Лабораторная работа №3. Обработка признаков (часть 2).

Задание:

Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:

1. масштабирование признаков (не менее чем тремя способами);
2. обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
3. обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
4. отбор признаков:

- один метод из группы методов фильтрации (filter methods);
- один метод из группы методов обертывания (wrapper methods);
- один метод из группы методов вложений (embedded methods).

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import MaxAbsScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

In [2]:

```
data_loaded = pd.read_csv('world-happiness-report-2021.csv', sep=',')
data = data_loaded.rename(columns={
}).dropna()
data.head()
```

Out[2]:

	Country name	Regional indicator	Ladder score	Standard error of ladder score	upperwhisker	lowerwhisker	Logged GDP per capita	Social support	He ex
0	Finland	Western Europe	7.842	0.032	7.904	7.780	10.775	0.954	
2	Switzerland	Western Europe	7.571	0.036	7.643	7.500	11.117	0.942	
3	Iceland	Western Europe	7.554	0.059	7.670	7.438	10.878	0.983	
4	Netherlands	Western Europe	7.464	0.027	7.518	7.410	10.932	0.942	
5	Norway	Western Europe	7.392	0.035	7.462	7.323	11.053	0.954	

Маштабирование признаков

In [3]:

```
data_to_scale = data.drop(['Country name','Regional indicator'], axis=1)
data_to_scale.describe()
```

Out[3]:

	Ladder score	Standard error of ladder score	upperwhisker	lowerwhisker	Logged GDP per capita	Social support	Healthy life expectancy	Freedon to mak lif choice
count	137.000	137.000	137.000	137.000	137.000	137.000	137.000	137.00
mean	5.497	0.059	5.612	5.382	9.428	0.812	64.855	0.78
std	1.098	0.022	1.078	1.119	1.168	0.115	6.844	0.11
min	2.523	0.026	2.596	2.449	6.635	0.463	48.478	0.38
25%	4.794	0.043	4.963	4.658	8.538	0.746	59.305	0.71
50%	5.466	0.054	5.541	5.380	9.569	0.830	66.601	0.79
75%	6.317	0.070	6.415	6.213	10.421	0.903	69.652	0.87
max	7.842	0.173	7.904	7.780	11.647	0.983	76.953	0.96

На основе Z-оценки

In [4]:

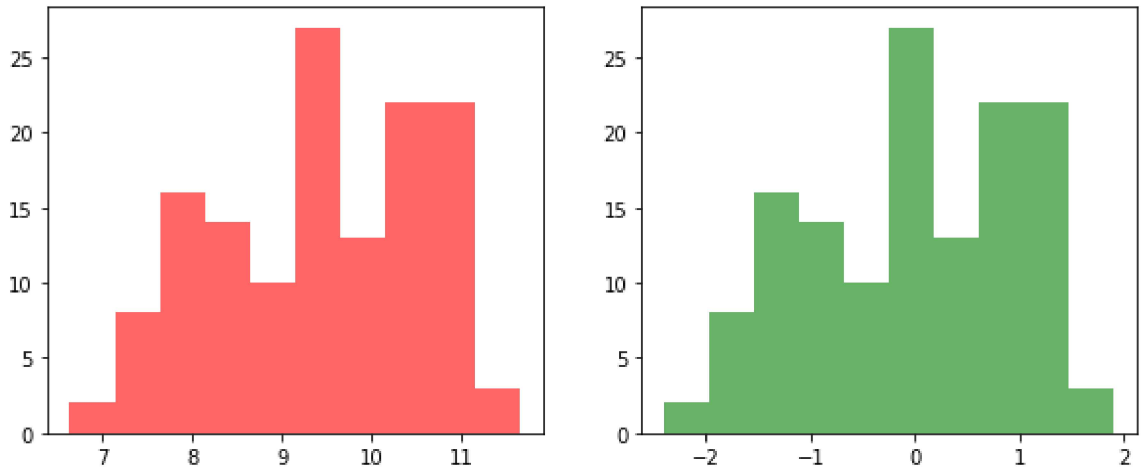
```
scaler1 = StandardScaler()
data_scaled1 = pd.DataFrame(scaler1.fit_transform(data_to_scale), columns=data_to_scale.c
data_scaled1.describe()
```

Out[4]:

	Ladder score	Standard error of ladder score	upperwhisker	lowerwhisker	Logged GDP per capita	Social support	Healthy life expectancy	Freedon to mak lif choice:
count	137.000	137.000	137.000	137.000	137.000	137.000	137.000	137.00(
mean	0.000	0.000	0.000	-0.000	0.000	-0.000	0.000	-0.00(
std	1.004	1.004	1.004	1.004	1.004	1.004	1.004	1.00
min	-2.719	-1.480	-2.807	-2.631	-2.400	-3.037	-2.402	-3.53
25%	-0.643	-0.708	-0.604	-0.650	-0.765	-0.576	-0.814	-0.61
50%	-0.028	-0.208	-0.066	-0.002	0.121	0.155	0.256	0.06
75%	0.749	0.519	0.748	0.745	0.854	0.790	0.703	0.77
max	2.144	5.200	2.134	2.151	1.907	1.486	1.774	1.50

In [5]:

```
fig, axs = plt.subplots(1, 2, figsize=(10,4))
axs[0].hist(data["Logged GDP per capita"], color="r", alpha=0.6)
axs[1].hist(data_scaled1["Logged GDP per capita"], color="g", alpha=0.6)
plt.show()
```



MinMax-масштабирование

In [6]:

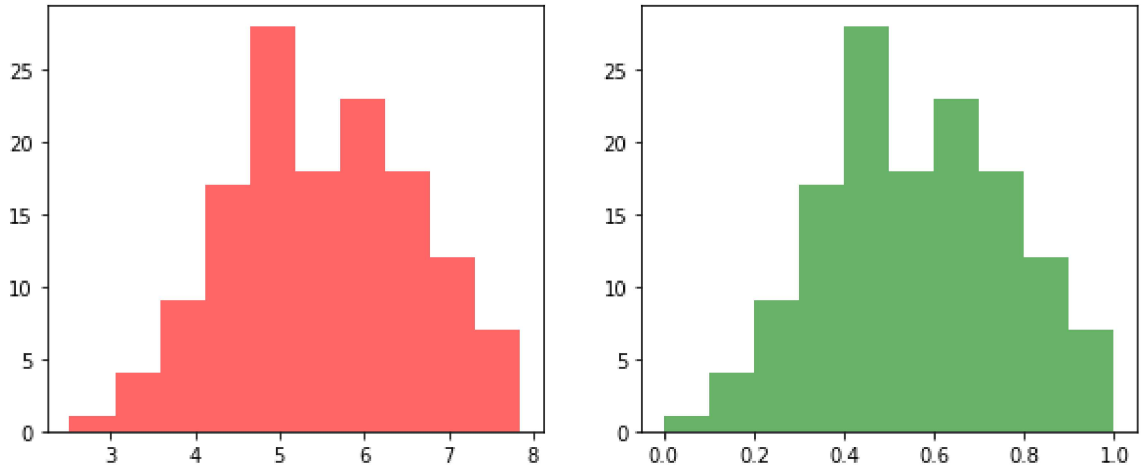
```
scaler2 = MinMaxScaler()
data_scaled2 = pd.DataFrame(scaler2.fit_transform(data_to_scale), columns=data_to_scale.c
data_scaled2.describe()
```

Out[6]:

	Ladder score	Standard error of ladder score	upperwhisker	lowerwhisker	Logged GDP per capita	Social support	Healthy life expectancy	Freedon to mak lif choice:
count	137.000	137.000	137.000	137.000	137.000	137.000	137.000	137.00
mean	0.559	0.222	0.568	0.550	0.557	0.672	0.575	0.70
std	0.206	0.150	0.203	0.210	0.233	0.222	0.240	0.19
min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
25%	0.427	0.116	0.446	0.414	0.380	0.544	0.380	0.58
50%	0.553	0.190	0.555	0.550	0.585	0.706	0.636	0.71
75%	0.713	0.299	0.719	0.706	0.755	0.846	0.744	0.85
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.00

In [7]:

```
fig, axs = plt.subplots(1, 2, figsize=(10,4))
axs[0].hist(data["Ladder score"], color="r", alpha=0.6)
axs[1].hist(data_scaled2["Ladder score"], color="g", alpha=0.6)
plt.show()
```



По максимальному значению

In [8]:

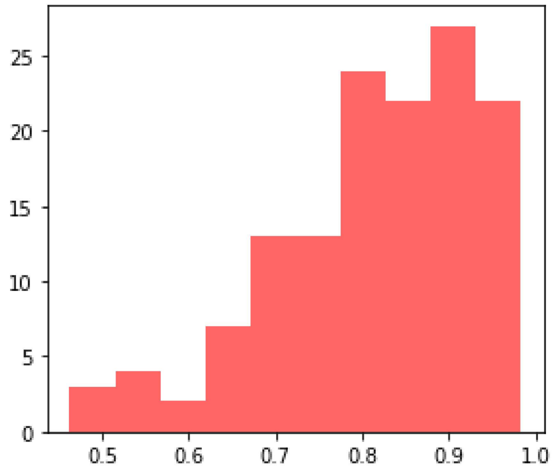
```
scaler3 = MaxAbsScaler()
data_scaled3 = pd.DataFrame(scaler2.fit_transform(data_to_scale), columns=data_to_scale.c
data_scaled3.describe()
```

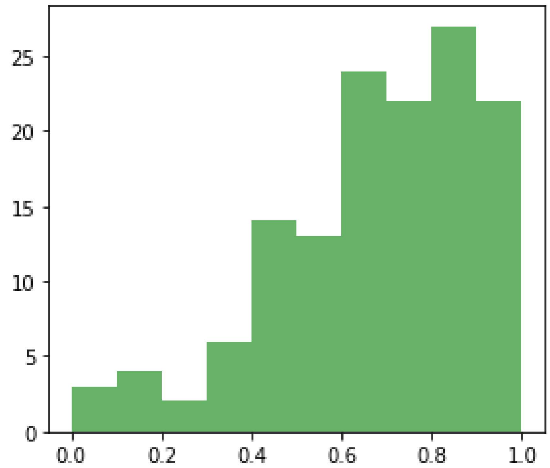
Out[8]:

	Ladder score	Standard error of ladder score	upperwhisker	lowerwhisker	Logged GDP per capita	Social support	Healthy life expectancy	Freedon to mak lif choice:
count	137.000	137.000	137.000	137.000	137.000	137.000	137.000	137.00
mean	0.559	0.222	0.568	0.550	0.557	0.672	0.575	0.70
std	0.206	0.150	0.203	0.210	0.233	0.222	0.240	0.19
min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
25%	0.427	0.116	0.446	0.414	0.380	0.544	0.380	0.58
50%	0.553	0.190	0.555	0.550	0.585	0.706	0.636	0.71
75%	0.713	0.299	0.719	0.706	0.755	0.846	0.744	0.85
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.00

In [9]:

```
fig, axs = plt.subplots(1, 2, figsize=(10,4))
axs[0].hist(data["Social support"], color="r", alpha=0.6)
axs[1].hist(data_scaled3["Social support"], color="g", alpha=0.6)
plt.show()
```





Обработка выбросов

In [10]:

```
# Тип вычисления верхней и нижней границы выбросов
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3
```

In [11]:

```
# Функция вычисления верхней и нижней границы выбросов
def get_outlier_boundaries(df, outlier_boundary_type: OutlierBoundaryType):
    if outlier_boundary_type == OutlierBoundaryType.SIGMA:
        K1 = 3
        lower_boundary = df.mean() - (K1 * df.std())
        upper_boundary = df.mean() + (K1 * df.std())

    elif outlier_boundary_type == OutlierBoundaryType.QUANTILE:
        lower_boundary = df.quantile(0.05)
        upper_boundary = df.quantile(0.95)

    elif outlier_boundary_type == OutlierBoundaryType.IRQ:
        K2 = 1.5
        IQR = df.quantile(0.75) - df.quantile(0.25)
        lower_boundary = df.quantile(0.25) - (K2 * IQR)
        upper_boundary = df.quantile(0.75) + (K2 * IQR)

    return lower_boundary, upper_boundary
```

In [12]:

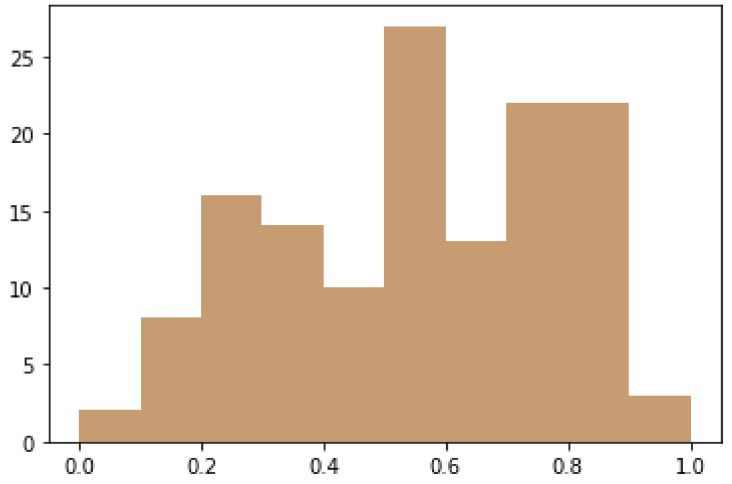
```
data2 = data_scaled3.copy()
```

Замена выбросов

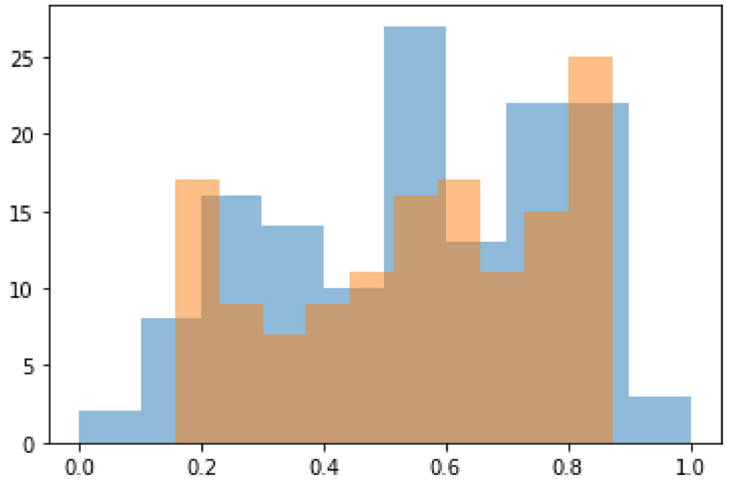
In [13]:

```
for obt in OutlierBoundaryType:
    lower_boundary, upper_boundary = get_outlier_boundaries(data_scaled3['Explained by: L
    data2['Explained by: Log GDP per capita'] = np.where(data_scaled3['Explained by: Log 
        np.where(data2['Explained by: Log GDP per capita'] < lower_boundary, lower_bounda
    plt.hist(data_scaled3['Explained by: Log GDP per capita'], alpha=0.5)
    plt.hist(data2['Explained by: Log GDP per capita'], alpha=0.5)
    print(obt)
    plt.show()
```

OutlierBoundaryType.SIGMA

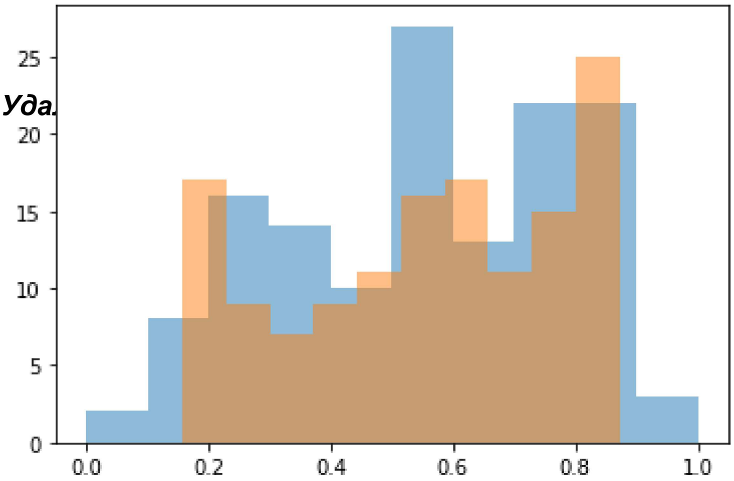


OutlierBoundaryType.QUANTILE



OutlierBoundaryType.IRQ

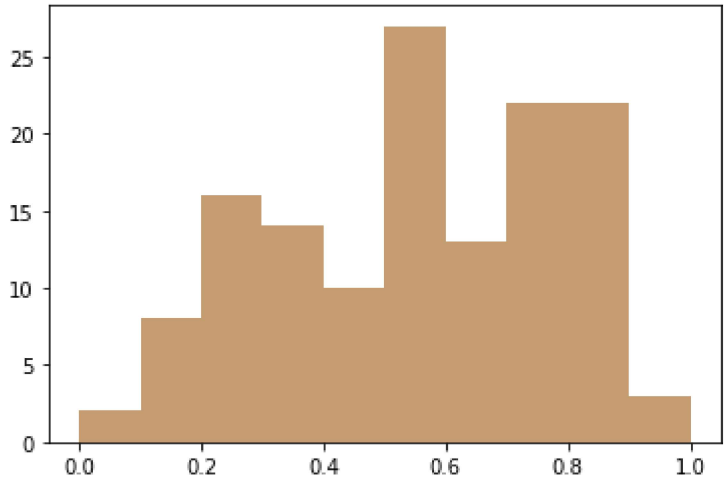
Уда.



