Data mining - assignment 5 (2 attestation)

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Assignment for second attestation (Unsupervised, 50%):

1. Explore the dataset. Do the descriptive statistics.
2. Explanatory data analysis. Exploring the features, visualizations etc. (https:// www.kaggle.com/learn/data-visualization (http://www.kaggle.com/learn/data-visualization), https://towardsdatascience.com/ (https://towardsdatascience.com/) exploratory-data-analysis-8fc1cb20fd15, https://www.mastersindatascience.org/ (https://www.mastersindatascience.org/) learning/what-is-exploratory-data-analysis/)
3. Feature engineering. Encodings, generating the features from date-time, sum and from other columns. (https://www.kaggle.com/learn/feature-engineering (https://www.kaggle.com/learn/feature-engineering), https:// www.kaggle.com/learn/data-cleaning (http://www.kaggle.com/learn/data-cleaning))
4. Unsupervised learning. Do the Cluster analysis. Segment the customers. K-means, Hierarchical Clustering. With different metrics, linkages. Visualize the clusters etc. Look for the optimal number of the clusters
5. Analyzing the results.
6. Conclusion.

Dataset Description:

- types.csv - reference of transaction types
- codes.csv - reference of transaction codes
- transactions.csv - transactional data on banking operations
- train_set.csv - training set with client gender marking (0/1 - client gender)
- test_set.csv - no need to use.

Transactions.csv columns description:

- client_id - client is id
- datetime -transaction date (format - ordered day number hh:mm:ss - 421 06:33:15)
- code - transaction code
- type - transaction type
- sum - sum of transaction

In [35]:

```
import datetime
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import scipy.cluster.hierarchy as model
from sklearn.metrics import silhouette_score
from sklearn.cluster import AgglomerativeClustering
from sklearn.preprocessing import StandardScaler, normalize
```

In [3]:

```
types = pd.read_csv('types.csv', sep = ';')
codes = pd.read_csv('codes.csv', sep = ';')
transactions = pd.read_csv('transactions.csv', sep = ';')
train_set = pd.read_csv('train_set.csv', sep = ';')
test_set = pd.read_csv('test_set.csv', sep = ';')
```

Descriptive Analysis

In [4]:

```
types.describe(include = 'all').T
```

Out[4]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	ma
type	155	NaN	NaN	NaN	10819	80000.3	1000	2385.5	4040	7027.5	99999
type_description	155	139	н/д	13	NaN	NaN	NaN	NaN	NaN	NaN	Nal

In [5]:

```
codes.describe(include = 'all').T
```

Out[5]:

	count	unique	top	freq	mean	std	min	25%	5
code	184	NaN	NaN	NaN	6046.79	1470.33	742	5208.25	581
code_description	184	184	Магазины фотооборудования и фотоприборов	1	NaN	NaN	NaN	NaN	N

In [6]:

```
transactions.describe(include = 'all').T
# mean value of sum(-18129.1) is less than median value(-5502.49)
# also we have very big difference between max value and 75%tile, it means that most of our
```

Out[6]:

	count	unique	top	freq	mean	std	min	25%
client_id	130039	NaN	NaN	NaN	5.08686e+07	2.87285e+07	22899	2.57717e+07
datetime	130039	114770	456 00:00:00	60	NaN	NaN	NaN	NaN
code	130039	NaN	NaN	NaN	5594.63	606.087	742	5211
type	130039	NaN	NaN	NaN	2489.37	2253.3	1000	1030
sum	130039	NaN	NaN	NaN	-18129.1	558445	-4.15003e+07	-22449.2

In [7]:

```
df = pd.merge(pd.merge(transactions, types), codes)
df.head()
```

Out[7]:

	client_id	datetime	code	type	sum	type_description	code_description
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
1	21717441	55 13:38:47	6011	2010	-44918.32	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
2	14331004	263 12:57:08	6011	2010	-3368873.66	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
3	2444292	355 09:47:45	6011	2010	-65131.56	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
4	2132533	184 20:09:07	6011	2010	-224591.58	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...

In [8]:

```
df.mode()
```

Out[8]:

	client_id	datetime	code	type	sum	type_description	code_description
0	70780820	456 00:00:00	6011	1010	-2245.92	Покупка. POS	Финансовые институты — снятие наличности автом...

In [9]:

```
print('Range:', max(transactions['sum']) - min(transactions['sum'])) # Measures of spread
print('IQR:', transactions['sum'].quantile(0.75) - transactions['sum'].quantile(0.25))
print('Variance:', transactions['sum'].var())
print('Standart deviation:',  transactions['sum'].std())
```

```
Range: 108877774.3
IQR: 21326.2
Variance: 311860284637.53296
Standart deviation: 558444.5224348905
```

Explanatory Data Analysis

In [10]:

```
df.shape
# Dataset comprises of 129998 observations and 7 characteristics
```

Out[10]:

```
(129998, 7)
```

In [11]:

```
df.columns
```

Out[11]:

```
Index(['client_id', 'datetime', 'code', 'type', 'sum', 'type_description',
       'code_description'],
      dtype='object')
```

In [12]:

```
df.nunique() # number of unique values for every column
```

Out[12]:

```
client_id              8656
datetime             114752
code                    175
type                     63
sum                   27446
type_description         57
code_description        175
dtype: int64
```

In [13]:

```
df.info()
# our data have integer, float and object values, object values used for datetime and text
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 129998 entries, 0 to 129997
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   client_id         129998 non-null  int64  
 1   datetime          129998 non-null  object 
 2   code              129998 non-null  int64  
 3   type              129998 non-null  int64  
 4   sum               129998 non-null  float64
 5   type_description  129998 non-null  object 
 6   code_description  129998 non-null  object 
dtypes: float64(1), int64(3), object(3)
memory usage: 7.9+ MB
```

In [14]:

```
df.isna().any()
# as we can see we have no null/missing values, so we dont need to delete them
```

Out[14]:

```
client_id           False
datetime            False
code                False
type                False
sum                 False
type_description    False
code_description    False
dtype: bool
```

In [15]:

```
clients = np.array(df['client_id'].unique())
len(clients) # number of unique clients
```

Out[15]:

```
8656
```

In [16]:

```
df.drop_duplicates(inplace = True)
df.shape
# shape of dataframe before deleting dublicates = (129998, 7)
# 129998-129969 = 29 rows was deleted
```

Out[16]:

```
(129969, 7)
```

In [17]:

```
df_sales = df.loc[df.type.isin([1000, 1100, 1110, 1010, 1210, 1200])]
df_sales # dataframe consist only sales type of transactions
```

