Customer Personality Analysis

In [1]:
```
# Need to perform clustering to summarize customer segments.
#
# The Company can analyze which customer segment is most likely
# to buy the product and then market the product only on that particular segment.
```

In [ ]:
```
# Проект построен следующим образом.
# Сначала определяются ф-ции, для последующего запуска генетического алгоритма по по
# гиперпараметров для модели регрессии XGBoost (градиентного бустинга)
# 1. Data Parsing - обработка сырых данных (оптимизация признаков, трансформация, оч
# 2. Проведение кластеризации пользователей
# 2.1 Определение метрики качества - силуэтного анализа
# 2.2 Стандартизация признаков
# 2.3 Кластеризация методом KNN: итоговое разбиение на 6 сегментов
# 2.4 Кластеризация методом Mini-Batch K-means: итоговое разбиение на 4 сегмента
# 2.5 Кластеризация методом Affinity Propagation: результат неудовлетворительный
# 2.6 Кластеризация методом Агломеративной иерархической кластеризации: результат ху

# В итоге разбиение на 4 сегмента методом KNN, либо на 6 сегментов методом Mini-Batc
# показывают наилучший результат
# Дальнейший анализ этих двух разбиений (статистика пользователей каждого сегмента)
# оптимального разбиения
```

In [16]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from datetime import datetime

from sklearn.svm import SVR

import warnings

%matplotlib inline
```

In [ ]:
```
####### People
#ID: Customer's unique identifier
#Year_Birth: Customer's birth year
#Education: Customer's education level
#Marital_Status: Customer's marital status
#Income: Customer's yearly household income
#Kidhome: Number of children in customer's household
#Teenhome: Number of teenagers in customer's household
#Dt_Customer: Date of customer's enrollment with the company
#Recency: Number of days since customer's last purchase
#Complain: 1 if the customer complained in the last 2 years, 0 otherwise

####### Products
#MntWines: Amount spent on wine in last 2 years
#MntFruits: Amount spent on fruits in last 2 years
#MntMeatProducts: Amount spent on meat in last 2 years
#MntFishProducts: Amount spent on fish in last 2 years
#MntSweetProducts: Amount spent on sweets in last 2 years
#MntGoldProds: Amount spent on gold in last 2 years

####### Promotion
```

```
#NumDealsPurchases: Number of purchases made with a discount
#AcceptedCmp1: 1 if customer accepted the offer in the 1st campaign, 0 otherwise
#AcceptedCmp2: 1 if customer accepted the offer in the 2nd campaign, 0 otherwise
#AcceptedCmp3: 1 if customer accepted the offer in the 3rd campaign, 0 otherwise
#AcceptedCmp4: 1 if customer accepted the offer in the 4th campaign, 0 otherwise
#AcceptedCmp5: 1 if customer accepted the offer in the 5th campaign, 0 otherwise
#Response: 1 if customer accepted the offer in the last campaign, 0 otherwise

####### Place
#NumWebPurchases: Number of purchases made through the company’s website
#NumCatalogPurchases: Number of purchases made using a catalogue
#NumStorePurchases: Number of purchases made directly in stores
#NumWebVisitsMonth: Number of visits to company’s website in the last month
```

In [84]:

```
df = pd.read_csv('Data/marketing_campaign.csv', sep='\t', skipinitialspace=True)
```

In [7]:

```
df.head()
```

Out[7]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recenc
0	5524	1957	Graduation	Single	58138.0	0	0	04-09-2012	5
1	2174	1954	Graduation	Single	46344.0	1	1	08-03-2014	3
2	4141	1965	Graduation	Together	71613.0	0	0	21-08-2013	2
3	6182	1984	Graduation	Together	26646.0	1	0	10-02-2014	2
4	5324	1981	PhD	Married	58293.0	1	0	19-01-2014	9

5 rows × 29 columns

1. Data Parsing

In [10]:

```
df.describe()
```

Out[10]:

	ID	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWine
count	2240.000000	2240.000000	2216.000000	2240.000000	2240.000000	2240.000000	2240.00000
mean	5592.159821	1968.805804	52247.251354	0.444196	0.506250	49.109375	303.93571
std	3246.662198	11.984069	25173.076661	0.538398	0.544538	28.962453	336.59739
min	0.000000	1893.000000	1730.000000	0.000000	0.000000	0.000000	0.00000
25%	2828.250000	1959.000000	35303.000000	0.000000	0.000000	24.000000	23.75000
50%	5458.500000	1970.000000	51381.500000	0.000000	0.000000	49.000000	173.50000
75%	8427.750000	1977.000000	68522.000000	1.000000	1.000000	74.000000	504.25000
max	11191.000000	1996.000000	666666.000000	2.000000	2.000000	99.000000	1493.00000

8 rows × 26 columns

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

1.1 Переводим столбец "Dt_Customer" во время, в течении которого пользователь с компанией

In [85]:
```
# сначала переводим столбец в формат datetime
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'],format='%d-%m-%Y')
```

In [86]:
```
# теперь рассчитываем время присутствия пользователя на сайте в месяцах
max_date = datetime(2014, 10, 4)
df['presence'] = df.apply(lambda x: (max_date - x['Dt_Customer']).days/30.0, axis =
```

1.2 Оптимизируем признаки

1.2.1 Education

In [88]:
```
df['Education'].unique()
```

Out[88]:
```
array(['Graduation', 'PhD', 'Master', 'Basic', '2n Cycle'], dtype=object)
```

In [89]:
```
df['Education'] = df['Education'].replace({'Basic':'Undergraduate','2n Cycle':'Under
```

In [91]:
```
df['Education'].unique()
```
Out[91]:
```
array(['Postgraduate', 'PhD', 'Undergraduate'], dtype=object)
```

1.2.2 Marital_Status

In [44]:
```
df['Marital_Status'].unique()
```
Out[44]:
```
array(['Single', 'Together', 'Married', 'Divorced', 'Widow', 'Alone',
       'Absurd', 'YOLO'], dtype=object)
```

In [28]:
```
#widow - вдова
#yolo = absurd
#together = married
#alone = single
```

In [92]:
```
df['Marital_Status'] = df['Marital_Status'].replace({'Divorced':'Alone','Single':'Al
```

In [94]:
```
df['Marital_Status'].unique()
```
Out[94]:
```
array(['Alone', 'Together'], dtype=object)
```

1.2.3 Year_Birth

In [97]:
```
# с возрастом работать удобнее, чем с годом рождения
df['Age'] = 2014 - df['Year_Birth']
```

1.2.4 Keedhome & Teenhome

In [105…
```
# Посчитаем общее кол-во детей
df['Children'] = df['Kidhome'] + df['Teenhome']
```

1.2.5 MntWines & MntFruits & MntMeatProducts & MntFishProducts & MntSweetProducts & MntGoldProds

In [104…
```
df['Spending']=df['MntWines']+df['MntFruits']+df['MntMeatProducts']+df['MntFishProdu
```

1.2.6 Переименуем некоторые столбцы для простоты

In [107…
```
df = df.rename(columns={'MntWines': "Wines",'MntFruits':'Fruits','MntMeatProducts':'
```

Оставляем только выборочные признаки для последующего анализа

In [114…
```
data=df[['Age','Education','Marital_Status','Income','Spending','presence','Children
```

In [115…
```
data.head()
```
Out[115…

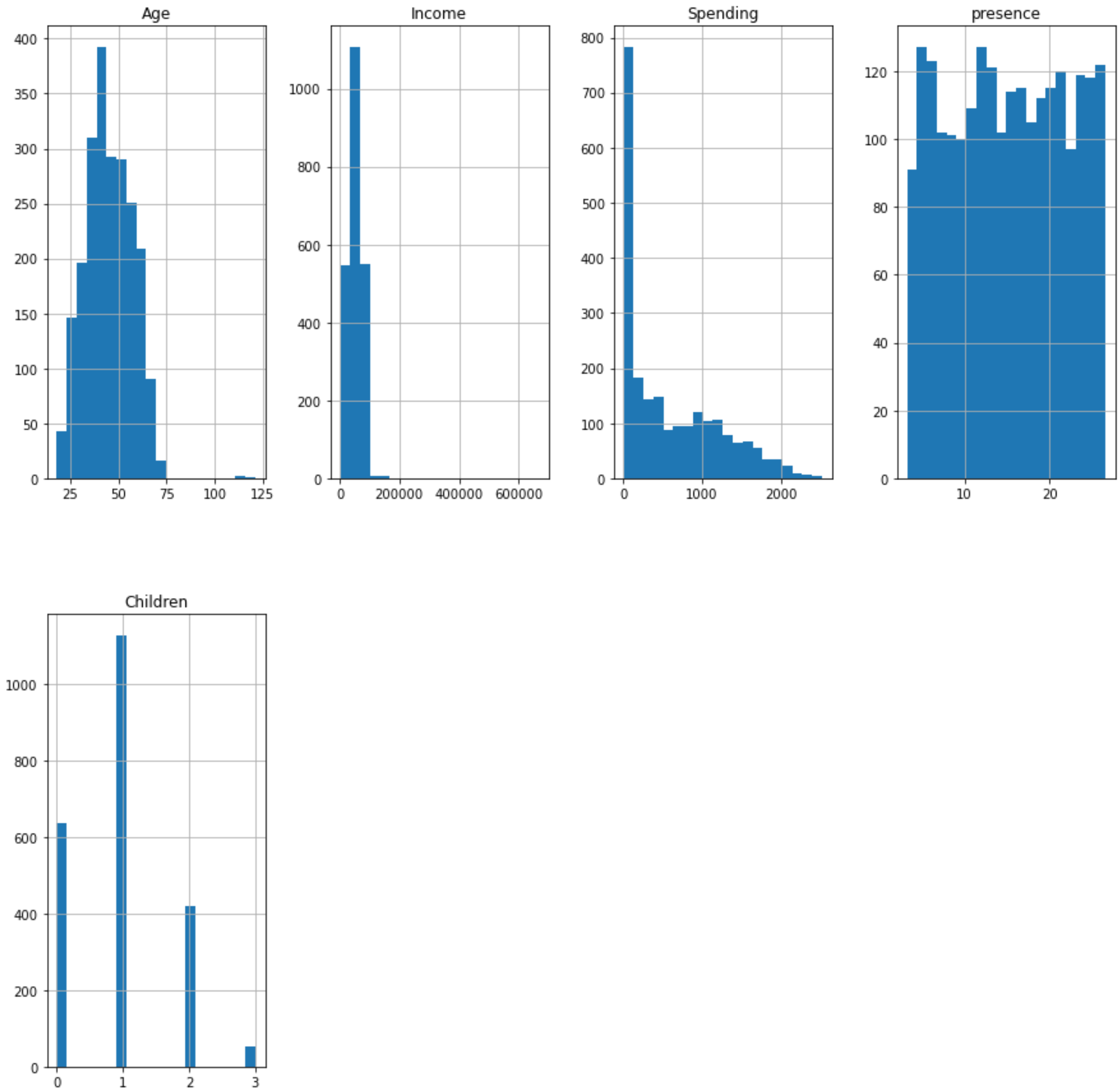
	Age	Education	Marital_Status	Income	Spending	presence	Children
0	57	Postgraduate	Alone	58138.0	1617	25.333333	0
1	60	Postgraduate	Alone	46344.0	27	7.000000	2
2	49	Postgraduate	Together	71613.0	776	13.633333	0
3	30	Postgraduate	Together	26646.0	53	7.866667	1

	Age	Education	Marital_Status	Income	Spending	presence	Children
4	33	PhD	Together	58293.0	422	8.600000	1

1.3 Убираем отсутствующие значения и выбросы

In [117…

```
# Сначала посмотрим на статистику
data.hist(bins=20, figsize=(15,15),layout=(2,4));
```



In [118…

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Age             2240 non-null   int64  
 1   Education       2240 non-null   object 
 2   Marital_Status  2240 non-null   object 
 3   Income          2216 non-null   float64
 4   Spending        2240 non-null   int64  
 5   presence        2240 non-null   float64
 6   Children        2240 non-null   int64  
```

```
dtypes: float64(2), int64(3), object(2)
memory usage: 122.6+ KB
```

In [83]:

```
# Параметр Income очень важен, и именно в нём есть несуществующие значения и выбросы
# Удаляем все такие строки, где Income либо выброс, либо отсутствует
```

In [119…

```
data = data.dropna(subset=['Income'])
data = data[data['Income'] < 600000]
```

In [124…

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2215 entries, 0 to 2239
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Age             2215 non-null   int64  
 1   Education       2215 non-null   object 
 2   Marital_Status  2215 non-null   object 
 3   Income          2215 non-null   float64
 4   Spending        2215 non-null   int64  
 5   presence        2215 non-null   float64
 6   Children        2215 non-null   int64  
dtypes: float64(2), int64(3), object(2)
memory usage: 138.4+ KB
```

1.4 Преобразуем нечисловые признаки Education и Marital_Status в набор числовых

In [122…

```
list(data['Education'].unique())
```

Out[122…

```
['Postgraduate', 'PhD', 'Undergraduate']
```

In [128…

```
# ф-ции для создания новых признаков-образования
def Edu1(education):
    if education == 'Postgraduate':
        return 1
    else:
        return 0
def Edu2(education):
    if education == 'PhD':
        return 1
    else:
        return 0
def Edu3(education):
    if education == 'Undergraduate':
        return 1
    else:
        return 0
```

In [126…

```
data['PostGr'] = data.apply(lambda x: Edu1(x['Education']), axis = 1)
data['PhD'] = data.apply(lambda x: Edu2(x['Education']), axis = 1)
data['UnderGr'] = data.apply(lambda x: Edu3(x['Education']), axis = 1)
```

In [123…

```
list(data['Marital_Status'].unique())
```

Out[123…

```
['Alone', 'Together']
```

In [140…

```
# ф-ции для создания новых признаков-семейного статуса
def Mar1(status):
    if status == 'Alone':
        return 1
    else:
        return 0
def Mar2(status):
    if status == 'Together':
        return 1
    else:
        return 0
```

In [141…

```
data['Alone'] = data.apply(lambda x: Mar1(x['Marital_Status']), axis = 1)
data['Together'] = data.apply(lambda x: Mar2(x['Marital_Status']), axis = 1)
```

1.5 Оставляем признаки для последующей кластеризации

In [147…

```
data_a = data[['Age','Income','Spending','presence','Children','PostGr','PhD','Under
```

In [148…

```
data_a
```

Out[148…

	Age	Income	Spending	presence	Children	PostGr	PhD	UnderGr	Alone	Together
0	57	58138.0	1617	25.333333	0	1	0	0	1	0
1	60	46344.0	27	7.000000	2	1	0	0	1	0
2	49	71613.0	776	13.633333	0	1	0	0	0	1
3	30	26646.0	53	7.866667	1	1	0	0	0	1
4	33	58293.0	422	8.600000	1	0	1	0	0	1
...	...	...	...	...	...	...	...	...	...	...
2235	47	61223.0	1341	15.933333	1	1	0	0	0	1
2236	68	64014.0	444	3.866667	3	0	1	0	0	1
2237	33	56981.0	1241	8.400000	0	1	0	0	1	0
2238	58	69245.0	843	8.433333	1	1	0	0	0	1
2239	60	52869.0	172	23.966667	2	0	1	0	0	1

2215 rows × 10 columns

2. Кластеризация

In [ ]:

```
# Основная задача заключается в оценке оптимального количества числа кластеров.

