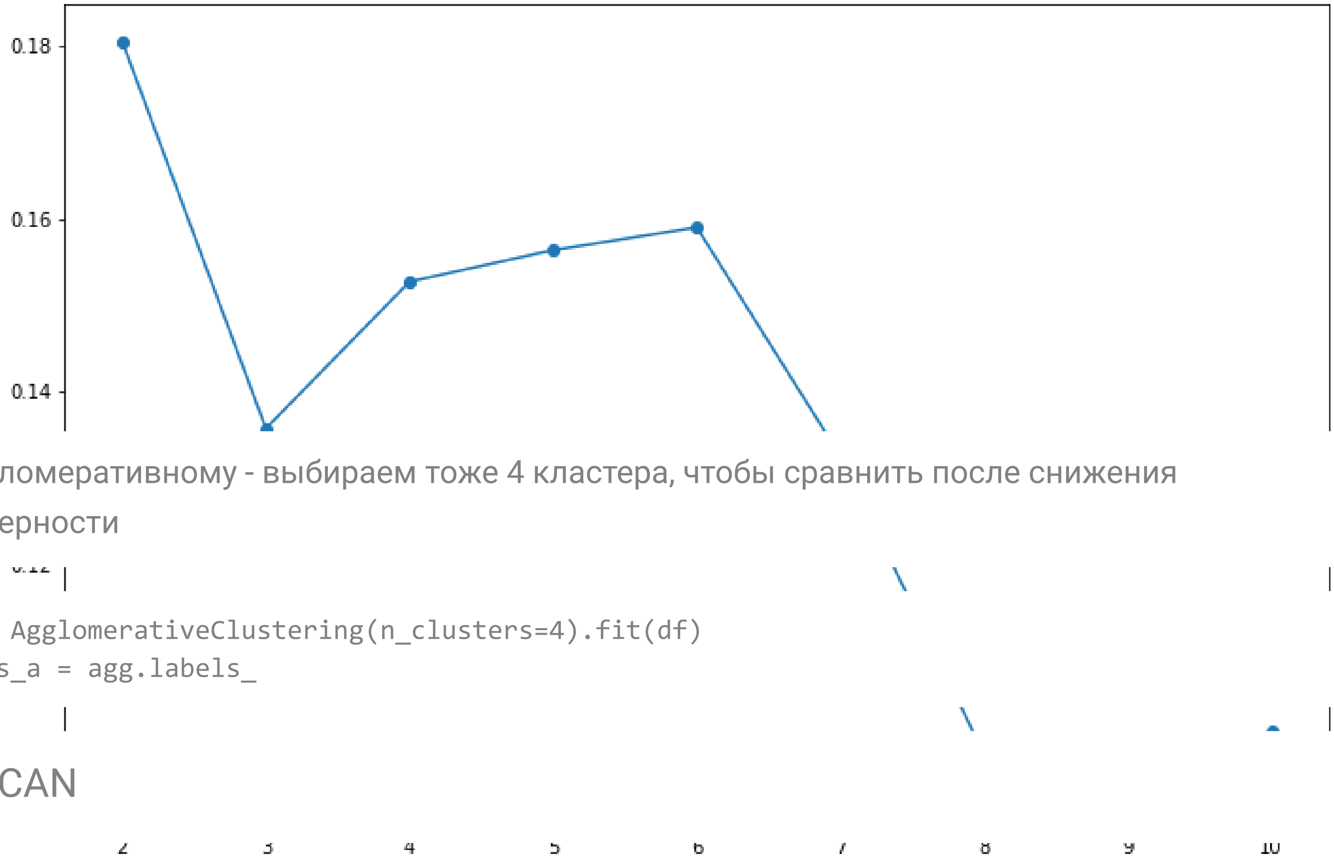


Silhouette plot

```
silhouette = []
for i in tqdm(range(2,11)):
    agg = AgglomerativeClustering(n_clusters=i).fit(df)
    labels_a = agg.labels_
    score = silhouette_score(df, labels_a)
    silhouette.append(score)
```

```
100%|██████████| 9/9 [00:00<00:00, 12.91it/s]
```

```
plt.plot(range(2,11), silhouette, marker='o');
```



по агломеративному - выбираем тоже 4 кластера, чтобы сравнить после снижения размерности

```
agg = AgglomerativeClustering(n_clusters=4).fit(df)
labels_a = agg.labels_
```

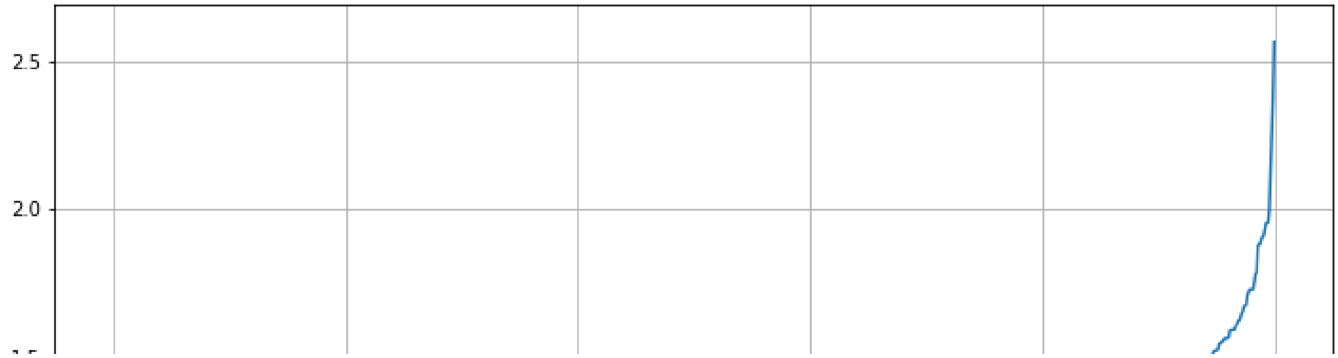
DBSCAN

найдем подходящий eps по методу NearestNeighbors

```
neighbors = NearestNeighbors(n_neighbors=5)
nbrs = neighbors.fit(df)
distance, indices = nbrs.kneighbors(df)

distance = np.sort(distance, axis=0)
distance = distance[:,1]
plt.grid()
plt.plot(distance)
```

```
[<matplotlib.lines.Line2D at 0x7f97f487f950>]
```



возьмем eps = 1,459

```
# This is formatted as code
```

```
dbscan = DBSCAN(eps=1.459, min_samples = 4).fit(df)
labels_d = dbscan.labels_
```

```
myset = set(labels_d)
print(myset)
```

```
{0, 1, 2, 3, -1}
```

dbscan разделил на 4 кластера

PCA

```
pca = PCA(random_state = 2021)
pca.fit(df)
```

```
PCA(copy=True, iterated_power='auto', n_components=None, random_state=2021,
    svd_solver='auto', tol=0.0, whiten=False)
```