Out[17]:

	client_id	datetime	code	type	sum	type_description	code_description
46278	90641486	175 15:29:58	4814	1110	-3279.04	Покупка. POS	Звонки с использованием телефонов, считывающих...
46279	45885513	291 08:44:26	4814	1110	-15496.82	Покупка. POS	Звонки с использованием телефонов, считывающих...
46280	95394912	325 00:00:00	4814	1110	-27849.36	Покупка. POS	Звонки с использованием телефонов, считывающих...
46281	89637426	335 07:59:09	4814	1110	-10960.07	Покупка. POS	Звонки с использованием телефонов, считывающих...
46282	84199917	379 00:00:00	4814	1110	-4581.67	Покупка. POS	Звонки с использованием телефонов, считывающих...
...	...	...	...	...	...	...	...
129993	51907756	136 00:00:00	4131	1200	-146433.71	Покупка. Зарубеж.	Автобусные линии
129994	61978280	401 00:00:00	5169	1200	-271194.78	Покупка. Зарубеж.	Химикалии и смежные вещества, не классифициров...
129995	97803699	371 19:47:00	6513	1210	-60792.00	Покупка. POS Зарубеж.	Агенты и менеджеры по аренде недвижимости
129996	63953233	15 00:00:00	4411	1210	-77535.30	Покупка. POS Зарубеж.	Круизные линии
129997	31009144	81 17:32:60	4411	1210	-904166.84	Покупка. POS Зарубеж.	Круизные линии

52842 rows × 7 columns

In [18]:

```
df_sum_positive = df[df['sum'] > 0]
df_sum_positive.head() # positive sum of transactions
```

Out[18]:

	client_id	datetime	code	type	sum	type_description	code_description
15758	69189450	389 00:00:00	6011	2010	44918.32	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
20204	24567813	377 17:20:40	6011	7010	67377.47	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...
20205	82840746	454 18:49:24	6011	7010	134754.95	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...
20206	74334566	187 16:36:30	6011	7010	134754.95	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...
20207	49760703	94 18:56:40	6011	7010	22459.16	Взнос наличных через АТМ (в своем тер.банке)	Финансовые институты — снятие наличности автом...

In [19]:

```
df_sum_negative = df[df['sum'] < 0]
df_sum_negative.head() # negative sum of transactions
```

Out[19]:

	client_id	datetime	code	type	sum	type_description	code_description
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
1	21717441	55 13:38:47	6011	2010	-44918.32	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
2	14331004	263 12:57:08	6011	2010	-3368873.66	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
3	2444292	355 09:47:45	6011	2010	-65131.56	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...
4	2132533	184 20:09:07	6011	2010	-224591.58	Выдача наличных в АТМ	Финансовые институты — снятие наличности автом...

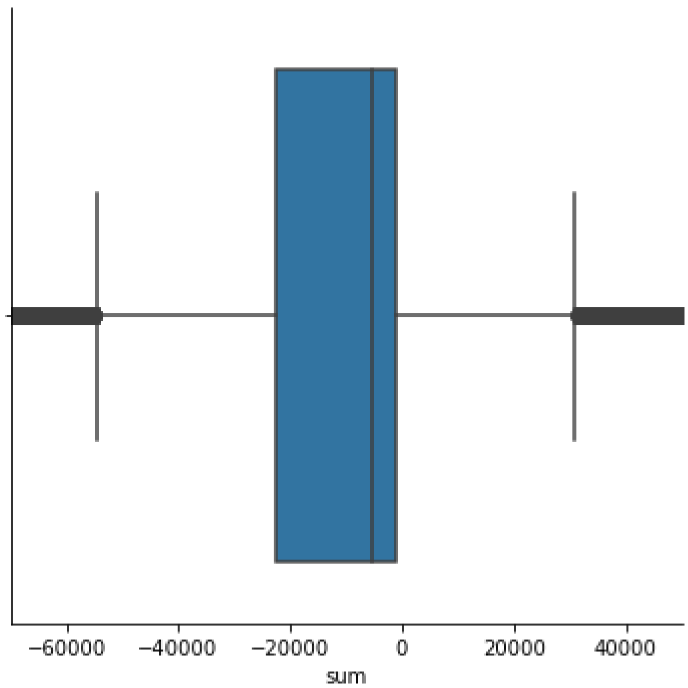
Visualizations

In [20]:

```
# Realtionship analysis based on correlation matrix
correlation = df.corr()
sns.heatmap(correlation, xticklabels = correlation.columns, yticklabels = correlation.colum
plt.show()
# the higher correlation coefficient between type and code
# type of transaction has the greatest influence on sum
```

In [21]:

```
# box plot
sns.catplot(x = 'sum', kind = 'box', data = df)
plt.xlim(-70000, 50000)
plt.show()
```

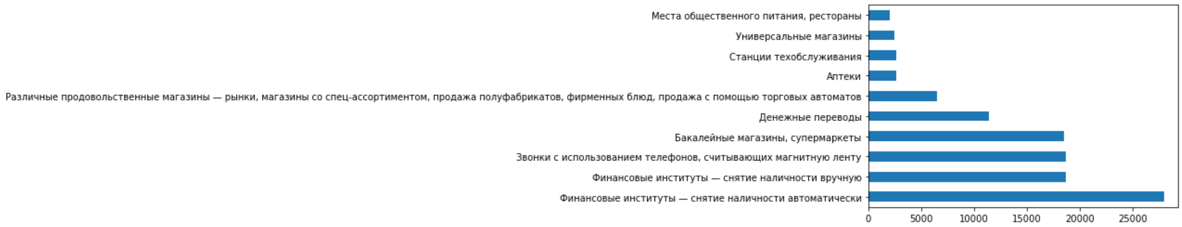


In [22]:

```
# graphs show Top 10 codes of transactions
df['code_description'].value_counts()[0:10].plot.barh()
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2551f5ce520>
```

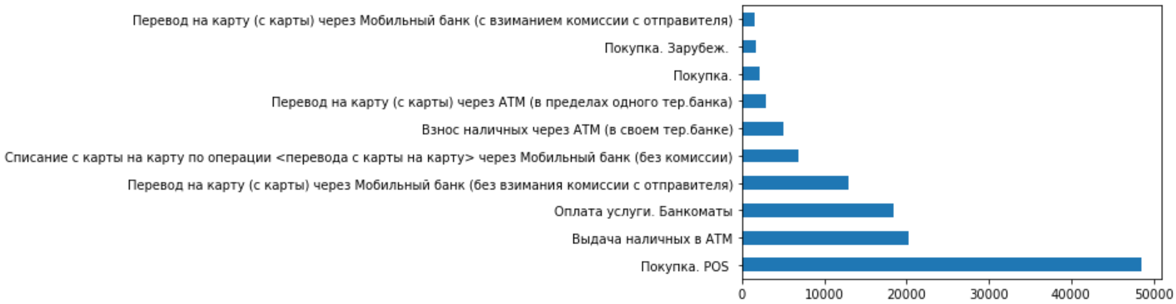


In [23]:

```
# graphs show Top 10 types of transactions
df['type_description'].value_counts()[0:10].plot.barh()
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2551db64280>
```