# Будем проводить оценку с помощью силуэтного анализа

# Суть анализа заключается в расчет пространственного расстояния между кластерами.
# Итоговый силуэтный график отображает близость каждой точки одного кластера с точка
# соседних кластеров и обеспечивает,таким образом, визуальный способ оценки кол-ва к
```

```
# Итоговая мера имеет диапазон [-1, 1].

# Коэффициенты силуэта вблизи +1 показывают, что точка далеко от соседних кластеров,
# 0 - точка на границе или рядом с соседним кластером и отрицательные значения показ

# Также по ширине силуэтов кластеров на графике можно визуализировать размер кластер
```

2.1 Определение метрики качества кластеризации

In [154…

```
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.cm as cm
```

In [152…

```
def sil_plot(model, data, n_clusters):
    result = model.fit_predict(data)
    sil = silhouette_samples(data, result)
    silhouette_avg = silhouette_score(data, result)
    print("For n_clusters =", n_clusters,
          "The average silhouette_score is :{:.3f}".format(silhouette_avg))
    y_lower = 10

    fig, ax = plt.subplots()
    fig.set_size_inches(18, 7)

    # The silhouette coefficient can range from -1, 1 but in this example all
    # lie within [-0.2, 1]
    ax.set_xlim([-0.2, 1])
    # The (n_clusters+1)*10 is for inserting blank space between silhouette
    # plots of individual clusters, to demarcate them clearly.
    ax.set_ylim([0, len(data) + (n_clusters + 1) * 10])

    for i in range(n_clusters):
        # Aggregate the silhouette scores for samples belonging to
        # cluster i, and sort them
        ith_cluster_silhouette_values = sil[result == i]

        ith_cluster_silhouette_values.sort()

        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        cmap = cm.get_cmap("Spectral")
        color = cmap(float(i) / n_clusters)

        ax.fill_betweenx(np.arange(y_lower, y_upper),
                         0, ith_cluster_silhouette_values,
                         facecolor=color, edgecolor=color, alpha=0.7)

        # Label the silhouette plots with their cluster numbers at the middle
        ax.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

        # Compute the new y_lower for next plot
        y_lower = y_upper + 10  # 10 for the 0 samples

    # The vertical line for average silhouette score of all the values
    ax.axvline(x=silhouette_avg, color="red", linestyle="--")
    ax.set_yticks([])  # Clear the yaxis labels / ticks
    ax.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])
    ax.set_xlabel("The silhouette coefficient values")
    ax.set_ylabel("Cluster label")
    plt.suptitle(("Silhouette analysis for clustering on sample data "
                  "with n_clusters = %d" % n_clusters),
                 fontsize=14, fontweight='bold')
```

2.2 Стандартизация признаков

In [178…

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_data = pd.DataFrame(scaler.fit_transform(data_a), columns = data_a.columns, i
scaled_data.head()
```

Out[178…

	Age	Income	Spending	presence	Children	PostGr	PhD	UnderGr	Alone
0	0.986016	0.286604	1.675011	1.528882	-1.264487	0.704714	-0.526681	-0.359897	1.348357
1	1.236344	-0.261407	-0.962727	-1.188066	1.405522	0.704714	-0.526681	-0.359897	1.348357
2	0.318476	0.912723	0.279830	-0.205025	-1.264487	0.704714	-0.526681	-0.359897	-0.741643
3	-1.266933	-1.176680	-0.919594	-1.059629	0.070517	0.704714	-0.526681	-0.359897	-0.741643
4	-1.016605	0.293806	-0.307440	-0.950951	0.070517	-1.419016	1.898681	-0.359897	-0.741643

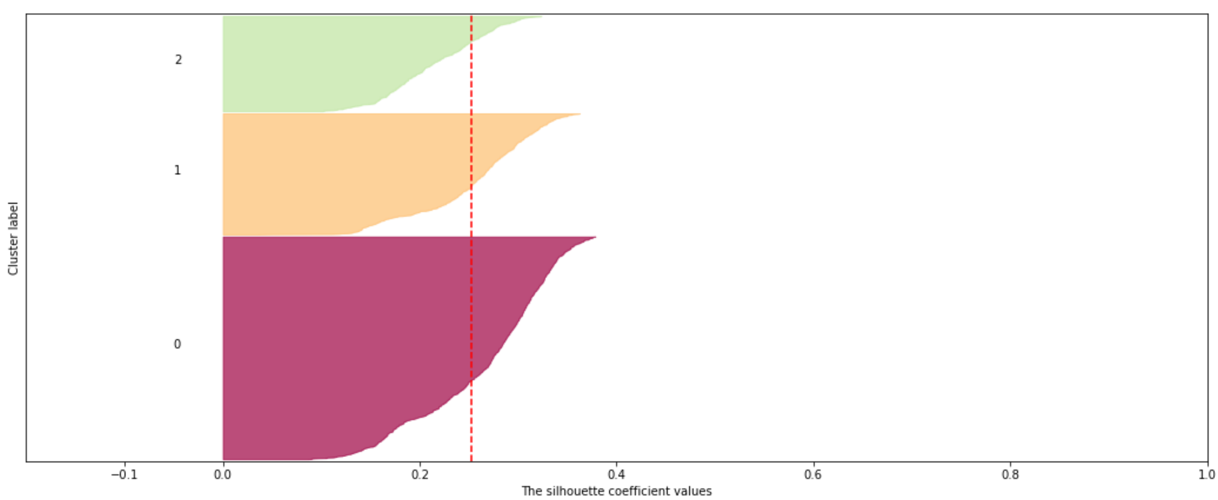
2.3 Метод KNN

In [179…

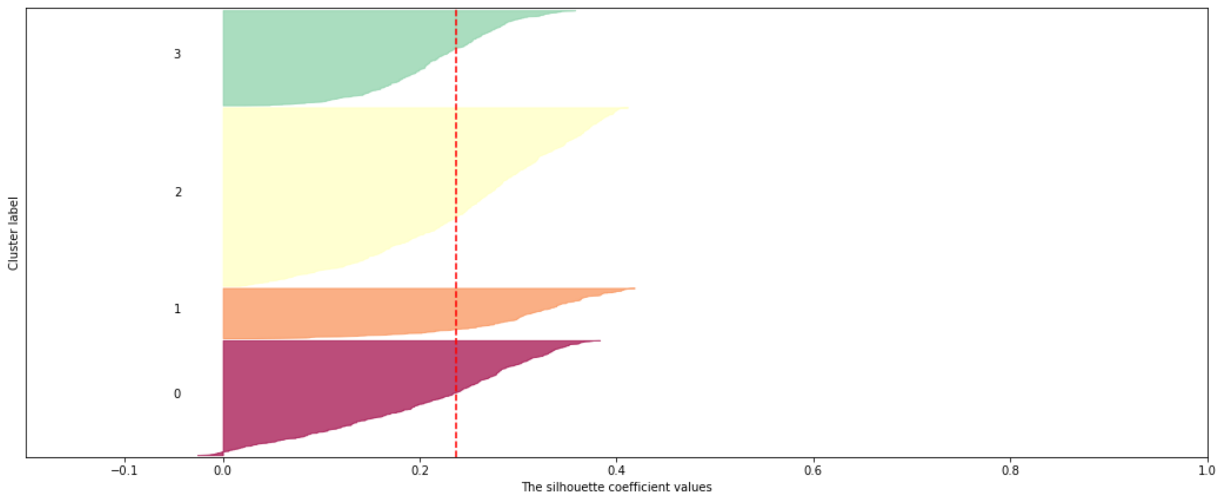
```
# попробуем пройтись по кол-ву кластеров от 3 до 15, оценивая результам по силуэтам
for n in range(3,16):
    KMN = KMeans(n_clusters=n, random_state=1)
    sil_plot(KMN, scaled_data, n)
```

```
For n_clusters = 3 The average silhouette_score is :0.253
For n_clusters = 4 The average silhouette_score is :0.237
For n_clusters = 5 The average silhouette_score is :0.251
For n_clusters = 6 The average silhouette_score is :0.280
For n_clusters = 7 The average silhouette_score is :0.285
For n_clusters = 8 The average silhouette_score is :0.287
For n_clusters = 9 The average silhouette_score is :0.255
For n_clusters = 10 The average silhouette_score is :0.265
For n_clusters = 11 The average silhouette_score is :0.259
For n_clusters = 12 The average silhouette_score is :0.262
For n_clusters = 13 The average silhouette_score is :0.241
For n_clusters = 14 The average silhouette_score is :0.244
For n_clusters = 15 The average silhouette_score is :0.243
```

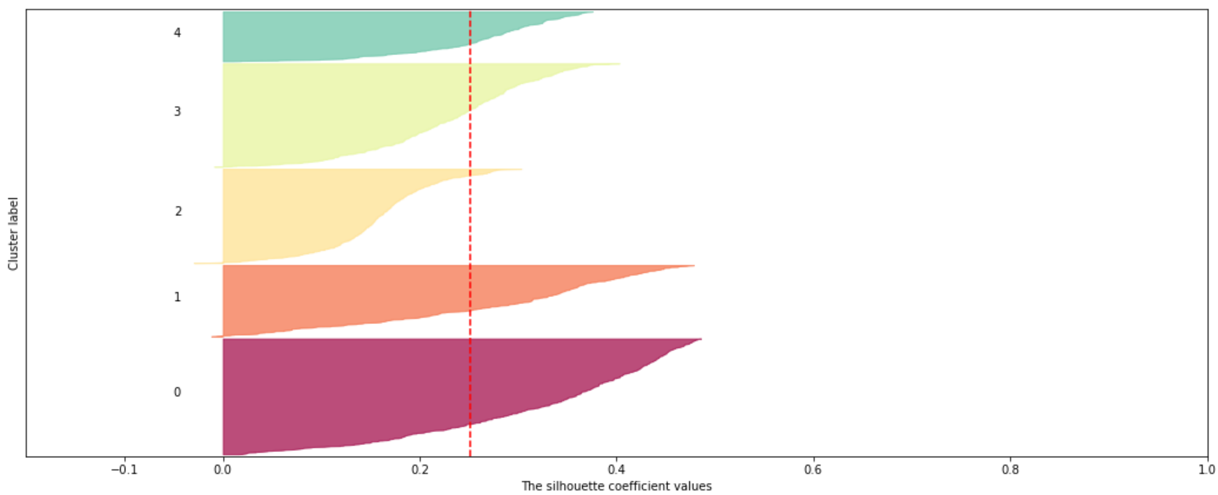
Silhouette analysis for clustering on sample data with n_clusters = 3



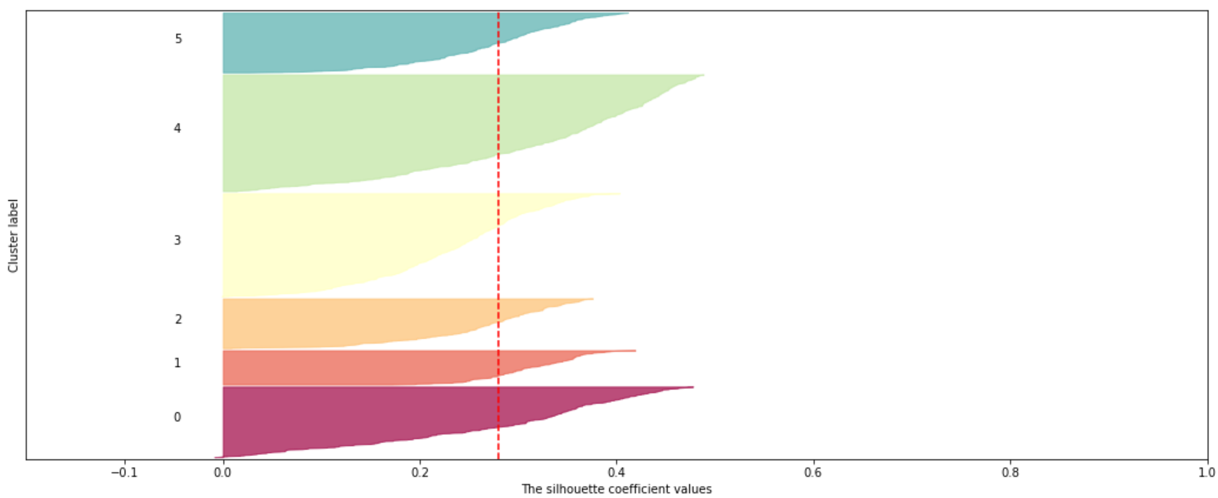
Silhouette analysis for clustering on sample data with n_clusters = 4