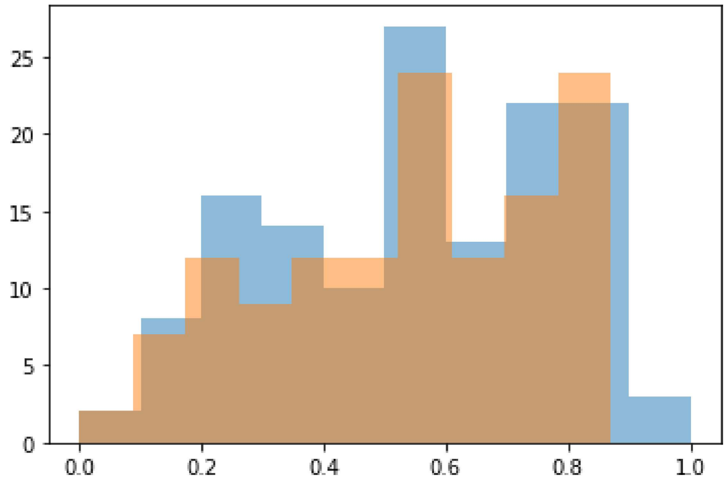
In [14]:

```
for obt in OutlierBoundaryType:
    lower_boundary, upper_boundary = get_outlier_boundaries(data_scaled3['Explained by: L
    temp_df = np.where(data_scaled3['Explained by: Log GDP per capita'] > upper_boundary,
        np.where(data2['Explained by: Log GDP per capita'] < lower_boundary, True, False)
    data_trimmed = data_scaled3.loc[~(temp_df), ]
    plt.hist(data_scaled3['Explained by: Log GDP per capita'], alpha=0.5)
    plt.hist(data_trimmed['Explained by: Log GDP per capita'], alpha=0.5)
    print(obt)
    plt.show()
```

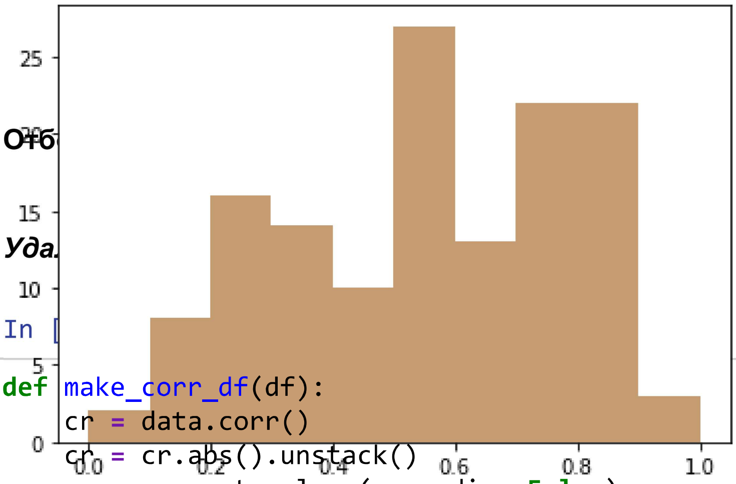
```
OutlierBoundaryType.SIGMA
```




```
OutlierBoundaryType.QUANTILE
```




```
OutlierBoundaryType.IRQ
```



Отб

Уда

In [

```
def make_corr_df(df):
    cr = data.corr()
    cr = cr.abs().unstack()
    cr = cr.sort_values(ascending=False)
    cr = cr[cr >= 0.80]
    cr = cr[cr < 1]
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']
    return cr
```

In [16]:

```
def corr_groups(cr):
    grouped_feature_list = []
    correlated_groups = []

    for feature in cr['f1'].unique():
        if feature not in grouped_feature_list:
            correlated_block = cr[cr['f1'] == feature]
            cur_dups = list(correlated_block['f2'].unique()) + [feature]
            grouped_feature_list = grouped_feature_list + cur_dups
            correlated_groups.append(cur_dups)
    return correlated_groups
```

