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Обработка признаков (часть 2)

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import datetime
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import MaxAbsScaler
import warnings
warnings.simplefilter("ignore", UserWarning)

data = pd.read_csv('bike-hour.csv', sep=",")

data.head()
```

```
   instant      dteday  season  mnth  hr  holiday  weekday  workingday
\
0        1  01-01-2011       1     1   0        0        6           0

1        2  01-01-2011       1     1   1        0        6           0

2        3  01-01-2011       1     1   2        0        6           0

3        4  01-01-2011       1     1   3        0        6           0

4        5  01-01-2011       1     1   4        0        6           0


   weathersit  temp   atemp   hum  windspeed  casual  cnt
0           1  0.24  0.2879  0.81        0.0       3   16
1           1  0.22  0.2727  0.80        0.0       8   40
2           1  0.22  0.2727  0.80        0.0       5   32
3           1  0.24  0.2879  0.75        0.0       3   13
4           1  0.24  0.2879  0.75        0.0       0    1
```

```
data.describe()
```

```
           instant       season         mnth           hr      holiday
\
count  8645.000000  8645.000000  8645.000000  8645.000000  8645.000000

mean   4323.000000     2.513592     6.573973    11.573626     0.027646

std    2495.740872     1.105477     3.428147     6.907822     0.163966
```

```
min       1.000000     1.000000     1.000000     0.000000     0.000000

25%    2162.000000     2.000000     4.000000     6.000000     0.000000

50%    4323.000000     3.000000     7.000000    12.000000     0.000000

75%    6484.000000     3.000000    10.000000    18.000000     0.000000

max    8645.000000     4.000000    12.000000    23.000000     1.000000


           weekday   workingday   weathersit         temp       atemp
\
count  8645.000000  8645.000000  8645.000000  8645.000000  8645.00000

mean      3.012724     0.683748     1.437594     0.489069     0.46900

std       2.006370     0.465040     0.653859     0.197943     0.17676

min       0.000000     0.000000     1.000000     0.020000     0.00000

25%       1.000000     0.000000     1.000000     0.320000     0.31820

50%       3.000000     1.000000     1.000000     0.500000     0.48480

75%       5.000000     1.000000     2.000000     0.660000     0.62120

max       6.000000     1.000000     4.000000     0.960000     1.00000


                hum    windspeed       casual          cnt
count  8645.000000  8645.000000  8645.000000  8645.000000
mean      0.643430     0.191172    28.600578   143.794448
std       0.196293     0.123191    38.840789   133.797854
min       0.000000     0.000000     0.000000     1.000000
25%       0.490000     0.104500     3.000000    31.000000
50%       0.650000     0.194000    14.000000   109.000000
75%       0.810000     0.283600    38.000000   211.000000
max       1.000000     0.850700   272.000000   651.000000

data.columns

Index(['instant', 'dteday', 'season', 'mnth', 'hr', 'holiday',
'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum',
'windspeed',
       'casual', 'cnt'],
      dtype='object')
```

#Масштабирование

```
# Функция для восстановления датафрейма
# на основе масштабированных данных
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res

data1 = data.drop('cnt', axis=1)
X_ALL = data1.drop('dteday', axis=1)

# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL,
data['cnt'],
                                                    test_size=0.2,
                                                    random_state=1)
# Преобразуем массивы в DataFrame
X_train_df = arr_to_df(X_train)
X_test_df = arr_to_df(X_test)

X_train_df.shape, X_test_df.shape
```

```
((6916, 13), (1729, 13))
```

##Масштабирование данных на основе Z-оценки

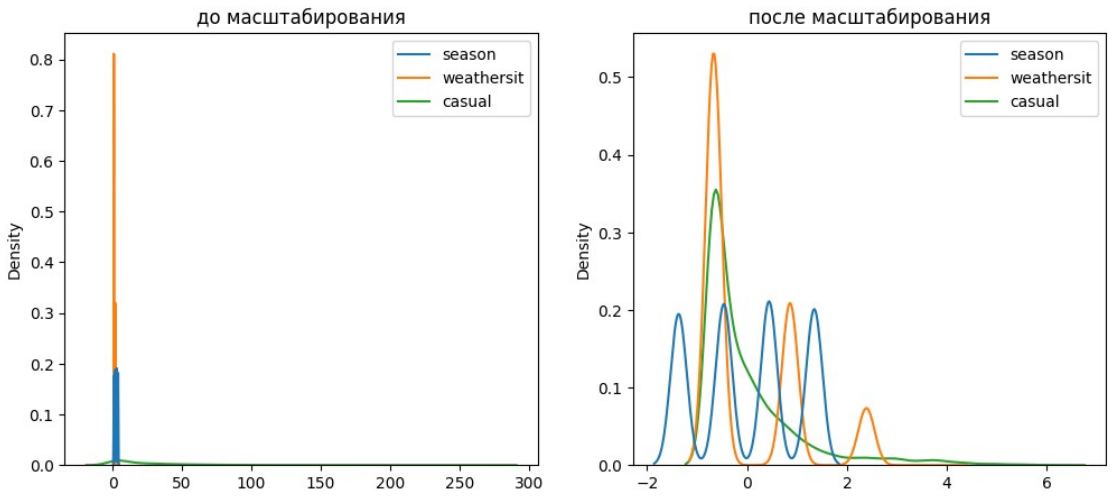
```
# Обучаем StandardScaler на всей выборке и масштабируем
cs11 = StandardScaler()
data_cs11_scaled_temp = cs11.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs11_scaled =  arr_to_df(data_cs11_scaled_temp)
data_cs11_scaled
```

```
       instant    season      mnth        hr   holiday   weekday
workingday  \
0    -1.731850 -1.369254 -1.626038 -1.675535 -0.168618  1.488982   -
1.470386
1    -1.731450 -1.369254 -1.626038 -1.530763 -0.168618  1.488982   -
1.470386
2    -1.731049 -1.369254 -1.626038 -1.385991 -0.168618  1.488982   -
1.470386
3    -1.730648 -1.369254 -1.626038 -1.241219 -0.168618  1.488982   -
1.470386
4    -1.730248 -1.369254 -1.626038 -1.096448 -0.168618  1.488982   -
1.470386
...        ...       ...       ...       ...       ...       ...
...
8640  1.730248 -1.369254  1.582879  1.075130 -0.168618  1.488982   -
1.470386
8641  1.730648 -1.369254  1.582879  1.219901 -0.168618  1.488982   -
1.470386
8642  1.731049 -1.369254  1.582879  1.364673 -0.168618  1.488982   -
```

```
1.470386
8643  1.731450 -1.369254  1.582879  1.509445 -0.168618  1.488982   -
1.470386
8644  1.731850 -1.369254  1.582879  1.654217 -0.168618  1.488982   -
1.470386

      weathersit      temp     atemp       hum  windspeed    casual
0      -0.669287 -1.258356 -1.024616  0.848628  -1.551923 -0.659154
1      -0.669287 -1.359400 -1.110613  0.797681  -1.551923 -0.530416
2      -0.669287 -1.359400 -1.110613  0.797681  -1.551923 -0.607659
3      -0.669287 -1.258356 -1.024616  0.542945  -1.551923 -0.659154
4      -0.669287 -1.258356 -1.024616  0.542945  -1.551923 -0.736397
...          ...       ...       ...       ...        ...       ...
8640   -0.669287 -0.348952 -0.253469 -0.526945   0.265681 -0.247192
8641   -0.669287 -0.348952 -0.253469 -0.526945   0.265681 -0.530416
8642   -0.669287 -0.449997 -0.338900 -0.323156   0.022955 -0.684902
8643   -0.669287 -0.551042 -0.424898 -0.119368  -0.461685 -0.684902
8644   -0.669287 -0.652087 -0.510329  0.084421  -1.551923 -0.633406

[8645 rows x 13 columns]

data_cs11_scaled.describe()

            instant        season          mnth            hr
holiday  \
count  8.645000e+03  8.645000e+03  8.645000e+03  8.645000e+03
8.645000e+03
mean  -1.052047e-16 -3.287647e-17  1.315059e-17  3.965724e-17 -
5.835574e-17
std    1.000058e+00  1.000058e+00  1.000058e+00  1.000058e+00
1.000058e+00
min   -1.731850e+00 -1.369254e+00 -1.626038e+00 -1.675535e+00 -
1.686181e-01
25%   -8.659252e-01 -4.646152e-01 -7.508786e-01 -8.069040e-01 -
1.686181e-01
50%    0.000000e+00  4.400241e-01  1.242803e-01  6.172688e-02 -
1.686181e-01
75%    8.659252e-01  4.400241e-01  9.994393e-01  9.303577e-01 -
1.686181e-01
max    1.731850e+00  1.344663e+00  1.582879e+00  1.654217e+00
5.930561e+00

            weekday    workingday    weathersit          temp
atemp  \
count  8.645000e+03  8.645000e+03  8.645000e+03  8.645000e+03
8.645000e+03
mean   5.753382e-18  5.999956e-17  1.890397e-17  1.972588e-16
1.183553e-16
std    1.000058e+00  1.000058e+00  1.000058e+00  1.000058e+00
1.000058e+00
```