объясненная дисперсия

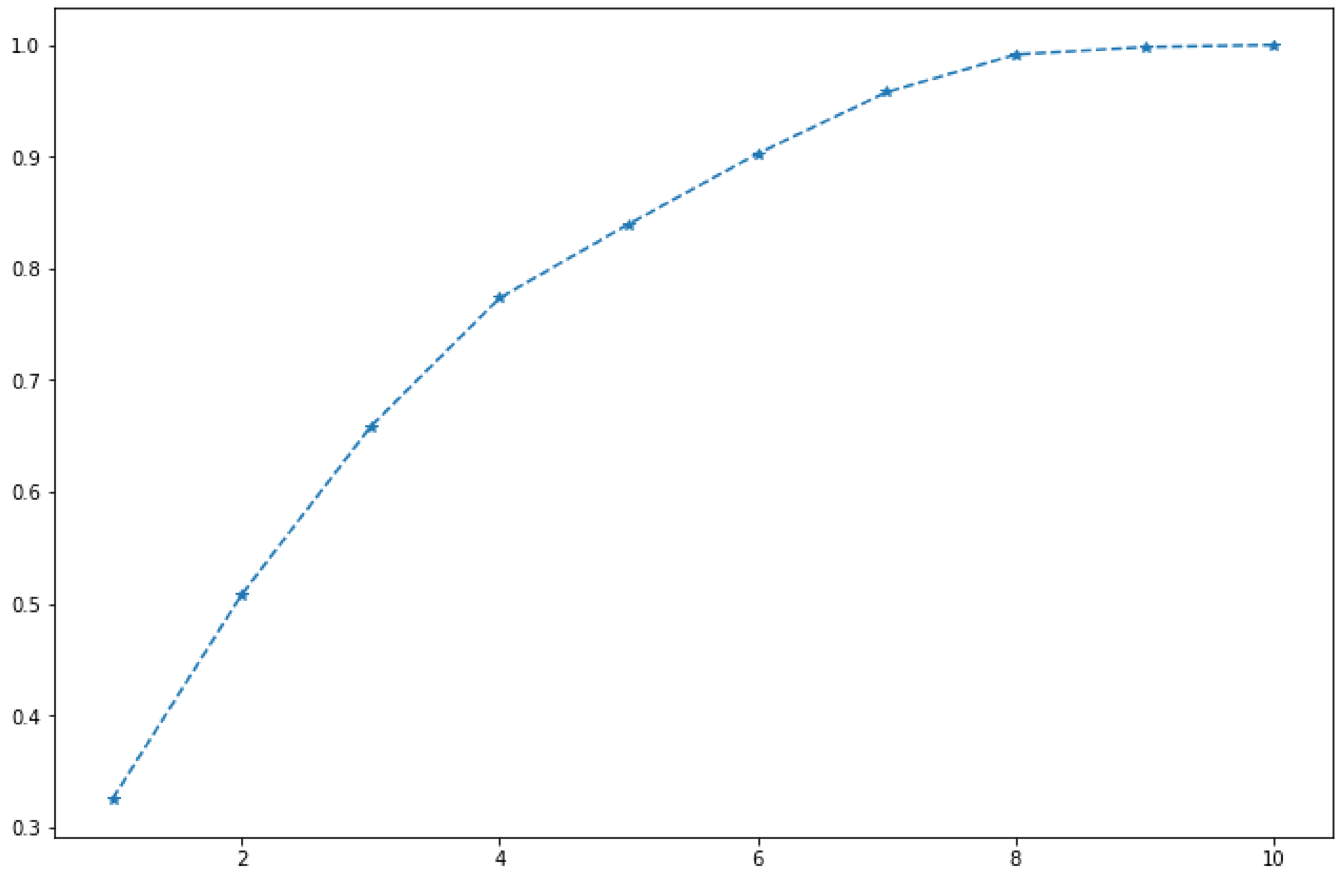
```
np.cumsum(pca.explained_variance_ratio_)
```

```
array([0.32528197, 0.50809756, 0.65834522, 0.77363087, 0.83967005,
       0.90279593, 0.95770418, 0.99133669, 0.99814958, 1.        ])
```

```
df.shape
```

```
(1000, 10)
```

```
plt.plot(range(1, 11), np.cumsum(pca.explained_variance_ratio_), '*--');
```



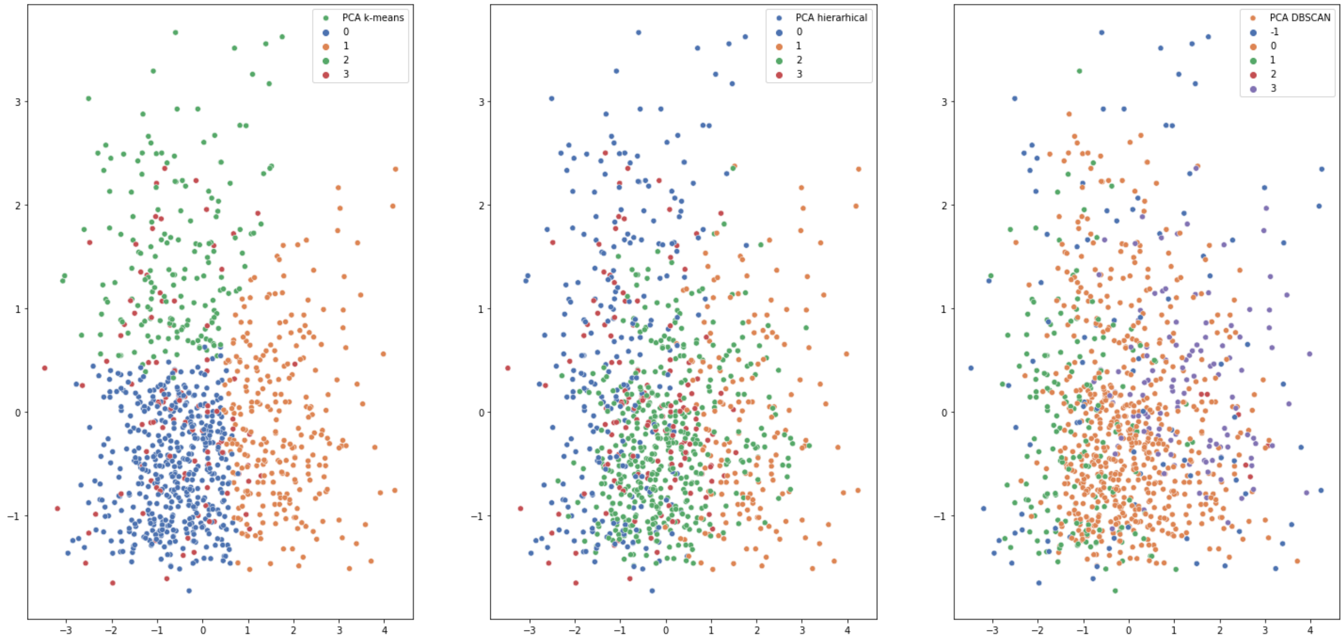
наверно мало объясним информации методом PCA (на 2 мерном пространстве потеряем большую часть информации)

```
x_new = PCA(n_components=2).fit_transform(df)
x_new.shape
```

```
(1000, 2)
```

```
f, axs = plt.subplots(1,3,figsize=(25,12))
plt.subplot(1, 3, 1)
sns.scatterplot(x=x_new[:, 0], y=x_new[:, 1], hue=labels_k.astype(int),palette= 'deep',legend
plt.subplot(1, 3, 2)
sns.scatterplot(x=x_new[:, 0], y=x_new[:, 1], hue=labels_a.astype(int),palette= 'deep',legend
plt.subplot(1, 3, 3)
sns.scatterplot(x=x_new[:, 0], y=x_new[:, 1], hue=labels_d.astype(int),palette= 'deep',legend
```

```
<matplotlib.legend.Legend at 0x7f97f455d6d0>
```

