Московский государственный технический университет им. Н.Э. Баумана Факультет «Информатика и системы управления» Кафедра «Системы обработки информации и управления»



Отчет Лабораторная работа № 3 По курсу «Методы машинного обучения»

Обработка признаков часть 3

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""	2022 г.			
ПРЕГ	ЮДАВАТЕЛЬ: Гапанюк Ю.Е.			
""	2022 г.			

Задание

- 1. Выбрать один или несколько наборов данных (датасетов) для решения следующих задач. Каждая задача может быть решена на отдельном датасете, или несколько задач могут быть решены на одном датасете. Просьба не использовать датасет, на котором данная задача решалась в лекции.
- 2. Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
 - і. масштабирование признаков (не менее чем тремя способами);
 - іі. обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
 - ііі. обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
 - iv. 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).

Выполнение

Popov I.A. IU5-23M lab3

15.000000

max

2410.000000

```
In [62]:
           import numpy as np
           import pandas as pd
           from sklearn.preprocessing import StandardScaler
           from sklearn.preprocessing import MinMaxScaler
           from sklearn.preprocessing import RobustScaler
           from sklearn.neighbors import KNeighborsClassifier
           from sklearn.svm import LinearSVC
           from sklearn.feature_selection import SelectFromModel
           from category encoders.count import CountEncoder as ce CountEncoder
           from mlxtend.feature selection import SequentialFeatureSelector as SFS
           import seaborn as sns
           import matplotlib.pyplot as plt
           import scipy.stats as stats
 In [3]:
           raw data = pd.read csv('kba data.csv', sep=',')
 In [4]:
           raw data.head()
                                                              County Sub.cell Season DEM
                                                                                               Cell.ID List.ID
                                     Date Time n.observers
 Out[4]:
          0
                        Asian Koel
                                 7/16/2015 16:30
                                                        2.0 Alappuzha
                                                                      [51,2,2]
                                                                                 Wet
                                                                                       5.0 [76.28,9.84]
                                                                                                       List.1
            Black-rumped Flameback
                                 7/16/2015 16:30
                                                                                          [76.28,9.84]
                                                        2.0 Alappuzha
                                                                      [51,2,2]
                                                                                 Wet
          2
                      Black Drongo 7/16/2015 16:30
                                                                                           [76.28,9.84]
                                                        2.0
                                                            Alappuzha
                                                                      [51.2.2]
                                                                                 Wet
                                                                                       5.0
                                                                                                       List.1
          3
                     Brahminy Kite
                                 7/16/2015 16:30
                                                        2.0
                                                           Alappuzha
                                                                      [51,2,2]
                                                                                 Wet
                                                                                       5.0
                                                                                           [76.28,9.84]
                                                                                                      List.1
          4
                    Common Myna 7/16/2015 16:30
                                                        2.0 Alappuzha
                                                                                 Wet
                                                                                          [76.28,9.84]
                                                                                                       List.1
                                                                      [51,2,2]
 In [5]:
           raw_data.dtypes
 Out[5]: Common.Name
                           object
          Date
                           object
          Time
                           object
          n.observers
                          float64
          County
                           object
          Sub.cell
                           object
          Season
                           object
          DEM
                          float64
          Cell.ID
                           object
          List.ID
                           object
          dtype: object
 In [6]:
           raw_data_with_na = [c for c in raw_data.columns if raw_data[c].isnull().sum() > 0]
           [(c, raw data[c].isnull().sum()) for c in raw data with na]
 Out[6]: [('Sub.cell', 127), ('Cell.ID', 127), ('List.ID', 127)]
           raw data = raw data.dropna()
 In [7]:
           raw data with na = [c for c in raw data.columns if raw data[c].isnull().sum() > 0]
 In [8]:
           [(c, raw_data[c].isnull().sum()) for c in raw_data_with_na]
 Out[8]: []
 In [9]:
           raw data.describe()
                  n.observers
                                      DEM
 Out[9]:
          count 300755.000000
                             300755 000000
                     2.351103
                                 225.631464
          mean
                                 346.708288
                     1.024697
            std
           min
                     1.000000
                                  0.000000
           25%
                     2.000000
                                 26.000000
           50%
                     2.000000
                                 69.000000
           75%
                     3.000000
                                 203.000000
```

```
def draw_kde(col_list, df1, df2, label1, label2):
               fig, (ax1, ax2) = plt.subplots(
                   ncols=2, figsize=(12, 5))
               # первый график
               ax1.set_title(label1)
               sns.kdeplot(data=df1[col_list], ax=ax1)
               # второй график
               ax2.set title(label2)
               sns.kdeplot(data=df2[col_list], ax=ax2)
               plt.show()
         Масштабирование признаков
          data to sc = raw data[{'n.observers', 'DEM'}]
In [11]:
           data_to_sc
                 DEM n.observers
Out[11]:
               0
                              2.0
                   5.0
                   5.0
                              2.0
               2
                   5.0
                              2.0
               3
                   5.0
                              2.0
               4
                   5.0
                              2.0
          300750 860.0
                              4 0
          300751 860.0
                              4.0
          300752 860.0
                              4.0
          300753 860 0
                              40
          300754 860.0
                              4.0
         300755 rows × 2 columns
In [12]:
           def arr_to_df(arr_scaled):
               res = pd.DataFrame(arr_scaled, columns=data_to_sc.columns)
               return res
          #Масштабирование данных на основе Z-оценки
In [13]:
           cs1 = StandardScaler()
           data cs1 scaled temp = cs1.fit transform(data to sc)
           data_cs1_scaled = arr_to_df(data_cs1_scaled_temp)
           data_cs1_scaled
Out[13]:
                     DEM n.observers
               0 -0.636362
                            -0.342641
              1 -0.636362
                            -0.342641
               2 -0.636362
                            -0.342641
               3 -0.636362
                            -0.342641
               4 -0.636362
                            -0.342641
          300750
                 1.829693
                             1.609158
          300751
                 1.829693
                             1.609158
          300752 1.829693
                             1.609158
          300753 1.829693
                             1.609158
          300754 1.829693
                             1.609158
         300755 rows × 2 columns
```

