Лабораторная работа №3. Обработка признаков, ч.2

Студент: Кривцов Н.А.
Группа: ИУ5-22М

Импорт библиотек

In [79]:

```
import joblib
import sys
sys.modules['sklearn.externals.joblib'] = joblib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.feature_selection import chi2, SelectKBest, SelectFromModel
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
import scipy.stats as stats
%matplotlib inline
```

Загрузка и просмотр датасета

Датасет содержит данные о качестве питьевой воды в 3276 водоемах мира. Для анализа качества используются 9 числовых показателей, таких как pH, жесткость и концентрация различных вредных веществ.

In [2]:

```
data = pd.read_csv('/content/drive/MyDrive/MMO/water_potability_filled.csv')
```

In [3]:

```
data.shape
```

Out[3]:

```
(3276, 11)
```

In [4]:

```
data.head()
```

Out[4]:

	Unnamed: 0	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Turbidity	KKN_3_ph	KKN_3_Sulfate	KKN_3_Trih
0	0	204.890455	20791.318981	7.300212	564.308654	10.379783	2.963135	6.655223	368.516441	
1	1	129.422921	18630.057858	6.635246	592.885359	15.180013	4.500656	3.716080	351.285226	
2	2	224.236259	19909.541732	9.275884	418.606213	16.868637	3.055934	8.099124	347.323743	
3	3	214.373394	22018.417441	8.059332	363.266516	18.436524	4.628771	8.316766	356.886136	
4	4	181.101509	17978.986339	6.546600	398.410813	11.558279	4.075075	9.092223	310.135738	

In [5]:

```
data = data.iloc[:,1:]
X_all = data.iloc[:,:-1]
Y_all = data.iloc[:,-1:]
```

1. Масштабирование

In [6]:

```
X_all.describe()
```

Out[6]:

	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Turbidity	KKN_3_ph	KKN_3_Sulfate	KKN_3_Trih
count	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	
mean	196.369496	22014.092526	7.122277	426.205111	14.284970	3.966786	7.078662	333.524002	
std	32.879761	8768.570828	1.583085	80.824064	3.308162	0.780382	1.515094	37.994764	
min	47.432000	320.942611	0.352000	181.483754	2.200000	1.450000	0.000000	129.000000	
25%	176.850538	15666.690297	6.127421	365.734414	12.065801	3.439711	6.145051	311.530079	
50%	196.967627	20927.833607	7.130299	421.884968	14.218338	3.955028	7.053692	333.282412	
75%	216.667456	27332.762127	8.114887	481.792304	16.557652	4.500320	7.977734	356.172936	
max	323.124000	61227.196008	13.127000	753.342620	28.300000	6.739000	14.000000	481.030642	

In [7]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X_all, data['Potability'], test_size=0.2)
```

In [8]:

```
def arr_to_df(arr):
  return pd.DataFrame(arr, columns=X_all.columns)
```

In [9]:

```
X_train_df = arr_to_df(X_train)
X_test_df = arr_to_df(X_test)

X_train_df.shape, X_test_df.shape
```

Out[9]:

```
((2620, 9), (656, 9))
```

In [10]:

```
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()
```

In [11]:

```
scalers= [
    'Масштабирование по Z-оценке',
    'Min-Max масштабирование',
```

```
    'Масштабирование по медиане',
]
```

In [12]:

```python
def get_scaler(label):
  if label == 'Масштабирование по Z-оценке':
    return StandardScaler()
  if label == 'Min-Max масштабирование':
    return MinMaxScaler()
  if label == 'Масштабирование по медиане':
    return RobustScaler()
  else:
    raise ValueError('Некорректный алгоритм масштабирования')
```

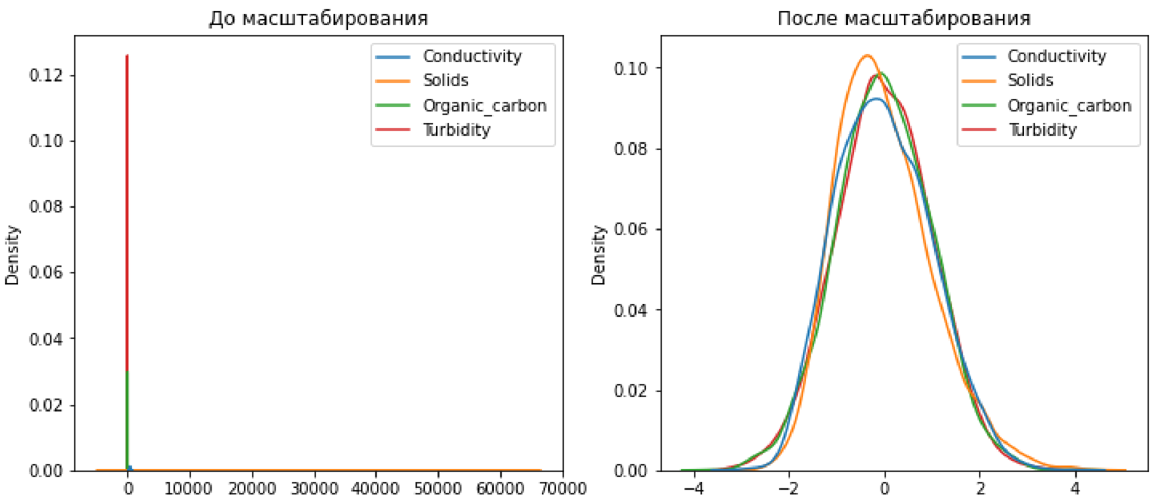
In [13]:

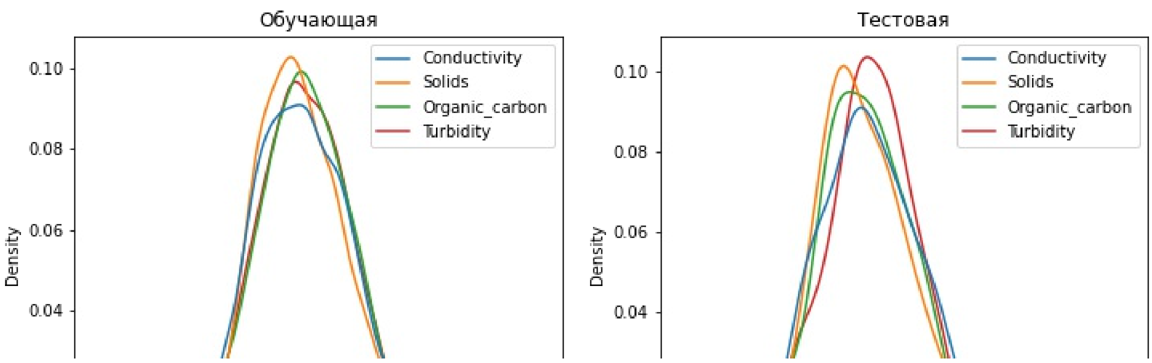
```python
def scaler_analysis(label):
  scaler = get_scaler(label)
  data_scaled = arr_to_df(scaler.fit_transform(X_all))
  scaler = get_scaler(label)
  scaler.fit(X_train)
  data_scaled_train = arr_to_df(scaler.transform(X_train))
  data_scaled_test = arr_to_df(scaler.transform(X_test))
  draw_kde(['Conductivity', 'Solids', 'Organic_carbon', 'Turbidity'], X_all, data_scaled, 'До масштабир
ования', 'После масштабирования')
  draw_kde(['Conductivity', 'Solids', 'Organic_carbon', 'Turbidity'], data_scaled_train, data_scaled_te
st, 'Обучающая', 'Тестовая')
  return data_scaled
```

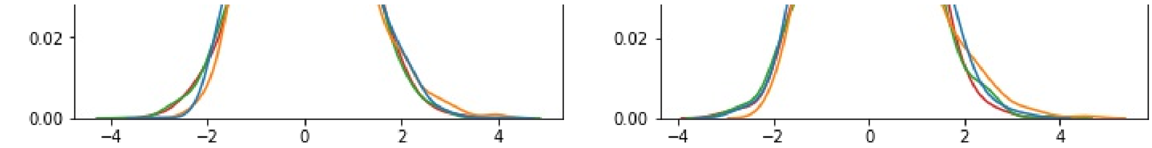
1.1. Масштабирование по Z-оценке

In [14]:

```python
scaler_analysis(scalers[0]).describe()
```







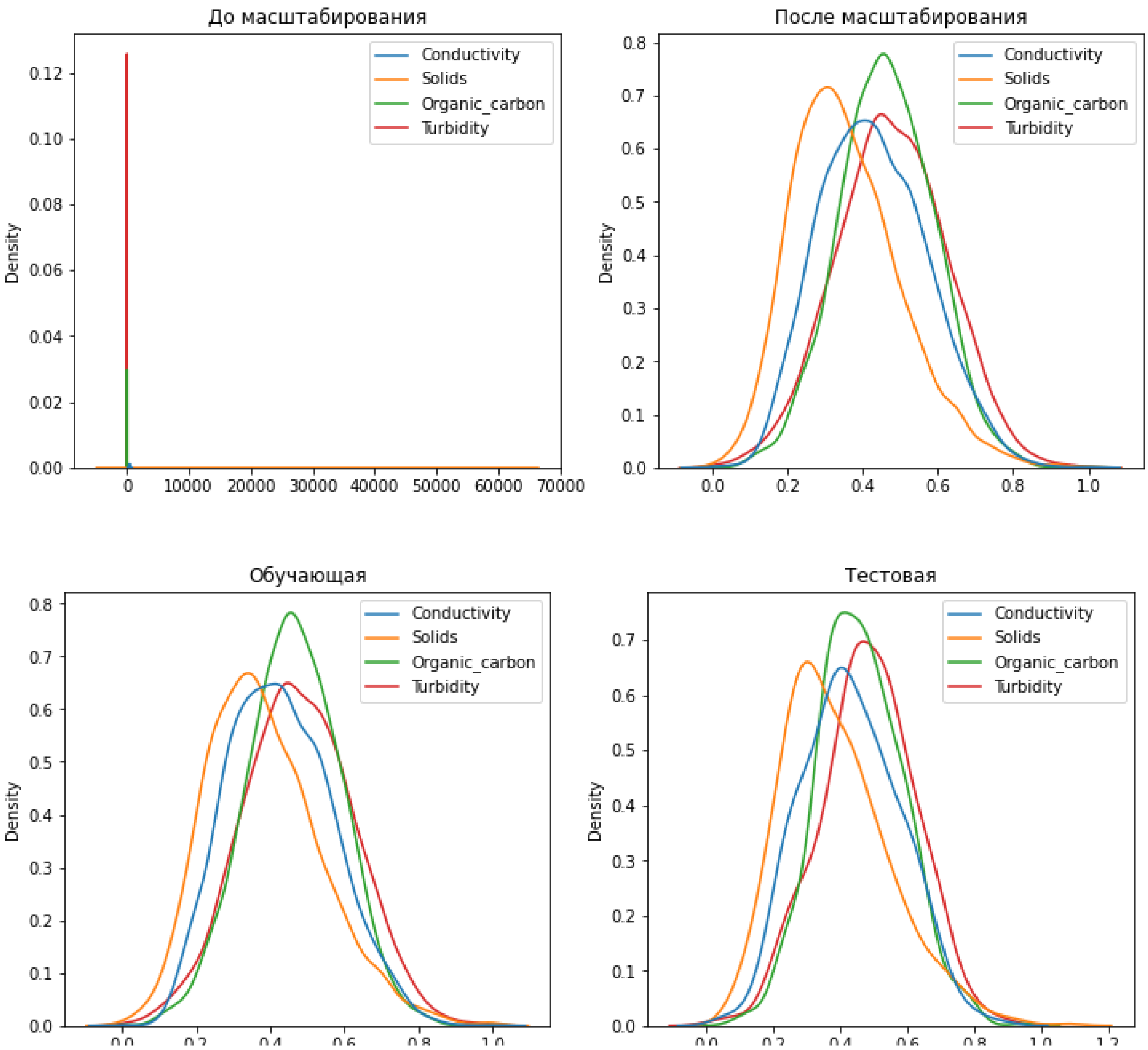
Out[14]:

	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Turbidity	KKN_3_ph	KKN_3_Sulfate	KKN_
count	3.276000e+03	3.276000e+03	3.276000e+03	3.276000e+03	3.276000e+03	3.276000e+03	3.276000e+03	3.276000e+03	
mean	1.048108e-15	-3.954915e-17	5.111482e-16	1.835460e-16	3.317791e-17	5.387089e-16	1.406079e-16	1.663395e-15	
std	1.000153e+00	1.000153e+00	1.000153e+00	1.000153e+00	1.000153e+00	1.000153e+00	1.000153e+00	1.000153e+00	
min	-4.530454e+00	-2.474344e+00	-4.277288e+00	-3.028290e+00	-3.653635e+00	-3.225560e+00	-4.672807e+00	-5.383774e+00	
25%	-5.937372e-01	-7.239916e-01	-6.285247e-01	-7.482911e-01	-6.709187e-01	-6.755095e-01	-6.163004e-01	-5.789556e-01	
50%	1.819424e-02	-1.238999e-01	5.068209e-03	-5.345935e-02	-2.014487e-02	-1.507005e-02	-1.648325e-02	-6.359479e-03	
75%	6.174333e-01	6.066532e-01	6.271058e-01	6.878605e-01	6.870970e-01	6.837866e-01	5.935007e-01	5.961977e-01	
max	3.855680e+00	4.472689e+00	3.793631e+00	4.048144e+00	4.237147e+00	3.552921e+00	4.568953e+00	3.882881e+00	

1.2. Min-Max масштабирование

In [15]:

```
scaler_analysis(scalers[1]).describe()
```



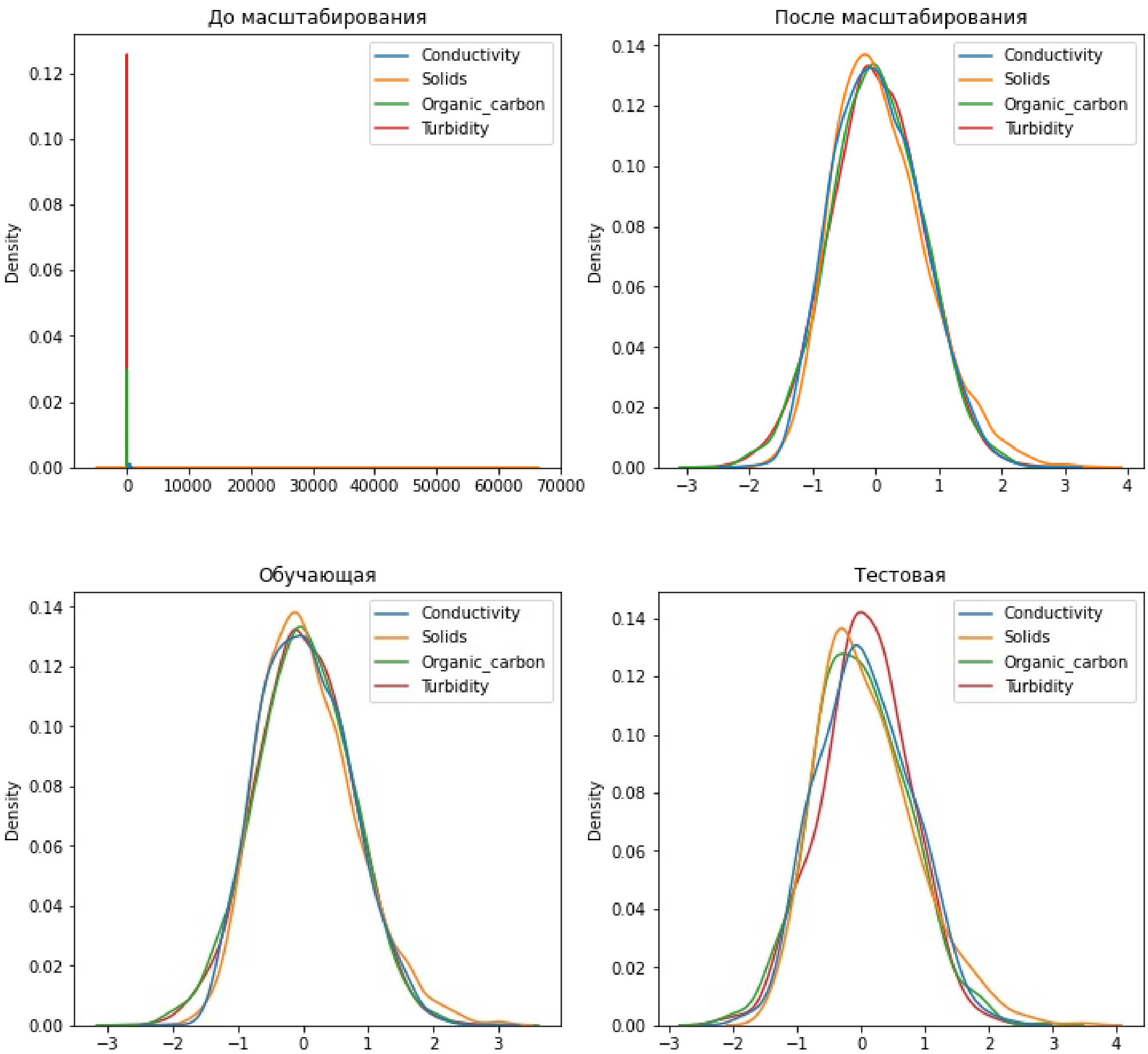
Out[15]:

	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Turbidity	KKN_3_ph	KKN_3_Sulfate	KKN_3_Triha
count	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3
mean	0.540231	0.356173	0.529963	0.427940	0.463026	0.475853	0.505619	0.580984	
std	0.119263	0.143968	0.123921	0.141336	0.126750	0.147548	0.108221	0.107930	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.469432	0.251957	0.452088	0.322196	0.378000	0.376198	0.438932	0.518506	
50%	0.542401	0.338338	0.530591	0.420386	0.460473	0.473630	0.503835	0.580297	
75%	0.613857	0.443498	0.607662	0.525145	0.550102	0.576729	0.569838	0.645321	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

1.3. Масштабирование по медиане

In [16]:

```
scaler_analysis(scalers[2]).describe()
```



Out[16]:

	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Turbidity	KKN_3_ph	KKN_3_Sulfate	KKN_3
count	3.276000e+03	3.276000e+03	3.276000e+03	3.276000e+03	3276.000000	3.276000e+03	3276.000000	3276.000000	

	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Turbidity	KKN_3_ph	KKN_3_Sulfate	KKN_3
mean	-1.502203e-02	9.3112[illegible]	-4.036386e-03	3.[illegible]	[illegible]	1.108[illegible]	[illegible]	[illegible]	
std	8.257736e-01	7.516301e-01	7.965342e-01	6.964116e-01	0.736481	7.357871e-01	0.826708	0.851083	
min	-3.755580e+00	-1.766395e+00	-3.410523e+00	-2.071391e+00	-2.675587	-2.361877e+00	-3.848834	-4.575926	
25%	-5.052397e-01	-4.509781e-01	-5.046014e-01	-4.838151e-01	-0.479209	-4.858687e-01	-0.495798	-0.487252	
50%	-3.568651e-16	-1.559083e-16	2.234541e-16	-2.448874e-16	0.000000	2.093594e-16	0.000000	0.000000	
75%	4.947603e-01	5.490219e-01	4.953986e-01	5.161849e-01	0.520791	5.141313e-01	0.504202	0.512748	
max	3.168411e+00	3.454407e+00	3.017259e+00	2.855968e+00	3.134936	2.624881e+00	3.790240	3.309560	

2. Устранение выбросов

In [17]:

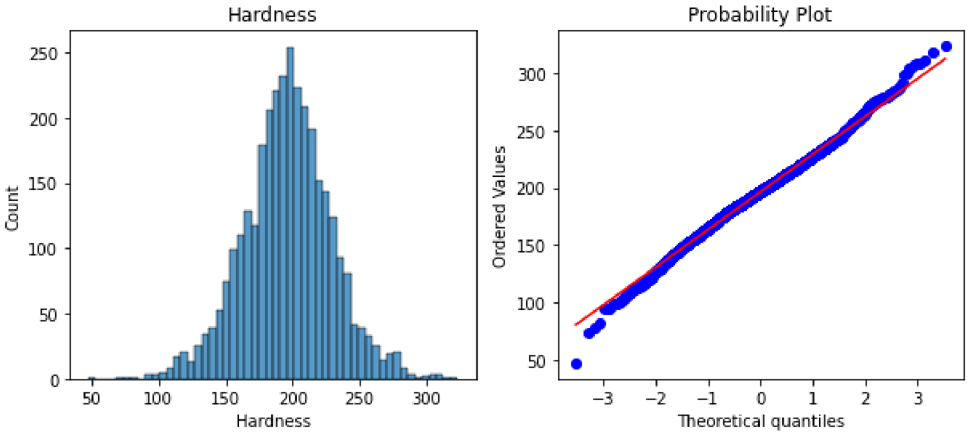
```
def diagnostic_plots(data, column):
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 4))