```
min   -1.501666e+00 -1.470386e+00 -6.692871e-01 -2.369848e+00 -
2.653474e+00
25%   -1.003225e+00 -1.470386e+00 -6.692871e-01 -8.541763e-01 -
8.531871e-01
50%   -6.342227e-03  6.800937e-01 -6.692871e-01  5.522692e-02
8.938946e-02
75%    9.905405e-01  6.800937e-01  8.601834e-01  8.635854e-01
8.611028e-01
max    1.488982e+00  6.800937e-01  3.919124e+00  2.379257e+00
3.004248e+00

                hum     windspeed        casual
count  8.645000e+03  8.645000e+03  8.645000e+03
mean  -6.871182e-16  6.164338e-17 -1.972588e-17
std    1.000058e+00  1.000058e+00  1.000058e+00
min   -3.278090e+00 -1.551923e+00 -7.363968e-01
25%   -7.816804e-01 -7.035993e-01 -6.591539e-01
50%    3.347365e-02  2.295538e-02 -3.759301e-01
75%    8.486277e-01  7.503219e-01  2.420127e-01
max    1.816623e+00  5.354000e+00  6.266956e+00
```

```python
# Построение плотности распределения
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()

draw_kde(['season', 'weathersit', 'casual'], data, data_cs11_scaled,
'до масштабирования', 'после масштабирования')
```



```
# Обучаем StandardScaler на обучающей выборке и масштабируем обучающую
и тестовую выборки
cs12 = StandardScaler()
cs12.fit(X_train)
data_cs12_scaled_train_temp = cs12.transform(X_train)
data_cs12_scaled_test_temp = cs12.transform(X_test)
# формируем DataFrame на основе массива
data_cs12_scaled_train = arr_to_df(data_cs12_scaled_train_temp)
data_cs12_scaled_test = arr_to_df(data_cs12_scaled_test_temp)

data_cs12_scaled_train.describe()
```

```
            instant        season          mnth            hr
holiday  \
count  6.916000e+03  6.916000e+03  6.916000e+03  6.916000e+03
6.916000e+03
mean   1.330470e-16  1.307353e-16  9.195138e-17  2.465735e-17 -
2.260257e-17
std    1.000072e+00  1.000072e+00  1.000072e+00  1.000072e+00
1.000072e+00
min   -1.724531e+00 -1.363995e+00 -1.619885e+00 -1.676533e+00 -
1.657853e-01
25%   -8.712143e-01 -4.605000e-01 -7.451195e-01 -8.072194e-01 -
1.657853e-01
50%    5.319695e-03  4.429945e-01  1.296465e-01  6.209380e-02 -
1.657853e-01
75%    8.662424e-01  4.429945e-01  1.004412e+00  9.314070e-01 -
1.657853e-01
max    1.735571e+00  1.346489e+00  1.587590e+00  1.655835e+00
6.031897e+00

            weekday    workingday    weathersit          temp
atemp  \
count  6.916000e+03  6.916000e+03  6.916000e+03  6.916000e+03
6.916000e+03
mean  -1.284237e-16  3.904081e-17 -9.400616e-17 -4.006820e-17
5.445166e-17
std    1.000072e+00  1.000072e+00  1.000072e+00  1.000072e+00
1.000072e+00
min   -1.499744e+00 -1.469992e+00 -6.676050e-01 -2.367586e+00 -
2.647696e+00
25%   -1.001606e+00 -1.469992e+00 -6.676050e-01 -8.503489e-01 -
8.489803e-01
50%   -5.329989e-03  6.802756e-01 -6.676050e-01  5.999331e-02
9.277322e-02
75%    9.909458e-01  6.802756e-01  8.683750e-01  8.691864e-01
8.638127e-01
max    1.489084e+00  6.802756e-01  3.940335e+00  2.386423e+00
3.005087e+00
```

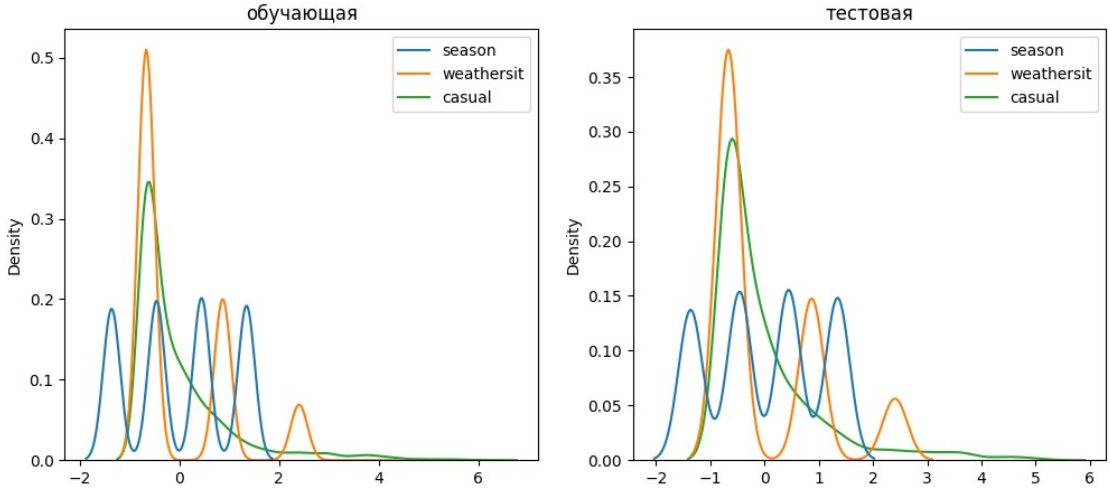
```
                hum     windspeed        casual
count  6.916000e+03  6.916000e+03  6.916000e+03
mean   1.808206e-16 -2.907513e-16  7.191728e-18
std    1.000072e+00  1.000072e+00  1.000072e+00
min   -3.288740e+00 -1.556399e+00 -7.355122e-01
25%   -7.805225e-01 -7.090772e-01 -6.583654e-01
50%    3.848730e-02  1.661976e-02 -3.754938e-01
75%    8.574971e-01  7.431275e-01  2.481094e-01
max    1.830071e+00  5.341370e+00  6.259130e+00
```

```
data_cs12_scaled_test.describe()
```

```
           instant       season         mnth           hr      holiday
\
count  1729.000000  1729.000000  1729.000000  1729.000000  1729.000000

mean      0.027599     0.017636     0.027110     0.001592     0.027780

std       0.994776     0.993819     0.997747     1.004211     1.078361

min      -1.721729    -1.363995    -1.619885    -1.676533    -0.165785

25%      -0.819077    -0.460500    -0.745119    -0.807219    -0.165785

50%       0.007121     0.442994     0.129646     0.062094    -0.165785

75%       0.903770     0.442994     1.004412     0.931407    -0.165785

max       1.735171     1.346489     1.587590     1.655835     6.031897


           weekday   workingday   weathersit         temp        atemp
\
count  1729.000000  1729.000000  1729.000000  1729.000000  1729.000000

mean      0.005042     0.001244     0.022653     0.023547     0.017309

std       0.997230     0.999797     1.021197     1.005222     0.995794

min      -1.499744    -1.469992    -0.667605    -2.266437    -2.476416

25%      -1.001606    -1.469992    -0.667605    -0.749200    -0.848980

50%      -0.005330     0.680276    -0.667605     0.059993     0.092773

75%       0.990946     0.680276     0.868375     0.869186     0.863813

max       1.489084     0.680276     2.404355     2.386423     2.491249
```

```
                hum    windspeed       casual
count  1729.000000  1729.000000  1729.000000
mean      0.024277    -0.031543    -0.000156
std       1.023498     0.993970     0.994054
min      -3.288740    -1.556399    -0.735512
25%      -0.780522    -0.709077    -0.658365
50%       0.089675     0.016620    -0.375494
75%       0.857497     0.500688     0.241681
max       1.830071     4.494859     5.230507
```

```
# распределения для обучающей и тестовой выборки немного отличаются
draw_kde(['season', 'weathersit', 'casual'], data_cs12_scaled_train,
data_cs12_scaled_test, 'обучающая', 'тестовая')
```



##Масштабирование "Mean Normalisation"

```
class MeanNormalisation:

    def fit(self, param_df):
        self.means = X_train.mean(axis=0)
        maxs = X_train.max(axis=0)
        mins = X_train.min(axis=0)
        self.ranges = maxs - mins

    def transform(self, param_df):
        param_df_scaled = (param_df - self.means) / self.ranges
        return param_df_scaled

    def fit_transform(self, param_df):
        self.fit(param_df)
        return self.transform(param_df)
```

```
sc21 = MeanNormalisation()
data_cs21_scaled = sc21.fit_transform(X_ALL)
data_cs21_scaled.describe()
```

	instant	season	mnth	hr	holiday
count	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000
mean	0.001595	0.001301	0.001690	0.000096	0.000896
std	0.288725	0.368492	0.311650	0.300340	0.163966
min	-0.498405	-0.503229	-0.505034	-0.503106	-0.026750
25%	-0.248405	-0.169896	-0.232307	-0.242236	-0.026750
50%	0.001595	0.163437	0.040420	0.018634	-0.026750
75%	0.251595	0.163437	0.313147	0.279503	-0.026750
max	0.501595	0.496771	0.494966	0.496894	0.973250

	weekday	workingday	weathersit	temp	atemp
count	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000
mean	0.000337	0.000116	0.000983	0.000991	0.000612
std	0.334395	0.465040	0.217953	0.210578	0.176760
min	-0.501783	-0.683632	-0.144881	-0.498019	-0.468388
25%	-0.335117	-0.683632	-0.144881	-0.178870	-0.150188
50%	-0.001783	0.316368	-0.144881	0.012620	0.016412
75%	0.331550	0.316368	0.188452	0.182832	0.152812
max	0.498217	0.316368	0.855119	0.501981	0.531612

	hum	windspeed	casual
count	8645.000000	8645.000000	8645.000000
mean	0.000949	-0.000915	-0.000004
std	0.196293	0.144812	0.142797
min	-0.642481	-0.225638	-0.105154
25%	-0.152481	-0.102798	-0.094124
50%	0.007519	0.002409	-0.053683