Построение плотности распределения

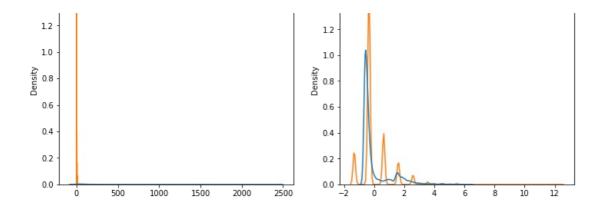
In [10]:

```
In [14]: draw_kde(['DEM', 'n.observers'], data_to_sc, data_cs1_scaled, 'до масштабирования', 'после масштабирования')

до масштабирования

— DEM
— nobservers

14
```

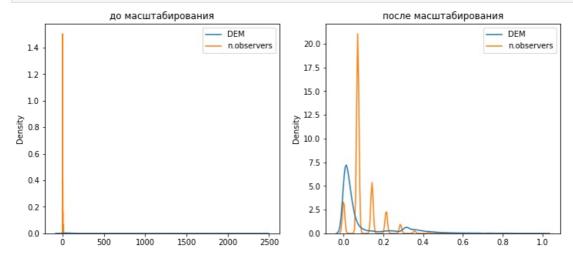


```
In [15]: #MinMax-масштабирование
    cs2 = MinMaxScaler()
    data_cs2_scaled_temp = cs2.fit_transform(data_to_sc)
    data_cs2_scaled = arr_to_df(data_cs2_scaled_temp)
    data_cs2_scaled
```

Out[15]:		DEM	n.observers
	0	0.002075	0.071429
	1	0.002075	0.071429
	2	0.002075	0.071429
	3	0.002075	0.071429
	4	0.002075	0.071429
	300750	0.356846	0.214286
	300751	0.356846	0.214286
	300752	0.356846	0.214286
	300753	0.356846	0.214286
	300754	0.356846	0.214286

300755 rows × 2 columns

```
In [16]: draw_kde(['DEM', 'n.observers'], data_to_sc, data_cs2_scaled, 'до масштабирования', 'после масштабирования')
```