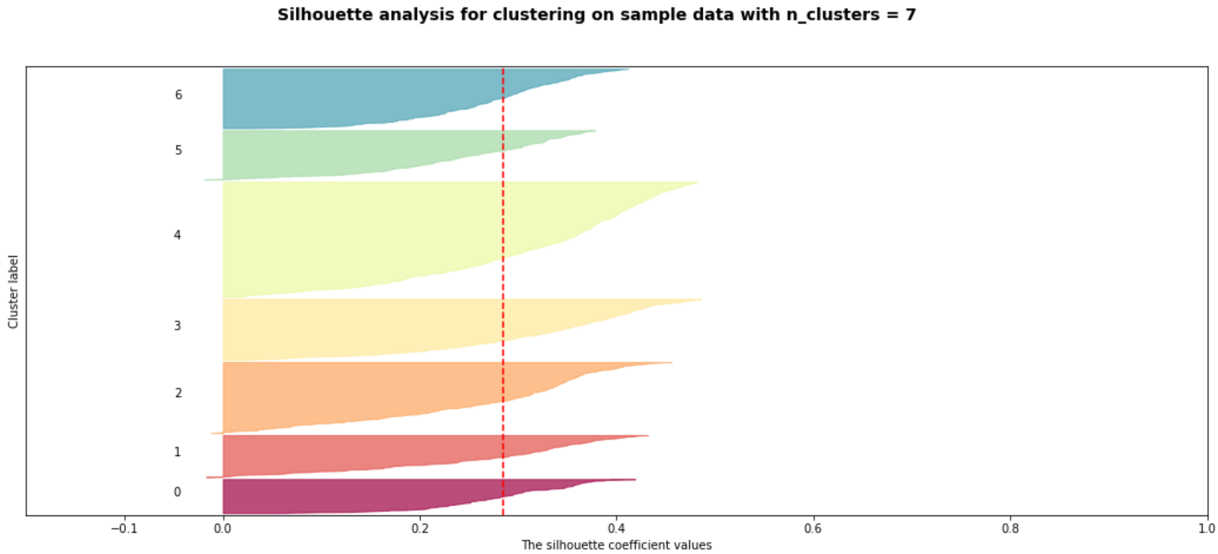


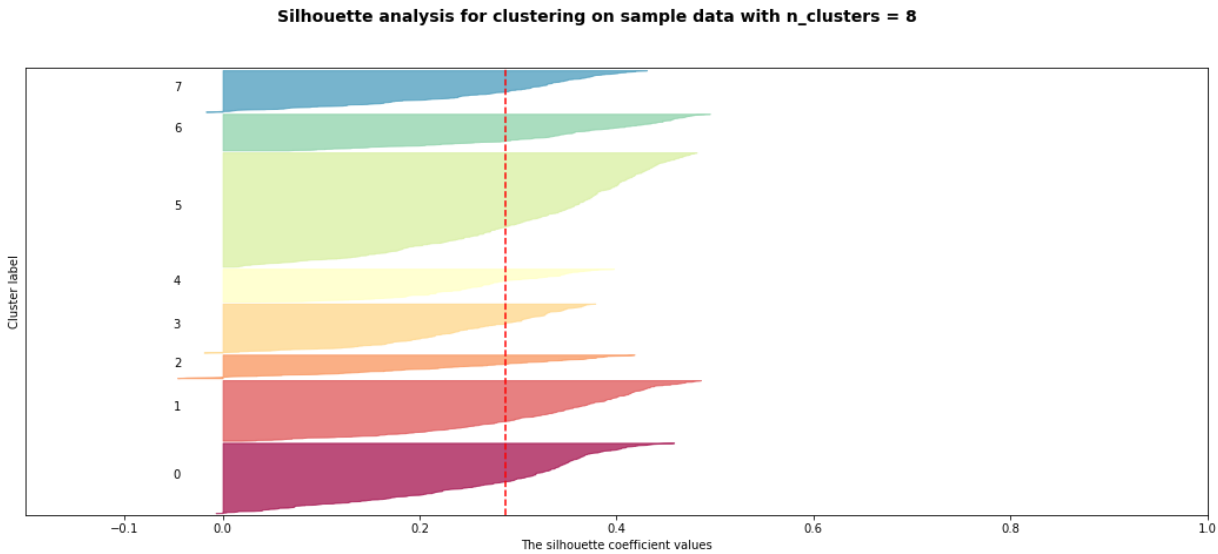
Silhouette analysis for clustering on sample data with n_clusters = 5

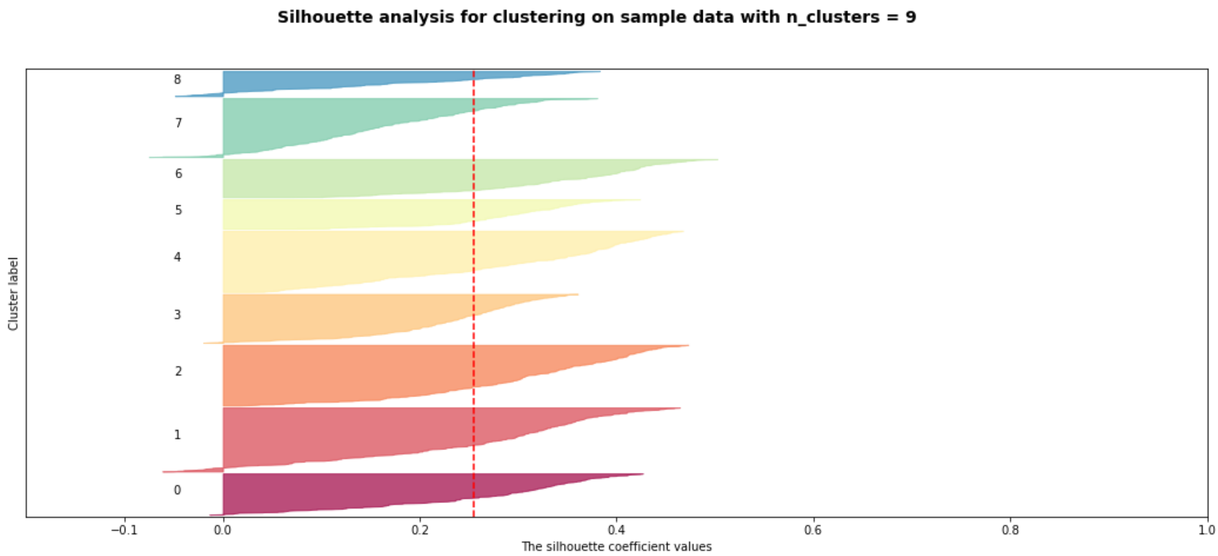


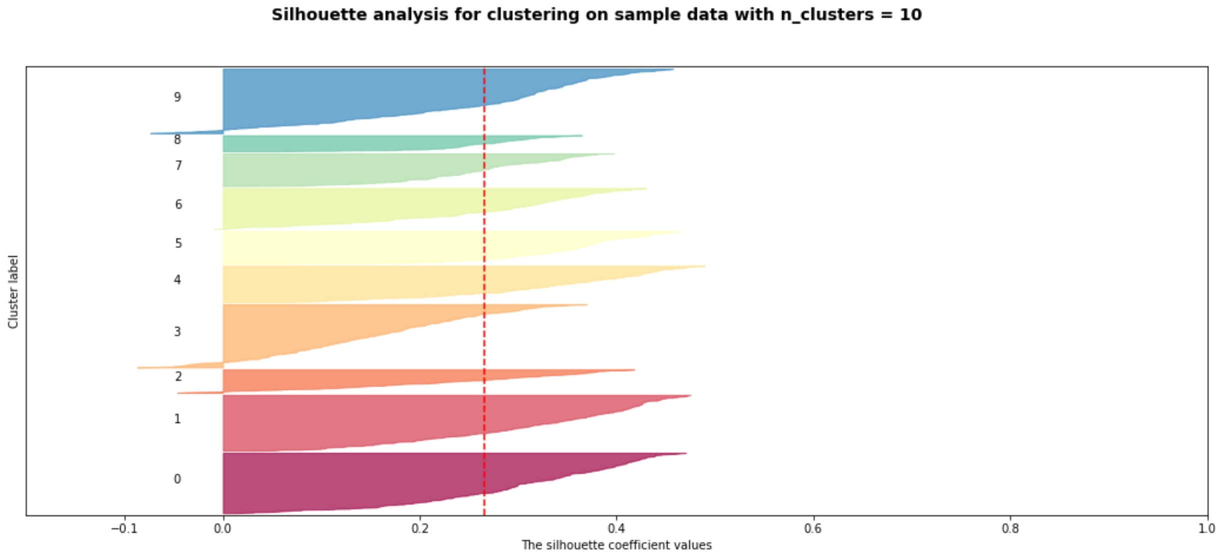
Silhouette analysis for clustering on sample data with n_clusters = 6

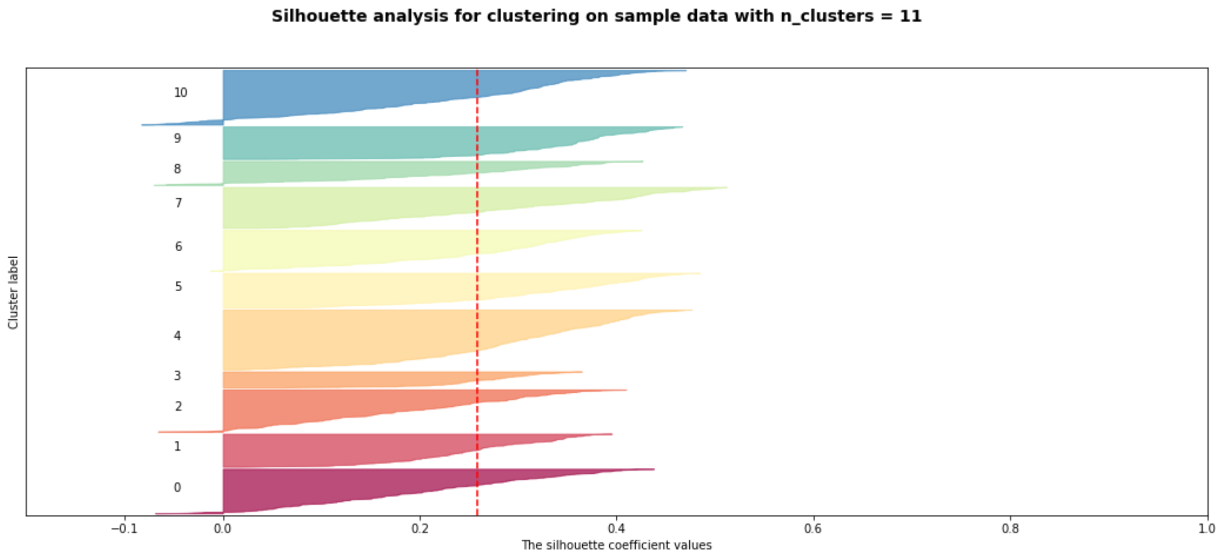


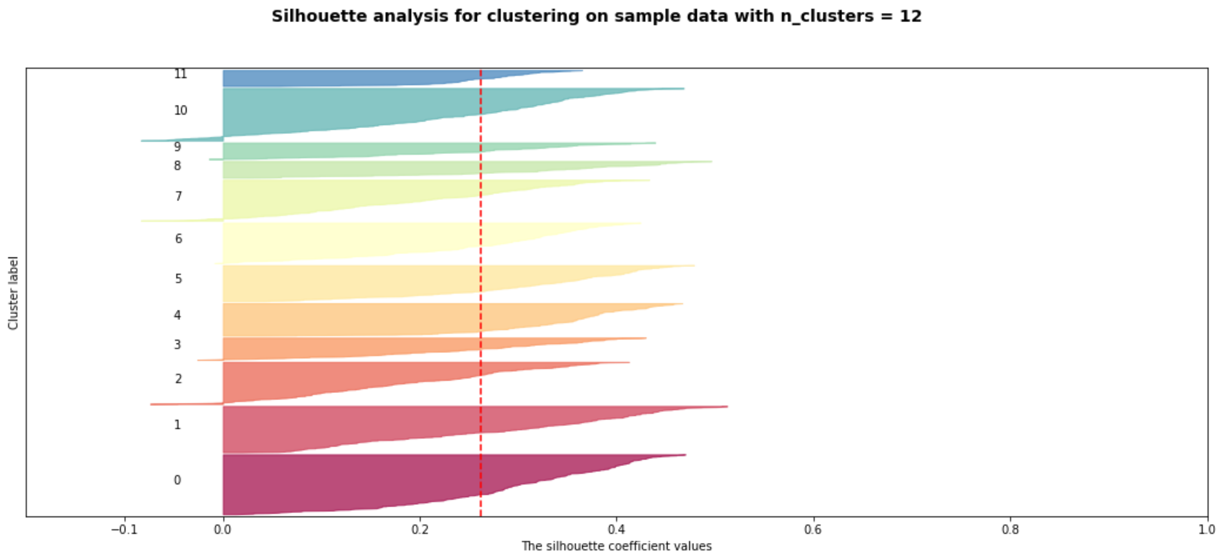

Silhouette analysis for clustering on sample data with n_clusters = 7
Cluster label
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values