```
75%       0.167519     0.107734     0.034552
max       0.357519     0.774362     0.894846
```

```
cs22 = MeanNormalisation()
cs22.fit(X_train)
data_cs22_scaled_train = cs22.transform(X_train)
data_cs22_scaled_test = cs22.transform(X_test)
```

```
data_cs22_scaled_train.describe()
```

```
            instant        season          mnth            hr
holiday  \
count  6.916000e+03  6.916000e+03  6.916000e+03  6.916000e+03
6.916000e+03
mean   3.852711e-17  6.369816e-17  2.825322e-17  1.284237e-17
1.053074e-17
std    2.890297e-01  3.689645e-01  3.117942e-01  3.001087e-01
1.613623e-01
min   -4.984047e-01 -5.032292e-01 -5.050344e-01 -5.031056e-01 -
2.674957e-02
25%   -2.517886e-01 -1.698959e-01 -2.323072e-01 -2.422360e-01 -
2.674957e-02
50%    1.537438e-03  1.634374e-01  4.042011e-02  1.863354e-02 -
2.674957e-02
75%    2.503516e-01  1.634374e-01  3.131474e-01  2.795031e-01 -
2.674957e-02
max    5.015953e-01  4.967708e-01  4.949656e-01  4.968944e-01
9.732504e-01

            weekday    workingday    weathersit          temp
atemp  \
count  6.916000e+03  6.916000e+03  6.916000e+03  6.916000e+03
6.916000e+03
mean  -2.722583e-17  2.773952e-17 -9.246508e-18 -1.181498e-17
9.246508e-18
std    3.346036e-01  4.650919e-01  2.170324e-01  2.103640e-01
1.769168e-01
min   -5.017833e-01 -6.836322e-01 -1.448814e-01 -4.980188e-01 -
4.683880e-01
25%   -3.351166e-01 -6.836322e-01 -1.448814e-01 -1.788698e-01 -
1.501880e-01
50%   -1.783304e-03  3.163678e-01 -1.448814e-01  1.261952e-02
1.641196e-02
75%    3.315500e-01  3.163678e-01  1.884519e-01  1.828323e-01
1.528120e-01
max    4.982167e-01  3.163678e-01  8.551186e-01  5.019812e-01
5.316120e-01

                hum     windspeed        casual
count  6.916000e+03  6.916000e+03  6.916000e+03
mean   3.133539e-17 -3.788500e-17  1.348449e-18
```

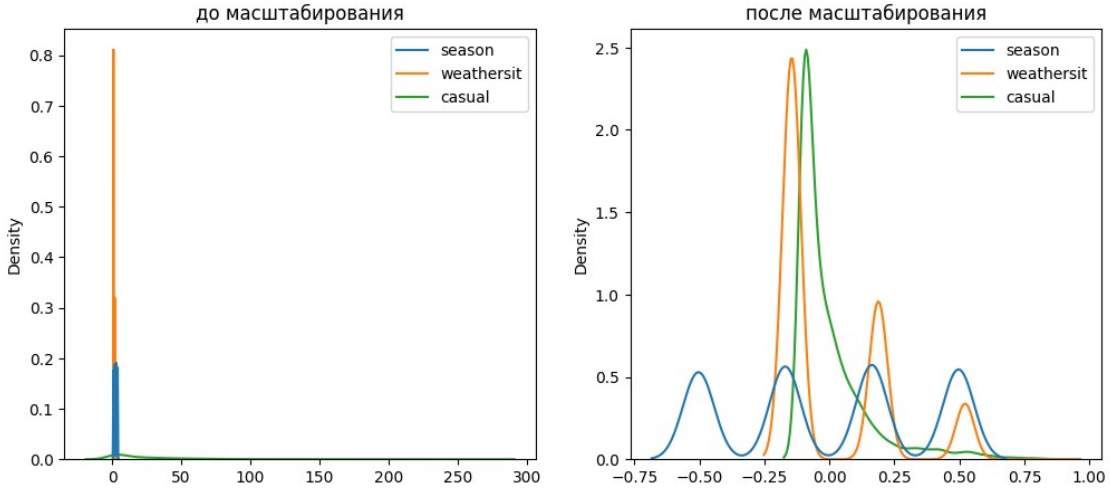
```
std    1.953720e-01  1.449849e-01  1.429769e-01
min   -6.424812e-01 -2.256381e-01 -1.051537e-01
25%   -1.524812e-01 -1.027980e-01 -9.412424e-02
50%    7.518797e-03  2.409440e-03 -5.368306e-02
75%    1.675188e-01  1.077345e-01  3.547135e-02
max    3.575188e-01  7.743619e-01  8.948463e-01
```

```
data_cs22_scaled_test.describe()
```

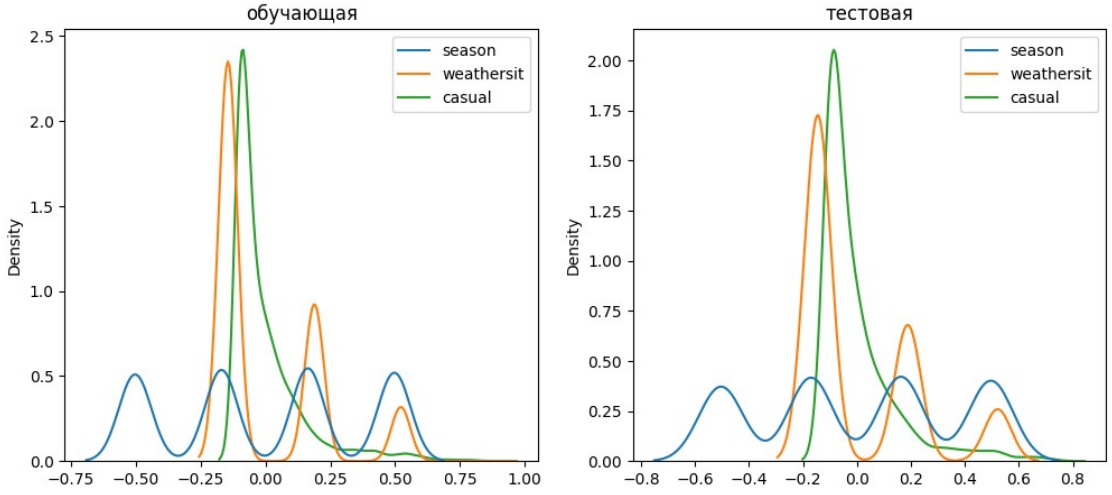
```
           instant       season         mnth           hr      holiday
\
count  1729.000000  1729.000000  1729.000000  1729.000000  1729.000000

mean      0.007976     0.006507     0.008452     0.000478     0.004482

std       0.287499     0.366657     0.311069     0.301351     0.173994

min      -0.497595    -0.503229    -0.505034    -0.503106    -0.026750

25%      -0.236720    -0.169896    -0.232307    -0.242236    -0.026750

50%       0.002058     0.163437     0.040420     0.018634    -0.026750

75%       0.261197     0.163437     0.313147     0.279503    -0.026750

max       0.501480     0.496771     0.494966     0.496894     0.973250


           weekday   workingday   weathersit         temp        atemp
\
count  1729.000000  1729.000000  1729.000000  1729.000000  1729.000000

mean      0.001687     0.000578     0.004916     0.004953     0.003062

std       0.333653     0.464964     0.221617     0.211447     0.176160

min      -0.501783    -0.683632    -0.144881    -0.476742    -0.438088

25%      -0.335117    -0.683632    -0.144881    -0.157593    -0.150188

50%      -0.001783     0.316368    -0.144881     0.012620     0.016412

75%       0.331550     0.316368     0.188452     0.182832     0.152812

max       0.498217     0.316368     0.521785     0.501981     0.440712


               hum    windspeed       casual
count  1729.000000  1729.000000  1729.000000
```

```
mean      0.004743    -0.004573    -0.000022
std       0.199948     0.144100     0.142116
min      -0.642481    -0.225638    -0.105154
25%      -0.152481    -0.102798    -0.094124
50%       0.017519     0.002409    -0.053683
75%       0.167519     0.072587     0.034552
max       0.357519     0.651639     0.747788
```

```
draw_kde(['season', 'weathersit', 'casual'], data, data_cs21_scaled,
'до масштабирования', 'после масштабирования')
```




```
draw_kde(['season', 'weathersit', 'casual'], data_cs22_scaled_train,
data_cs22_scaled_test, 'обучающая', 'тестовая')
```



##MinMax-масштабирование