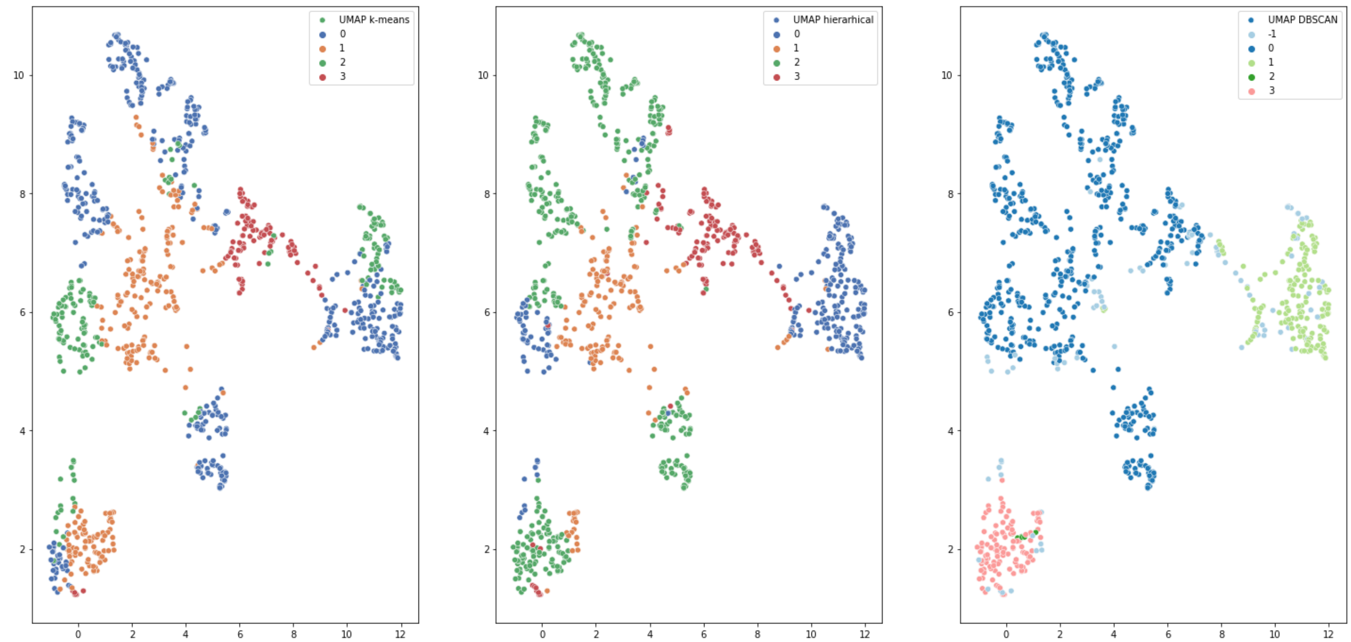


UMAP

```
reducer = umap.UMAP(random_state=2021)
X_UMAP = reducer.fit_transform(df)
```

```
f, axs = plt.subplots(1,3,figsize=(25,12))
plt.subplot(1, 3, 1)
sns.scatterplot(x=X_UMAP[:, 0], y=X_UMAP[:, 1], hue=labels_k.astype(int),palette= 'deep',lege
plt.subplot(1, 3, 2)
sns.scatterplot(x=X_UMAP[:, 0], y=X_UMAP[:, 1], hue=labels_a.astype(int),palette= 'deep',lege
plt.subplot(1, 3, 3)
sns.scatterplot(x=X_UMAP[:, 0], y=X_UMAP[:, 1], hue=labels_d.astype(int),palette= 'Paired',le
```

```
<matplotlib.legend.Legend at 0x7f97f4cffe50>
```



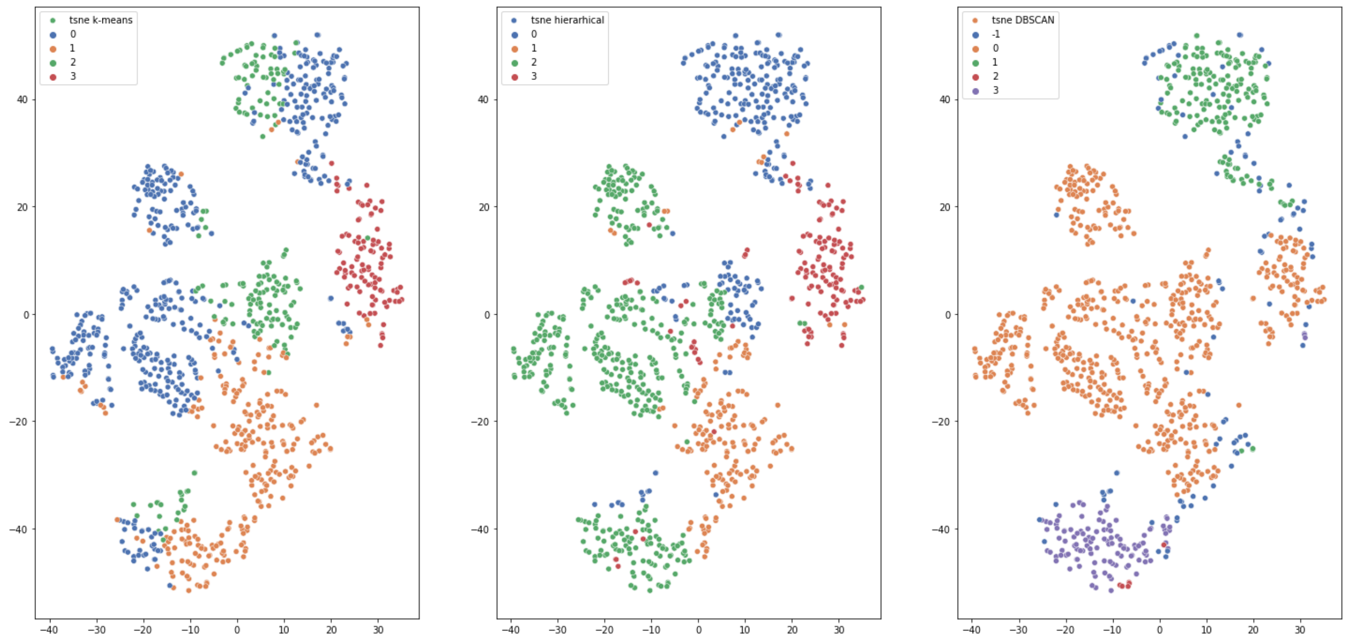
t-SNE

```
tsne = TSNE(n_components=2, random_state=2021)
```

```
X_tsne = tsne.fit_transform(df)
```

```
f, axs = plt.subplots(1,3,figsize=(25,12))
plt.subplot(1, 3, 1)
sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=labels_k.astype(int),palette= 'deep',lege
plt.subplot(1, 3, 2)
sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=labels_a.astype(int),palette= 'deep',lege
plt.subplot(1, 3, 3)
sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=labels_d.astype(int),palette= 'deep',lege
```

```
<matplotlib.legend.Legend at 0x7f97f2982a90>
```