Feature engineering and Data cleaning

In [24]:

```
# divide datetime column to date and time columns
df[['day', 'time']] = df['datetime'].str.split(' ', expand = True)
df[['hour', 'minute','second']] = df['time'].str.split(':', expand=True)
```

In [25]:

```
df.head()
```

Out[25]:

	client_id	datetime	code	type	sum	type_description	code_description	day	ti
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	421	06:33
1	21717441	55 13:38:47	6011	2010	-44918.32	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	55	13:38
2	14331004	263 12:57:08	6011	2010	-3368873.66	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	263	12:57
3	2444292	355 09:47:45	6011	2010	-65131.56	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	355	09:47
4	2132533	184 20:09:07	6011	2010	-224591.58	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	184	20:09

In [26]:

```
# change types of columns to int
df = df.astype({'day': int})
df = df.astype({'hour': int})
df = df.astype({'minute': int})
df = df.astype({'second': int})
```

In [27]:

```
df['day'].max() # find number of dates in database
```

Out[27]:

456

In [28]:

```
date = datetime.datetime(2021, 1, 1) # start date is 1 january of 2021
step = datetime.timedelta(days = 1)
dates = {} # dictionary will store the serial number of the date and date
date_list = []
for i in range(0, 457):
    dates[i] = date.strftime('%Y-%m-%d')
    date += step

for i in df['day']:
    date_list.append(dates[i])
#new column date
df['date'] = date_list
df
```

Out[28]:

	client_id	datetime	code	type	sum	type_description	code_description	day
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	421
1	21717441	55 13:38:47	6011	2010	-44918.32	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	55
2	14331004	263 12:57:08	6011	2010	-3368873.66	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	263
3	2444292	355 09:47:45	6011	2010	-65131.56	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	355
4	2132533	184 20:09:07	6011	2010	-224591.58	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	184
...	...	...	...	...	...	...	...	...
129993	51907756	136 00:00:00	4131	1200	-146433.71	Покупка. Зарубеж.	Автобусные линии	136
129994	61978280	401 00:00:00	5169	1200	-271194.78	Покупка. Зарубеж.	Химикалии и смежные вещества, не классифициров...	401
129995	97803699	371 19:47:00	6513	1210	-60792.00	Покупка. POS Зарубеж.	Агенты и менеджеры по аренде недвижимости	371
129996	63953233	15 00:00:00	4411	1210	-77535.30	Покупка. POS Зарубеж.	Круизные линии	15
129997	31009144	81 17:32:60	4411	1210	-904166.84	Покупка. POS Зарубеж.	Круизные линии	81

129969 rows × 13 columns

In [29]:

```
def f(x):
    if (x > 4) and (x <= 8):
        return 'Early Morning'
    elif (x > 8) and (x <= 12 ):
        return 'Morning'
    elif (x > 12) and (x <= 16):
        return'Noon'
    elif (x > 16) and (x <= 20) :
        return 'Eve'
    elif (x > 20) and (x <= 23):
        return'Night'
    elif (x <= 4):
        return'Late Night'
```

In [30]:

```
# new column sessions
df['sessions'] = df['hour'].apply(f)
df
```

Out[30]:

	client_id	datetime	code	type	sum	type_description	code_description	day
0	96372458	421 06:33:15	6011	2010	-561478.94	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	421
1	21717441	55 13:38:47	6011	2010	-44918.32	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	55
2	14331004	263 12:57:08	6011	2010	-3368873.66	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	263
3	2444292	355 09:47:45	6011	2010	-65131.56	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	355
4	2132533	184 20:09:07	6011	2010	-224591.58	Выдача наличных в ATM	Финансовые институты — снятие наличности автом...	184
...	...	...	...	...	...	...	...	...
129993	51907756	136 00:00:00	4131	1200	-146433.71	Покупка. Зарубеж.	Автобусные линии	136
129994	61978280	401 00:00:00	5169	1200	-271194.78	Покупка. Зарубеж.	Химикалии и смежные вещества, не классифициров...	401
129995	97803699	371 19:47:00	6513	1210	-60792.00	Покупка. POS Зарубеж.	Агенты и менеджеры по аренде недвижимости	371
129996	63953233	15 00:00:00	4411	1210	-77535.30	Покупка. POS Зарубеж.	Круизные линии	15
129997	31009144	81 17:32:60	4411	1210	-904166.84	Покупка. POS Зарубеж.	Круизные линии	81

129969 rows × 14 columns

Having studied the data set, we found out that there are still rows in the types that do not carry informational significance, namely, there were several rows without a description.

In [31]:

```
types.loc[types['type_description'].isin(['н/д(нет данных)','н/д']),['type_description']] =
types.head()
```

Out[31]:

	type	type_description
0	8001	Установление расх. лимита по карте
1	2411	Перевод с карты на счет др.лица в одном тер. б...
2	4035	NaN
3	3001	Комиссия за обслуживание ссудного счета
4	2420	Перевод с карты на счет физ.лица в другом тер....

In [32]:

```
# setting monetary
transcactions_sum = transactions.groupby('client_id').sum().drop(columns = ['code','type'])
# setting frequency
transcactions_count = aggregated_1 = transactions.groupby('client_id').count().drop(columns
transcactions_sum_count = pd.concat([transcactions_sum, transcactions_count], axis=1, join
transcactions_sum_count.head()
```

Out[32]:

	sum	count_transactions
client_id		
22899	50847.54	9
27914	74115.21	4
28753	-2589800.29	13
31385	-83525.38	13
38084	693495.66	26

In [33]:

```
#scoring functions
def FMScore(x, p, d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1
```

In [34]:

```
fm_table = transcactions_sum_count
quantiles = fm_table.quantile(q = [0.25, 0.5, 0.75])
quantiles = quantiles.to_dict()
#setting score
# calculate frequence and monetary quantiles
fm_table['f_quartile'] = fm_table['count_transactions'].apply(FMScore, args = ('count_trans
fm_table['m_quartile'] = fm_table['sum'].apply(FMScore, args = ('sum', quantiles,))
fm_table.head()
```

Out[34]:

client_id	sum	count_transactions	f_quartile	m_quartile
22899	50847.54	9	3	1
27914	74115.21	4	4	1
28753	-2589800.29	13	2	4
31385	-83525.38	13	2	2
38084	693495.66	26	1	1

In [36]:

```
time = transactions.drop(columns = ['code', 'type'])
time['day_number'] = transactions['datetime'].str[:3]
time['time'] = transactions['datetime'].str[-8:].str[:2]
time['time'] = time['time'].astype(int)
time.head()
```