```
# Обучаем StandardScaler на всей выборке и масштабируем
cs31 = MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(X_ALL)
# формируем DataFrame на основе массива
```

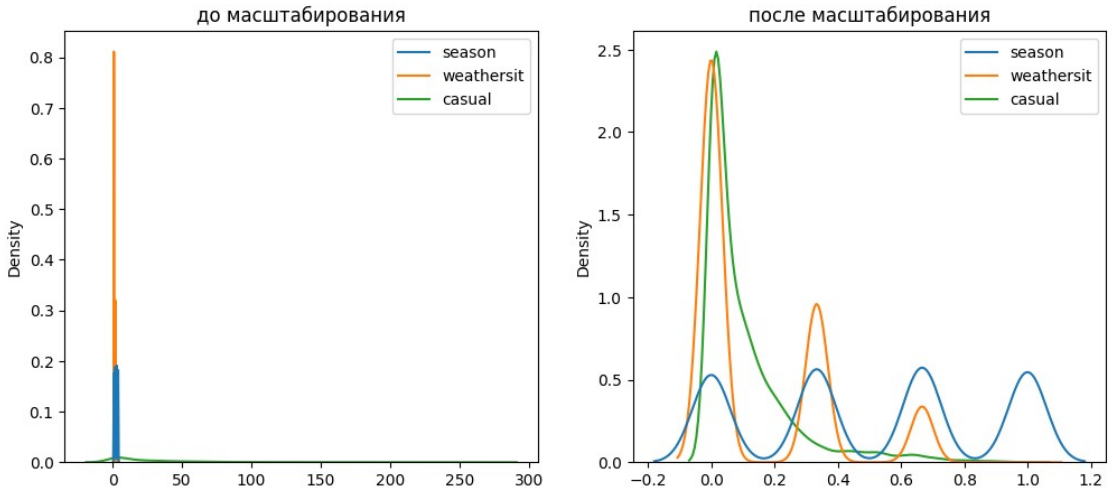
```
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()
```

```
           instant       season         mnth           hr      holiday
\
count  8645.000000  8645.000000  8645.000000  8645.000000  8645.000000

mean      0.500000     0.504531     0.506725     0.503201     0.027646

std       0.288725     0.368492     0.311650     0.300340     0.163966

min       0.000000     0.000000     0.000000     0.000000     0.000000

25%       0.250000     0.333333     0.272727     0.260870     0.000000

50%       0.500000     0.666667     0.545455     0.521739     0.000000

75%       0.750000     0.666667     0.818182     0.782609     0.000000

max       1.000000     1.000000     1.000000     1.000000     1.000000


           weekday   workingday   weathersit         temp       atemp
\
count  8645.000000  8645.000000  8645.000000  8645.000000  8645.00000

mean      0.502121     0.683748     0.145865     0.499009     0.46900

std       0.334395     0.465040     0.217953     0.210578     0.17676

min       0.000000     0.000000     0.000000     0.000000     0.00000

25%       0.166667     0.000000     0.000000     0.319149     0.31820

50%       0.500000     1.000000     0.000000     0.510638     0.48480

75%       0.833333     1.000000     0.333333     0.680851     0.62120

max       1.000000     1.000000     1.000000     1.000000     1.00000


              hum    windspeed       casual
count  8645.000000  8645.000000  8645.000000
mean      0.643430     0.224723     0.105149
std       0.196293     0.144812     0.142797
min       0.000000     0.000000     0.000000
25%       0.490000     0.122840     0.011029
50%       0.650000     0.228047     0.051471
```

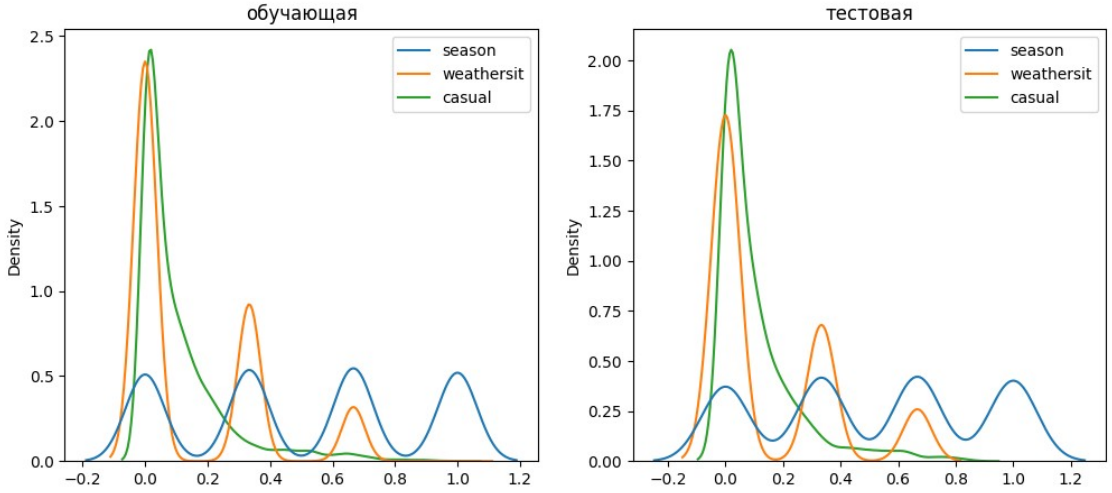
```
75%       0.810000     0.333373     0.139706
max       1.000000     1.000000     1.000000
```

```
cs32 = MinMaxScaler()
cs32.fit(X_train)
data_cs32_scaled_train_temp = cs32.transform(X_train)
data_cs32_scaled_test_temp = cs32.transform(X_test)
# формируем DataFrame на основе массива
data_cs32_scaled_train = arr_to_df(data_cs32_scaled_train_temp)
data_cs32_scaled_test = arr_to_df(data_cs32_scaled_test_temp)
```

```
draw_kde(['season', 'weathersit', 'casual'], data, data_cs31_scaled,
'до масштабирования', 'после масштабирования')
```




```
draw_kde(['season', 'weathersit', 'casual'], data_cs32_scaled_train,
data_cs32_scaled_test, 'обучающая', 'тестовая')
```



#Обработка выбросов

##Удаление выбросов

```
data = pd.read_csv('games.csv', sep=",")

data = data.drop('Publisher', 1)
data = data.drop('Unnamed: 0', 1)
data = data.dropna(axis=0, subset=['Name', 'SteamURL'])
data.shape
```

```
<ipython-input-88-aefd0e2a8e93>:1: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
  data = data.drop('Publisher', 1)
<ipython-input-88-aefd0e2a8e93>:2: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
  data = data.drop('Unnamed: 0', 1)
```

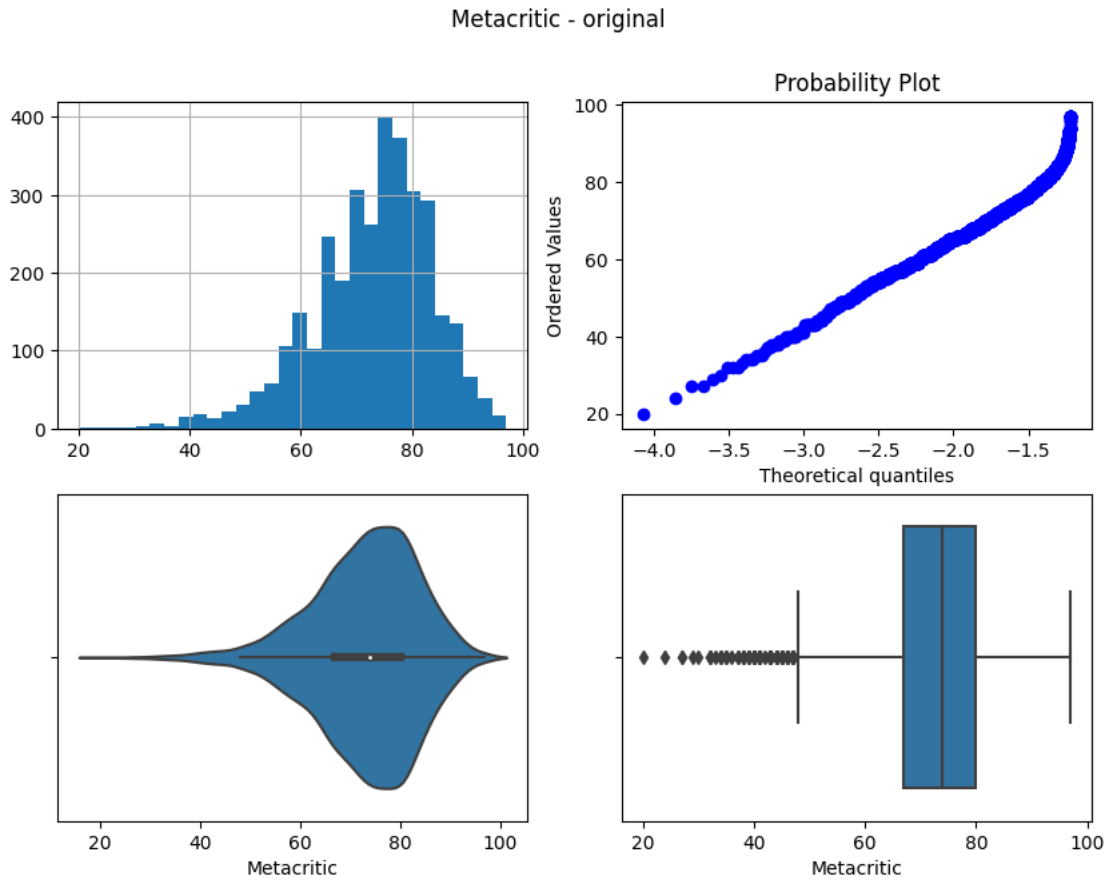
```
(30101, 25)
```