Silhouette analysis for clustering on sample data with n_clusters = 8
Cluster label
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values

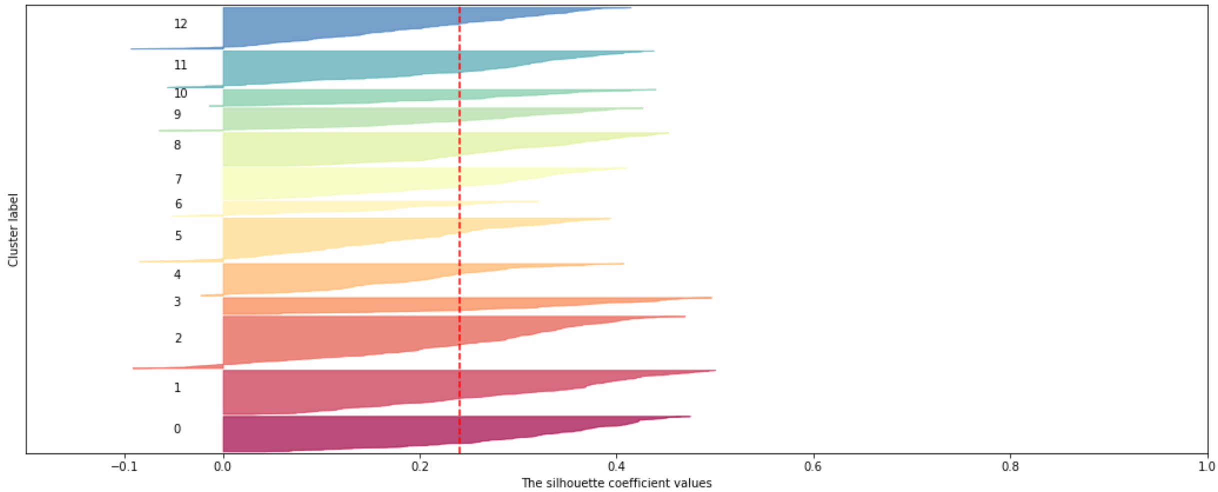

Silhouette analysis for clustering on sample data with n_clusters = 9
Cluster label
8
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values


Silhouette analysis for clustering on sample data with n_clusters = 10
Cluster label
9
8
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values

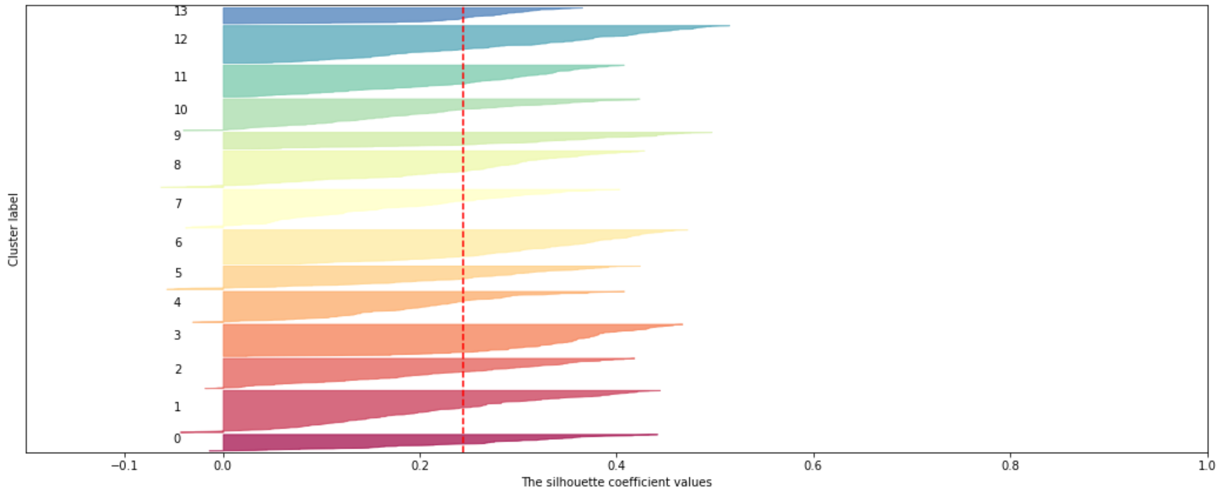

Silhouette analysis for clustering on sample data with n_clusters = 11
Cluster label
10
9
8
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values


Silhouette analysis for clustering on sample data with n_clusters = 12
Cluster label
11
10
9
8
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values

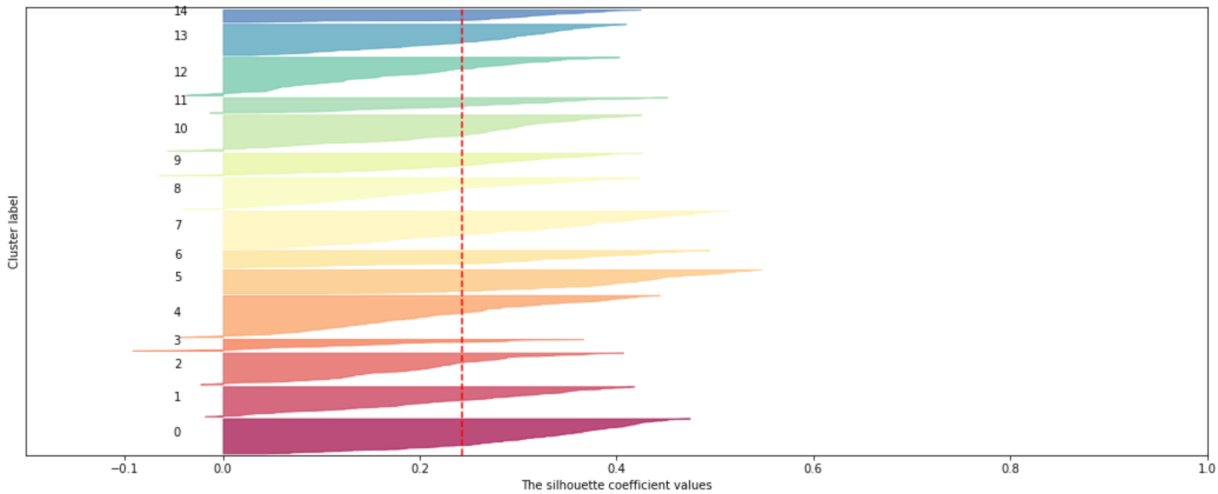
Silhouette analysis for clustering on sample data with n_clusters = 13



Silhouette analysis for clustering on sample data with n_clusters = 14



Silhouette analysis for clustering on sample data with n_clusters = 15



In [180…

```
# Визуально наилучшая картинка при разбиении на 3 и 6 кластеров
# При этом, средний коэффициент силуэта больший при 6 кластерах, остановимся на этом

KNM = KMeans(n_clusters=6, random_state=1)
resultKNM = KNM.fit_predict(scaled_data)
# кол-во пользователей в каждом кластере при разбиении на 6 кластеров
np.unique(resultKNM, return_counts=True)
```

Out[180…

```
(array([0, 1, 2, 3, 4, 5]), array([360, 175, 254, 526, 595, 305], dtype=int64))
```

In [182…

```
print("в первом сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.inde
print("во втором сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.ind
print("в третьем сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.ind
print("в четвертом сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.i
print("в пятом сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.index
print("в шестом сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.inde
```

```
в первом сегменте средние затраты: 1271
во втором сегменте средние затраты: 646
в третьем сегменте средние затраты: 407
в четвертом сегменте средние затраты: 636
в пятом сегменте средние затраты: 211
в шестом сегменте средние затраты: 691
```

In [183…

```
# Первый сегмент представляет наибольший интерес, поскольку средние затраты покупате
```

2.4 Метод Mini-Batch K-means

In [175…

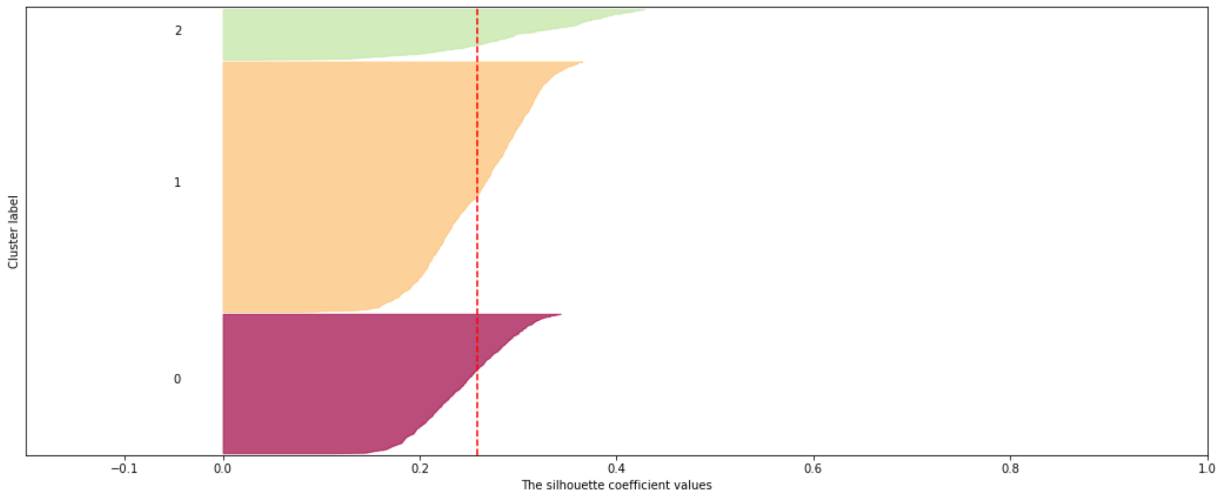
```
from sklearn.cluster import KMeans, MiniBatchKMeans, AffinityPropagation
```

In [184…

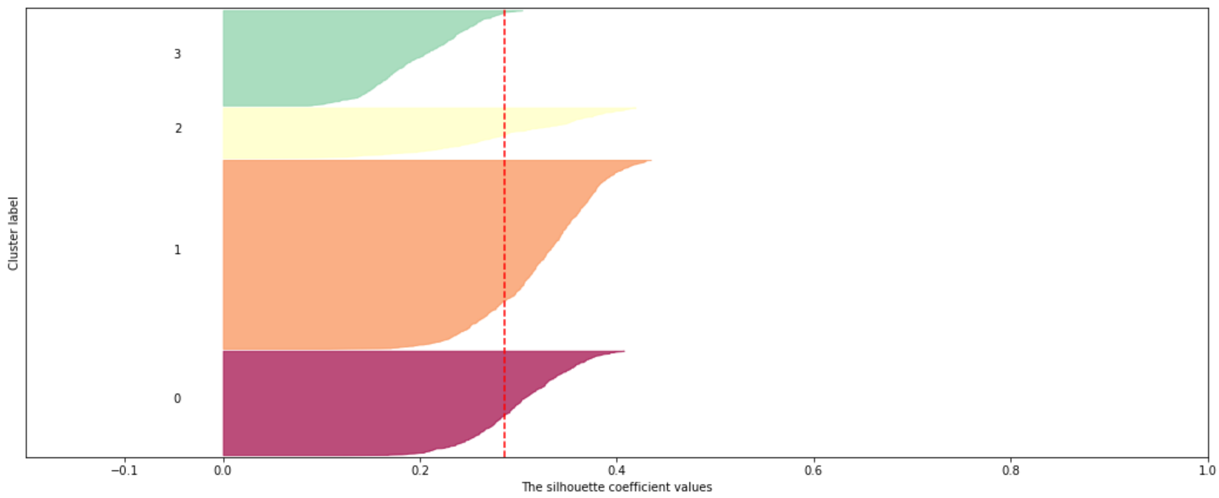
```
# попробуем пройтись по кол-ву кластеров от 3 до 15, оценивая результам по силуэтам
warnings.filterwarnings('ignore')
for n in range(3,16):
    MBKM = MiniBatchKMeans(n_clusters=n, random_state=1)
    sil_plot(MBKM, scaled_data, n)
```

```
For n_clusters = 3 The average silhouette_score is :0.259
For n_clusters = 4 The average silhouette_score is :0.287
For n_clusters = 5 The average silhouette_score is :0.252
For n_clusters = 6 The average silhouette_score is :0.257
For n_clusters = 7 The average silhouette_score is :0.265
For n_clusters = 8 The average silhouette_score is :0.246
For n_clusters = 9 The average silhouette_score is :0.238
For n_clusters = 10 The average silhouette_score is :0.233
For n_clusters = 11 The average silhouette_score is :0.225
For n_clusters = 12 The average silhouette_score is :0.241
For n_clusters = 13 The average silhouette_score is :0.242
For n_clusters = 14 The average silhouette_score is :0.245
For n_clusters = 15 The average silhouette_score is :0.207
```

