Гаврилов Л.Я. ИУ5-23М

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	weathersit	temp	atemp	hum	windspeed	casual	cnt
0	1	01-01-2011	1	1	0	0	6	0	1	0.24	0.2879	0.81	0.0	3	16
1	2	01-01-2011	1	1	1	0	6	0	1	0.22	0.2727	0.80	0.0	8	40
2	3	01-01-2011	1	1	2	0	6	0	1	0.22	0.2727	0.80	0.0	5	32
3	4	01-01-2011	1	1	3	0	6	0	1	0.24	0.2879	0.75	0.0	3	13
4	5	01-01-2011	1	1	4	0	6	0	1	0.24	0.2879	0.75	0.0	0	1

```
data.describe()
```

	instant	season	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp
count	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.00000
mean	4323.000000	2.513592	6.573973	11.573626	0.027646	3.012724	0.683748	1.437594	0.489069	0.46900
std	2495.740872	1.105477	3.428147	6.907822	0.163966	2.006370	0.465040	0.653859	0.197943	0.17676
min	1.000000	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.020000	0.00000
25%	2162.000000	2.000000	4.000000	6.000000	0.000000	1.000000	0.000000	1.000000	0.320000	0.31820
50%	4323.000000	3.000000	7.000000	12.000000	0.000000	3.000000	1.000000	1.000000	0.500000	0.48480
75%	6484.000000	3.000000	10.000000	18.000000	0.000000	5.000000	1.000000	2.000000	0.660000	0.62120
max	8645.000000	4.000000	12.000000	23.000000	1.000000	6.000000	1.000000	4.000000	0.960000	1.00000

```
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	weathersit	temp	atemp	hum	windspeed
0	-1.731850	-1.369254	-1.626038	-1.675535	-0.168618	1.488982	-1.470386	-0.669287	-1.258356	-1.024616	0.848628	-1.551923
1	-1.731450	-1.369254	-1.626038	-1.530763	-0.168618	1.488982	-1.470386	-0.669287	-1.359400	-1.110613	0.797681	-1.551923
2	-1.731049	-1.369254	-1.626038	-1.385991	-0.168618	1.488982	-1.470386	-0.669287	-1.359400	-1.110613	0.797681	-1.551923
3	-1.730648	-1.369254	-1.626038	-1.241219	-0.168618	1.488982	-1.470386	-0.669287	-1.258356	-1.024616	0.542945	-1.551923
4	-1.730248	-1.369254	-1.626038	-1.096448	-0.168618	1.488982	-1.470386	-0.669287	-1.258356	-1.024616	0.542945	-1.551923
...	...	...	...	...	...	...	...	...	...	...	...	...
8640	1.730248	-1.369254	1.582879	1.075130	-0.168618	1.488982	-1.470386	-0.669287	-0.348952	-0.253469	-0.526945	0.265681
8641	1.730648	-1.369254	1.582879	1.219901	-0.168618	1.488982	-1.470386	-0.669287	-0.348952	-0.253469	-0.526945	0.265681
8642	1.731049	-1.369254	1.582879	1.364673	-0.168618	1.488982	-1.470386	-0.669287	-0.449997	-0.338900	-0.323156	0.022955
8643	1.731450	-1.369254	1.582879	1.509445	-0.168618	1.488982	-1.470386	-0.669287	-0.551042	-0.424898	-0.119368	-0.461685
8644	1.731850	-1.369254	1.582879	1.654217	-0.168618	1.488982	-1.470386	-0.669287	-0.652087	-0.510329	0.084421	-1.551923

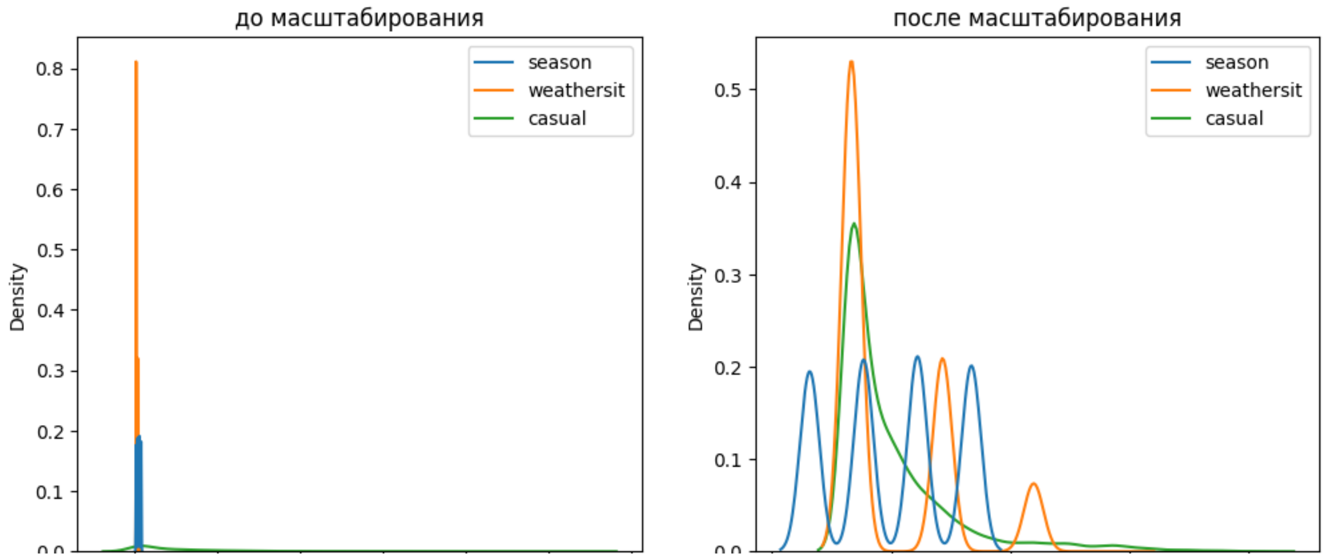
8645 rows × 13 columns