```
x_col_list = ['Metacritic']
```

```
import scipy.stats as stats
def diagnostic_plots(df, variable, title):
    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()

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

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

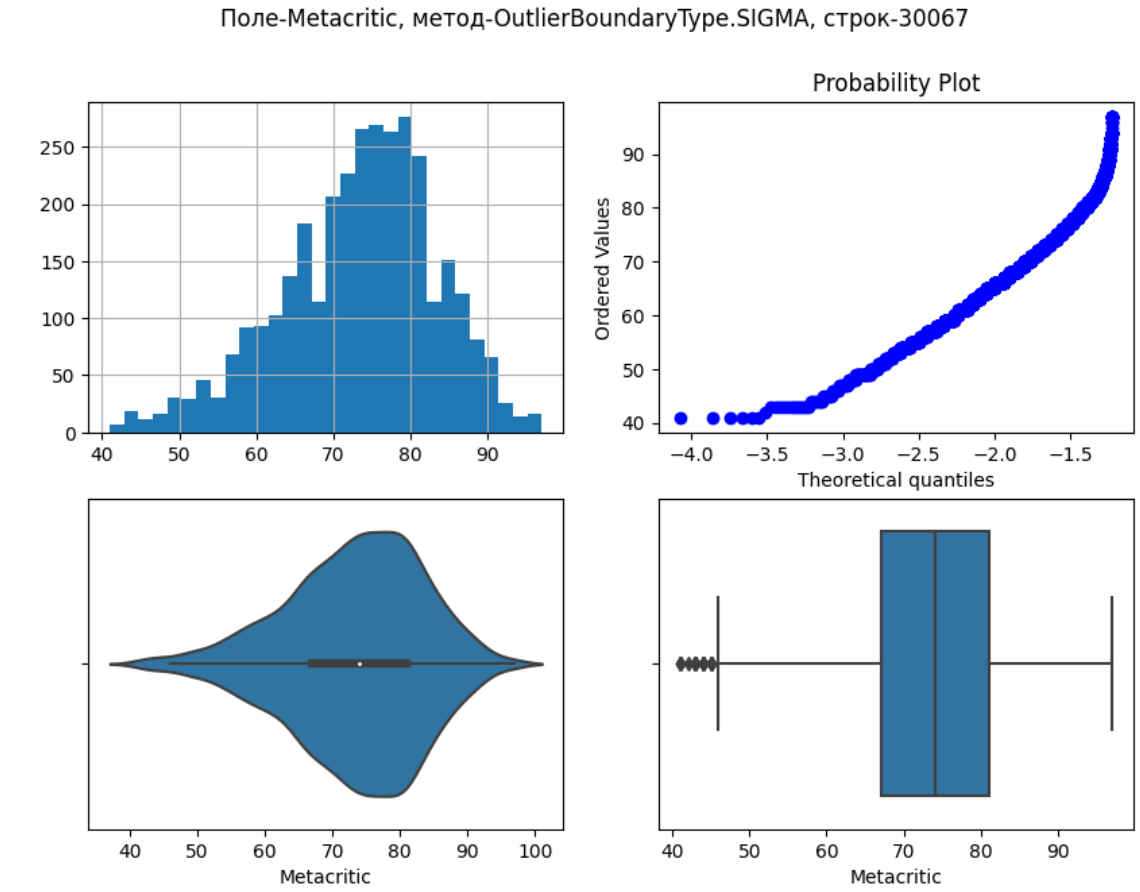
```
    elif outlier_boundary_type == OutlierBoundaryType.QUANTILE:
        lower_boundary = df[col].quantile(0.05)
        upper_boundary = df[col].quantile(0.95)

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

    else:
        raise NameError('Unknown Outlier Boundary Type')

    return lower_boundary, upper_boundary

diagnostic_plots(data, 'Metacritic', 'Metacritic - original')
```

```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```



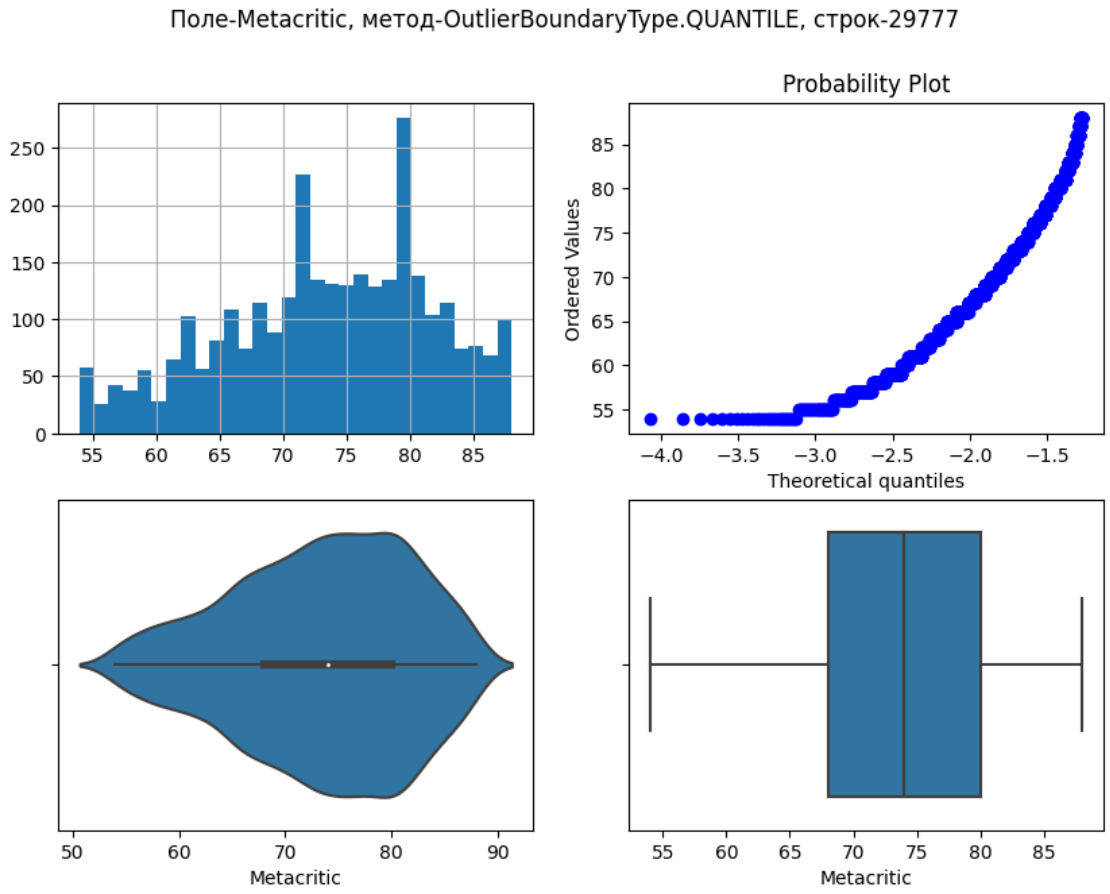
```
for col in x_col_list:
    for obt in OutlierBoundaryType:
        # Вычисление верхней и нижней границы
        lower_boundary, upper_boundary = get_outlier_boundaries(data,
col, obt)
        # Флаги для удаления выбросов
        outliers_temp = np.where(data[col] > upper_boundary, True,
                                 np.where(data[col] < lower_boundary,
True, False))
        # Удаление данных на основе флага
        data_trimmed = data.loc[~(outliers_temp), ]
        title = 'Поле-{}, метод-{}, строк-{}'.format(col, obt,
data_trimmed.shape[0])
        diagnostic_plots(data_trimmed, col, title)
```