методом PCA хорошо визуализируется k-means

методом UMAP хорошо визуализируется иерархическая и DBSCAN

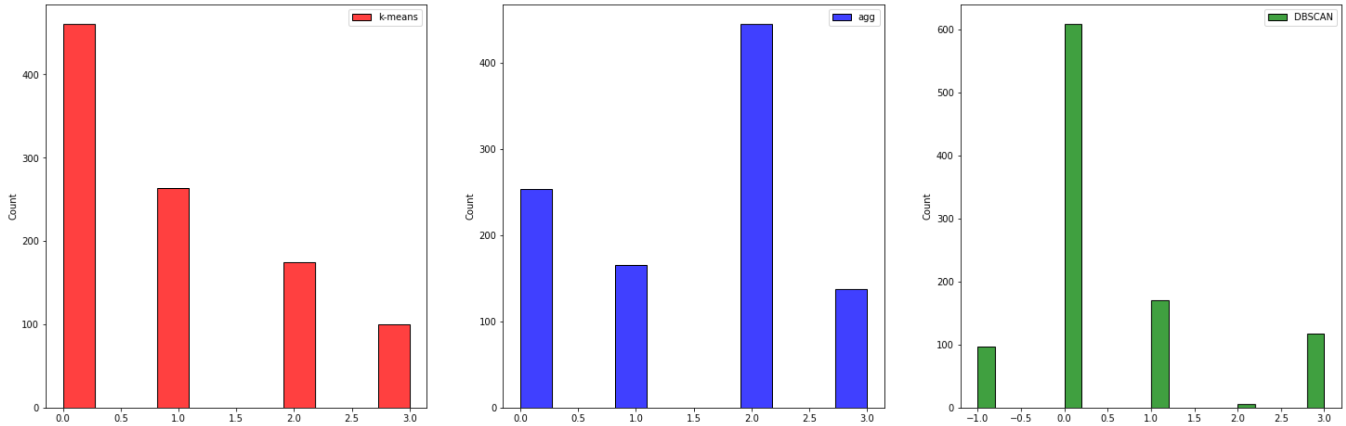
методом t-SNE хорошо визуализируется иерархическая кластеризация

Часть 3. Интерпретация

размеры кластеров в зависимости от метода кластеризации

```
f, axs = plt.subplots(1,3,figsize=(25,8))
plt.subplot(1, 3, 1)
sns.histplot(x=labels_k, label = 'k-means', color = 'red').legend()
plt.subplot(1, 3, 2)
sns.histplot(x=labels_a, label = 'agg', color = 'blue').legend()
plt.subplot(1, 3, 3)
sns.histplot(x=labels_d, label = 'DBSCAN', color = 'green').legend()
```

```
<matplotlib.legend.Legend at 0x7f97f2c98bd0>
```



chtlybt

```
data['labels_k'] = labels_k
data['labels_a'] = labels_a
data['labels_d'] = labels_d
df['labels_d'] = labels_d
```

```
data.groupby('labels_k').mean().T.round(2)
```

labels_k	0	1	2	3
Age	29.39	34.75	52.82	35.78
Job	1.77	2.26	1.76	1.85
Credit amount	2006.53	6444.50	2393.59	2260.19

```
data.groupby('labels_a').mean().T.round(2)
```

labels_a	0	1	2	3
Age	42.72	36.07	31.30	35.47
Job	1.27	1.99	2.23	1.91
Credit amount	2083.25	6865.34	2901.16	2338.69
Duration	15.17	40.12	18.00	17.77
labels_k	0.98	1.03	0.41	2.30
labels_d	0.49	0.09	0.66	0.07

Проинтерпретируем метод DBSCAN (хорошо провизуализировался методом t-sne и UMAP)

```
data.groupby('labels_d').mean().T.round(2)
```

labels_d	-1	0	1	2	3
Age	43.69	34.02	35.83	32.50	36.46
Job	1.48	2.00	1.00	3.00	3.00
Credit amount	4504.53	2977.12	2148.01	7831.00	5161.92
Duration	26.11	20.95	15.01	33.33	24.25
labels_k	1.63	0.87	0.66	1.00	0.91
labels_a	1.06	1.80	0.19	1.83	1.91

```
df.groupby('labels_d').mean().T.round(2)
```

labels_d	-1	0	1	2	3
Age	0.72	-0.13	0.02	-0.27	0.08
Job	-0.64	0.15	-1.38	1.68	1.68
Saving accounts	0.98	0.38	0.18	0.50	0.12