```
data_cs11_scaled.describe()
```

	instant	season	mnth	hr	holiday	weekday	workingday	weathersit	tem
count	8.645000e+03	8.645000e+03	8.645000e+03	8.645000e+03	8.645000e+03	8.645000e+03	8.645000e+03	8.645000e+03	8.645000e+0
mean	-1.052047e-16	-3.287647e-17	1.315059e-17	3.965724e-17	-5.835574e-17	5.753382e-18	5.999956e-17	1.890397e-17	1.972588e-1
std	1.000058e+00	1.000058e+00	1.000058e+00	1.000058e+00	1.000058e+00	1.000058e+00	1.000058e+00	1.000058e+00	1.000058e+0
min	-1.731850e+00	-1.369254e+00	-1.626038e+00	-1.675535e+00	-1.686181e-01	-1.501666e+00	-1.470386e+00	-6.692871e-01	-2.369848e+0
25%	-8.659252e-01	-4.646152e-01	-7.508786e-01	-8.069040e-01	-1.686181e-01	-1.003225e+00	-1.470386e+00	-6.692871e-01	-8.541763e-0
50%	0.000000e+00	4.400241e-01	1.242803e-01	6.172688e-02	-1.686181e-01	-6.342227e-03	6.800937e-01	-6.692871e-01	5.522692e-0
75%	8.659252e-01	4.400241e-01	9.994393e-01	9.303577e-01	-1.686181e-01	9.905405e-01	6.800937e-01	8.601834e-01	8.635854e-0