Out[36]:

	client_id	datetime	sum	day_number	time
0	96372458	421 06:33:15	-561478.94	421	6
1	24567813	377 17:20:40	67377.47	377	17
2	21717441	55 13:38:47	-44918.32	55	13
3	14331004	263 12:57:08	-3368873.66	263	12
4	85302434	151 10:34:12	-3368.87	151	10

In [37]:

```
# finding the type and code mode for each client
buffer = transactions.groupby('client_id').agg({'code': lambda x: x.value_counts().index[0]
predictors = pd.concat([transcactions_sum_count, buffer], axis = 1, join = 'outer')
predictors = predictors.rename(columns = {'sum': 'sum_of_transactions', 'code': 'Code_mode'
# change type of columns
predictors['Code_mode'] = predictors['Code_mode'].astype('category')
predictors['Type_mode'] = predictors['Type_mode'].astype('category')
buffer = time.drop(columns = ['sum', 'day_number', 'datetime']).groupby('client_id').mean()
# rename columns
buffer = buffer.rename(columns = {'time': 'hour_mean'})
# merge datasets
predictors = pd.merge(predictors, buffer, on = 'client_id', how = 'left')
train_set = pd.merge(train_set, predictors, on = 'client_id', how = 'left')
predictors.head()
```

Out[37]:

	sum_of_transactions	count_transactions	Code_mode	Type_mode	hour_mean
client_id					
22899	50847.54	9	6011	4010	13.555556
27914	74115.21	4	4814	1030	12.250000
28753	-2589800.29	13	4814	1010	7.000000
31385	-83525.38	13	4814	1030	14.538462
38084	693495.66	26	6011	1010	13.000000

In [38]:

```
# calculating positive, negative and eman transactions
train_set['Transactions_tendency'] = '0'
train_set.loc[train_set['sum_of_transactions'] > 0, 'Transactions_tendency'] = '+'
train_set.loc[train_set['sum_of_transactions'] < 0, 'Transactions_tendency'] = '-'
train_set['Transaction_mean'] = train_set['sum_of_transactions'] / train_set['count_transac
train_set.head()
```

Out[38]:

	client_id	target	sum_of_transactions	count_transactions	Code_mode	Type_mode	hour_m
0	75063019	0	89032.60	29	6011	1010	15.068
1	86227647	1	-606058.60	27	6011	1030	11.222
2	6506523	0	2635753.74	53	6010	7070	13.735
3	50615998	0	-42672.40	7	4814	1030	14.142
4	95213230	0	214292.66	34	4814	1030	9.617

Unsupervised learning. Cluster analysis.

K-means clustering

In [108]:

```
X = df[['code', 'sum', 'type']]
X
```

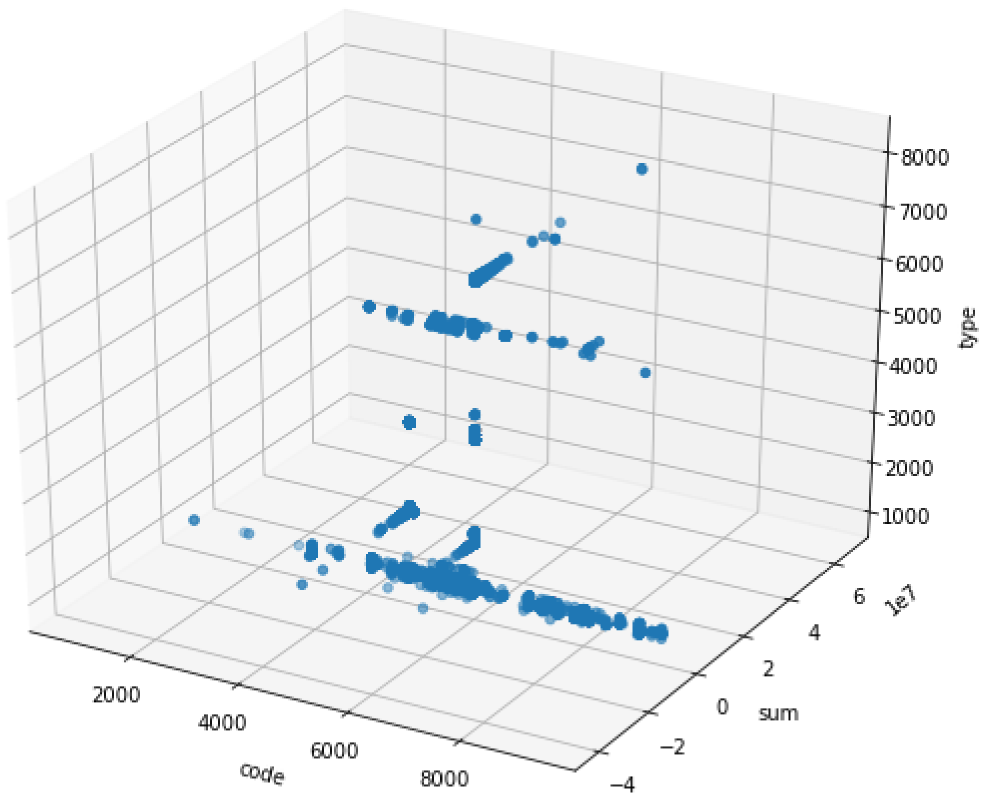
Out[108]:

	code	sum	type
0	6011	-561478.94	2010
1	6011	-44918.32	2010
2	6011	-3368873.66	2010
3	6011	-65131.56	2010
4	6011	-224591.58	2010
...	...	...	...
129993	4131	-146433.71	1200
129994	5169	-271194.78	1200
129995	6513	-60792.00	1210
129996	4411	-77535.30	1210
129997	4411	-904166.84	1210

129969 rows × 3 columns

In [110]:

```
fig = plt.figure(figsize = (10, 8))
ax = plt.axes(projection = '3d')
# plot 3d graph
ax.scatter3D(X.loc[:, 'code'], X.loc[:, 'sum'], X.loc[:, 'type'])
# det labels
ax.set_xlabel('\ncode')
ax.set_ylabel('\nsum')
ax.set_zlabel('\ntype')
plt.show()
```



In [121]:

```
kmeans = KMeans(n_clusters = 4)
kmeans.fit(X)
X1 = X
# show dataset with ading class values
X1['Class'] = kmeans.labels_
X1
```