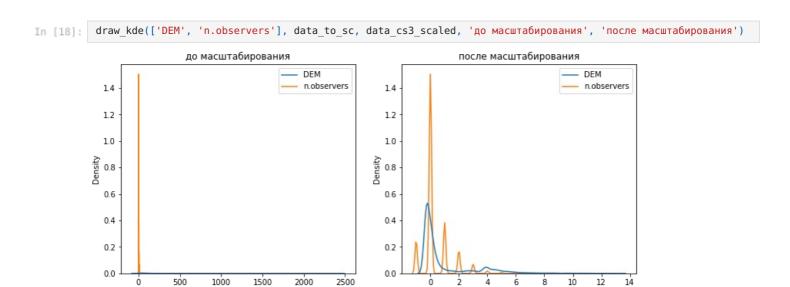


```
In [17]: #Масштабирование по медиане
  cs3 = RobustScaler()
  data_cs3_scaled_temp = cs3.fit_transform(data_to_sc)
  data_cs3_scaled = arr_to_df(data_cs3_scaled_temp)
  data_cs3_scaled
```

Out[17]:		DEM	n.observers
	0	-0.361582	0.0
	1	-0.361582	0.0
	2	-0.361582	0.0
	3	-0.361582	0.0

4	-0.361582	0.0
300750	4.468927	2.0
300751	4.468927	2.0
300752	4.468927	2.0
300753	4.468927	2.0
300754	4.468927	2.0

300755 rows × 2 columns

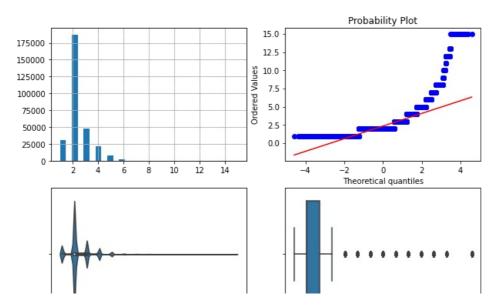


Обработка выбросов

```
def diagnostic_plots(df, variable, title):
In [19]:
              fig, ax = plt.subplots(figsize=(10,7))
              # гистограмма
              plt.subplot(2, 2, 1)
              df[variable].hist(bins=30)
              ## Q-Q plot
              plt.subplot(2, 2, 2)
              stats.probplot(df[variable], dist="norm", plot=plt)
              # ящик с усами
              plt.subplot(2, 2, 3)
              sns.violinplot(x=df[variable])
              # ящик с усами
              plt.subplot(2, 2, 4)
              sns.boxplot(x=df[variable])
              fig.suptitle(title)
              plt.show()
```

In [20]: diagnostic_plots(data_to_sc, 'n.observers', 'n.observers - original')

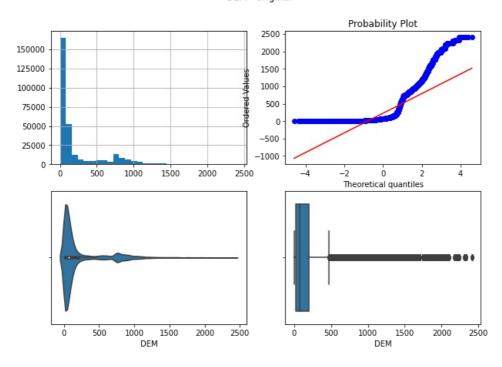
n.observers - original



```
2 4 6 8 10 12 14 2 4 6 8 10 12 14 nobservers
```

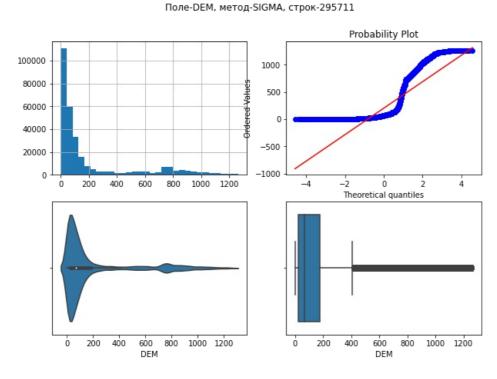
```
In [21]: diagnostic_plots(raw_data, 'DEM', 'DEM - original')
```

DEM - original



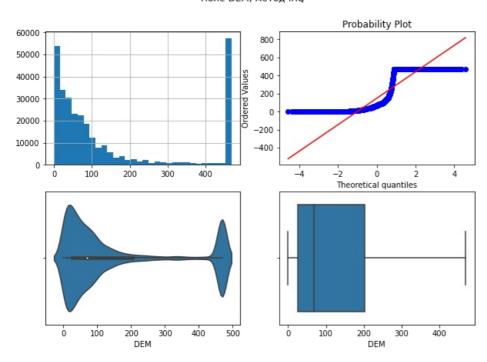
B 854 61044 205734

In [23]: del_sigma(raw_data, 'DEM')



```
In [25]: repl_IRQ(raw_data, 'DEM')
```