```
# 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)
```

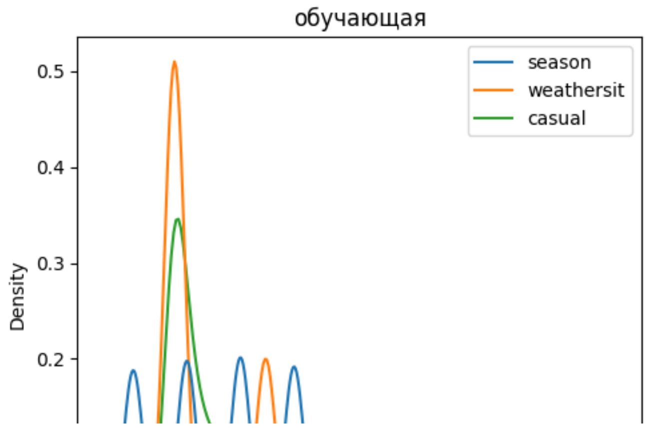
```
data_cs12_scaled_train.describe()
```

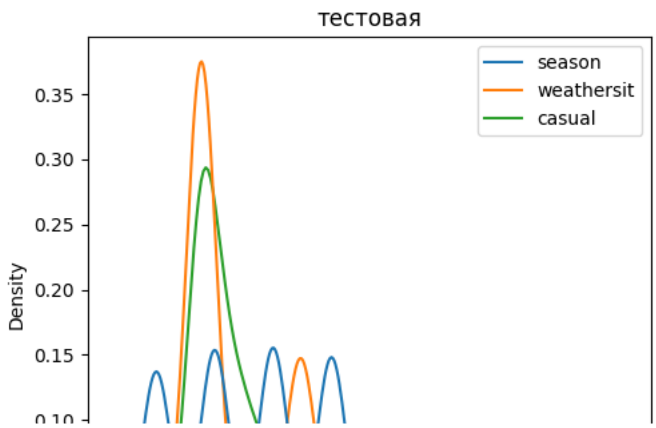
	instant	season	mnth	hr	holiday	weekday	workingday	weathersit	tem
count	6.916000e+03	6.916000e+03	6.916000e+03	6.916000e+03	6.916000e+03	6.916000e+03	6.916000e+03	6.916000e+03	6.916000e+0
mean	1.330470e-16	1.307353e-16	9.195138e-17	2.465735e-17	-2.260257e-17	-1.284237e-16	3.904081e-17	-9.400616e-17	-4.006820e-1
std	1.000072e+00	1.000072e+00	1.000072e+00	1.000072e+00	1.000072e+00	1.000072e+00	1.000072e+00	1.000072e+00	1.000072e+0
min	-1.724531e+00	-1.363995e+00	-1.619885e+00	-1.676533e+00	-1.657853e-01	-1.499744e+00	-1.469992e+00	-6.676050e-01	-2.367586e+0
25%	-8.712143e-01	-4.605000e-01	-7.451195e-01	-8.072194e-01	-1.657853e-01	-1.001606e+00	-1.469992e+00	-6.676050e-01	-8.503489e-0
50%	5.319695e-03	4.429945e-01	1.296465e-01	6.209380e-02	-1.657853e-01	-5.329989e-03	6.802756e-01	-6.676050e-01	5.999331e-0
75%	8.662424e-01	4.429945e-01	1.004412e+00	9.314070e-01	-1.657853e-01	9.909458e-01	6.802756e-01	8.683750e-01	8.691864e-0

```
data_cs12_scaled_test.describe()
```

	instant	season	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp
count	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000
mean	0.027599	0.017636	0.027110	0.001592	0.027780	0.005042	0.001244	0.022653	0.023547	0.017309
std	0.994776	0.993819	0.997747	1.004211	1.078361	0.997230	0.999797	1.021197	1.005222	0.995794
min	-1.721729	-1.363995	-1.619885	-1.676533	-0.165785	-1.499744	-1.469992	-0.667605	-2.266437	-2.476416
25%	-0.819077	-0.460500	-0.745119	-0.807219	-0.165785	-1.001606	-1.469992	-0.667605	-0.749200	-0.848980
50%	0.007121	0.442994	0.129646	0.062094	-0.165785	-0.005330	0.680276	-0.667605	0.059993	0.092773
75%	0.903770	0.442994	1.004412	0.931407	-0.165785	0.990946	0.680276	0.868375	0.869186	0.863813
max	1.735171	1.346489	1.587590	1.655835	6.031897	1.489084	0.680276	2.404355	2.386423	2.491249

```
# 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	weekday	workingday	weathersit	temp	atemp
count	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000
mean	0.001595	0.001301	0.001690	0.000096	0.000896	0.000337	0.000116	0.000983	0.000991	0.000612
std	0.288725	0.368492	0.311650	0.300340	0.163966	0.334395	0.465040	0.217953	0.210578	0.176760
min	-0.498405	-0.503229	-0.505034	-0.503106	-0.026750	-0.501783	-0.683632	-0.144881	-0.498019	-0.468388
25%	-0.248405	-0.169896	-0.232307	-0.242236	-0.026750	-0.335117	-0.683632	-0.144881	-0.178870	-0.150188
50%	0.001595	0.163437	0.040420	0.018634	-0.026750	-0.001783	0.316368	-0.144881	0.012620	0.016412
75%	0.251595	0.163437	0.313147	0.279503	-0.026750	0.331550	0.316368	0.188452	0.182832	0.152812
max	0.501595	0.496771	0.494966	0.496894	0.973250	0.498217	0.316368	0.855119	0.501981	0.531612