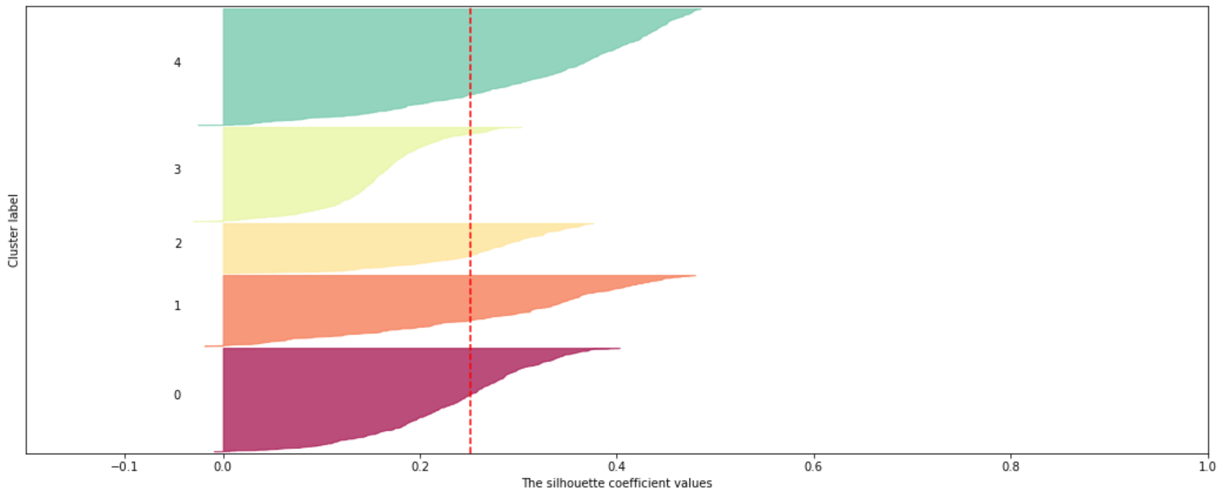
Silhouette analysis for clustering on sample data with n_clusters = 3



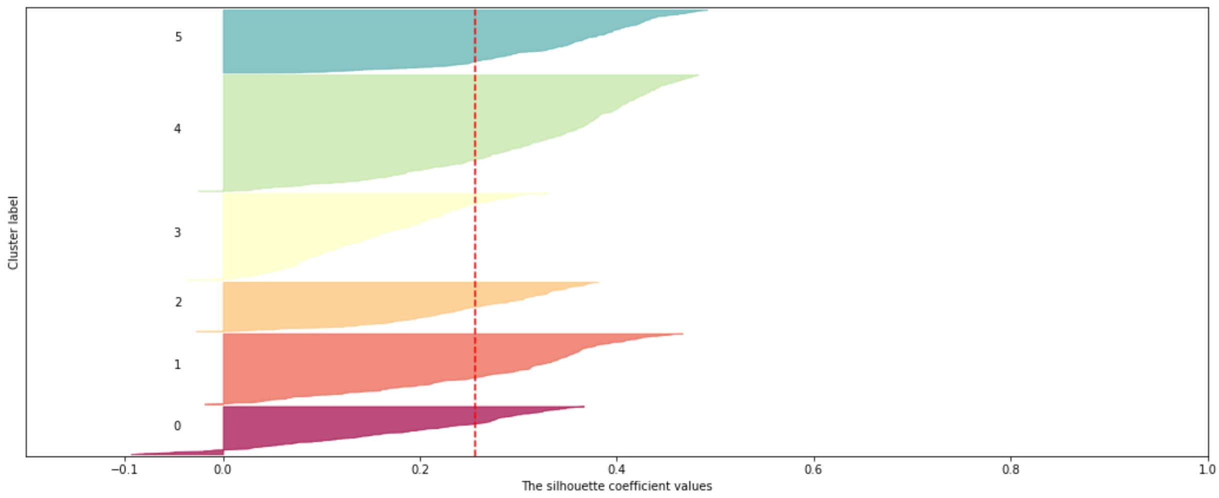
Silhouette analysis for clustering on sample data with n_clusters = 4

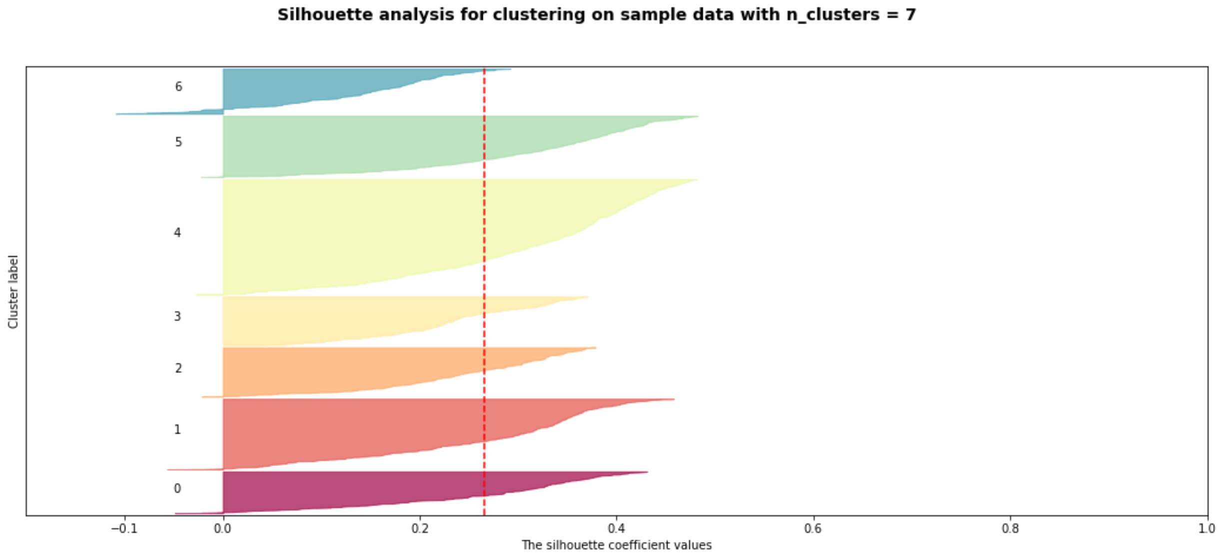


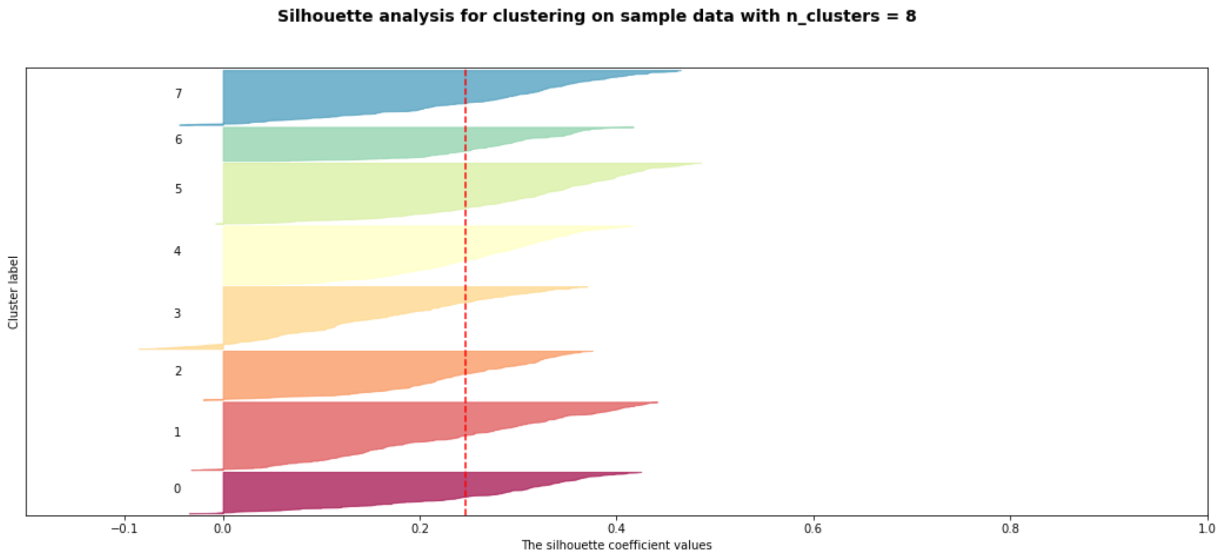
Silhouette analysis for clustering on sample data with n_clusters = 5

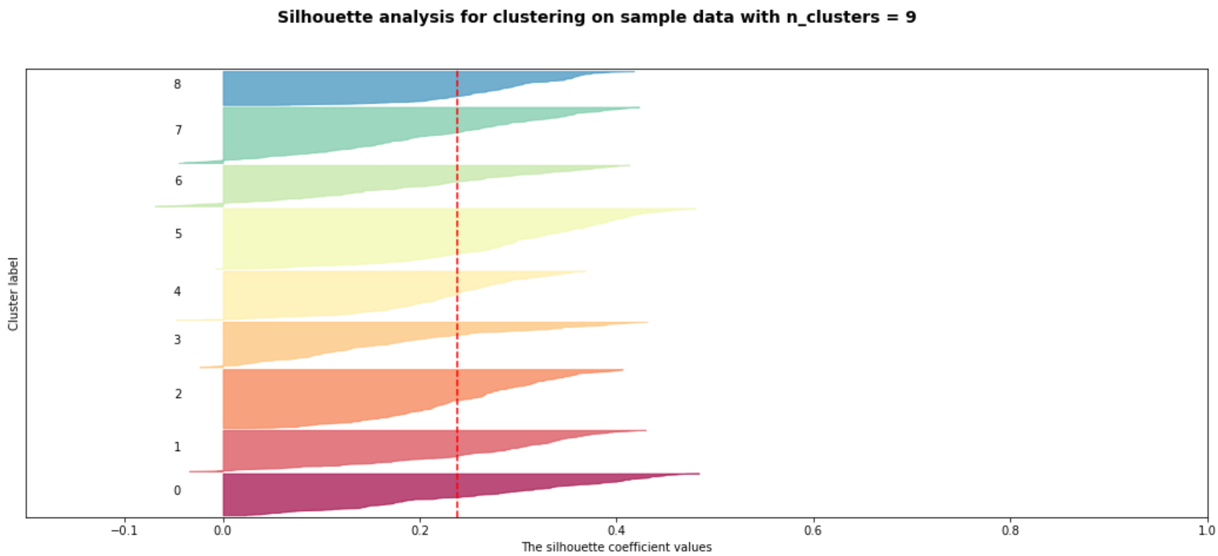


Silhouette analysis for clustering on sample data with n_clusters = 6

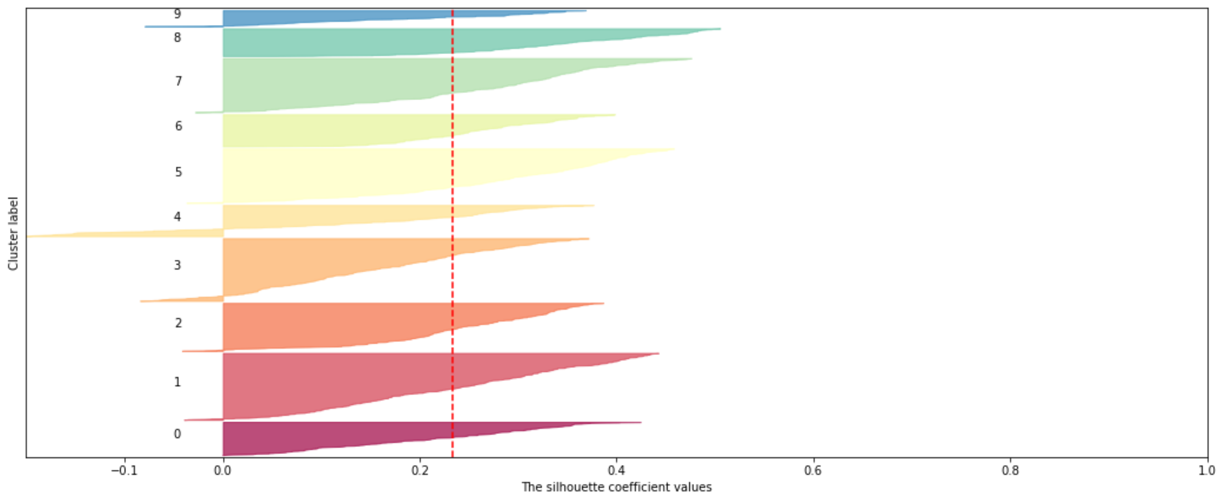



Silhouette analysis for clustering on sample data with n_clusters = 7
Cluster label
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values

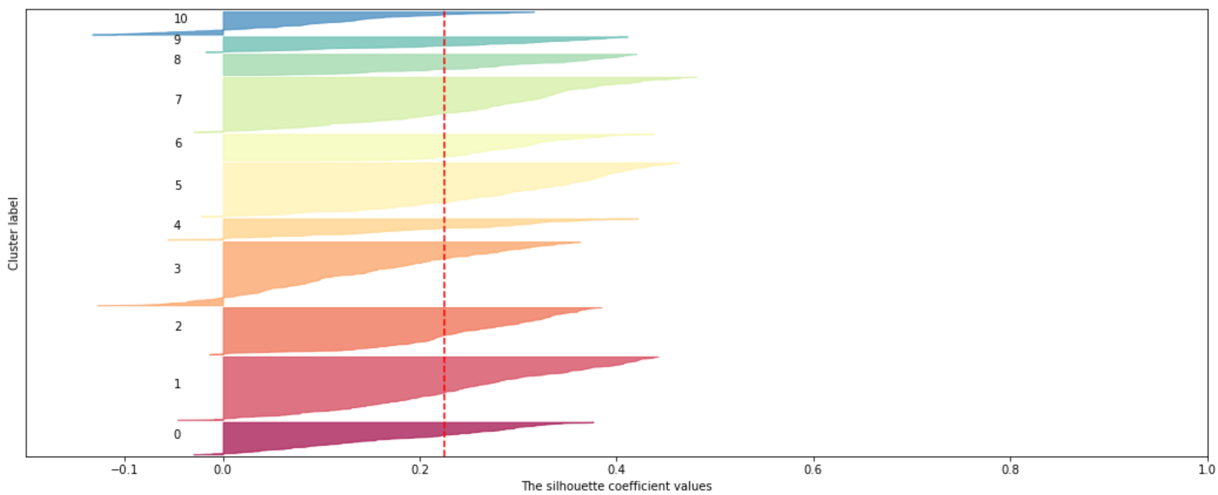

Silhouette analysis for clustering on sample data with n_clusters = 8
Cluster label
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values