```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```

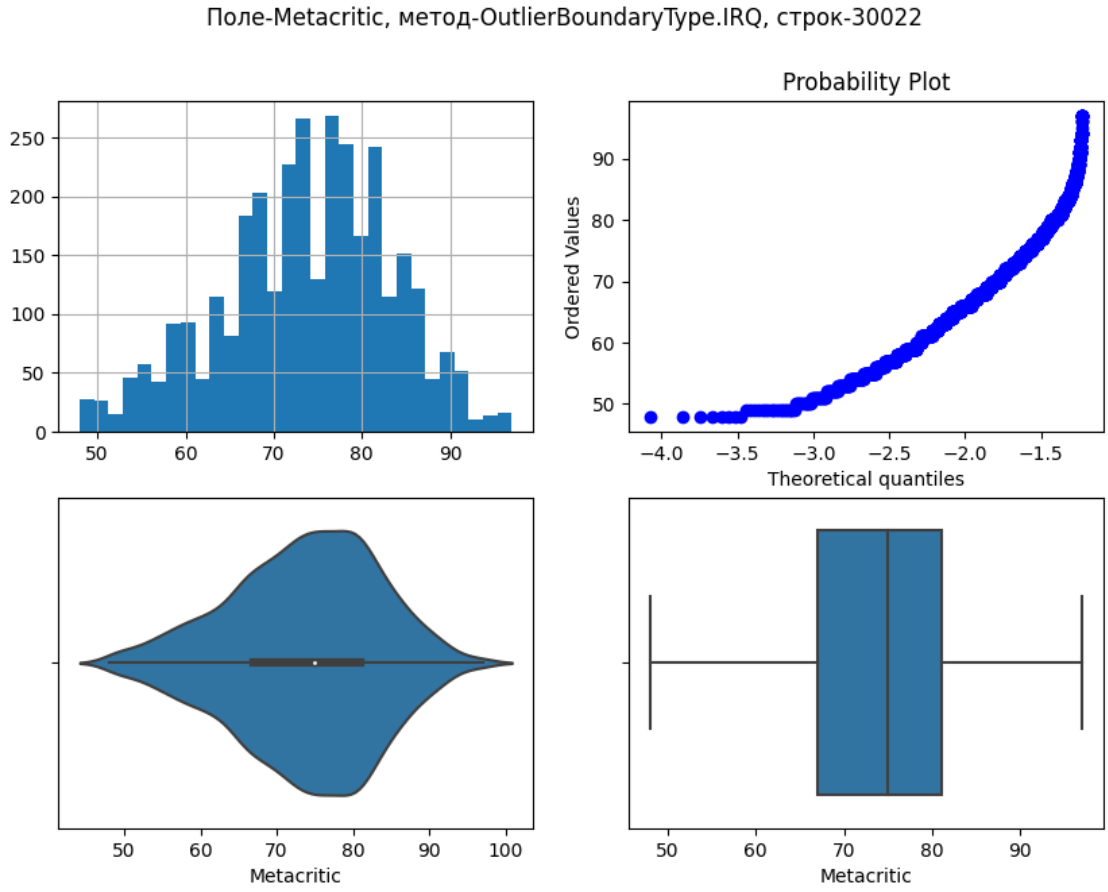



```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
```

```
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```



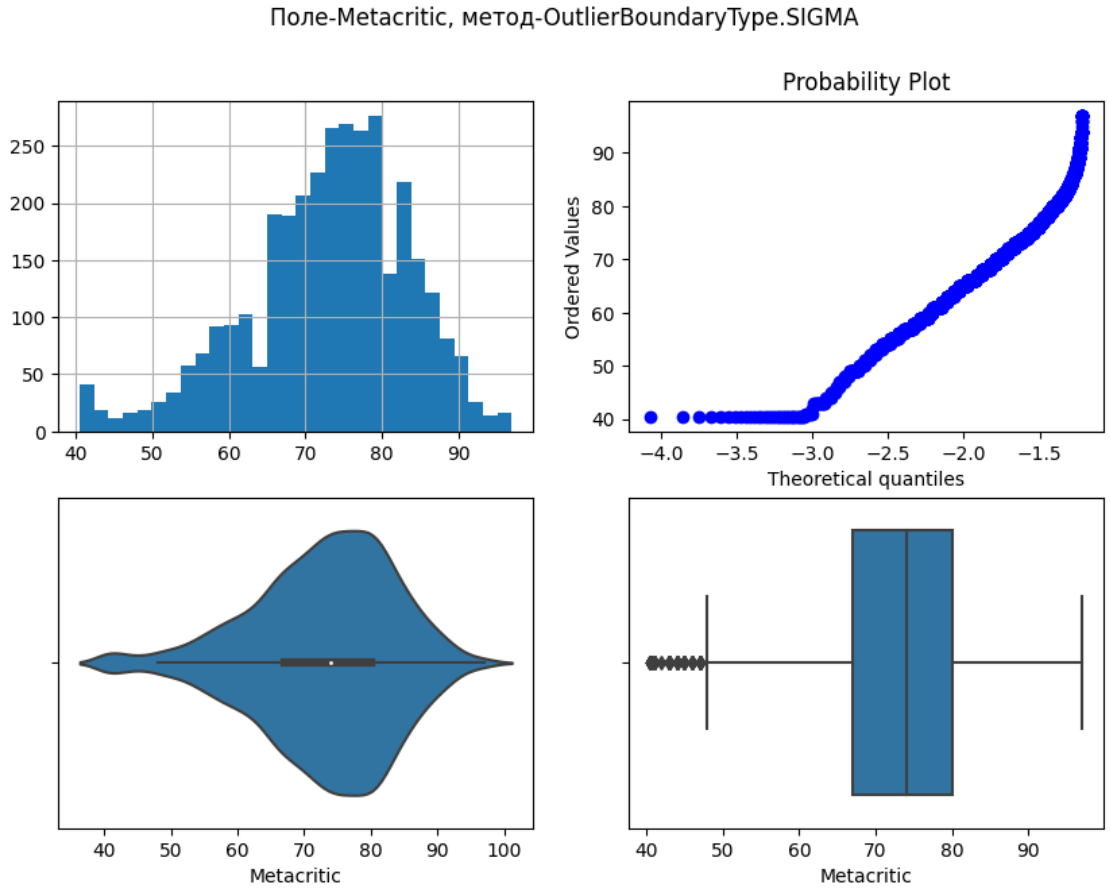

```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```



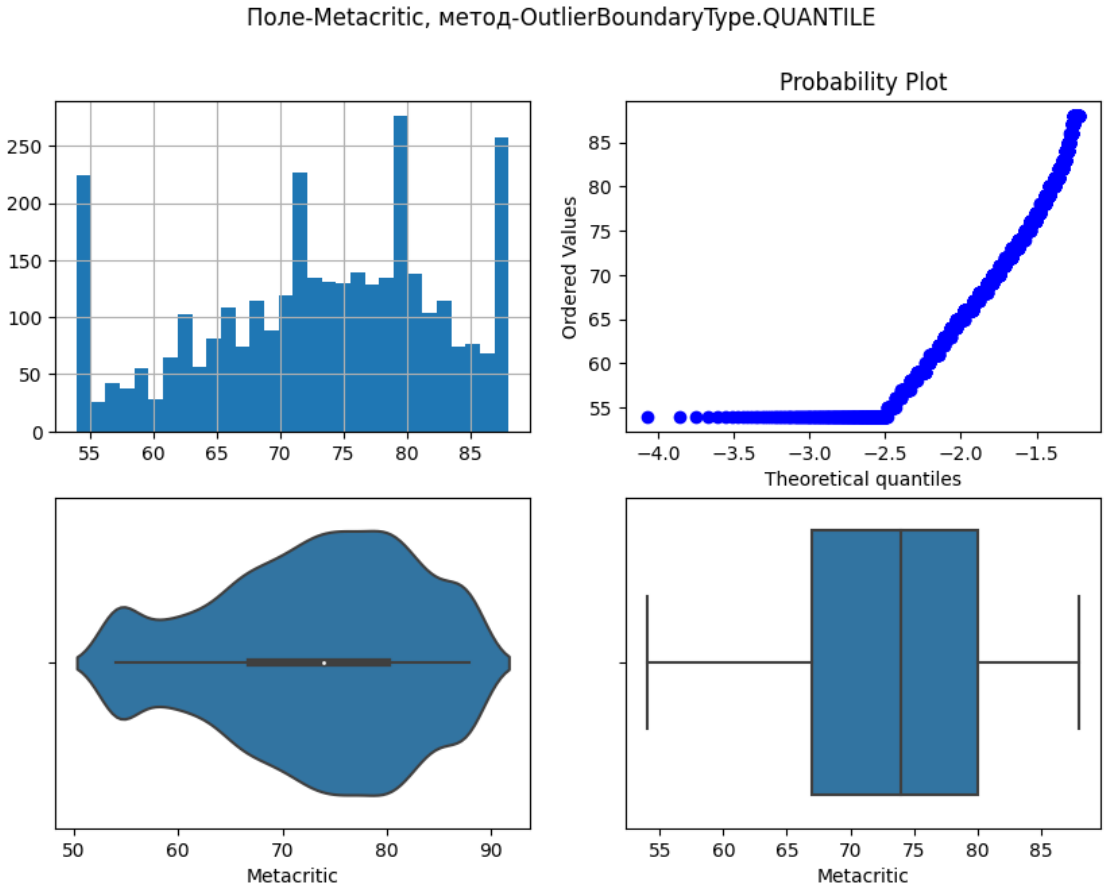
##Замена выбросов

```
for col in x_col_list:
    for obt in OutlierBoundaryType:
        # Вычисление верхней и нижней границы
        lower_boundary, upper_boundary = get_outlier_boundaries(data,
col, obt)
        # Изменение данных
        data[col] = np.where(data[col] > upper_boundary,
upper_boundary,
                             np.where(data[col] < lower_boundary,
lower_boundary, data[col]))
        title = 'Поле-{}, метод-{}'.format(col, obt)
        diagnostic_plots(data, col, title)
```