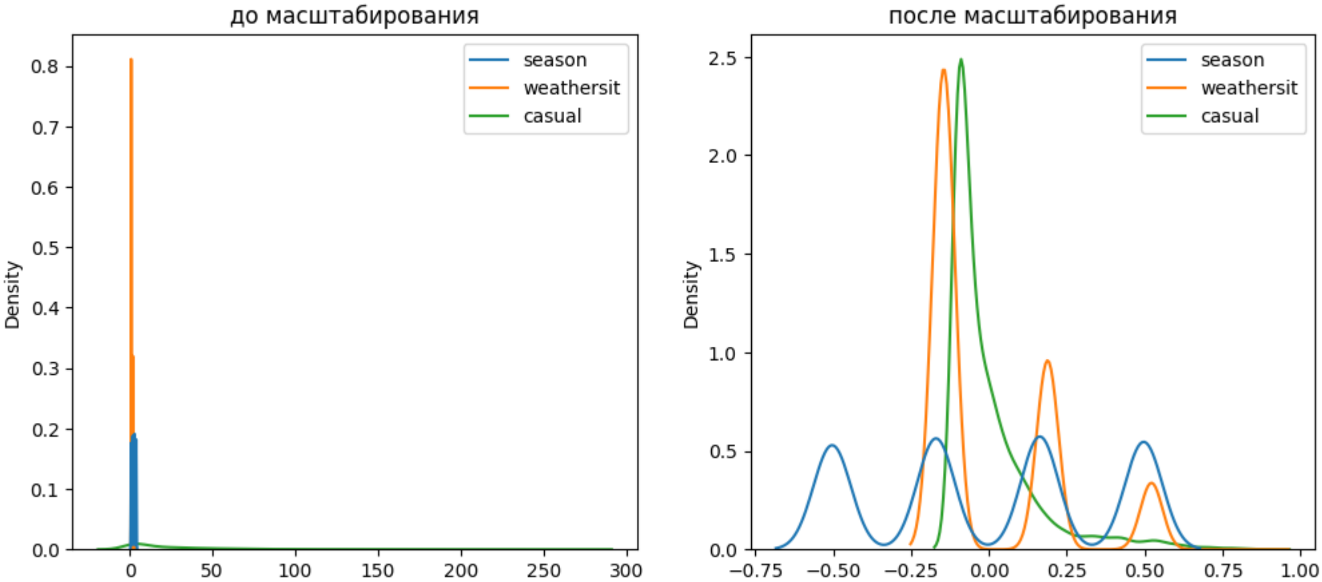
```
cs22 = MeanNormalisation()
cs22.fit(X_train)
data_cs22_scaled_train = cs22.transform(X_train)
data_cs22_scaled_test = cs22.transform(X_test)
```

```
data_cs22_scaled_train.describe()
```

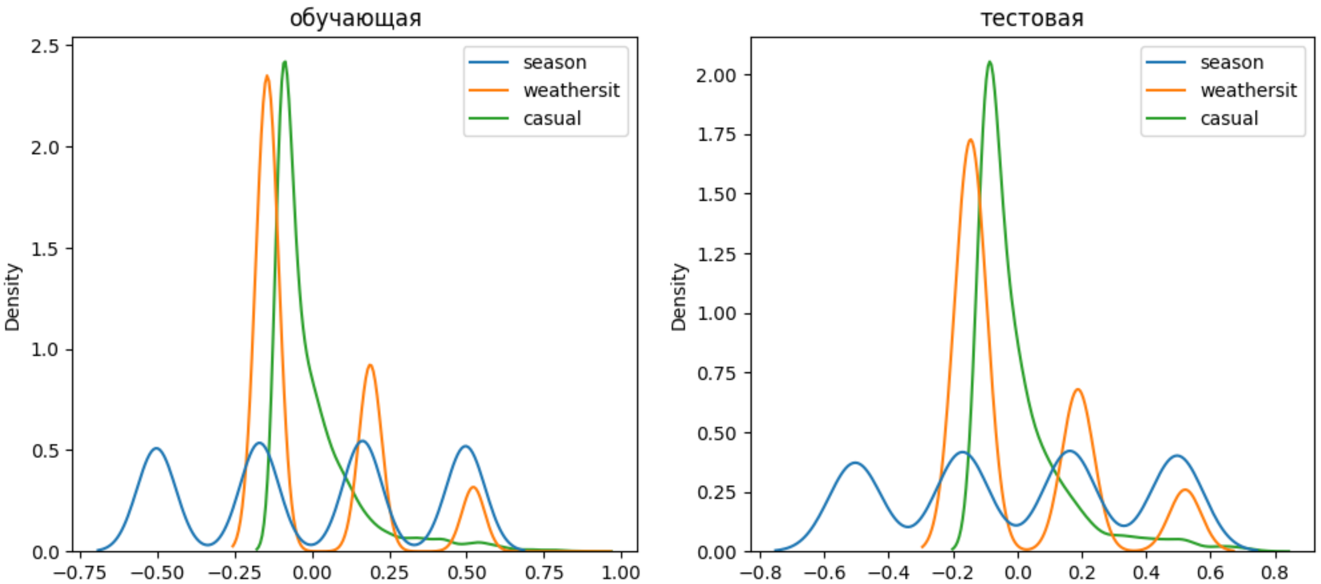
```
data_cs22_scaled_test.describe()
```