Silhouette analysis for clustering on sample data with n_clusters = 9
Cluster label
8
7
6
5
4
3
2
1
0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
The silhouette coefficient values

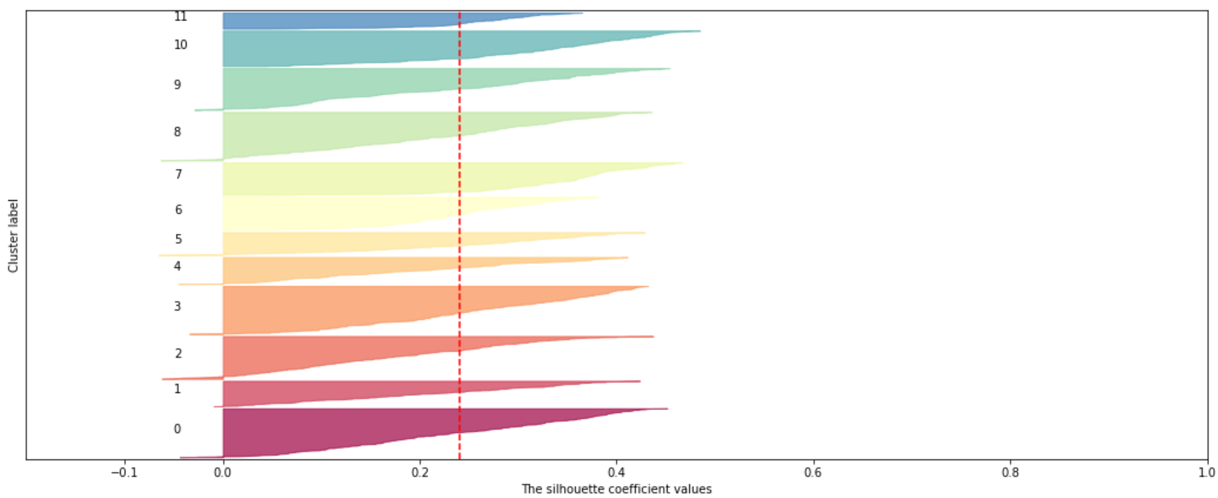
Silhouette analysis for clustering on sample data with n_clusters = 10



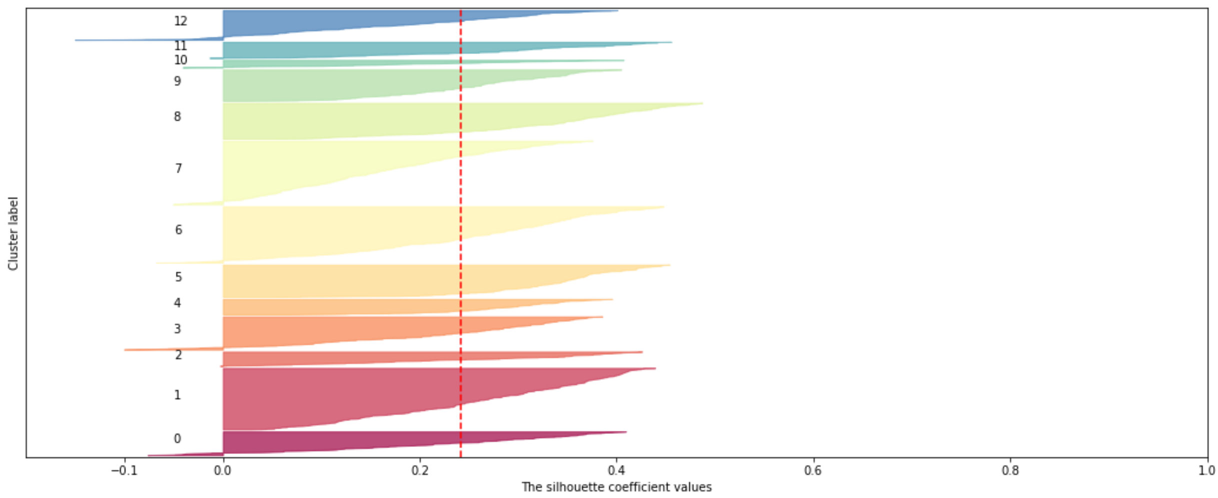
Silhouette analysis for clustering on sample data with n_clusters = 11



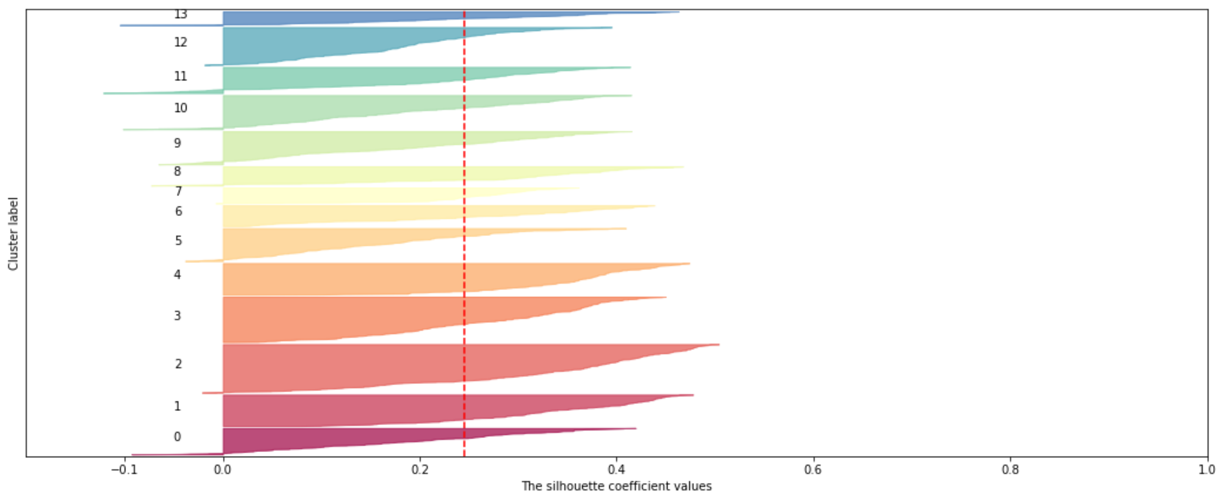
Silhouette analysis for clustering on sample data with n_clusters = 12



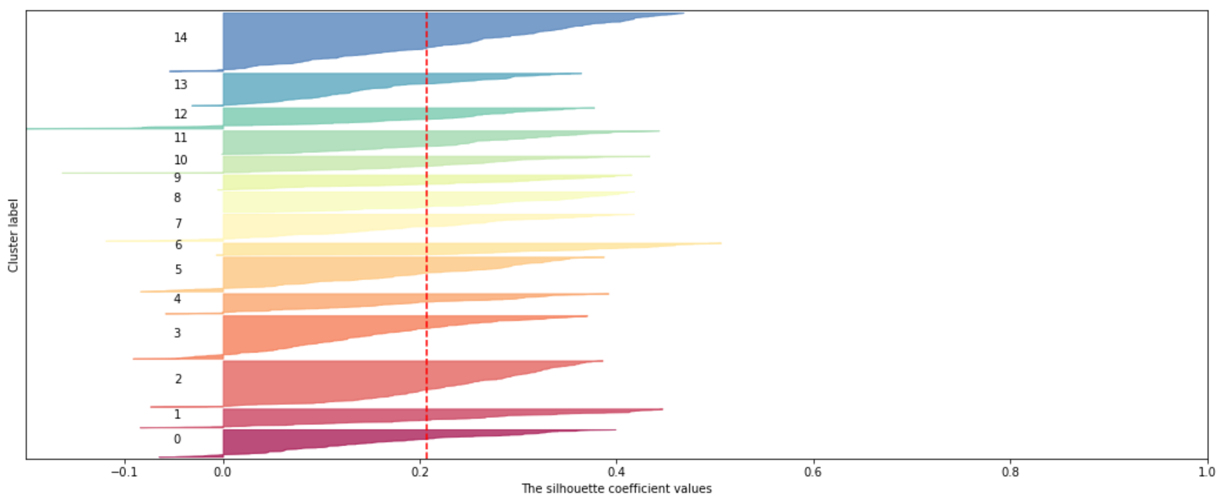
Silhouette analysis for clustering on sample data with n_clusters = 13



Silhouette analysis for clustering on sample data with n_clusters = 14



Silhouette analysis for clustering on sample data with n_clusters = 15



In [185…

```
# Определенно, разбиение на 4 кластера наилучшее

MBKM = MiniBatchKMeans(n_clusters=6, random_state=1)
resultMBKM = MBKM.fit_predict(scaled_data)
# кол-во пользователей в каждом кластере при разбиении на 4 кластера
np.unique(resultMBKM, return_counts=True)
```

Out[185…

```
(array([0, 1, 2, 3, 4, 5]), array([245, 361, 252, 443, 593, 321], dtype=int64))
```

In [186…
```
print("в первом сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.inde
print("во втором сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.ind
print("в третьем сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.ind
print("в четвертом сегменте средние затраты: {:.0f}".format(data_a.loc[scaled_data.i
```

```
в первом сегменте средние затраты: 1328
во втором сегменте средние затраты: 1265
в третьем сегменте средние затраты: 397
в четвертом сегменте средние затраты: 609
```

In [ ]:
```
# Первый и второй сегменты представляют наибольший интерес, поскольку средние затрат
```

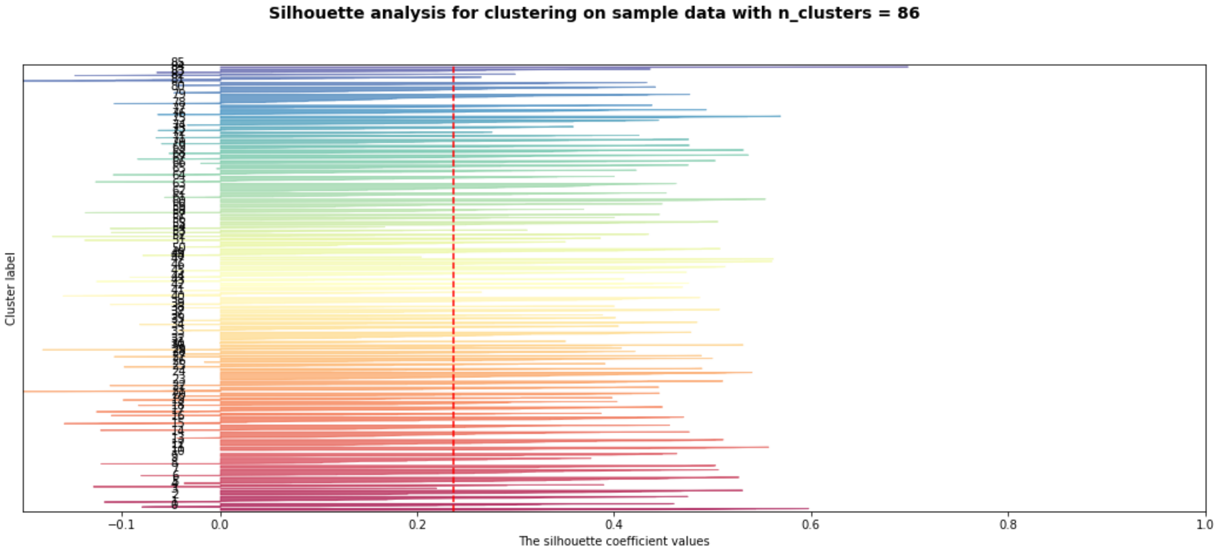
2.5 Метод Affinity Propagation

In [198…
```
# данный подход не требует заранее определять число кластеров, он определяет их сам
AFP = AffinityPropagation(random_state=1).fit(scaled_data)
np.sort(AFP.labels_)
```

Out[198…
```
array([ 0,  0,  0, ..., 85, 85, 85], dtype=int64)
```

In [188…
```
sil_plot(AFP, scaled_data, len(set(AFP.labels_)))
```

```
For n_clusters = 86 The average silhouette_score is :0.237
```