Поле-DEM, метод-IRQ



Обработка нестандартного признака

```
In [26]:
           #Обработка времени
           raw time = raw data[{'Time'}]
           raw time
Out[26]:
                  Time
               0 16:30
               1 16:30
               2 16:30
               3 16:30
               4 16:30
          300750
                  7.17
          300751 7:17
          300752
          300753
                  7.17
          300754
                 7:17
         300755 rows × 1 columns
```

```
p_time = raw_time
p_time['hour'] = pd.to_datetime(p_time['Time'], format='%H:%M').dt.hour
p_time['minute'] = pd.to_datetime(p_time['Time'], format='%H:%M').dt.minute
p_time

c:\users\ilya\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopy
Warning:
```

Warning:
A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret urning-a-view-versus-a-copy

c:\users\ilya\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:3: SettingWithCopy
Warning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret urning-a-view-versus-a-copy

This is separate from the ipykernel package so we can avoid doing imports until

Out[27]:

	Time	hour	minute	
0	16:30	16	30	
1	16:30	16	30	
2	16:30	16	30	
3	16:30	16	30	
4	16:30	16	30	
300750	7:17	7	17	
300751	7:17	7	17	
300752	7:17	7	17	
300753	7:17	7	17	
300754	7:17	7	17	

300755 rows × 3 columns

```
In [28]: def round_code(v, T, cos_flag = True):
    x = 2*np.pi*v/T
    if cos_flag:
        return np.cos(x)
    else:
        return np.sin(x)
```

```
In [29]: p_time['hour_cos'] = p_time.apply(lambda x: round_code(x['hour'], 24), axis=1)
    p_time['hour_sin'] = p_time.apply(lambda x: round_code(x['hour'], 24, False), axis=1)
    p_time['minute_cos'] = p_time.apply(lambda x: round_code(x['minute'], 60), axis=1)
    p_time['minute_sin'] = p_time.apply(lambda x: round_code(x['minute'], 60, False), axis=1)
    p_time
```

c:\users\ilya\appdata\local\programs\python\python37\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopy
Warning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret urning-a-view-versus-a-copy

"""Entry point for launching an IPython kernel.

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret urning-a-view-versus-a-copy

 $c: \label{localprograms} $$ c: \site-packages \ipykernel_launcher.py: 3: Setting With Copy Warning: $$ \site-packages \ipykernel_launcher.py: 3: Setting With Copy Warning: 3: Setting With Copy Warning: 3: Setting With Copy With$

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret urning-a-view-versus-a-copy

This is separate from the ipykernel package so we can avoid doing imports until

 $c: \undersity a \app data \ocal \programs \python \python 37 \lib\site-packages \ipykernel_launcher.py: 4: Setting \with Copy \warning:$

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: $https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html \#returning-a-view-versus-a-copy$

after removing the cwd from sys.path.

	Time	hour	minute	hour_cos	hour_sin	minute_cos	minute_sin
0	16:30	16	30	-0.500000	-0.866025	-1.000000	5.665539e-16
1	16:30	16	30	-0.500000	-0.866025	-1.000000	5.665539e-16
2	16:30	16	30	-0.500000	-0.866025	-1.000000	5.665539e-16
3	16:30	16	30	-0.500000	-0.866025	-1.000000	5.665539e-16
4	16:30	16	30	-0.500000	-0.866025	-1.000000	5.665539e-16
300750	7:17	7	17	-0.258819	0.965926	-0.207912	9.781476e-01
300751	7:17	7	17	-0.258819	0.965926	-0.207912	9.781476e-01
300752	7:17	7	17	-0.258819	0.965926	-0.207912	9.781476e-01
300753	7:17	7	17	-0.258819	0.965926	-0.207912	9.781476e-01
300754	7:17	7	17	-0.258819	0.965926	-0.207912	9.781476e-01