	instant	season	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp
count	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000	1729.000000
mean	0.007976	0.006507	0.008452	0.000478	0.004482	0.001687	0.000578	0.004916	0.004953	0.003062
std	0.287499	0.366657	0.311069	0.301351	0.173994	0.333653	0.464964	0.221617	0.211447	0.176160
min	-0.497595	-0.503229	-0.505034	-0.503106	-0.026750	-0.501783	-0.683632	-0.144881	-0.476742	-0.438088
25%	-0.236720	-0.169896	-0.232307	-0.242236	-0.026750	-0.335117	-0.683632	-0.144881	-0.157593	-0.150188
50%	0.002058	0.163437	0.040420	0.018634	-0.026750	-0.001783	0.316368	-0.144881	0.012620	0.016412
75%	0.261197	0.163437	0.313147	0.279503	-0.026750	0.331550	0.316368	0.188452	0.182832	0.152812
max	0.501480	0.496771	0.494966	0.496894	0.973250	0.498217	0.316368	0.521785	0.501981	0.440712

```
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

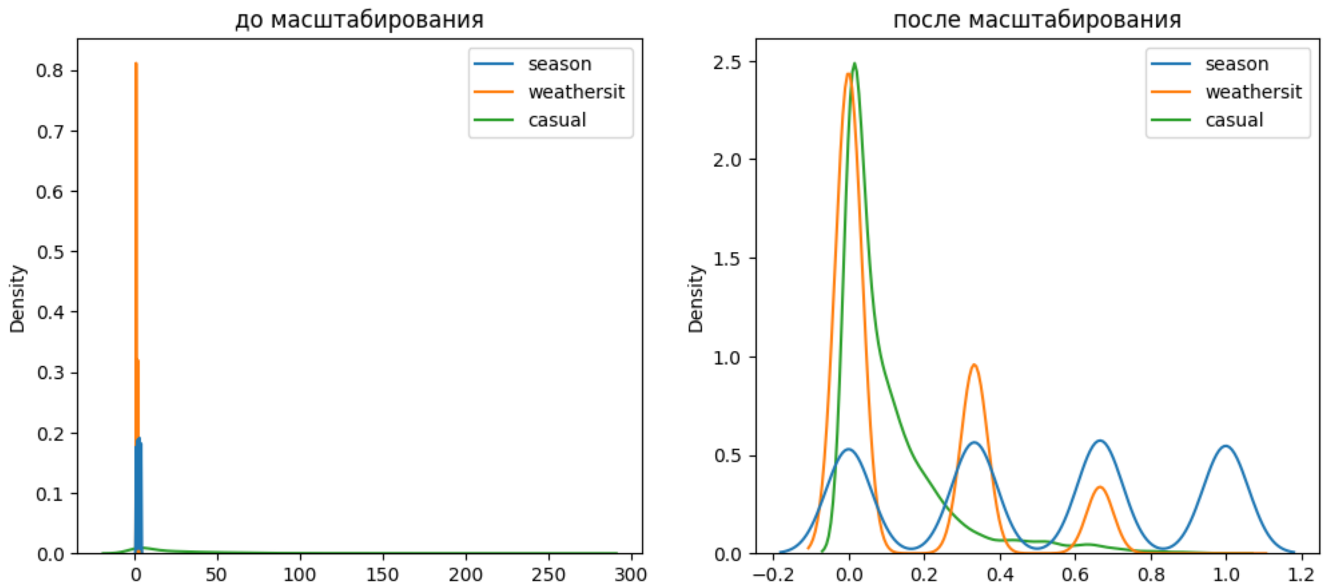
```
# Обучаем StandardScaler на всей выборке и масштабируем
cs31 = MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(X_ALL)
```