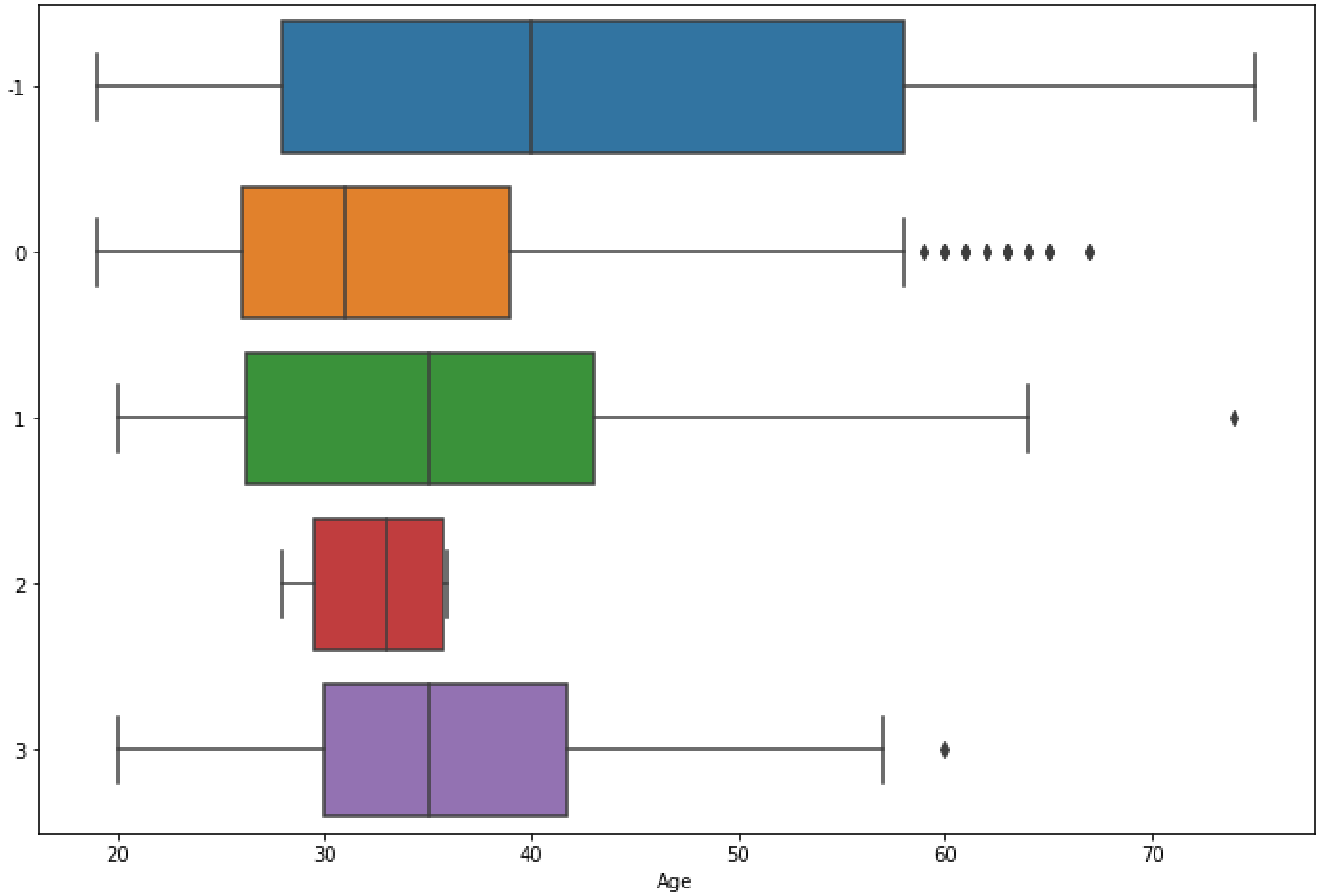
```
data.labels_d.value_counts()
```

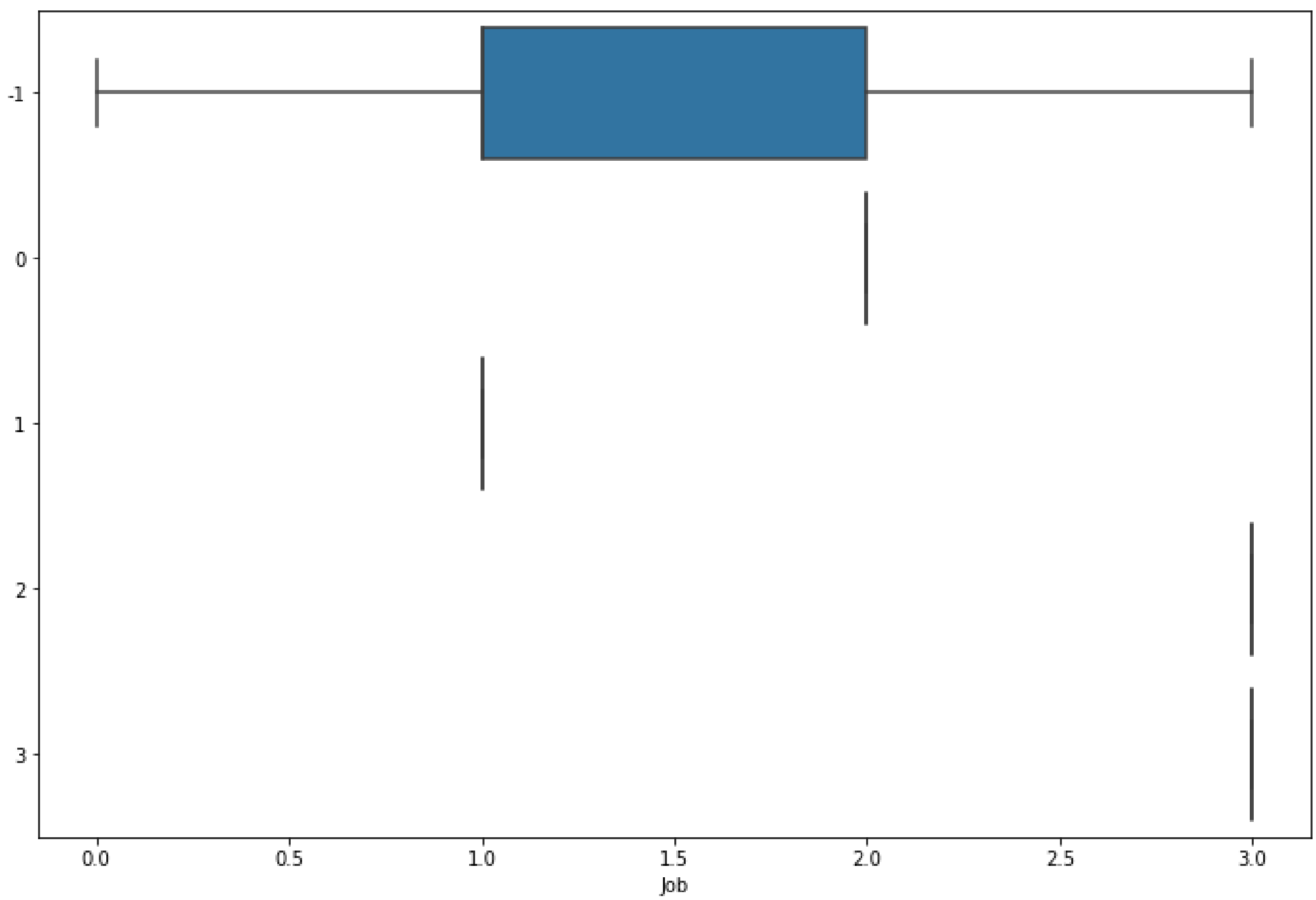
```
 0    609
 1    170
 3    118
-1     97
 2      6
Name: labels_d, dtype: int64
```

Housing_own	0.53	0.73	0.80	0.00	0.67

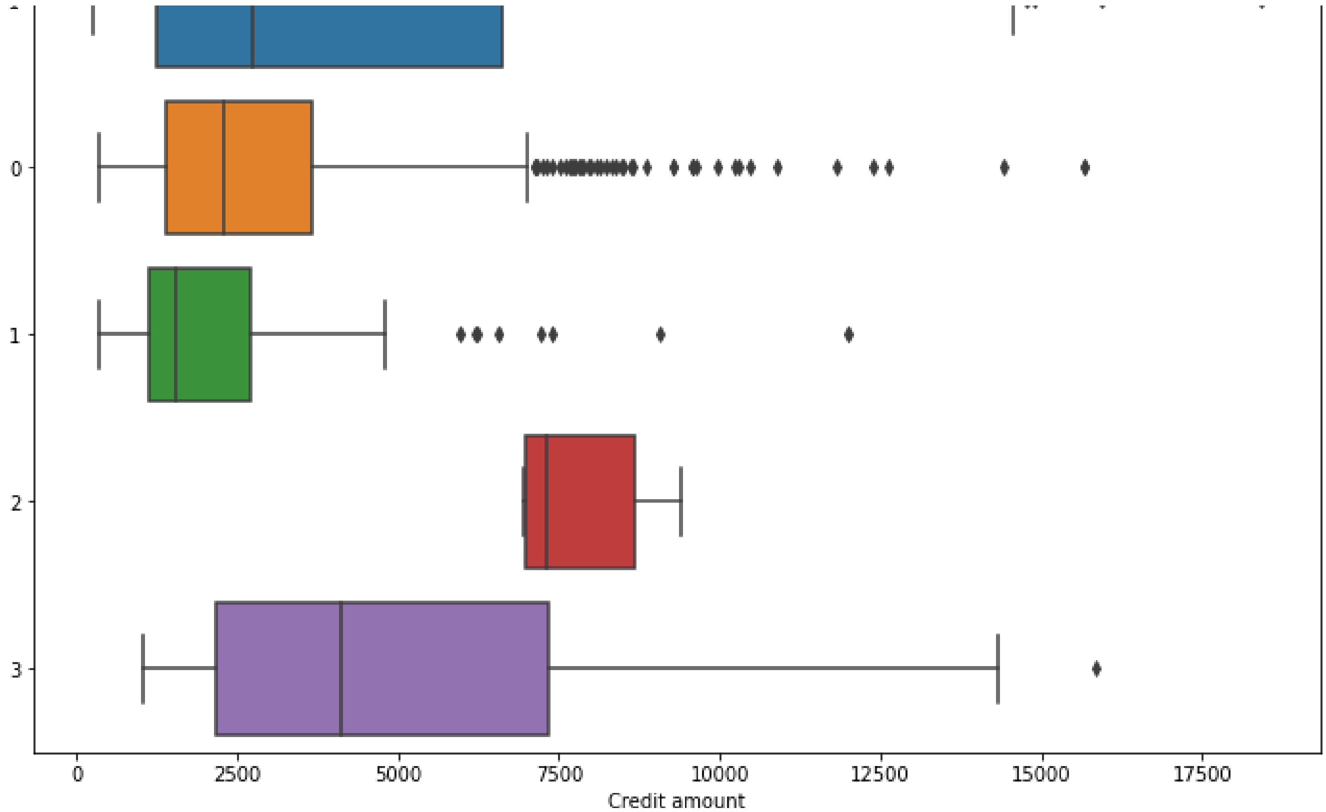
второй кластер получился очень маленьким, посмотрим на box-plot-ы

```
for col in ['Age', 'Job', 'Credit amount', 'Duration']:
    sns.boxplot(data=data, x=col, y=labels_d, orient = 'h')
    plt.show();
```