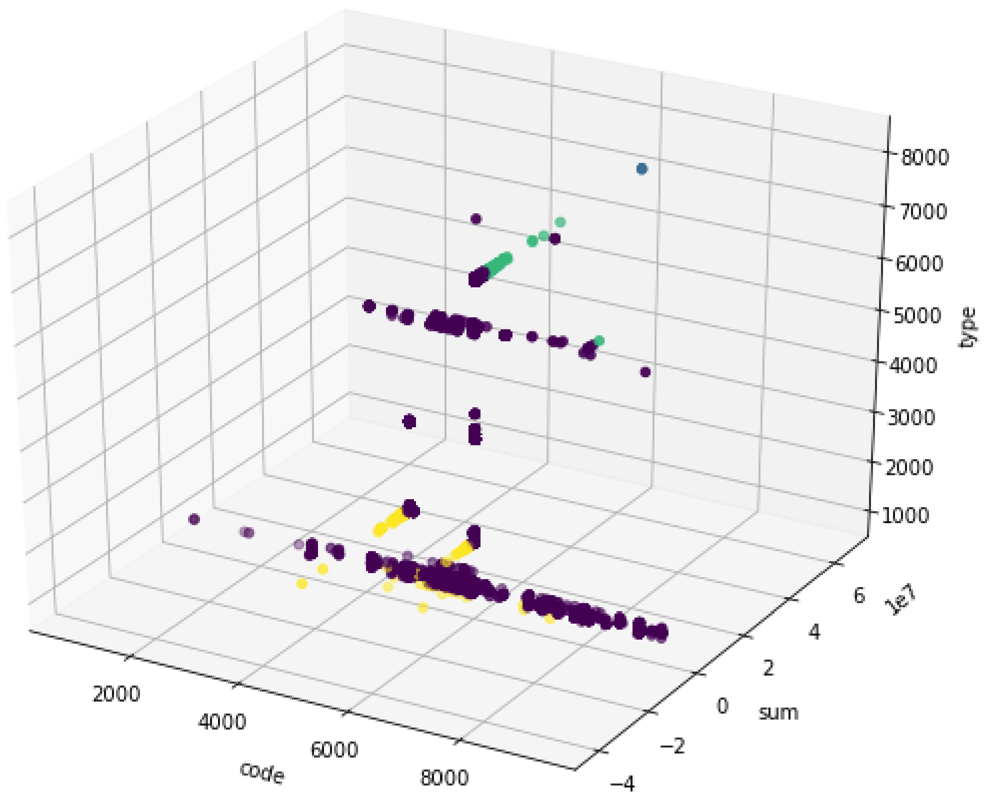
Out[121]:

	code	sum	type	Class
0	6011	-561478.94	2010	0
1	6011	-44918.32	2010	0
2	6011	-3368873.66	2010	2
3	6011	-65131.56	2010	0
4	6011	-224591.58	2010	0
...	...	...	...	...
129993	4131	-146433.71	1200	0
129994	5169	-271194.78	1200	0
129995	6513	-60792.00	1210	0
129996	4411	-77535.30	1210	0
129997	4411	-904166.84	1210	0

129969 rows × 4 columns

In [113]:

```
fig = plt.figure(figsize = (10, 8))

ax = plt.axes(projection = '3d')

ax.scatter3D(X.iloc[:, 0], X.iloc[:, 1], X.iloc[:, 2], c = kmeans.labels_)
#ax.scatter3D(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], c = [0, 1, 2, 3
ax.set_xlabel('\ncode')
ax.set_ylabel('\nsum')
ax.set_zlabel('\ntype')
plt.show()
```



In [123]:

```
# do the same thing for 2 classes
kmeans = KMeans(n_clusters = 2)
kmeans.fit(X)
X1 = X
X1['Class'] = kmeans.labels_
X1
```

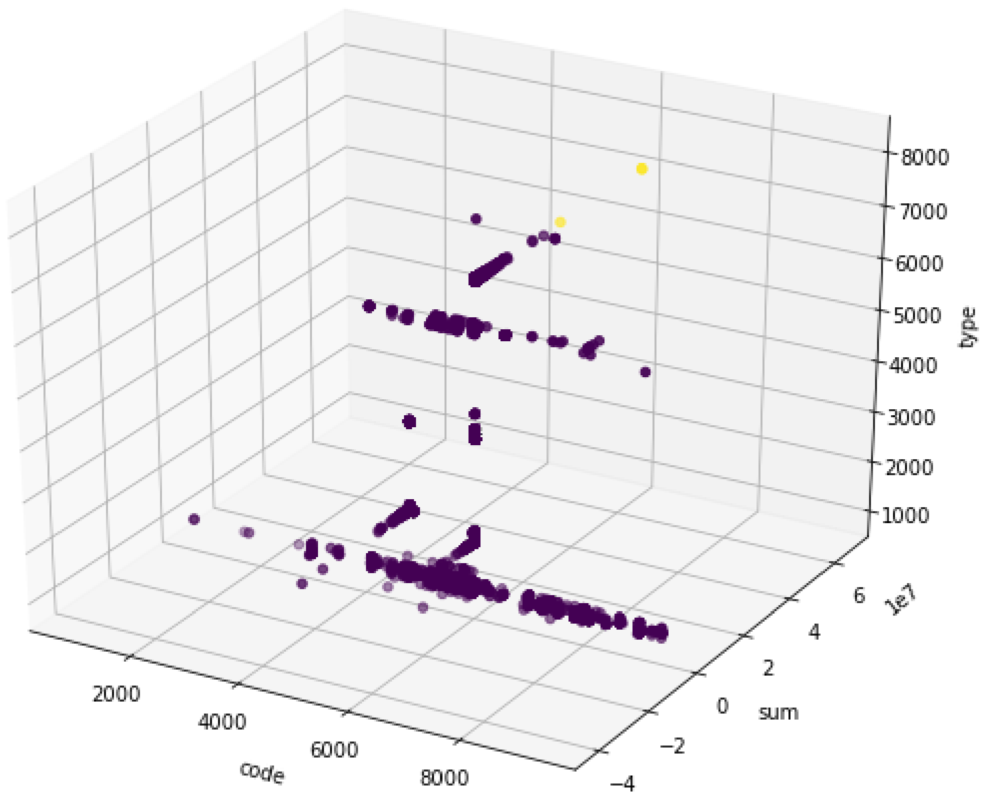
Out[123]:

	code	sum	type	Class
0	6011	-561478.94	2010	0
1	6011	-44918.32	2010	0
2	6011	-3368873.66	2010	0
3	6011	-65131.56	2010	0
4	6011	-224591.58	2010	0
...	...	...	...	...
129993	4131	-146433.71	1200	0
129994	5169	-271194.78	1200	0
129995	6513	-60792.00	1210	0
129996	4411	-77535.30	1210	0
129997	4411	-904166.84	1210	0