```
# формируем DataFrame на основе массива
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()
```

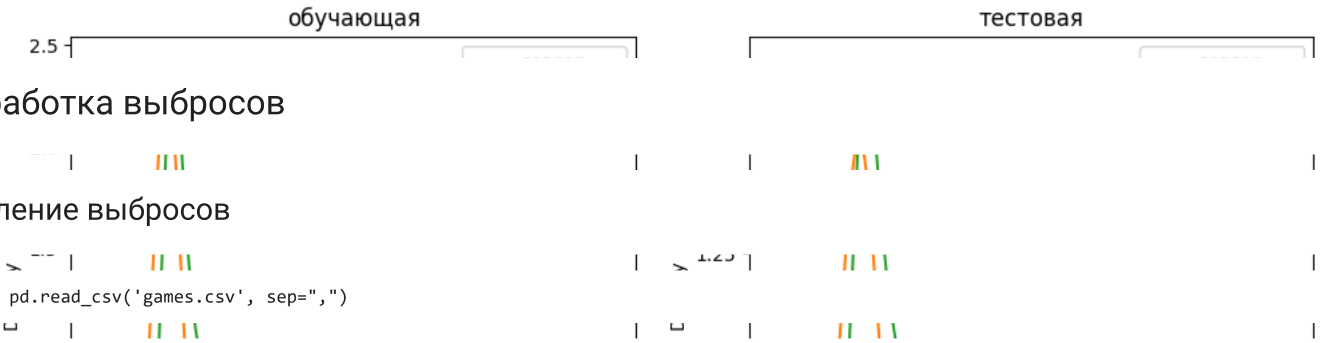
	instant	season	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp
count	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.000000	8645.00000
mean	0.500000	0.504531	0.506725	0.503201	0.027646	0.502121	0.683748	0.145865	0.499009	0.46900
std	0.288725	0.368492	0.311650	0.300340	0.163966	0.334395	0.465040	0.217953	0.210578	0.17676
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	0.250000	0.333333	0.272727	0.260870	0.000000	0.166667	0.000000	0.000000	0.319149	0.31820
50%	0.500000	0.666667	0.545455	0.521739	0.000000	0.500000	1.000000	0.000000	0.510638	0.48480
75%	0.750000	0.666667	0.818182	0.782609	0.000000	0.833333	1.000000	0.333333	0.680851	0.62120
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00000