300755 rows × 7 columns

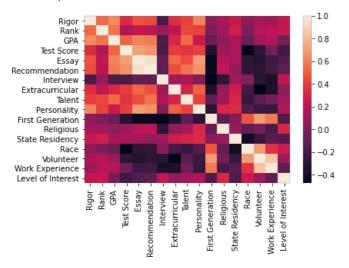
Отбор признаков

```
In [30]: #Методы, основанные на корреляции
fs_data = pd.read_csv('Admission_Data.csv', sep=',')
fs_data.head()
```

Out[30]: Essay Recommendation Interview Extracurricular Talent Personality Generation Name of Test First Religious Rigor Rank GPA University Score Res Princeton 0 3 3 3 3 3 3 3 3 1 0.0 University Brown 3 3 3 1 0.0 3 3 University California Institute of 2 1 2 3 3 3 0 2 1 3 0.0 3 Technology (Caltech) Cornell 1 3 3 2 3 3 3 3 NaN University Dartmouth 2 3 3 3 3 3 3 1 3 3 0 1.0 College

```
In [31]: sns.heatmap(fs_data.corr(), annot=False, fmt='.3f')
```

Out[31]: <AxesSubplot:>



```
In [32]: cr = fs_data.corr()
    cr = cr.abs().unstack()
    cr = cr.sort_values(ascending=False)
    cr = cr[cr >= 0.8]
    cr = cr[cr < 1]
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']</pre>
```

```
f1
                                          f2
                                                 corr
           0 Recommendation
                                      Essay 0.959114
                       Essay Recommendation 0.959114
           2
                             Work Experience 0.848387
                    Volunteer
           3 Work Experience
                                    Volunteer 0.848387
In [59]:
           #Метод обратный Sequential Feature Selector (Методы обертывания)
            fs2_data = pd.read_csv('wines_SPA.csv', sep=',')
            fs2 data.head()
                   winery
                                  wine year rating num_reviews country
                                                                                          price
                                                                                                                    body
                                                                                                                          acidity
Out[59]:
                                                                                  region
                                                                                                              type
           0 Teso La Monja
                                                                                    Toro 995.00
                                                                                                           Toro Red
                                  Tinto 2013
                                                4.9
                                                              58
                                                                  Espana
                                                                                                                      5.0
                                                                                                                             3.0
                     Artadi
                           Vina El Pison
                                       2018
                                                4.9
                                                              31
                                                                  Espana
                                                                           Vino de Espana
                                                                                         313.50
                                                                                                         Tempranillo
                                                                                                                      4.0
                                                                                                                             2.0
           2
                Vega Sicilia
                                 Unico 2009
                                                4.8
                                                            1793
                                                                         Ribera del Duero 324.95 Ribera Del Duero Red
                                                                                                                      5.0
                                                                                                                             3.0
                                                                  Espana
           3
                Vega Sicilia
                                                4.8
                                                                                                                             3.0
                                 Unico
                                       1999
                                                            1705
                                                                  Espana
                                                                         Ribera del Duero 692.96 Ribera Del Duero Red
                                                                                                                      5.0
                Vega Sicilia
                                 Unico
                                       1996
                                                4.8
                                                            1309
                                                                         Ribera del Duero 778.06 Ribera Del Duero Red
                                                                                                                      5.0
                                                                                                                             3.0
            raw_data_with_na = [c for c in fs2_data.columns if fs2_data[c].isnull().sum() > 0]
In [50]:
            [(c, fs2 data[c].isnull().sum()) for c in raw data with na]
Out[50]: [('year', 2), ('type', 545), ('body', 1169), ('acidity', 1169)]
In [52]:
           fs2_data = fs2_data.dropna()
            #Кодируем категориальные признаки
In [53]:
            CE1 = ce CountEncoder()
            encoded_data = CE1.fit_transform(fs2_data[fs2_data.columns])
            encoded_data
                winery wine
                                                                        price type body acidity
                             year rating num_reviews country region
              0
                    15
                          53
                                58
                                      4.9
                                                    58
                                                          6329