-1
0
1
2
3
20
30
40
50
60
70
Age


-1
0
1
2
3
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Job


-1

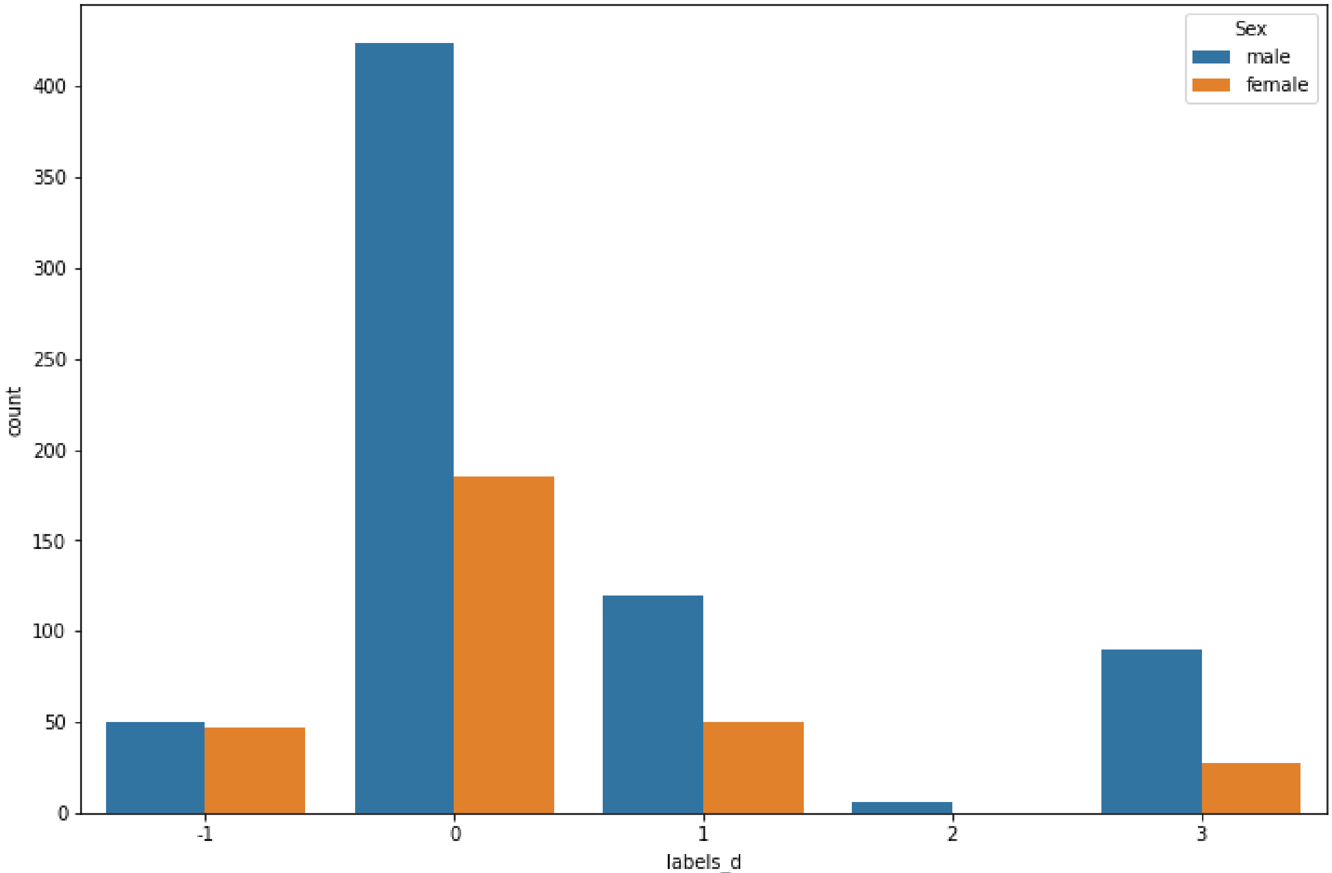


```
sns.boxplot(data=data, x='Saving accounts', y=labels_d)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f97f2861850>
```

```
sns.countplot(data = data, x= 'labels_d', hue = 'Sex')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f97f516b450>
```