```
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 argu
  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 argu
  data = data.drop('Unnamed: 0', 1)
(30101, 25)
```

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

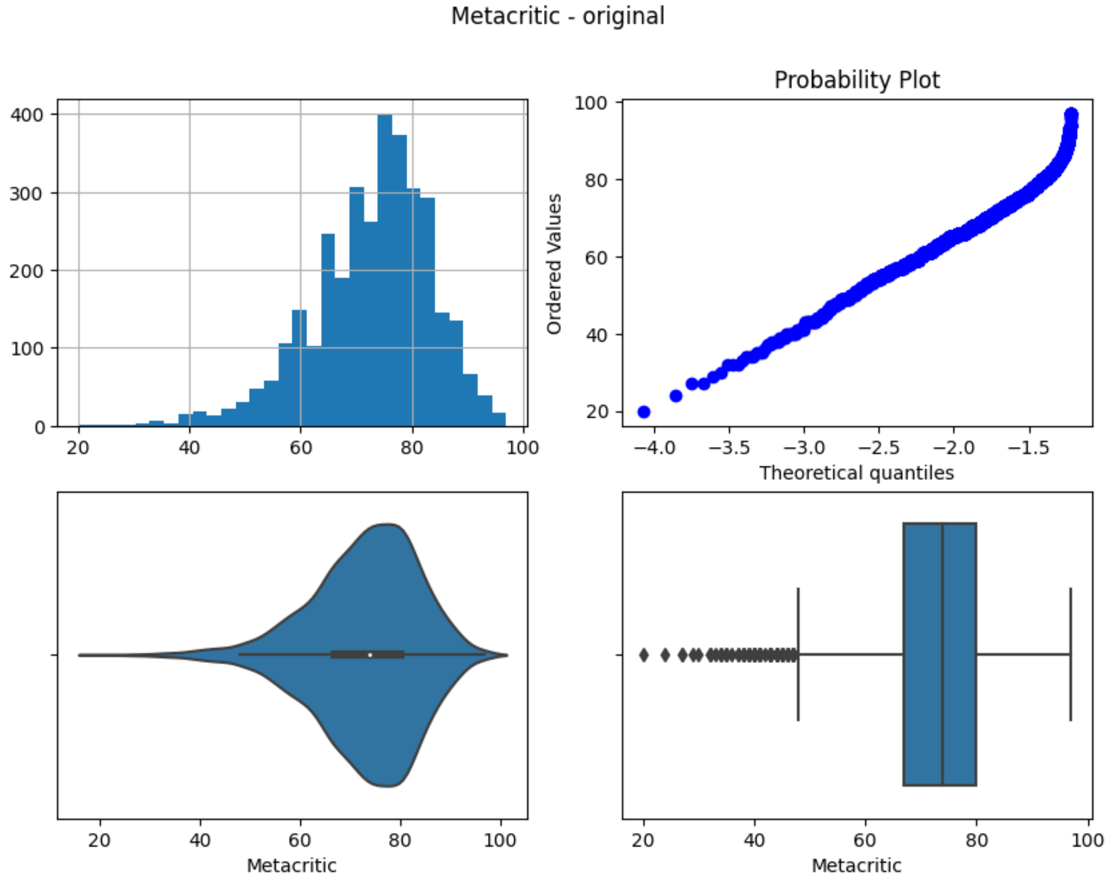
```
import scipy.stats as stats
def diagnostic_plots(df, variable, title):
    fig, ax = plt.subplots(figsize=(10,7))
    # гистограмма
    plt.subplot(2, 2, 1)
    df[variable].hist(bins=30)
    ## Q-Q plot
    plt.subplot(2, 2, 2)
    stats.probplot(df[variable], dist="norm", plot=plt)
    # ящик с 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
```

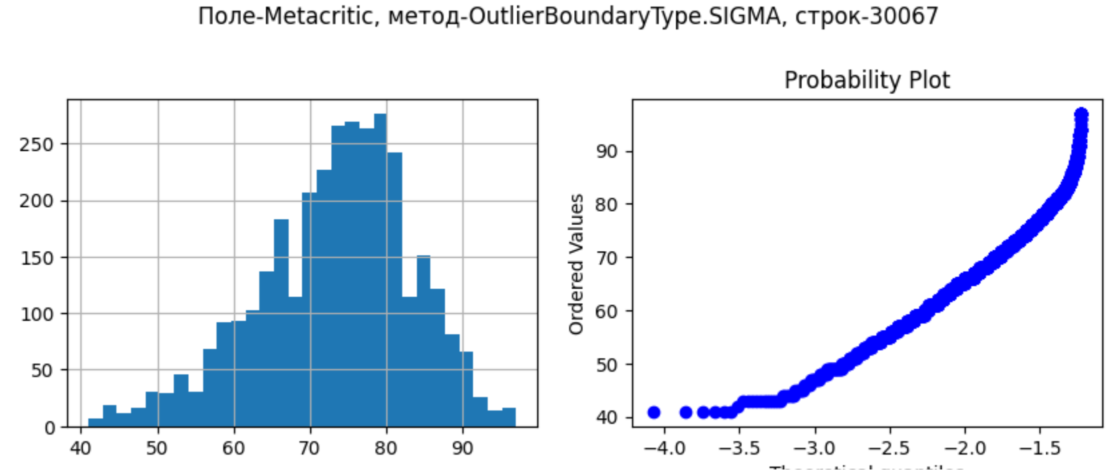
```
diagnostic_plots(data, 'Metacritic', 'Metacritic - original')
```

```
<ipython-input-82-2de3f422987c>:5: MatplotlibDeprecationWarning: Auto-removal of overlapping axes is deprecated since 3.6 and will
  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
  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
  plt.subplot(2, 2, 1)
```

Поле-Metacritic, метод-OutlierBoundaryType.SIGMA

Probability Plot

Обработка нестандартного признака

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

150 70