                                                                  264
                                                                       995.00
                                                                               261
                                                                                      5.0
                                                                                              3.0
                                                    31
                                                                                      4.0
                   239
                          16
                               752
                                      4.9
                                                          6329
                                                                  239
                                                                       313.50
                                                                               267
                                                                                              2.0
              2
                    95
                          41
                                39
                                      4.8
                                                  1793
                                                          6329
                                                                 1280
                                                                       324.95 1277
                                                                                      5.0
                                                                                              3.0
              3
                    95
                          41
                                10
                                      4.8
                                                  1705
                                                          6329
                                                                  1280
                                                                       692.96
                                                                               1277
                                                                                      5.0
                                                                                              3.0
              4
                          41
                    95
                                11
                                      4.8
                                                  1309
                                                          6329
                                                                 1280
                                                                       778.06 1277
                                                                                      5.0
                                                                                              3.0
           7495
                   414
                         422
                               810
                                      4.2
                                                   392
                                                          6329
                                                                 2221
                                                                        19.98 2143
                                                                                      4.0
                                                                                              3.0
           7496
                   201
                         199
                               752
                                      4.2
                                                   390
                                                          6329
                                                                  622
                                                                        16.76
                                                                               620
                                                                                      4.0
                                                                                              3.0
           7497
                   201
                         200
                               652
                                      42
                                                   390
                                                          6329
                                                                  201
                                                                        24 45
                                                                               787
                                                                                      4 0
                                                                                              3.0
           7498
                   206
                         415
                              1078
                                      4.2
                                                   389
                                                          6329
                                                                 1280
                                                                        64.50 1277
                                                                                      5.0
                                                                                              3.0
           7499
                   204
                         201
                               810
                                      4.2
                                                   388
                                                          6329
                                                                 1280
                                                                        31.63 1277
                                                                                      5.0
                                                                                              3.0
          6329 rows × 11 columns
           X = encoded_data.drop('wine', axis=1)
In [54]:
           Y = encoded data['wine']
In [55]:
           knn = KNeighborsClassifier(n_neighbors=3)
            sfs1 = SFS(knn,
                        k features=3,
                         forward=True,
                         floating=False,
                        verbose=2.
                        scoring='accuracy',
                        cv=0)
            sfs1 = sfs1.fit(X, Y)
```