129969 rows × 4 columns

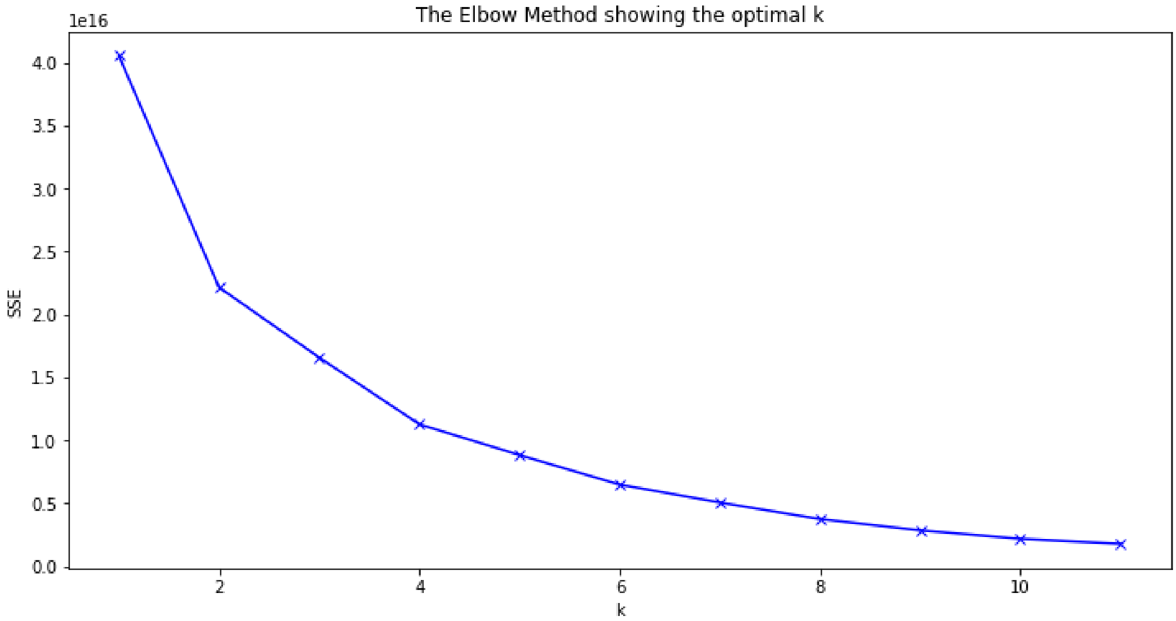
In [126]:

```
fig = plt.figure(figsize = (10, 8))

ax = plt.axes(projection = '3d')

ax.scatter3D(X.iloc[:, 0], X.iloc[:, 1], X.iloc[:, 2], c = kmeans.labels_)
#ax.scatter3D(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], c = [0, 1, 2, 3
ax.set_xlabel('\ncode')
ax.set_ylabel('\nsum')
ax.set_zlabel('\ntype')
plt.show()
```



In [129]:

```
SSE = []

for k in range(1, 12):
    kmeans = KMeans(n_clusters = k)
    kmeans.fit(X)
    # calculating the values of the Inertia
    SSE.append(kmeans.inertia_)
plt.figure(figsize = (12, 6))
plt.plot(range(1, 12), SSE, 'bx-')
plt.xlabel('k')
plt.ylabel('SSE')
plt.title('The Elbow Method showing the optimal k')
plt.show()
##best k = 4
```



To determine the optimal number of clusters, we choose the value of k at the "elbow", that is, at the point after which the distortion/inertia begins to decrease linearly. So for the given data, we conclude that the optimal number of clusters for the data is 4.

Hierarchical clustering

In [36]:

```
df_work = df[['sum', 'code', 'type']]
# первично мы очистили наш dataframe от ненужных колонок чтобы не отвлекали и не занимали м
# мы выбрали 'sum','code','type'
df_work = df_work.drop_duplicates()
# тут мы убераем дубликаты потому что для класстеризаций будликаты не несут ценности а наоб
df_work.index = pd.RangeIndex(len(df_work.index))
df_work.index = range(len(df_work.index))
# обычная переиндексация для удобства и визуального удовлетворения
df_work
```

Out[36]:

	sum	code	type
0	-561478.94	6011	2010
1	-44918.32	6011	2010
2	-3368873.66	6011	2010
3	-65131.56	6011	2010
4	-224591.58	6011	2010
...	...	...	...
50215	-146433.71	4131	1200
50216	-271194.78	5169	1200
50217	-60792.00	6513	1210
50218	-77535.30	4411	1210
50219	-904166.84	4411	1210

50220 rows × 3 columns

In [37]:

```
# Standardize data
scaler = StandardScaler()
scaled_df = scaler.fit_transform(df_work)
# стандартизация это метод масштабирования, при котором данные не масштабируются
# путем преобразования статистического распределения данных это используется когда
# данные содержат в совокупности признаки разного размера и масштаба.
# Различные масштабы функций данных отрицательно влияют на моделирование набора данных.
# Вот тут-то и появляется стандартизация.
# Особенность стандартизаций в том что она весь набор данных масштабируется вместе с нулевы
# z-преобразование

# Normalizing the Data
normalized_df = normalize(scaled_df)
# normalization is a procedure of preprocessing of input information(training,test and vali
# in which values of features in the input vector are reduced to a certain given range
# for example, [0...1] or [-1...1]

# Converting the numpy array into a pandas DataFrame
normalized_df = pd.DataFrame(normalized_df)


# Reducing the dimensions of the data
pca = PCA(n_components = 2)
X_principal = pca.fit_transform(normalized_df)
X_principal = pd.DataFrame(X_principal)
X_principal.columns = ['P1', 'P2']
# Principal component analysis (PCA). L
# inear dimensionality reduction using Singular Value Decomposition of the data to project
# The input data is centered but not scaled for each feature before applying the SVD.

X_principal
```

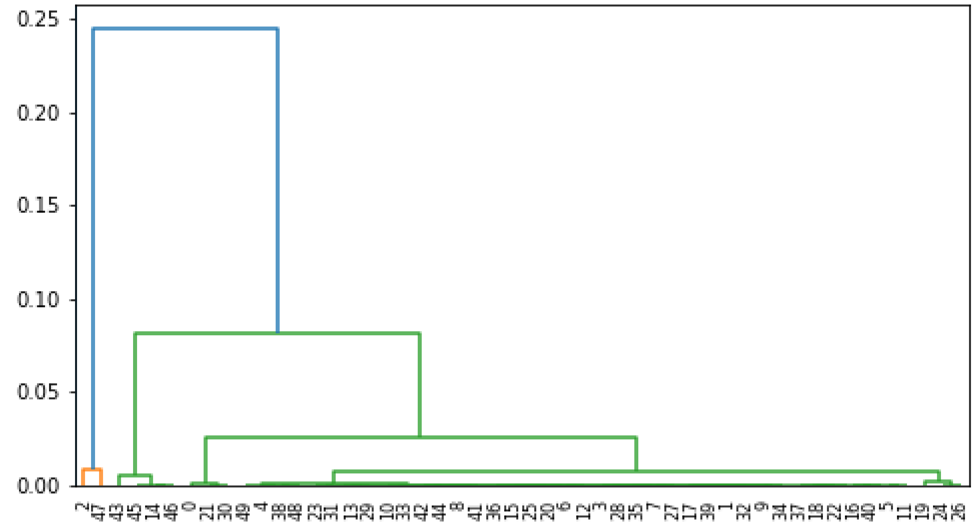
Out[37]:

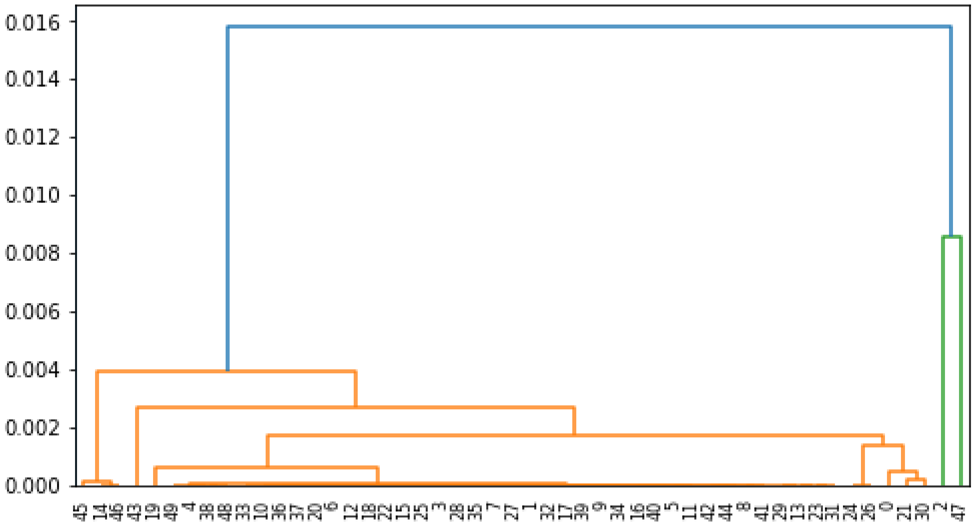
	P1	P2
0	0.640703	-0.377627
1	0.884476	-0.761129
2	0.422282	0.002127
3	0.879708	-0.756491
4	0.805251	-0.648976
...	...	...
50215	-0.300364	0.818826
50216	-0.416985	0.508742
50217	0.709206	-0.840211
50218	-0.325732	0.796079
50219	-0.205530	0.658419

50220 rows × 2 columns

In [49]:

```
import matplotlib.gridspec as gridspec
gs = gridspec.GridSpec(3, 1)
fig = plt.figure(figsize = (8, 15))

ax1 = fig.add_subplot(gs[0, 0]) # row 0, col 0
ax1.plot([0,1])
model.dendrogram((model.linkage(X_principal[:50], method ='complete', metric = 'cosine')))

ax2 = fig.add_subplot(gs[1, 0]) # row 0, col 1
ax2.plot([0,1])
model.dendrogram((model.linkage(X_principal[:50], method ='single', metric = 'cosine')))

ax3 = fig.add_subplot(gs[2, 0]) # row 1, span all columns
ax3.plot([0,1])
model.dendrogram((model.linkage(X_principal[:50], method ='average', metric = 'cosine')))

plt.show()
```

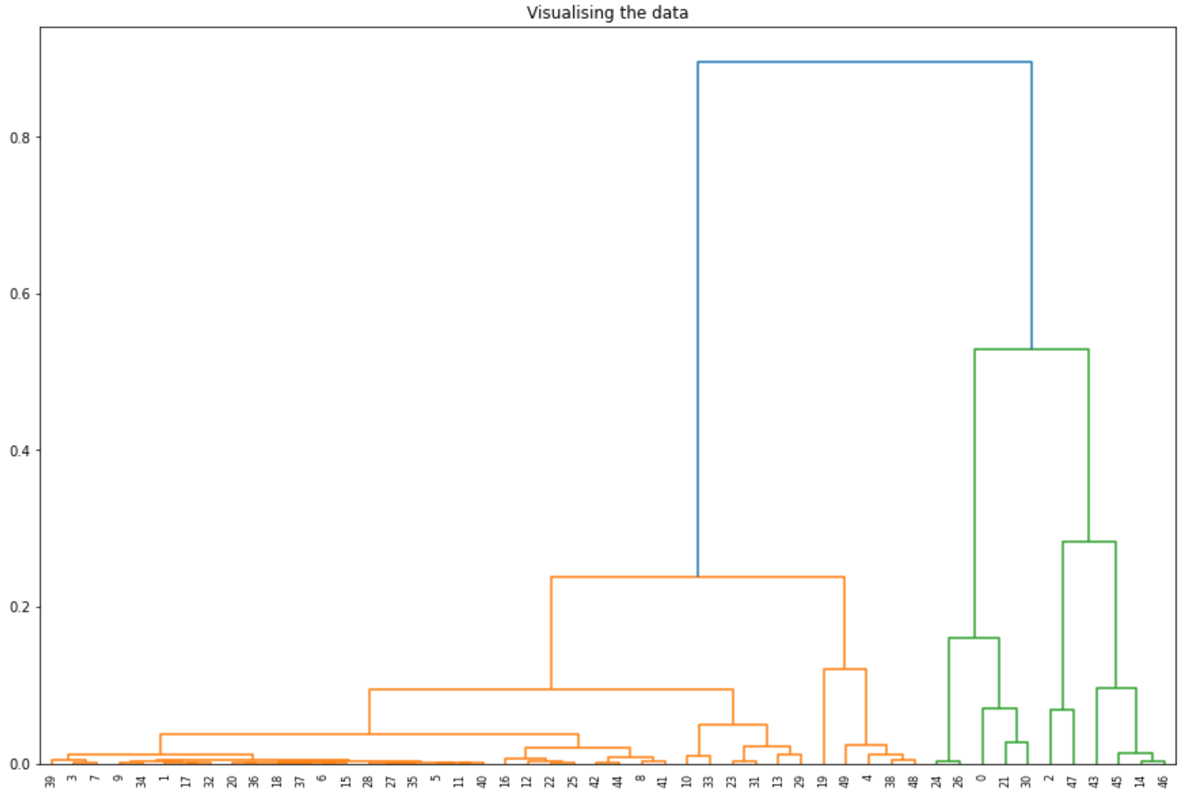

0.25
0.20
0.15
0.10
0.05
0.00
2 47 43 45 14 46 0 21 30 49 4 38 48 23 31 13 29 10 33 42 44 8 41 36 15 25 20 6 12 3 28 35 7 27 17 39 1 32 9 34 37 18 22 16 40 5 11 19 24 26