In [ ]:
```
# Этот результат, конечно, никуда не годится
```

2.6 Метод Агломеративной иерархической кластеризации

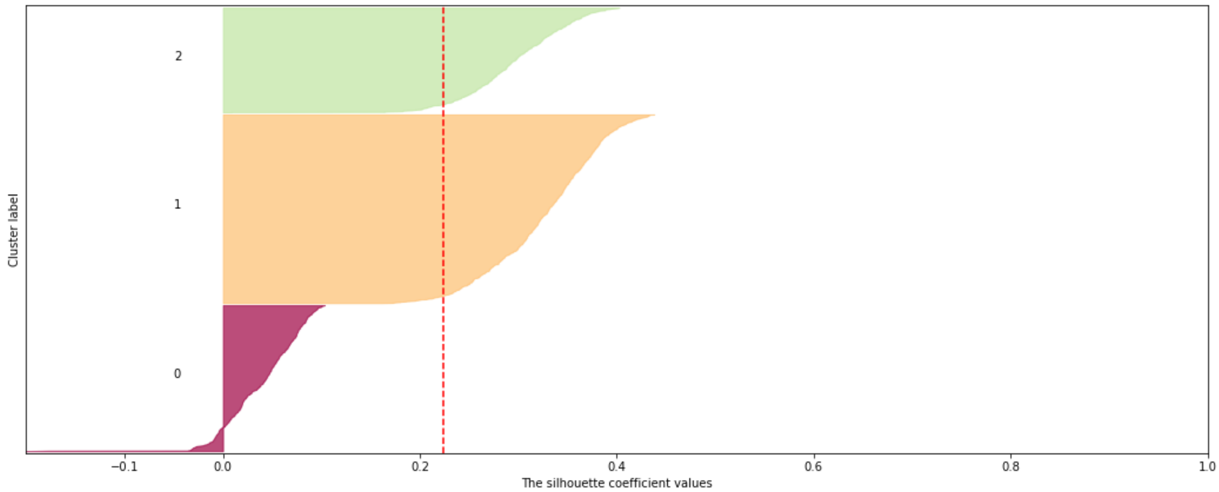
In [193…
```
from sklearn.cluster import AgglomerativeClustering
```

In [199…
```
# попробуем пройтись по кол-ву кластеров от 3 до 15, оценивая результат по силуэтам
for n in range(3,16):
    AMC = AgglomerativeClustering(n_clusters=n)
    sil_plot(AMC, scaled_data, n)
```

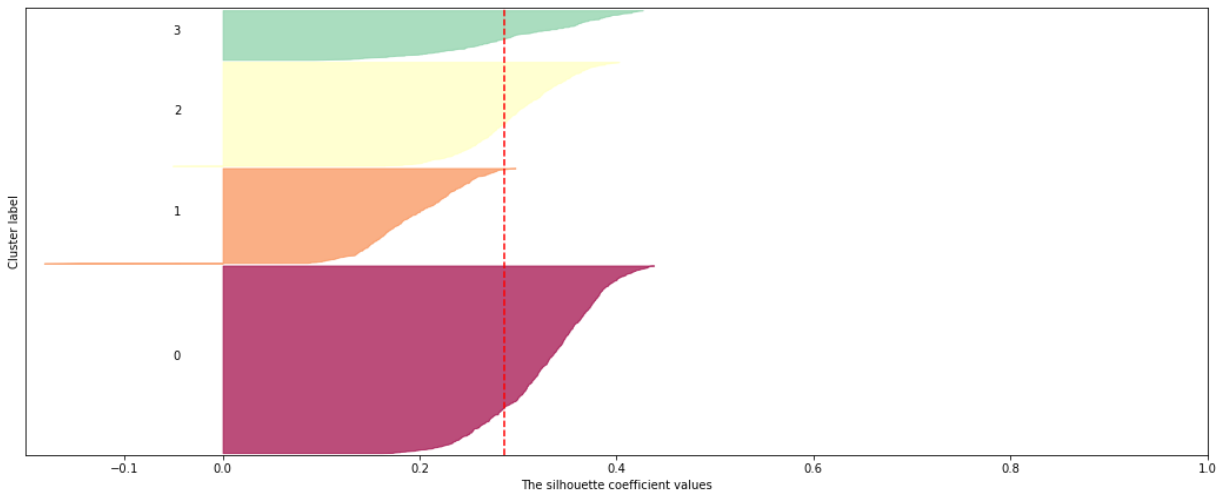
```
For n_clusters = 3 The average silhouette_score is :0.223
For n_clusters = 4 The average silhouette_score is :0.286
For n_clusters = 5 The average silhouette_score is :0.244
For n_clusters = 6 The average silhouette_score is :0.272
For n_clusters = 7 The average silhouette_score is :0.272
```

```
For n_clusters = 8 The average silhouette_score is :0.273
For n_clusters = 9 The average silhouette_score is :0.236
For n_clusters = 10 The average silhouette_score is :0.237
For n_clusters = 11 The average silhouette_score is :0.244
For n_clusters = 12 The average silhouette_score is :0.242
For n_clusters = 13 The average silhouette_score is :0.243
For n_clusters = 14 The average silhouette_score is :0.234
For n_clusters = 15 The average silhouette_score is :0.233
```

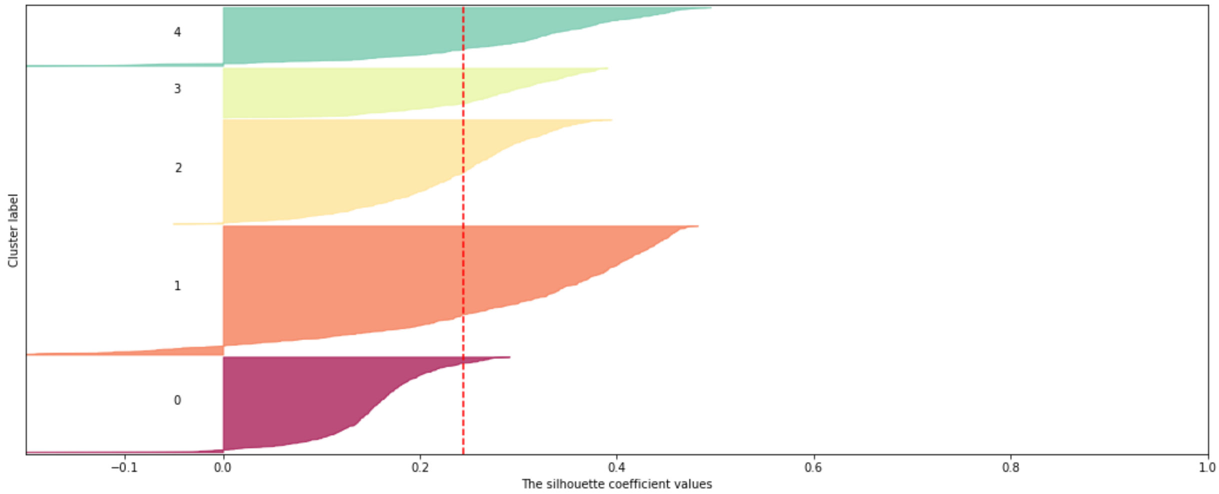
Silhouette analysis for clustering on sample data with n_clusters = 3



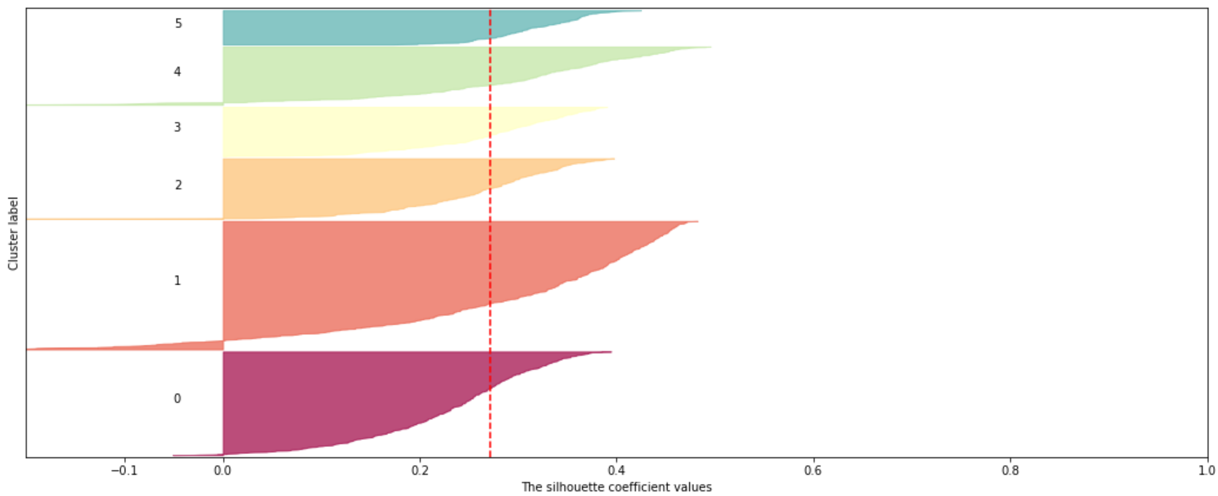
Silhouette analysis for clustering on sample data with n_clusters = 4



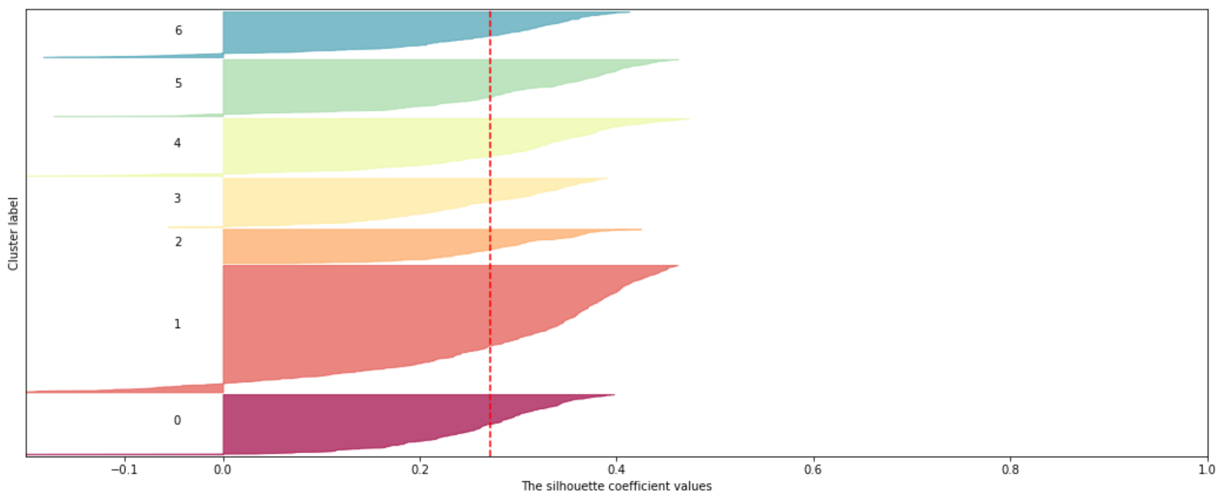
Silhouette analysis for clustering on sample data with n_clusters = 5



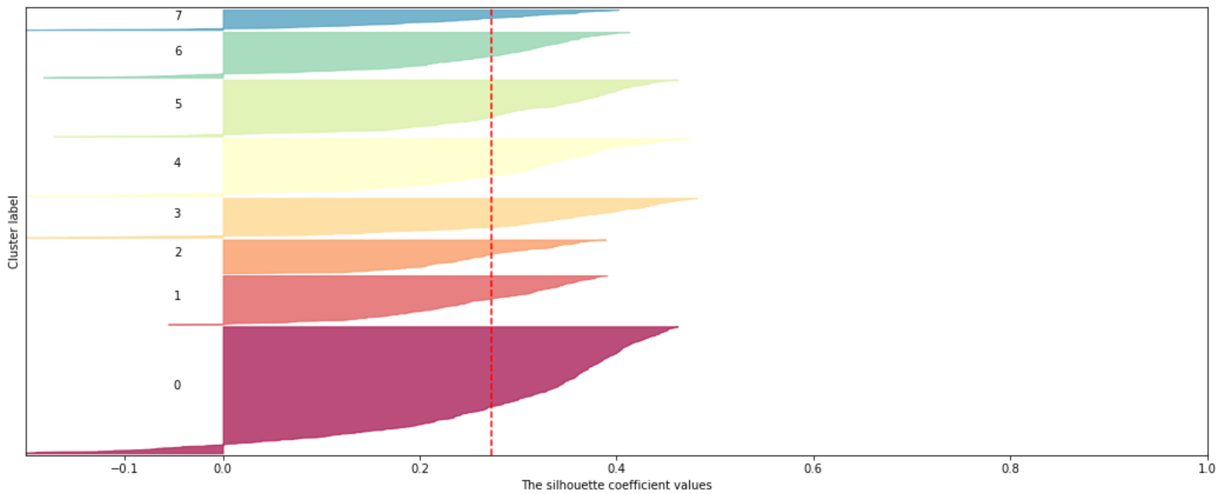
Silhouette analysis for clustering on sample data with n_clusters = 6