[Parallel(n jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

cr

```
[Parallel(n_jobs=1)]: Done 10 out of 10 | elapsed:
                                                                                                            2.7s finished
                [2022-06-01 23:02:23] Features: 1/3 -- score: 0.6958445252014537[Parallel(n jobs=1)]: Using backend SequentialB
               ackend with 1 concurrent workers.
                [Parallel(n_jobs=1)]: Done  1 out of  1 | elapsed:
                                                                                                            0.1s remaining:
                                                                                                                                            0.0s
               [Parallel(n_jobs=1)]: Done 9 out of 9 | elapsed:
                                                                                                            1.6s finished
                [2022-06-01 23:02:25] Features: 2/3 -- score: 0.8996681940274925[Parallel(n_jobs=1)]: Using backend SequentialB
               ackend with 1 concurrent workers.
                [Parallel(n jobs=1)]: Done 1 out of
                                                                                 1 | elapsed:
                                                                                                             0.1s remaining:
                                                                                                                                            0.0s
                [Parallel(n_jobs=1)]: Done
                                                               8 out of
                                                                                  8 | elapsed:
                                                                                                            1.4s finished
                [2022-06-01 23:02:26] Features: 3/3 -- score: 0.9270026860483489
In [56]: sfs1.k feature names
Out[56]: ('winery', 'price', 'type')
In [60]:
                #Линейный классификатор на основе SVM (Методы вложений)
                e_lr2 = LinearSVC(C=0.01, penalty="l1", max_iter=2000, dual=False)
                e lr2.fit(X, Y)
                # Коэффициенты регрессии
                e lr2.coef
               \verb|c: \users| ilya \appdata \local \\programs \\python \\python 37 \\lib \\site-packages \\sklearn \\svm \\\_base.py: 1208: Convergence \\Was applated \\packages \\py: 1208: Convergence \\py: 120
                rning: Liblinear failed to converge, increase the number of iterations.
               ConvergenceWarning,
Out[60]: array([[-4.14722706e-03, -1.87267540e-05, 0.00000000e+00,
                             -9.62723602e-05, 1.22223923e-05, -1.06654764e-04,
                             -1.14004799e-03, -3.69213146e-05, -3.70210947e-02,
                              0.00000000e+00],
                           [-1.97898498e-03, 1.17959306e-04, 0.00000000e+00,
                             -2.10716906e-05, -1.10699056e-04, -5.62420368e-05,
                             -3.87233829e-04, 7.25856322e-05, 0.00000000e+00,
                              0.00000000e+00],
                           [-1.33135871e-03, 2.99970309e-05, 0.00000000e+00,
                              1.03043963e-05, -1.18424528e-04, -2.79947576e-05,
                             -5.95992293e-05, 8.17499446e-06, 0.00000000e+00,
                              0.00000000e+00],
                           \hbox{[-8.06972526e-04,}\quad 4.52158355e-06,\quad 0.00000000e+00,}\\
                             \hbox{-1.60281193e-06, -1.30094168e-04, -3.23688982e-05,}\\
                             -5.37869160e-05, 2.12967257e-05, 0.00000000e+00,
                              0.00000000e+001,
                           [-8.40528153e-04, 1.61444515e-05, 0.00000000e+00,
                             -2.47825654e-06, -1.45886294e-04, -1.18966455e-05,
                             -5.40899939e-05, 4.95265144e-05, 0.00000000e+00,
                              0.00000000e+00],
                           \hbox{$[\, \hbox{-}4.48969713e\hbox{-}04, \, \hbox{-}1.50715117e\hbox{-}05, \, \, 0.00000000e\hbox{+}00,}\\
                              8.80785329e-06, -1.43474930e-04, -1.55120875e-05,
                              3.70883928e \hbox{-} 05\,, \quad 3.25527533e \hbox{-} 05\,, \quad 0.00000000e \hbox{+} 00\,,
                              0.00000000e+001.
                           [-3.09145368e-04, -5.07858242e-05, 0.00000000e+00,
                             -1.66936222e-05, -1.48969936e-04, -5.58886784e-06,
                             -1.17390445e-05, 3.60335141e-05, 0.00000000e+00,
                              0.00000000e+00],
                           \hbox{[-1.98322663e-05, -5.10818189e-05, 0.00000000e+00,}\\
                              2.85246756e-05, -1.55926494e-04, 9.19221178e-06,
                              7.78473502e-05, 5.60317884e-08, 0.00000000e+00,
                              0.00000000e+00],
                           [-1.76042940e-04, -9.36123886e-06, 0.00000000e+00,
                              1.38040528e-05, -1.51738149e-04, 1.74848496e-07,
                             -4.27304720e-05, -3.98140334e-06, 0.00000000e+00,
                              0.00000000e+00],
                           [-3.92045944e-04, -4.91063502e-05, 0.00000000e+00,
                             -1.56693306e-05, -1.75799073e-04, 4.03502559e-05,
                             -9.28907035e-05, 5.86673704e-05, 0.00000000e+00,
                              0.00000000e+00],
                           [-2.79020688e-04, -3.18026677e-05, 0.00000000e+00,
                              1.49750933e-06, -1.53467901e-04, 1.01881252e-05,
                             -2.43839169e-05, 8.38150948e-06, 0.00000000e+00,
                              0.00000000e+00],
                           [-1.02201907e-03, -1.87101908e-04, 0.00000000e+00,
                              3.07566010e-05, -8.06007156e-04, 1.03365452e-03,
                              8.86321461e-04, 8.65998719e-04, 0.00000000e+00,
                              0.00000000e+001,
                           [-2.37951907e-04, -5.85316433e-05, 0.00000000e+00,
```

0.1s remaining:

0.0s

[Parallel(n jobs=1)]: Done 1 out of 1 | elapsed:

```
-5.17576327e-06, -1.43925680e-04, -2.55347405e-06,
 -2.80491158e-05, -1.82938259e-05, 0.00000000e+00,
 0.00000000e+00],
[ 3.08266397e-02, -2.82702735e-04, 0.00000000e+00,
 -8.03348919e-04, -7.31670483e-04, -9.17214610e-03,
 2.79149810e-03, -4.23052565e-03, 0.00000000e+00,
 0.00000000e+001,
[-4.88595998e-03, -7.68569238e-07, 0.00000000e+00,
 6.18026384e-06, -2.44271111e-04, 1.93374391e-04,
 6.58008076e-04, 6.34045552e-05, 0.00000000e+00,
 0.00000000e+00],
[ 2.12789279e-04, 3.03796600e-06, 0.00000000e+00,
 -1.42203163e-03, -1.48540819e-04, 8.34710020e-06,
 6.04750067e-04, -3.35944334e-04, 0.00000000e+00,
 0.00000000e+00],
[-2.45004745e-05, -4.19997018e-05, 0.00000000e+00,
 4.65135570e-06, -1.69951317e-04, 5.98621973e-05,
 -9.37500694e-05, -3.98857188e-06, 0.00000000e+00,
 0.00000000e+00],
[-1.55909644e-04, -2.73627094e-05, 0.00000000e+00,
 2.55500579e-05, -1.62498598e-04, 8.23409006e-06,
 1.71675262e-04, 1.97155680e-06, 1.01376063e-02,
 0.00000000e+00],
[-3.90579776e-04, -4.69116363e-05, 0.00000000e+00,
 -6.38678100e-08, -1.45444480e-04, -1.46474067e-06,
 3.62039431e-05, -2.47622432e-05, 0.00000000e+00,
 0.00000000e+001,
[ 5.29870723e-06, -1.77778292e-04, 0.00000000e+00,
 3.47574588e-05, -1.50556170e-04, 1.14481018e-05,
 2.57954108e-05, -1.03181939e-05, 0.00000000e+00,
 0.00000000e+001.
[ 6.59823326e-04, -6.60094758e-04, 0.00000000e+00,
 2.89128015e-05, -1.64437505e-04, 0.00000000e+00,
 4.42845320e-04, 1.63262738e-05, 0.00000000e+00,
 0.00000000e+00],
[-5.06717788e-04, 3.75401081e-05, 0.00000000e+00,
 1.00495147e-05, -1.49611348e-04, -4.31767573e-05,
 7.56816674e-05, 2.77940534e-05, 0.00000000e+00,
 0.00000000e+001,
 \hbox{ [ 1.94344924e-02, } \quad 4.51059283e-04, \quad 0.00000000e+00, \\
 2.08042189e-04, -8.50632661e-04, 2.21382190e-03,
 -2.39274910e-03, -4.19920615e-03, 0.00000000e+00,
 0.00000000e+00],
[ 9.65949398e-04, -1.63644675e-03, 0.00000000e+00,
 \hbox{-} 1.01380875e\hbox{-}04 \hbox{, } \hbox{-} 3.03189019e\hbox{-}04 \hbox{, } \hbox{3.48772785e\hbox{-}04} \hbox{,}
-6.66310043e-04, 4.12092412e-04, 0.00000000e+00,
 0.00000000e+00],
[ 2.19456404e-02, 5.84086379e-03, 0.00000000e+00,
 -1.05548972e-03, -6.47450828e-04, -4.18071954e-03,
-4.67463420e-01, 1.09503315e-03, 1.51678081e+00,
 0.00000000e+00],
[ 4.11858946e-04, -5.57022581e-04, 0.00000000e+00,
 -2.31526344e-04, -5.14404310e-05, -8.12974710e-04,
 -3.36167454e-02, 1.34456488e-03, 0.00000000e+00,
 0.00000000e+00],
[ 7.47625982e-04, 7.54027917e-05, -1.03608134e-01,
 -2.26323863e-05, -7.68557108e-05, 1.35557169e-04,
 -4.32750995e-04, -1.27814527e-04, -9.76273961e-02,
 1.69793747e-01],
[ 1.47712975e-02, 6.47707850e-04, 0.00000000e+00,
 1.23492591e-04, -1.16035576e-03, 3.33123089e-04,
 -9.30285353e-04, -1.93861342e-03, 1.24527823e+00,
 -3.25708725e-01],
[ 5.05396867e-03, -3.87775689e-03, 0.00000000e+00,
 4.05529620e-05, -3.66984602e-04, 6.07365775e-04,
 -1.20028155e-02, 6.01038299e-04, 0.00000000e+00,
 0.00000000e+00],
[ 2.78707539e-04, 3.14800202e-03, 0.00000000e+00,
 -1.73961862e-04, -1.33537127e-03, 2.69358145e-04,
 0.00000000e+00, -3.29599733e-04, 1.08670612e+00,
 0.00000000e+001,
[ 3.61422078e-03, 2.39041676e-04, 0.00000000e+00,
 -1.57105679e-05, -3.39437722e-04, -3.61791676e-05,
                  4.30147752e-04, 1.32912805e-01,
 -2.85778732e-02,
 0.00000000e+00]])
```

rning: Liblinear failed to converge, increase the number of iterations.

ConvergenceWarning,

Out[63]: array([True, True, True, True, True, True, True, True, True])

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