0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
45 14 46 43 19 49 4 38 48 33 10 36 37 20 6 12 18 22 15 25 3 28 35 7 27 1 32 17 39 9 34 16 40 5 11 42 44 8 41 29 13 23 31 24 26 0 21 30 2 47


0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
2 47 10 33 42 44 8 41 37 18 22 15 25 36 20 6 12 16 40 5 11 3 28 35 7 27 17 39 1 32 9 34 29 13 23 31 49 4 38 48 19 24 26 0 21 30 43 45 14 46

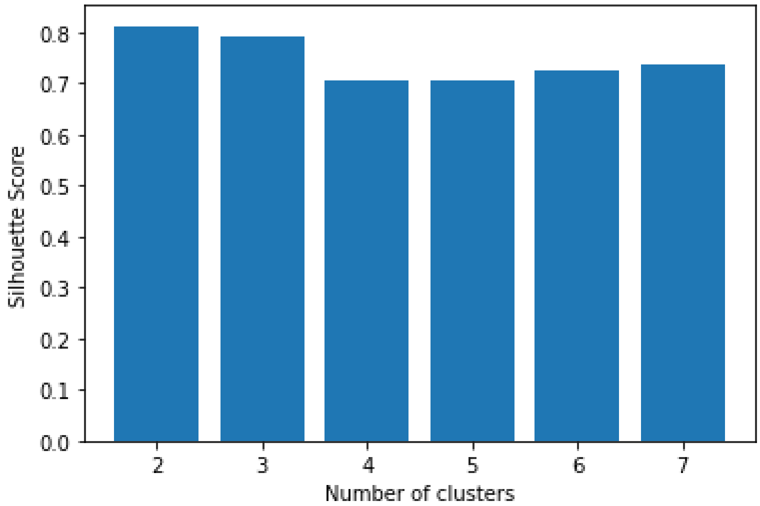
In [45]:

```
# тут мы строим дендаграмму с различными  linkages
plt.figure(figsize =(15, 10))
plt.title('Visualising the data')
Dendrogram = model.dendrogram((model.linkage(X_principal[:50], method ='complete',metric='e
# Dendrogram = model.dendrogram((model.linkage(X_principal[:50], method ='complete',metric=
# Dendrogram = model.dendrogram((model.linkage(X_principal[:50], method ='complete',metric=
# Dendrogram = model.dendrogram((model.linkage(X_principal[:50], method ='complete',metric=
# Dendrogram = model.dendrogram((model.linkage(X_principal[:50], method ='complete',metric=
# https://docs.scipy.org/doc/scipy/reference/generated/scipy.spatial.distance.pdist.html#:~
# ссылка на другие метрики
```



In [46]:

```
silhouette_scores = []

for n_cluster in range(2, 8):
    silhouette_scores.append(
        silhouette_score(X_principal[:50], AgglomerativeClustering(n_clusters = n_cluster).

# Plotting a bar graph to compare the results
k = [2, 3, 4, 5, 6,7]
plt.bar(k, silhouette_scores)
plt.xlabel('Number of clusters', fontsize = 10)
plt.ylabel('Silhouette Score', fontsize = 10)
plt.show()
```



In [47]:

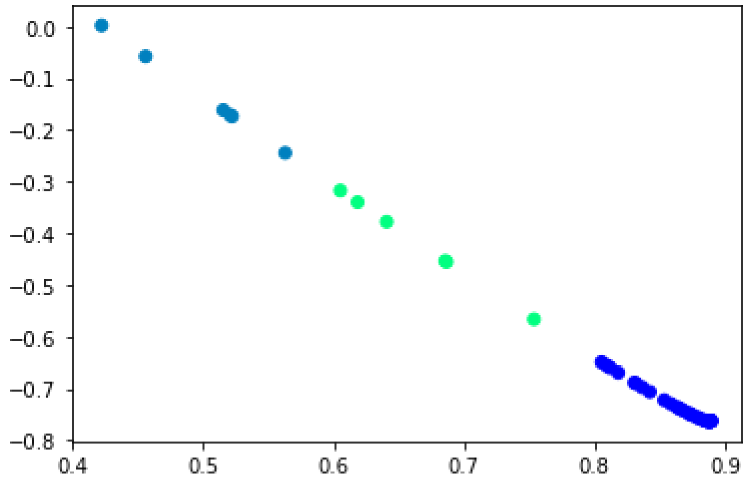
```
agg = AgglomerativeClustering(n_clusters=4)
agg.fit(X_principal[:50])
```

Out[47]:

```
AgglomerativeClustering(n_clusters=4)
```

In [48]:

```
plt.scatter(X_principal['P1'][:50], X_principal['P2'][:50],
            c = AgglomerativeClustering(n_clusters = 3).fit_predict(X_principal[:50]), cmap
plt.show()
```



Analysis

1. We can see from the data visualization analysis that the transaction code "financial institution - manual withdrawal" appears the most in the transaction data. The highest number of transaction code descriptions were "Calls Using a Recorded Phone," "Grocery Stores, Supermarkets," and "Financial Institutions - Manual Withdrawals," all of which had similar numbers.
2. If we talk about the types of transactions, then most often we met "Purchase. Foreign POS." .
3. By evaluating the correlation between the values in our database, we can conclude that the values among themselves have a low correlation, which indicates a weak relationship. At the same time, the largest correlation coefficient was found between the type and transaction code.
4. If we talk about the amount of the transaction, then it has too much difference, since it includes both negative and positive values (depending on the operation), therefore they have a huge number of deviations
5. Based on 2 different clustering methods, we came to the same result that the optimal number of clusters is 4
6. Graphics of clusterizations shows that the most common transaction code for customers is 6000 (described as "Financial Institution - Manual Withdrawal"), and the most common transaction type is 1500. (described as "Purchase. Foreign POS").

Conclusion

1. We have started to analyze with raw data. Where we begin with merging in transaction type. Also, in descriptive analysis our group identified information about our dataset. Evaluated on sales type of transactions where visualized by using graphs. Focused on sum and sales type by organizing time of dataframe. In feature engineering we started to group inside dataset by using function in order to make distribution of time.
2. We note that the construction of signs is a working technique for solving the problem, which allowed us to equalize the quality of the algorithm we developed, for example, in showing positive and negative transactions, we were able to get a complete result

3. Hierarchical clustering is a powerful technique that allows you to build tree structures based on data similarity. You can see how the different subclusters are related to each other and how far apart the data points are.
4. Talking about k-means clustering gives us the ability to build a three-dimensional graph and show the relationship between all three variables taken

In [ ]:

```

```