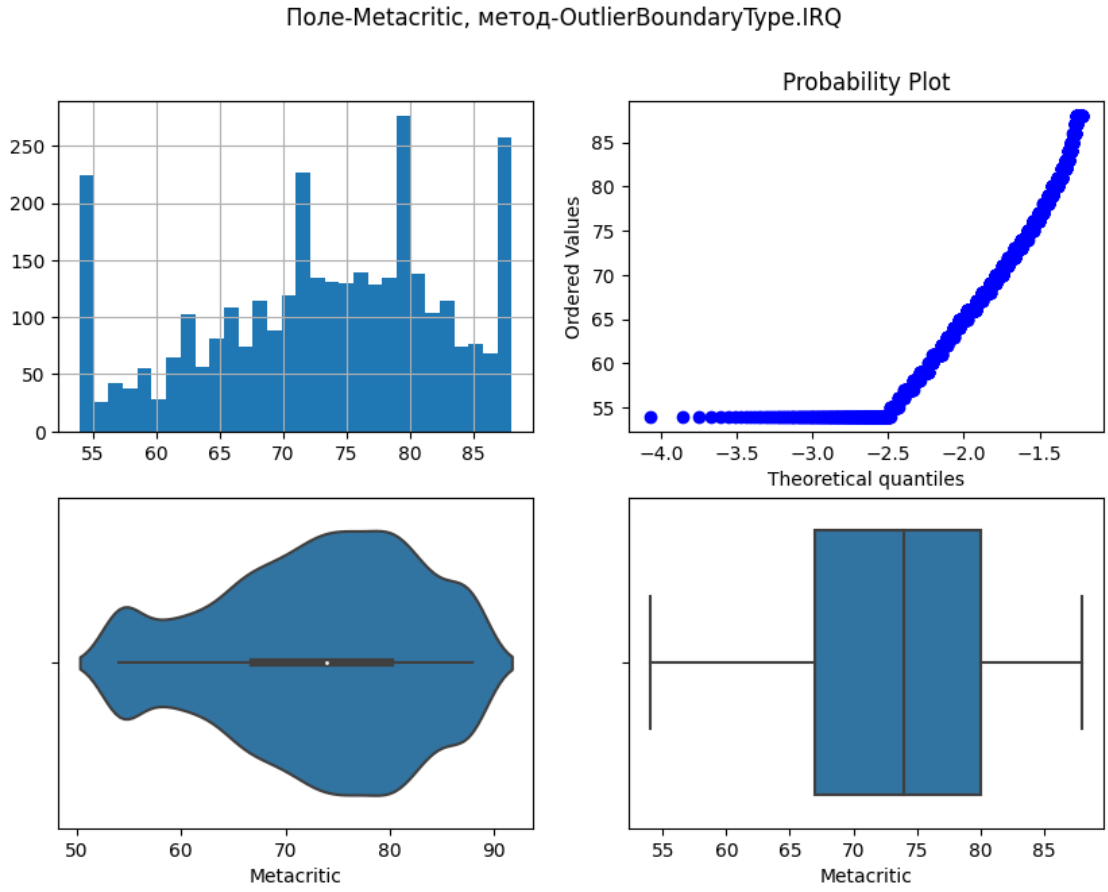
```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```




```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```




```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```



#Обработка нестандартного признака

```
data = pd.read_csv('bike-hour.csv', sep=",")
```

```
data
```

```
      instant      dteday  season  mnth  hr  holiday  weekday
workingday  \
0           1  01-01-2011       1     1   0        0        6
0
1           2  01-01-2011       1     1   1        0        6
0
2           3  01-01-2011       1     1   2        0        6
0
3           4  01-01-2011       1     1   3        0        6
0
4           5  01-01-2011       1     1   4        0        6
0
...       ...         ...     ...   ...  ..      ...      ...
...
8640     8641  31-12-2011       1    12  19        0        6
0
8641     8642  31-12-2011       1    12  20        0        6
0
```

```
8642     8643  31-12-2011       1    12  21        0        6
0
8643     8644  31-12-2011       1    12  22        0        6
0
8644     8645  31-12-2011       1    12  23        0        6
0
```

	weathersit	temp	atemp	hum	windspeed	casual	cnt
0	1	0.24	0.2879	0.81	0.0000	3	16
1	1	0.22	0.2727	0.80	0.0000	8	40
2	1	0.22	0.2727	0.80	0.0000	5	32
3	1	0.24	0.2879	0.75	0.0000	3	13
4	1	0.24	0.2879	0.75	0.0000	0	1
...	...	...	...	...	...	...	...
8640	1	0.42	0.4242	0.54	0.2239	19	92
8641	1	0.42	0.4242	0.54	0.2239	8	71
8642	1	0.40	0.4091	0.58	0.1940	2	52
8643	1	0.38	0.3939	0.62	0.1343	2	38
8644	1	0.36	0.3788	0.66	0.0000	4	31

[8645 rows x 15 columns]

```
data.dtypes
```

```
instant         int64
dteday         object
season          int64
mnth            int64
hr              int64
holiday         int64
weekday         int64
workingday      int64
weathersit      int64
temp          float64
atemp         float64
hum           float64
windspeed     float64
casual          int64
cnt             int64
dtype: object
```

```
data = data.drop('season', 1)
data = data.drop('mnth', 1)
data = data.drop('holiday', 1)
data = data.drop('weekday', 1)
data = data.drop('workingday', 1)
data.shape
```

```
<ipython-input-38-bb9f60cb547b>:1: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
```

```
  data = data.drop('season', 1)
<ipython-input-38-bb9f60cb547b>:2: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
  data = data.drop('mnth', 1)
<ipython-input-38-bb9f60cb547b>:3: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
  data = data.drop('holiday', 1)
<ipython-input-38-bb9f60cb547b>:4: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
  data = data.drop('weekday', 1)
<ipython-input-38-bb9f60cb547b>:5: FutureWarning: In a future version
of pandas all arguments of DataFrame.drop except for the argument
'labels' will be keyword-only.
  data = data.drop('workingday', 1)
```

```
(8645, 10)
```

```
# Сконвертируем дату и время в нужный формат
data['dt'] = data.apply(lambda x: pd.to_datetime(x['dteday'],
format='%d-%m-%Y'), axis=1)
```

```
data.head()
```

```
   instant      dteday  hr  weathersit  temp   atemp   hum  windspeed
casual  \
0        1  01-01-2011   0           1  0.24  0.2879  0.81        0.0
3
1        2  01-01-2011   1           1  0.22  0.2727  0.80        0.0
8
2        3  01-01-2011   2           1  0.22  0.2727  0.80        0.0
5
3        4  01-01-2011   3           1  0.24  0.2879  0.75        0.0
3
4        5  01-01-2011   4           1  0.24  0.2879  0.75        0.0
0


   cnt         dt
0   16 2011-01-01
1   40 2011-01-01
2   32 2011-01-01
3   13 2011-01-01
4    1 2011-01-01
```

```
data.dtypes
```

```
instant               int64
dteday               object
hr                    int64
```

```
weathersit             int64
temp                 float64
atemp                float64
hum                  float64
windspeed            float64
casual                 int64
cnt                    int64
dt            datetime64[ns]
dtype: object
```

```
# День
data['day'] = data['dt'].dt.day
# Месяц
data['month'] = data['dt'].dt.month
# Год
data['year'] = data['dt'].dt.year
#Неделя года
data['week'] = data['dt'].dt.isocalendar().week
#Квартал
data['quarter'] = data['dt'].dt.quarter
#День недели
data['dayofweek'] = data['dt'].dt.dayofweek
#Выходной день
data['day_name'] = data['dt'].dt.day_name()
data['is_holiday'] = data.apply(lambda x: 1 if x['dt'].dayofweek in
[5,6] else 0, axis=1)
```

```
data.head()
```

```
   instant      dteday  hr  weathersit  temp   atemp   hum  windspeed
casual  \
0        1  01-01-2011   0           1  0.24  0.2879  0.81        0.0
3
1        2  01-01-2011   1           1  0.22  0.2727  0.80        0.0
8
2        3  01-01-2011   2           1  0.22  0.2727  0.80        0.0
5
3        4  01-01-2011   3           1  0.24  0.2879  0.75        0.0
3
4        5  01-01-2011   4           1  0.24  0.2879  0.75        0.0
0

   cnt         dt  day  month  year  week  quarter  dayofweek
day_name  \
0   16 2011-01-01    1      1  2011    52        1          5
Saturday
1   40 2011-01-01    1      1  2011    52        1          5
Saturday
2   32 2011-01-01    1      1  2011    52        1          5
Saturday
3   13 2011-01-01    1      1  2011    52        1          5
```

```
Saturday
4    1 2011-01-01    1      1  2011    52        1          5
Saturday
```

```
   is_holiday
0           1
1           1
2           1
3           1
4           1
```

```
# Разница между датами
data['now'] = datetime.datetime.today()
data['diff'] = data['now'] - data['dt']
data.dtypes
```

```
instant                 int64
dteday                 object
hr                      int64
weathersit              int64
temp                  float64
atemp                 float64
hum                   float64
windspeed             float64
casual                  int64
cnt                     int64
dt             datetime64[ns]
day                     int64
month                   int64
year                    int64
week                   UInt32
quarter                 int64
dayofweek               int64
day_name               object
is_holiday              int64
now            datetime64[ns]
diff          timedelta64[ns]
dtype: object
```

```
data.head()
```

```
   instant      dteday  hr  weathersit  temp   atemp   hum  windspeed
casual  \
0        1  01-01-2011   0           1  0.24  0.2879  0.81        0.0
3
1        2  01-01-2011   1           1  0.22  0.2727  0.80        0.0
8
2        3  01-01-2011   2           1  0.22  0.2727  0.80        0.0
5
3        4  01-01-2011   3           1  0.24  0.2879  0.75        0.0
3
```