In [17]:

```
corr_groups(make_corr_df(data_trimmed))
```

Out[17]:

```
[['Logged GDP per capita',
  'Explained by: Healthy life expectancy',
  'Healthy life expectancy',
  'lowerwhisker',
  'Ladder score',
  'Explained by: Log GDP per capita'],
 ['Perceptions of corruption', 'Explained by: Perceptions of corruption'],
 ['Explained by: Social support', 'Social support'],
 ['Explained by: Freedom to make life choices',
  'Freedom to make life choices'],
 ['Generosity', 'Explained by: Generosity'],
 ['Ladder score', 'lowerwhisker', 'upperwhisker']]
```

Метод обёртывания

In [18]:

```
knn = KNeighborsClassifier(n_neighbors=3)
```

In [19]:

```
X_columns = ['Ladder score','Standard error of ladder score','Ladder score in Dystopia',
Y1_columns = ['Regional indicator']
Y2_columns = ['Explained by: Log GDP per capita']
X = data2[X_columns]
Y1 = np.ravel(np.where(data[Y1_columns] == 'Latin America and Caribbean', 'Central Americ
    np.where(data[Y1_columns] == 'North America and ANZ', 'North America',
    np.where(data[Y1_columns] == 'Middle East and North Africa', 'Africa', data[Y1_column
Y2 = np.ravel(data2[Y2_columns])
```

In [20]:

```
efs1 = EFS(knn,
           min_features=2,
           max_features=4,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs1 = efs1.fit(X, Y1)

print('Best accuracy score: %.2f' % efs1.best_score_)
print('Best subset:', efs1.best_feature_names_)
```

```
  warnings.warn(
C:\Users\user\AppData\Roaming\Python\Python38\site-packages\sklearn\model_selection\_split.py:700: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
C:\Users\user\AppData\Roaming\Python\Python38\site-packages\sklearn\model_selection\_split.py:700: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
C:\Users\user\AppData\Roaming\Python\Python38\site-packages\sklearn\model_selection\_split.py:700: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
C:\Users\user\AppData\Roaming\Python\Python38\site-packages\sklearn\model_selection\_split.py:700: UserWarning: The least populated class in y has only 4 members, which is less than n_splits=5.
  warnings.warn(
Features: 50/50

Best accuracy score: 0.36
Best subset: ('Standard error of ladder score', 'lowerwhisker', 'Dystopia + residual')
```

Метод вложений

In [21]:

```
e_lr1 = LogisticRegression(C=1000, solver='liblinear', penalty='l1', max_iter=500, random
e_lr1.fit(X, Y1)
e_lr1.coef_
```

Out[21]:

```
array([[-1.60468633e-01, -1.17504023e+00,  0.00000000e+00,
        -8.13333712e-01, -6.58372870e-05, -1.51040660e+00],
       [ 3.08297295e+00,  4.62340016e+00,  0.00000000e+00,
         3.95440674e+00,  5.55805493e+00,  1.20691437e+00],
       [ 1.13543381e-02, -3.34306907e+00,  0.00000000e+00,
         0.00000000e+00, -2.37442281e+00,  2.23475823e+00],
       [-1.41673194e+00, -5.83196356e+00,  0.00000000e+00,
        -7.49060962e-01, -5.67568838e+00, -1.38257965e+00],
       [ 1.16781923e+00, -7.31195947e+00,  0.00000000e+00,
         4.97971476e-01, -8.17635931e+00, -4.82023446e+00],
       [ 9.13019711e+00,  9.97922717e-01,  0.00000000e+00,
         9.12020354e+00,  3.20998740e+00, -6.68956247e+00],
       [-1.31185607e+00, -3.11298322e+00,  0.00000000e+00,
        -4.83166068e+00, -2.09403259e+00, -4.80975290e-01],
       [ 8.00556537e-01, -3.85412243e+00,  0.00000000e+00,
         5.59713137e-01,  0.00000000e+00, -4.71755957e+00],
       [-8.10691643e+00,  2.24813776e+00,  0.00000000e+00,
        -7.20685920e+00,  0.00000000e+00,  7.53674142e+00],
       [ 5.43146783e+00, -6.70076167e-01,  0.00000000e+00,
         7.54752418e+00, -6.28103229e+00, -3.99592605e+00]])
```

In [22]:

```
sel_e_lr1 = SelectFromModel(e_lr1)
sel_e_lr1.fit(X, Y1)
sel_e_lr1.get_support()
```

Out[22]:

```
array([ True,  True, False,  True,  True,  True])
```

In [ ]:

```
```