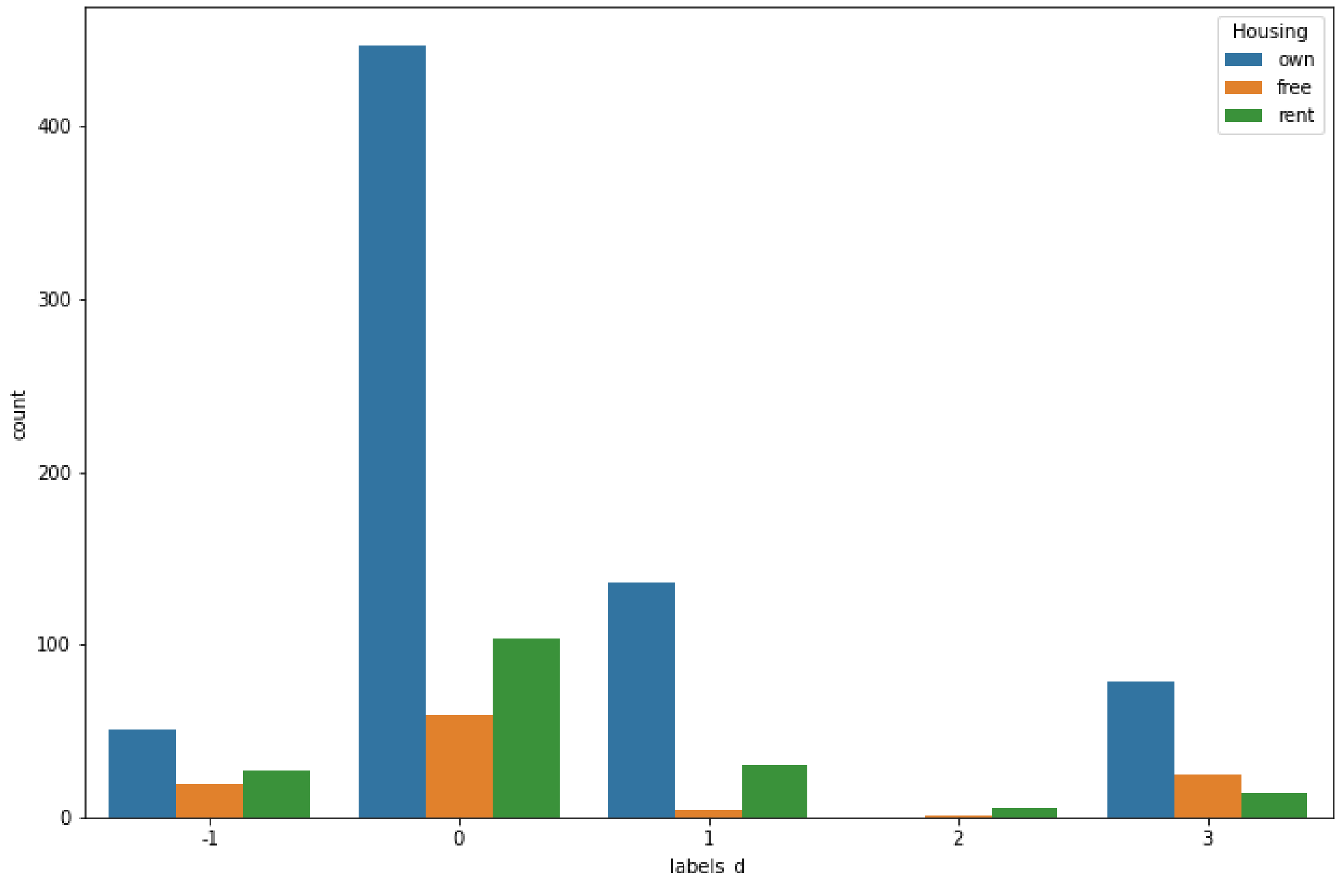



```
sns.countplot(data = data, x= 'labels_d', hue = 'Job')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f97f4d63ed0>

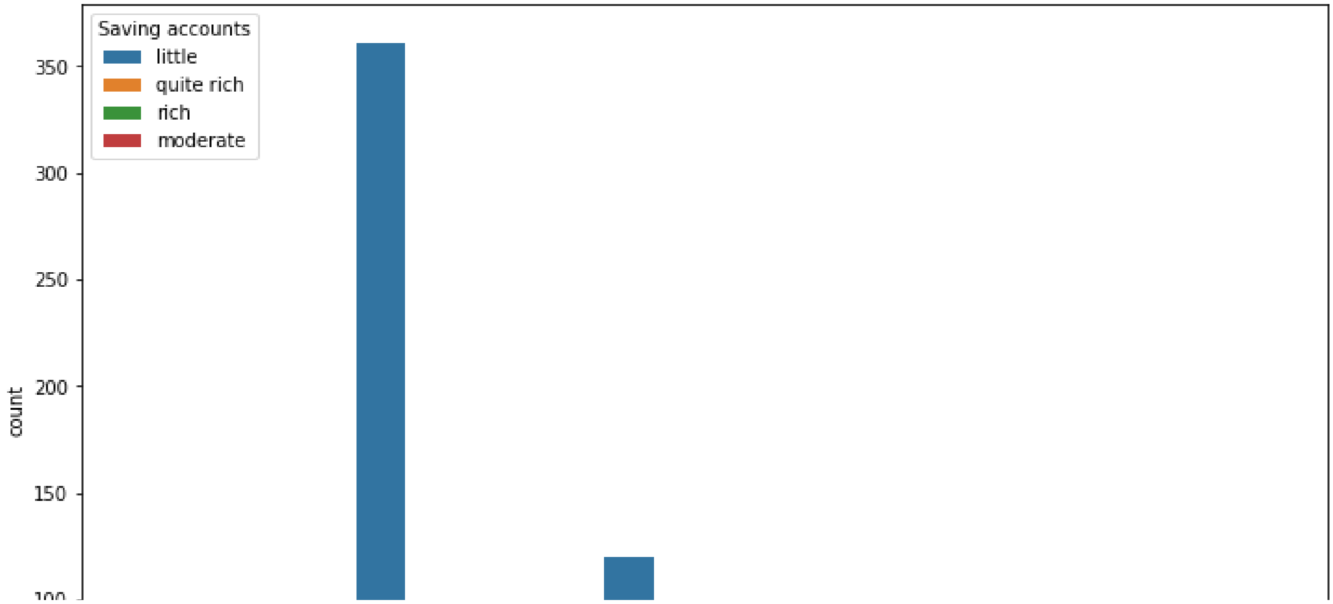

```
sns.countplot(data = data, x= 'labels_d', hue = 'Housing')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f97f4e23f10>



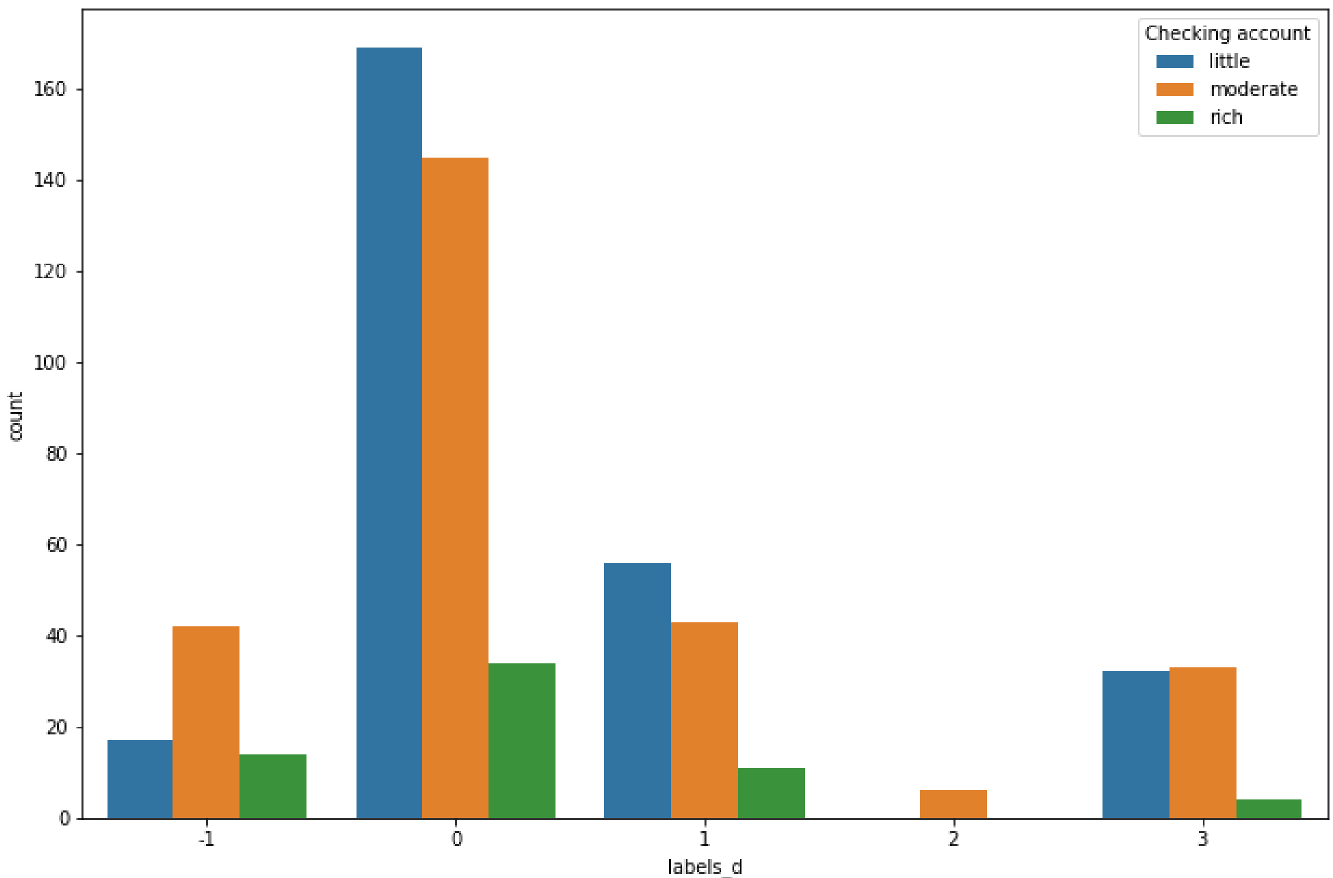

```
sns.countplot(data = data, x= 'labels_d', hue = 'Saving accounts')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f97f504d550>
```