```
4        5  01-01-2011   4           1  0.24  0.2879  0.75        0.0
0

   cnt  ... day  month  year  week  quarter  dayofweek  day_name
is_holiday  \
0   16  ...   1      1  2011    52        1          5  Saturday
1
1   40  ...   1      1  2011    52        1          5  Saturday
1
2   32  ...   1      1  2011    52        1          5  Saturday
1
3   13  ...   1      1  2011    52        1          5  Saturday
1
4    1  ...   1      1  2011    52        1          5  Saturday
1

                          now                      diff
0 2023-04-02 16:35:24.795190 4474 days 16:35:24.795190
1 2023-04-02 16:35:24.795190 4474 days 16:35:24.795190
2 2023-04-02 16:35:24.795190 4474 days 16:35:24.795190
3 2023-04-02 16:35:24.795190 4474 days 16:35:24.795190
4 2023-04-02 16:35:24.795190 4474 days 16:35:24.795190

[5 rows x 21 columns]
```

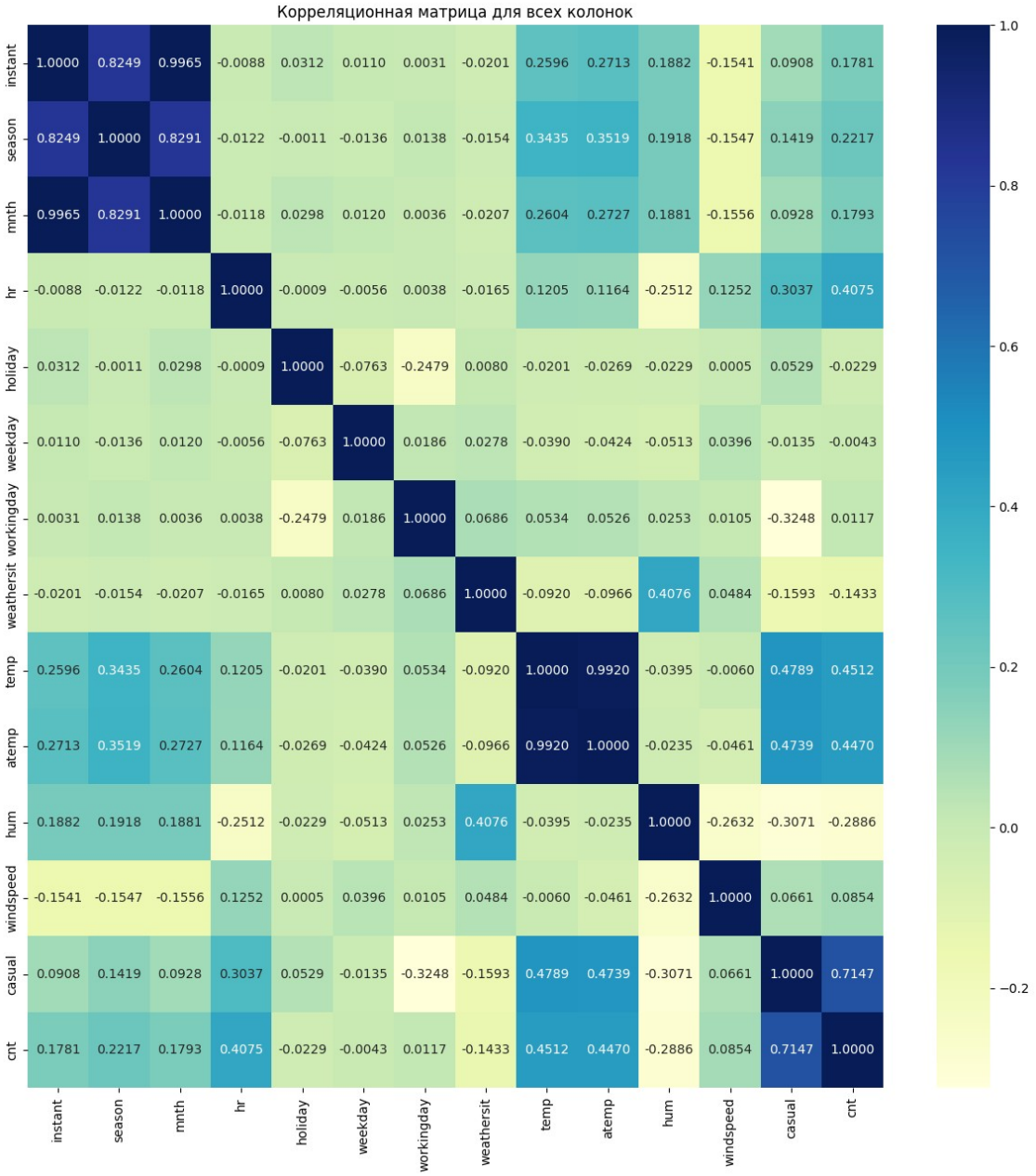
#Отбор признаков

##Отбор признаков из группы методом фильтрации (корреляция признаков)

```
data = pd.read_csv('bike-hour.csv', sep=",")
```

```
col_ch=['instant', 'dteday', 'season', 'mnth', 'hr', 'holiday',
'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum',
'windspeed',
       'casual','cnt']
fig, ax = plt.subplots(figsize=(15,15))
sns.heatmap(data[col_ch].corr(), annot=True, fmt='.4f', cmap="YlGnBu")
ax.set_title('Корреляционная матрица для всех колонок')
```

```
Text(0.5, 1.0, 'Корреляционная матрица для всех колонок')
```




```python
# Формирование DataFrame с сильными корреляциями
def make_corr_df(df):
    cr = data.corr()
    cr = cr.abs().unstack()
    cr = cr.sort_values(ascending=False)
    cr = cr[cr >= 0.45]
    cr = cr[cr < 1]
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']
    return cr

make_corr_df(data)
```

```
         f1       f2      corr
0   instant     mnth  0.996461
1      mnth  instant  0.996461
2      temp    atemp  0.992022
3     atemp     temp  0.992022
4    season     mnth  0.829054
5      mnth   season  0.829054
6    season  instant  0.824925
7   instant   season  0.824925
8       cnt   casual  0.714742
9    casual      cnt  0.714742
10     temp   casual  0.478931
11   casual     temp  0.478931
12    atemp   casual  0.473859
13   casual    atemp  0.473859
14      cnt     temp  0.451233
15     temp      cnt  0.451233
```

```
# Обнаружение групп коррелирующих признаков
def corr_groups(cr):
    grouped_feature_list = []
    correlated_groups = []

    for feature in cr['f1'].unique():
        if feature not in grouped_feature_list:
            # находим коррелирующие признаки
            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

# Группы коррелирующих признаков
corr_groups(make_corr_df(data))
```

```
[['mnth', 'season', 'instant'], ['atemp', 'casual', 'cnt', 'temp']]
```

##Отбор признаков из группы методом обертывания (алгоритм полного перебора)

```
import joblib
import sys
sys.modules['sklearn.externals.joblib'] = joblib
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=3)

col_ch=['season', 'mnth', 'hr', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum',
```

```
'windspeed',
       'casual']

iris_X = data[col_ch]
iris_y = data['cnt']
iris_feature_names = col_ch

efs1 = EFS(knn,
           min_features=1,
           max_features=2,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs1 = efs1.fit(iris_X, iris_y,
custom_feature_names=iris_feature_names)

print('Best subset (indices):', efs1.best_idx_)
print('Best subset (corresponding names):', efs1.best_feature_names_)
```

```
Features: 78/78

Best subset (indices): (2, 11)
Best subset (corresponding names): ('hr', 'casual')
```

##Отбор признаков из группы методов вложения (логистическая регрессия)

```
from sklearn.linear_model import LogisticRegression
# Используем L1-регуляризацию
e_lr1 = LogisticRegression(C=1000, solver='liblinear', penalty='l1',
max_iter=500, random_state=1)
e_lr1.fit(iris_X, iris_y)
# Коэффициенты регрессии
e_lr1.coef_
```

```
array([[-1.79803706e-01, -7.48908923e-02, -1.70834448e-01, ...,
         5.41522385e-01,  1.94308626e+00, -1.65263659e+00],
       [-3.08821362e-01,  3.75976134e-03, -1.68993067e-01, ...,
         1.26470983e-01, -4.68818557e-01, -1.11936699e+00],
       [-9.77261731e-02,  6.76173561e-03, -1.66651060e-01, ...,
        -1.25060669e-01, -7.10751734e-01, -8.62844296e-01],
       ...,
       [-4.87437825e-01,  2.59064130e+00,  1.37191532e-01, ...,
         5.34606024e+00,  3.62448873e+00,  3.92293263e-02],
       [-3.63688746e+01,  3.57562898e+00,  1.77341113e+00, ...,
        -1.53237722e+02, -9.47353916e+01,  4.10587087e-01],
       [-2.11368802e+00,  1.10130679e+00, -1.87572443e+00, ...,
        -6.04493952e+01, -7.86759346e+01,  2.20013824e-01]])
```

```
from sklearn.feature_selection import SelectFromModel
sel_e_lr1 = SelectFromModel(e_lr1)
```

```
sel_e_lr1.fit(iris_X, iris_y)
sel_e_lr1.get_support()
```

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

```
list(zip(col_ch, sel_e_lr1.get_support()))
```

```
[('season', True),
 ('mnth', True),
 ('hr', True),
 ('holiday', True),
 ('weekday', True),
 ('workingday', True),
 ('weathersit', True),
 ('temp', True),
 ('atemp', True),
 ('hum', True),
 ('windspeed', True),
 ('casual', True)]
```