```
data
```

	instant	dteday	season	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	cnt
0	1	01-01-2011	1	1	0	0	6	0	1	0.24	0.2879	0.81	0.0000	3	16
1	2	01-01-2011	1	1	1	0	6	0	1	0.22	0.2727	0.80	0.0000	8	40
2	3	01-01-2011	1	1	2	0	6	0	1	0.22	0.2727	0.80	0.0000	5	32
3	4	01-01-2011	1	1	3	0	6	0	1	0.24	0.2879	0.75	0.0000	3	13
4	5	01-01-2011	1	1	4	0	6	0	1	0.24	0.2879	0.75	0.0000	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8640	8641	31-12-2011	1	12	19	0	6	0	1	0.42	0.4242	0.54	0.2239	19	92
8641	8642	31-12-2011	1	12	20	0	6	0	1	0.42	0.4242	0.54	0.2239	8	71
8642	8643	31-12-2011	1	12	21	0	6	0	1	0.40	0.4091	0.58	0.1940	2	52
8643	8644	31-12-2011	1	12	22	0	6	0	1	0.38	0.3939	0.62	0.1343	2	38
8644	8645	31-12-2011	1	12	23	0	6	0	1	0.36	0.3788	0.66	0.0000	4	31

8645 rows × 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 argu
  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 argu
  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 argu
  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 argu
  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 argu
  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	cnt	dt
0	1	01-01-2011	0	1	0.24	0.2879	0.81	0.0	3	16	2011-01-01
1	2	01-01-2011	1	1	0.22	0.2727	0.80	0.0	8	40	2011-01-01
2	3	01-01-2011	2	1	0.22	0.2727	0.80	0.0	5	32	2011-01-01
3	4	01-01-2011	3	1	0.24	0.2879	0.75	0.0	3	13	2011-01-01
4	5	01-01-2011	4	1	0.24	0.2879	0.75	0.0	0	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	cnt	dt	day	month	year	week	quarter	dayofweek	day_
0	1	01-01-2011	0	1	0.24	0.2879	0.81	0.0	3	16	2011-01-01	1	1	2011	52	1	5	Sat
1	2	01-01-2011	1	1	0.22	0.2727	0.80	0.0	8	40	2011-01-01	1	1	2011	52	1	5	Sat

```
# 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	cnt	...	day	month	year	week	quarter	dayofweek	day_n
0	1	01-01-2011	0	1	0.24	0.2879	0.81	0.0	3	16	...	1	1	2011	52	1	5	Satur
1	2	01-01-2011	1	1	0.22	0.2727	0.80	0.0	8	40	...	1	1	2011	52	1	5	Satur
2	3	01-01-2011	2	1	0.22	0.2727	0.80	0.0	5	32	...	1	1	2011	52	1	5	Satur
3	4	01-01-2011	3	1	0.24	0.2879	0.75	0.0	3	13	...	1	1	2011	52	1	5	Satur
4	5	01-01-2011	4	1	0.24	0.2879	0.75	0.0	0	1	...	1	1	2011	52	1	5	Satur

5 rows × 21 columns

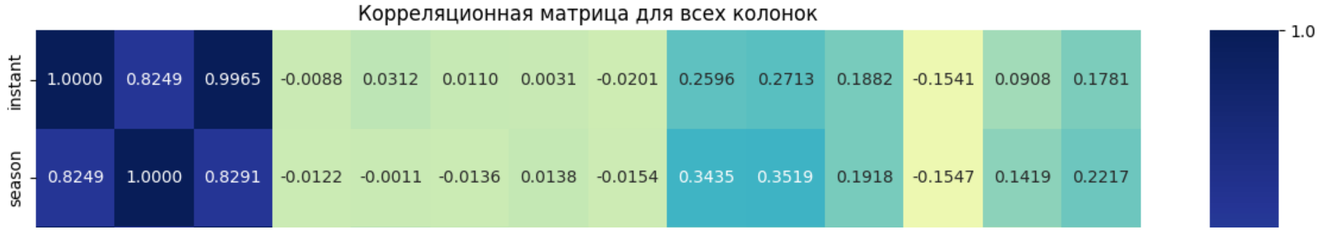
Отбор признаков

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')
```




```
# 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: 78/78Best 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)]
```