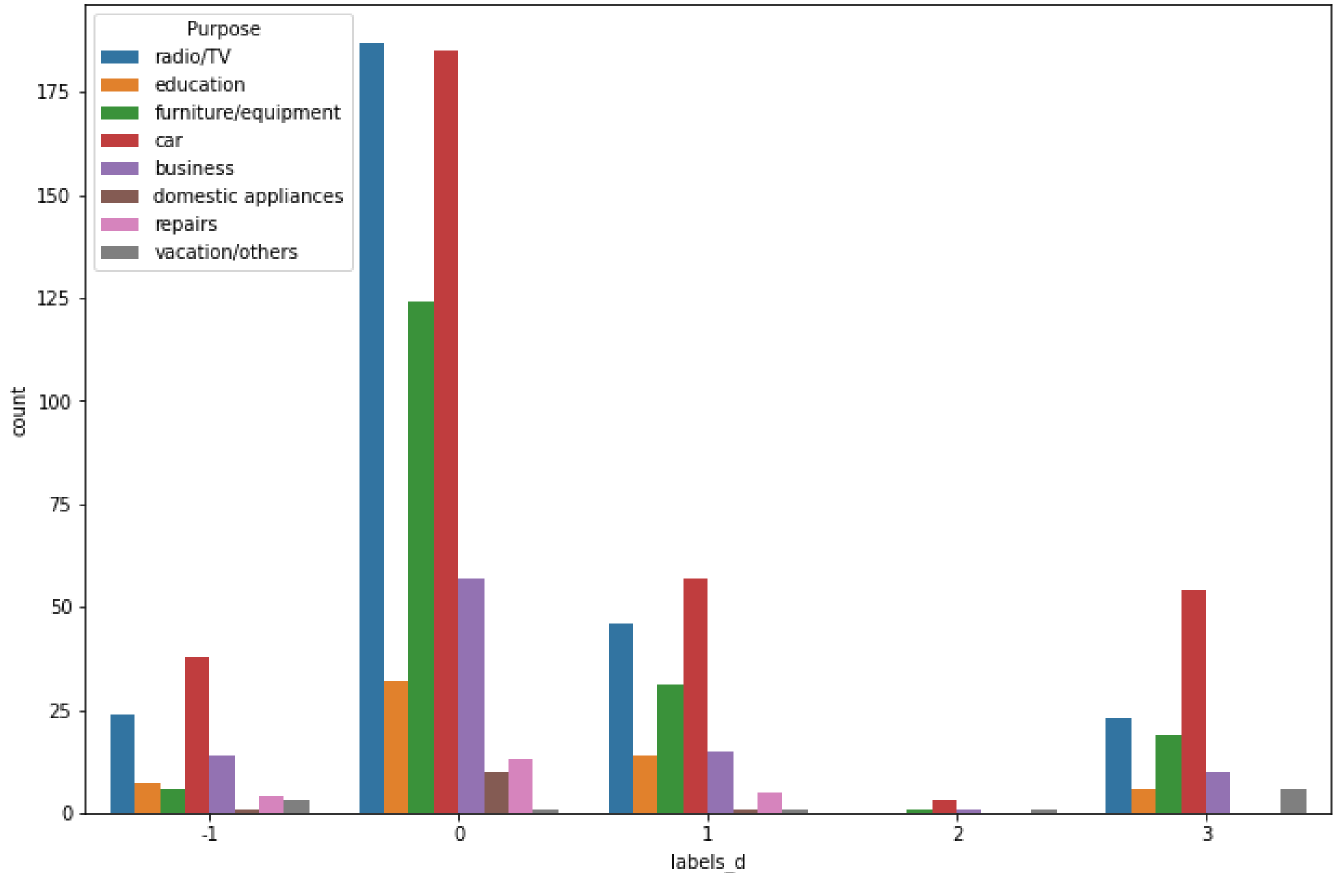

```
sns.countplot(data = data, x= 'labels_d', hue = 'Checking account')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f97f1bd8c10>
```




```
sns.countplot(data = data, x= 'labels_d', hue = 'Purpose')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f97f1b74290>
```




```
data.head()
```

	Age	Sex	Job	Housing	Saving accounts	Checking account	Credit amount	Duration	Purpose	lal
0	67	male	2	own	NaN	little	1169	6	radio/TV	
1	22	female	2	own	little	moderate	5951	48	radio/TV	
2	49	male	1	own	little	NaN	2096	12	education	
3	45	male	2	free	little	little	7882	42	furniture/equipment	
4	53	male	2	free	little	little	4870	24	car	

```
data[data['labels_d'] == 2]
```

Saving Checking Credit

```
df.groupby('labels_d').mean().T.round(2)
```

labels_d	-1	0	1	2	3
Age	0.72	-0.13	0.02	-0.27	0.08
Job	-0.64	0.15	-1.38	1.68	1.68
Saving accounts	0.98	0.38	0.18	0.50	0.12
Checking account	0.72	0.35	0.38	1.00	0.35
Credit amount	0.18	-0.04	-0.46	1.51	0.67
Duration	0.43	0.00	-0.49	1.03	0.28
Purpose	0.23	0.24	0.24	0.22	0.25
Sex_male	0.52	0.70	0.71	1.00	0.76
Housing_own	0.53	0.73	0.80	0.00	0.67
Housing_rent	0.28	0.17	0.18	0.83	0.12

в нашем самом маленьком кластере - мужчины с хорошей работой, высоким кредито, и дом - который в аренде

- возраст - сложно проинтерпретировать, возрастная категория у наших кластеров +-
- пол - во втором маленьком кластере нет женгщин
- Housing - в 0 кластере много клиентов с Housing free (видимо беспл жилье)
- Saving accounts - все богатые сконцентрировались в 0 кластере
- Credit amount - 2 группа берет больше всего денег, следующая по рангу - 3 группа, причем в 3 группе много "бедных"
- Duration - 2 группа берет кредит на больше всего месяцев, 3 группа бедных на 2ом месте
- Цели - на первый взгляд распределены равномерно, учитывая неравномерность распределения целей

Итого можно охарактеризовать группы:

1 - с плохой работой (наибольшие риски)

2 - с хорошей работой, с хорошим счетом, долгим сроком погашения, и большой суммой кредита (похожа на группу 3)

3 - с хорошей работой