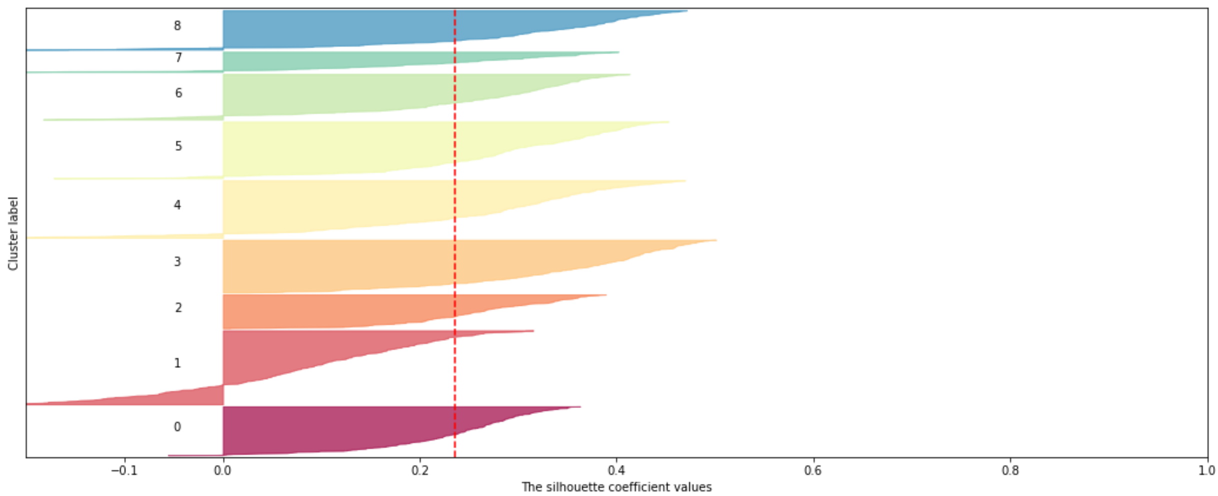
Silhouette analysis for clustering on sample data with n_clusters = 7



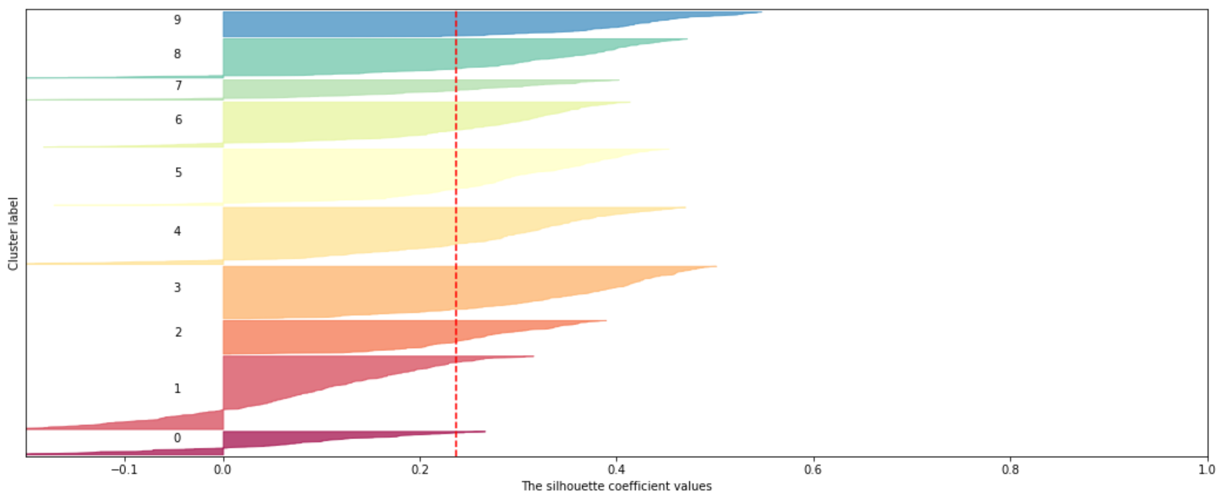
Silhouette analysis for clustering on sample data with n_clusters = 8



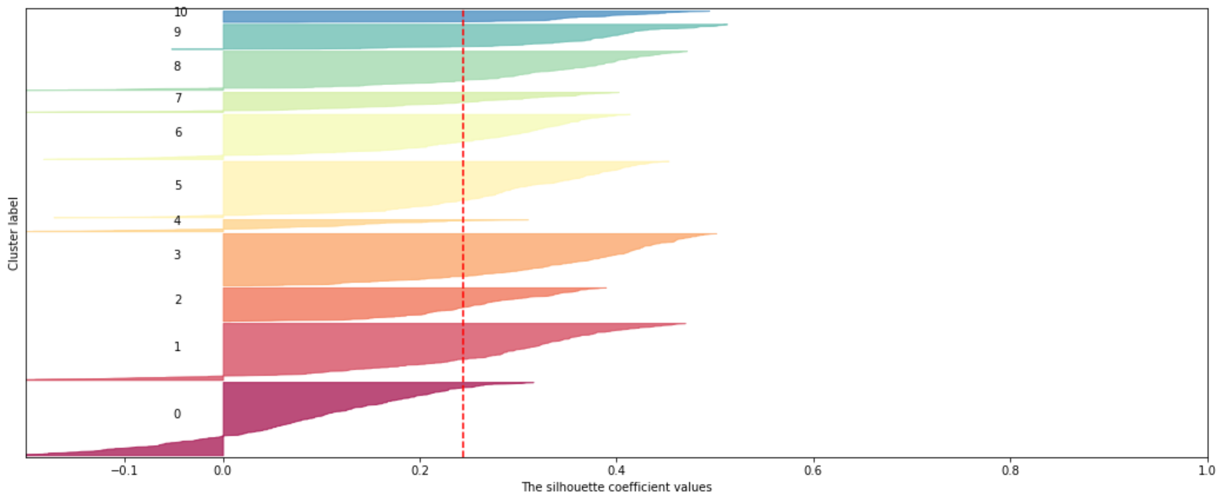
Silhouette analysis for clustering on sample data with n_clusters = 9



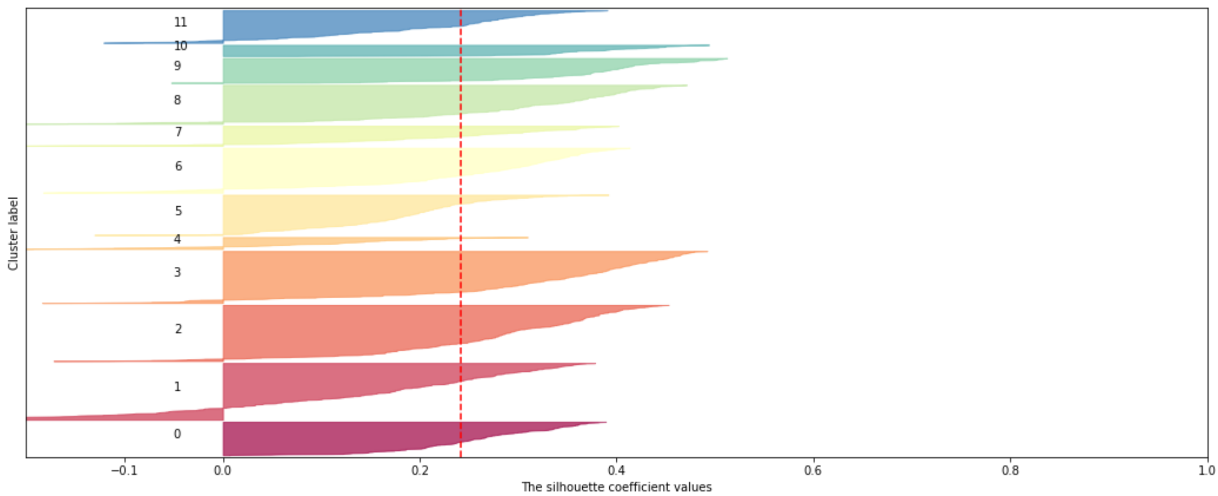
Silhouette analysis for clustering on sample data with n_clusters = 10



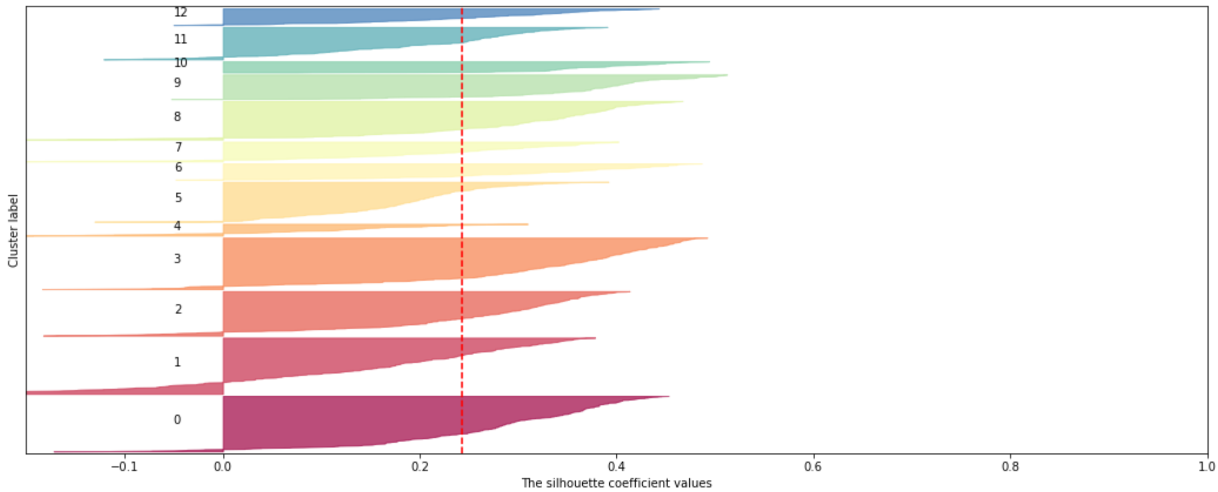
Silhouette analysis for clustering on sample data with n_clusters = 11



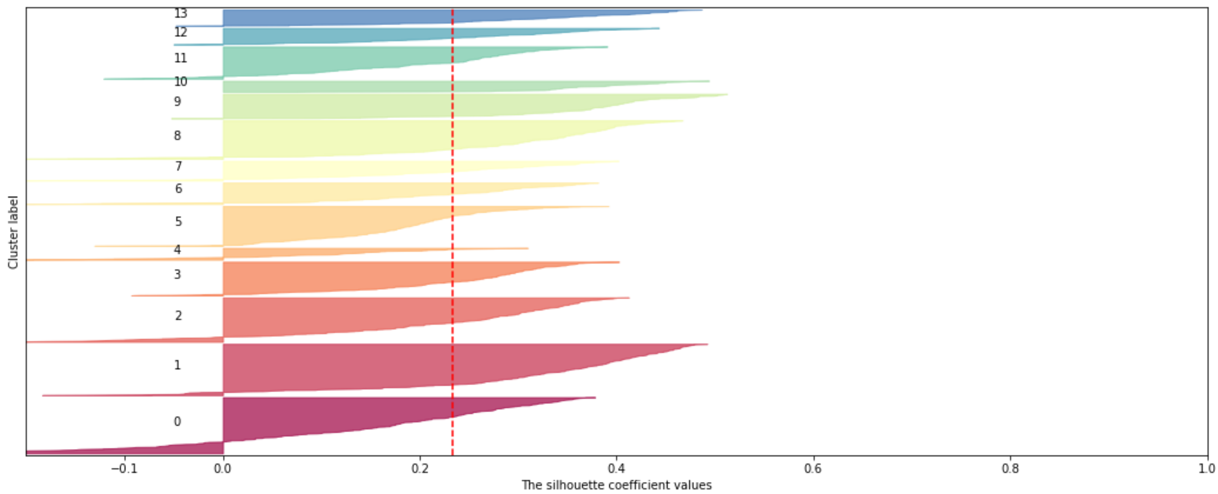
Silhouette analysis for clustering on sample data with n_clusters = 12

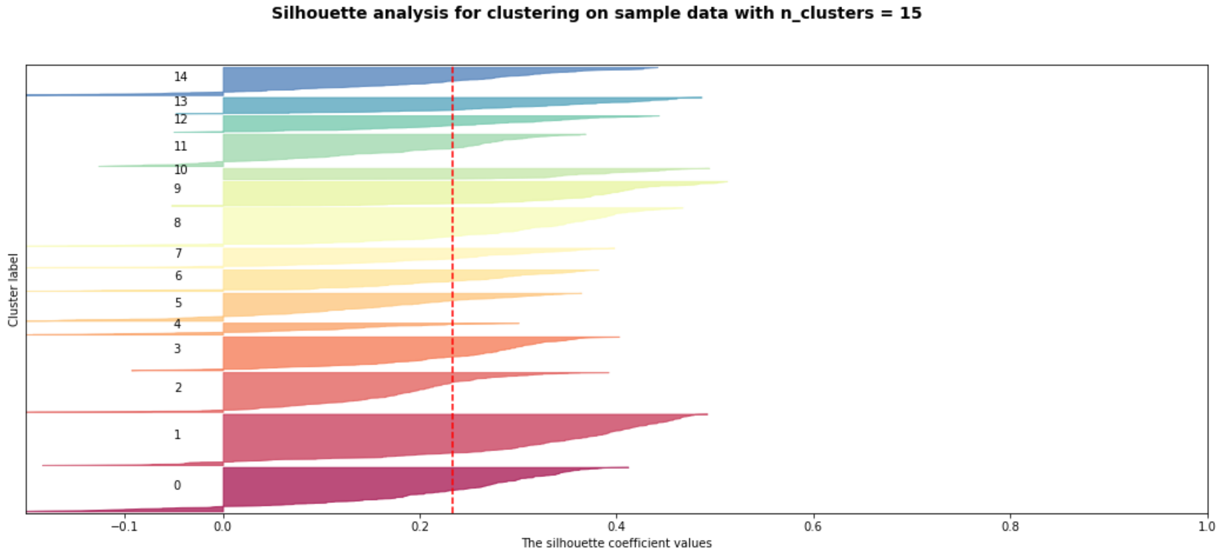


Silhouette analysis for clustering on sample data with n_clusters = 13



Silhouette analysis for clustering on sample data with n_clusters = 14





In [ ]:

```
# Более-менее разбиение на 4 сегмента, но результат визуально хуже, чем в K-Means
```