    plt.axes(axes[0])
    plt.title(column)
    sns.histplot(data[column], ax=axes[0])
    stats.probplot(data[column], dist='norm', plot=axes[1])
```

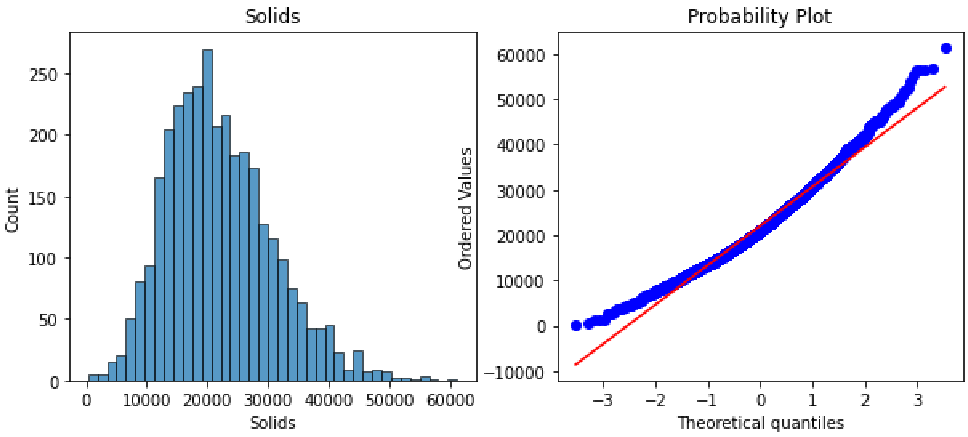
In [18]:

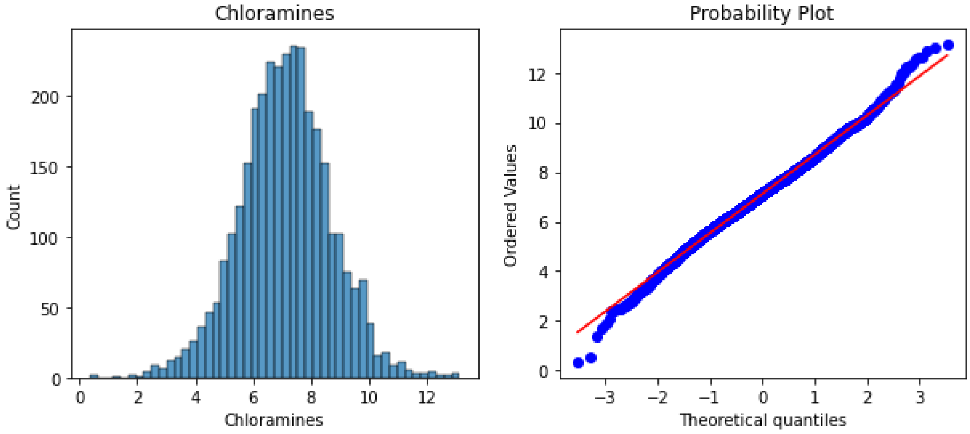
```
[diagnostic_plots(X_all, c) for c in X_all]
```

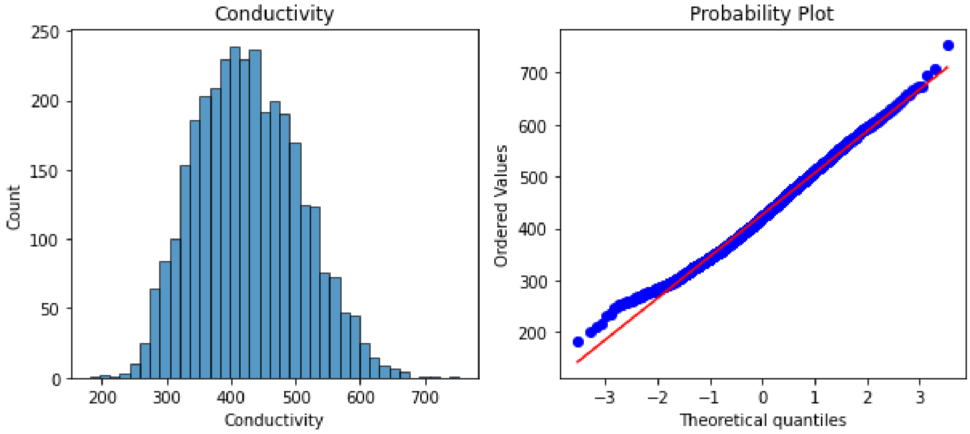
Out[18]:

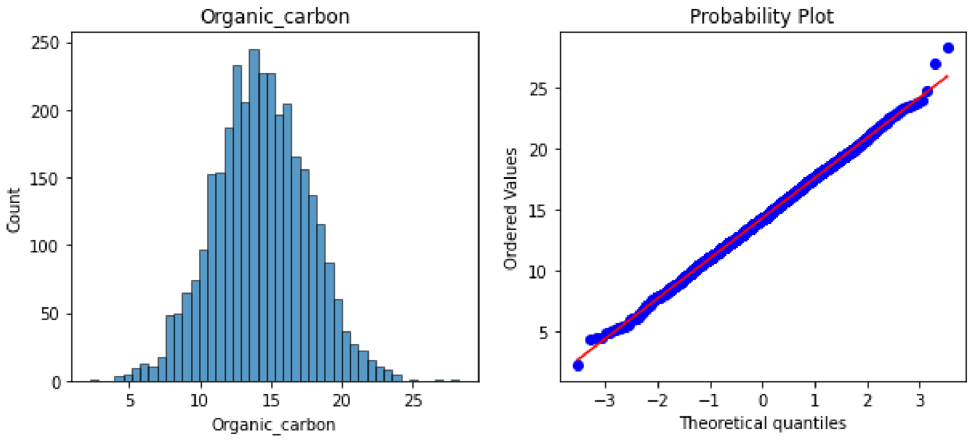
```
[None, None, None, None, None, None, None, None, None]
```

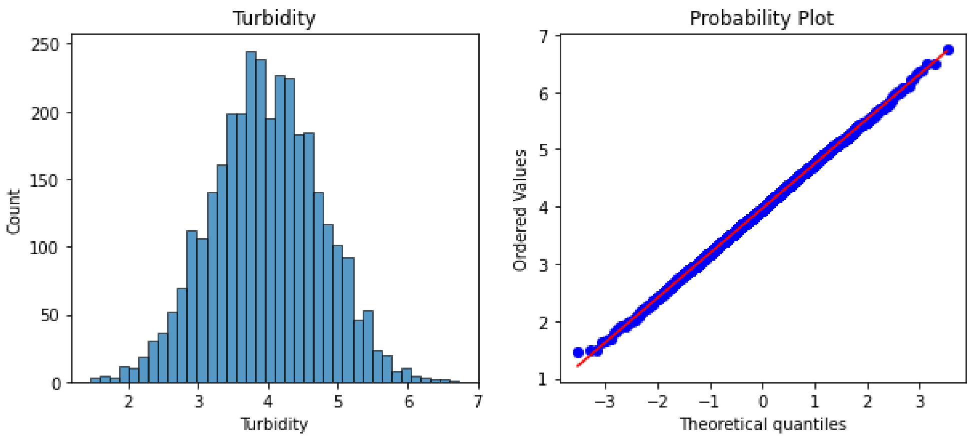


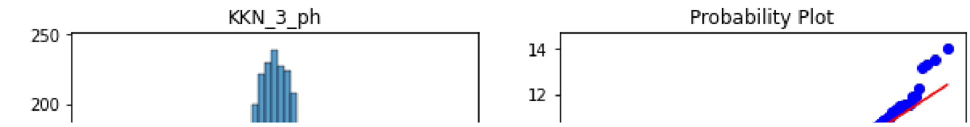


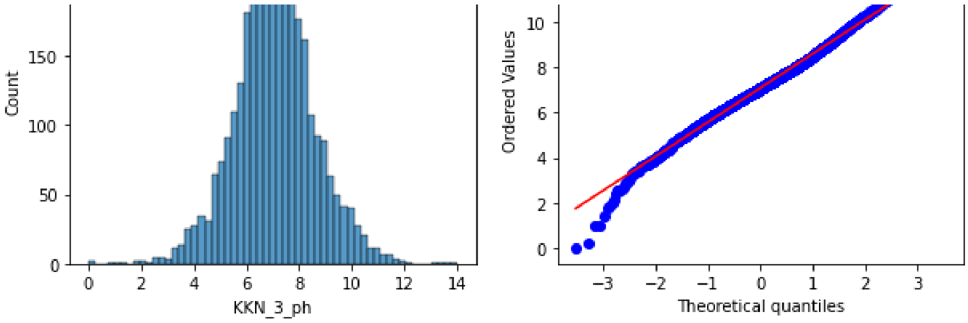

Chloramines
Count
Chloramines
Probability Plot
Ordered Values
Theoretical quantiles

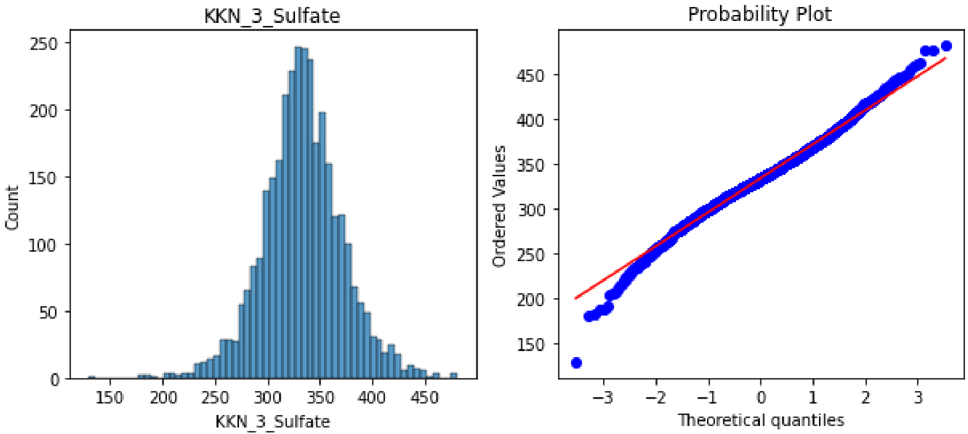

Conductivity
Count
Conductivity
Probability Plot
Ordered Values
Theoretical quantiles

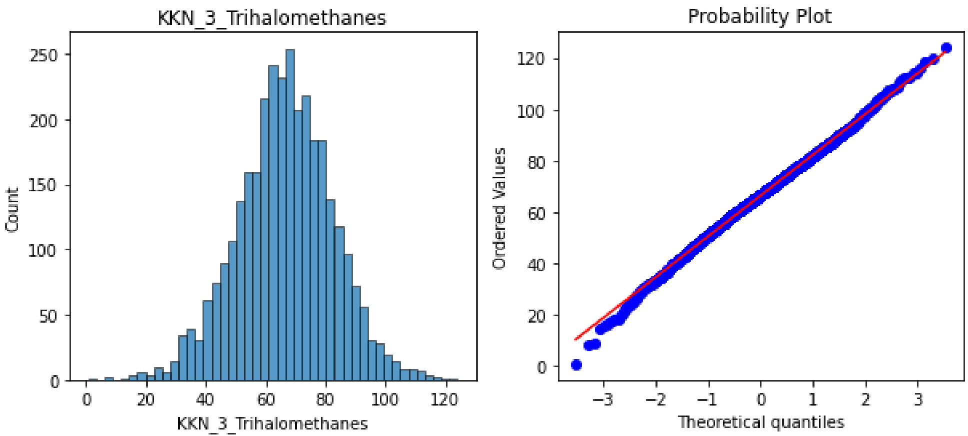

Organic_carbon
Count
Organic_carbon
Probability Plot
Ordered Values
Theoretical quantiles


Turbidity
Count
Turbidity
Probability Plot
Ordered Values
Theoretical quantiles


KKN_3_ph
Probability Plot







2.1. Удаление выбросов

Для удаления выбросов применим метод квантилей 5% и 95% к признаку `Turbidity`, т.к. его распределение близко к нормальному.

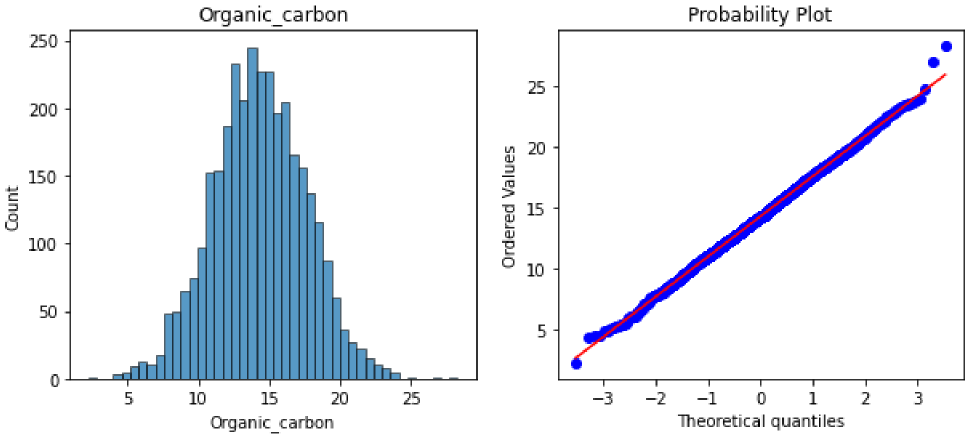
In [19]:

```
col_name = 'Organic_carbon'
col = X_all[col_name]

# верхняя и нижняя границы
lower_bound = col.quantile(0.05)
upper_bound = col.quantile(0.95)

print(lower_bound, upper_bound)
```

```
8.81536170240254 19.63725444952086
```

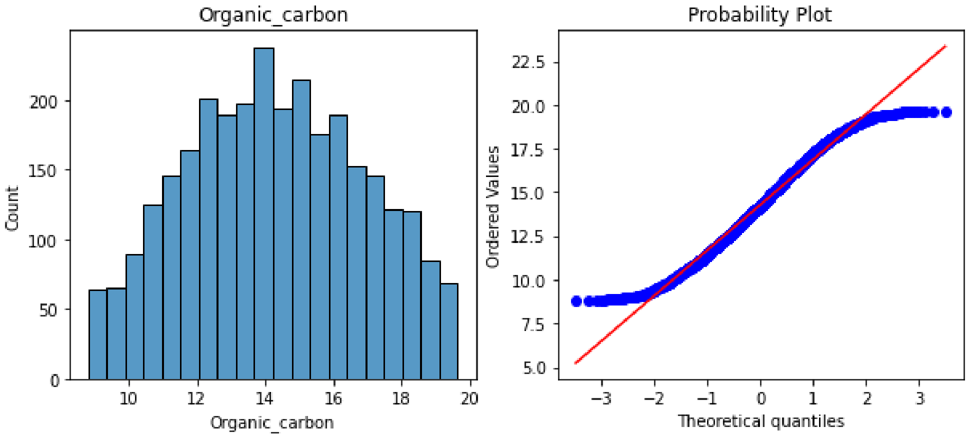
In [20]:

```
diagnostic_plots(X_all, col_name)
```



In [21]:

```
outliers_temp = np.where(col > upper_bound, True,
                         np.where(col < lower_bound, True, False))
data_trimmed = X_all.loc[~(outliers_temp), ]
diagnostic_plots(data_trimmed, col_name)
```



2.2. Замена выбросов

Для замены выбросов применим метод `Inter-Quantile Range` к признаку `Solids`, т.к. его распределение асимметрично (вытянуто вправо).

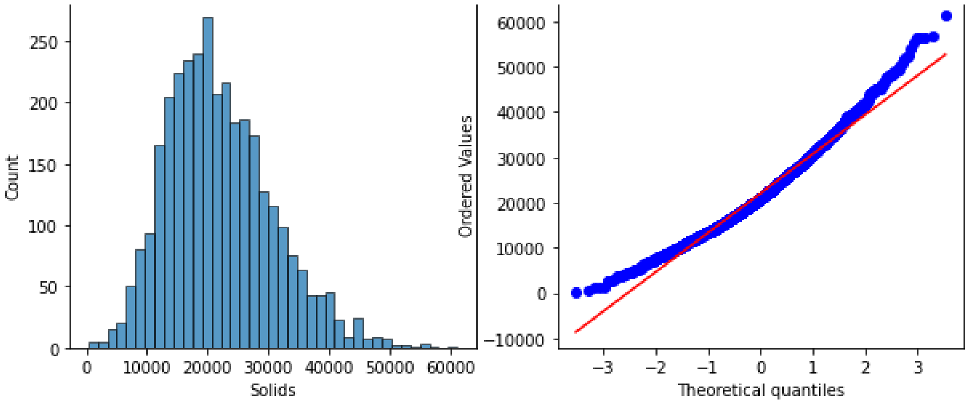
In [22]:

```
col_name = 'Solids'
col = X_all[col_name]

K2 = 1.5
IQR = col.quantile(0.75) - col.quantile(0.25)
# верхняя и нижняя границы
lower_bound = col.quantile(0.25) - (K2*IQR)
upper_bound = col.quantile(0.75) + (K2*IQR)

print(lower_bound, upper_bound)
```

```
-1832.4174487462951 44831.86987314956
```

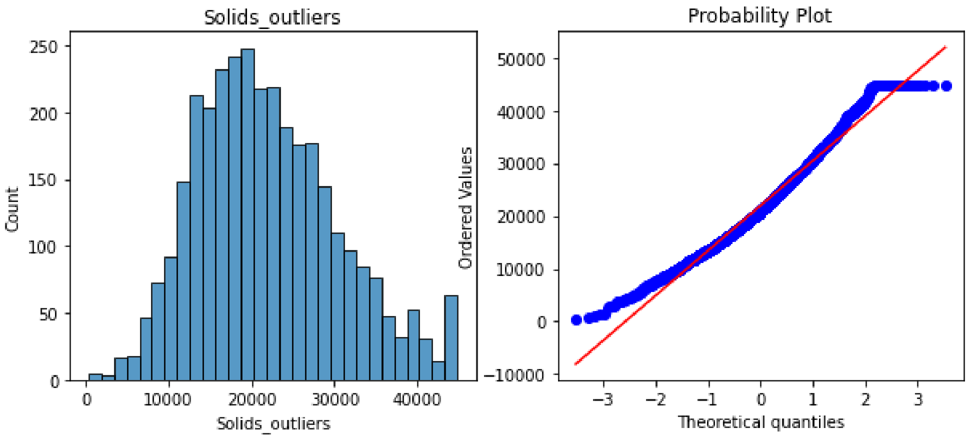
In [23]:

```
diagnostic_plots(X_all, col_name)
```



In [24]:

```
new_col_name = 'Solids_outliers'
data[new_col_name] = np.where(col > upper_bound, upper_bound, np.where(col < lower_bound, lower_bound,
col))
diagnostic_plots(data, new_col_name)
```



In [28]:

```
data = data.drop(['Solids_outliers'], axis=1)
```

3. Feature Selection

3.1. Методы фильтрации

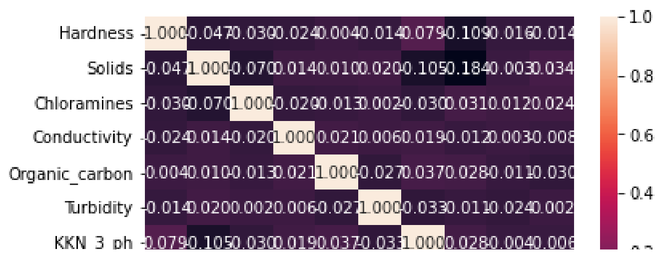
Ознакомимся с корреляционной матрицей рассматриваемых признаков

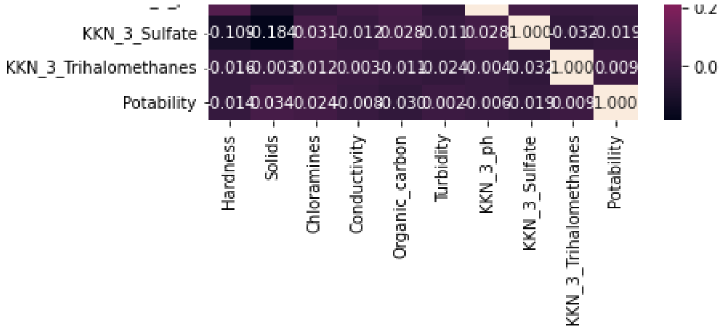
In [29]:

```
sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff372baeed0>
```





Ни один из признаков не обладает сильной корреляцией с целевым. Применять корреляционные методы фильтрации в таком случае нецелесообразно.

Перейдем к методу из группы `univariate feature selection`. Для выбора признаков будет использоваться класс `SelectKBest` с критерием хи-квадрат.

In [60]:

```
# Хи-квадрат
chi2_values, p_values = chi2(X_all, Y_all)
chi2_values = pd.Series(chi2_values)
p_values = pd.Series(p_values)
feat_data = pd.concat([chi2_values, p_values], axis=1)
feat_data.columns = ['chi2_score', 'p_value']
feat_data.index = X_all.columns
feat_data.sort_values(by=['p_value'])
```

Out[60]:

	chi2_score	p_value
Solids	13023.976277	0.000000
KKN_3_Sulfate	4.977437	0.025680
Hardness	3.451841	0.063181
Conductivity	3.316466	0.068589
Organic_carbon	2.258331	0.132897
KKN_3_Trihalomethanes	0.911194	0.339798
Chloramines	0.651609	0.419538
KKN_3_ph	0.033103	0.855628
Turbidity	0.001256	0.971726

In [61]:

```
sel_chi2 = SelectKBest(chi2, k=4).fit(X_all, Y_all)

list(zip(X_all.columns, sel_chi2.get_support()))
```

Out[61]:

```
[('Hardness', True),
 ('Solids', True),
 ('Chloramines', False),
 ('Conductivity', True),
 ('Organic_carbon', False),
 ('Turbidity', False),
 ('KKN_3_ph', False),
 ('KKN_3_Sulfate', True),
 ('KKN_3_Trihalomethanes', False)]
```

3.2. Методы обертывания

In [72]:

```
knn = KNeighborsClassifier(n_neighbors=5)
```

In [78]:

```
efs1 = EFS(knn,
           min_features=3,
           max_features=6,
           scoring='f1',
           print_progress=True,
           cv=5)
Y = Y_all.values.ravel()
efs1 = efs1.fit(X_all, Y, custom_feature_names=X_all.columns)

print('\nBest f1: %.2f' % efs1.best_score_)
print('Best subset (indices):', efs1.best_idx_)
print('Best subset (corresponding names):', efs1.best_feature_names_)
```

```
Features: 420/420
```

```
Best f1: 0.43
Best subset (indices): (4, 6, 7)
Best subset (corresponding names): ('Organic_carbon', 'KKN_3_ph', 'KKN_3_Sulfate')
```

3.3. Методы вложений

In [66]:

```
gbc = GradientBoostingClassifier()
gbc.fit(X_all, Y_all)
gbc.feature_importances_, sum(gbc.feature_importances_)
```

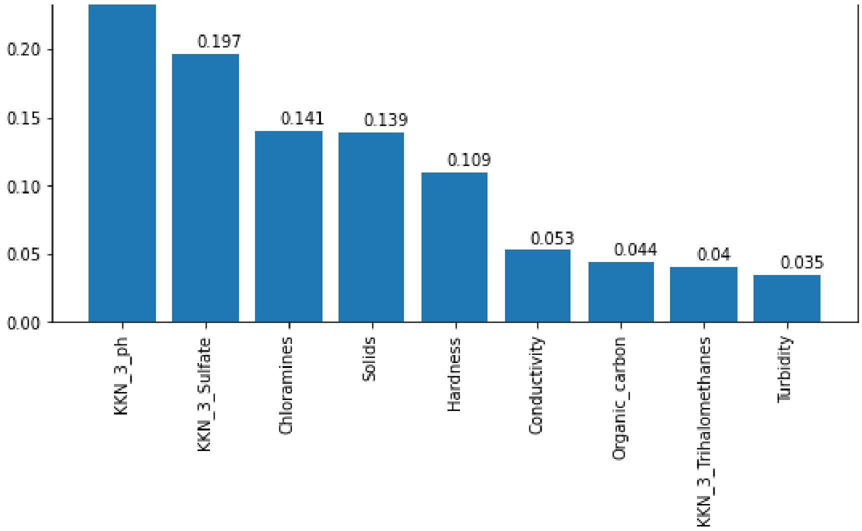
```
/usr/local/lib/python3.7/dist-packages/sklearn/ensemble/_gb.py:494: DataConversionWarning: A column-vec
tor y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for examp
le using ravel().
  y = column_or_1d(y, warn=True)
```

Out[66]:

```
(array([0.10938488, 0.13882553, 0.14055908, 0.05264054, 0.04375816,
        0.03469432, 0.24307573, 0.19691922, 0.04014254]), 0.9999999999999998)
```

In [67]:

```
from operator import itemgetter

list_to_sort = list(zip(X_all.columns.values, gbc.feature_importances_))
sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
# Названия признаков
labels = [x for x,_ in sorted_list]
# Важности признаков
data = [x for _,x in sorted_list]
# Вывод графика
fig, ax = plt.subplots(figsize=(9, 4))
ax.set_title('Градиентный бустинг')
ind = np.arange(len(labels))
plt.bar(ind, data)
plt.xticks(ind, labels, rotation='vertical')
# Вывод значений
for a,b in zip(ind, data):
  plt.text(a-0.1, b+0.005, str(round(b,3)))
plt.show()
```



In [81]:

```
list(zip(X_all.columns, SelectFromModel(gbc).fit(X_all, Y_all).get_support()))
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/ensemble/_gb.py:494: DataConversionWarning: A column-vec
tor y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for examp
le using ravel().
  y = column_or_1d(y, warn=True)
```

Out[81]:

```
[('Hardness', False),
 ('Solids', True),
 ('Chloramines', True),
 ('Conductivity', False),
 ('Organic_carbon', False),
 ('Turbidity', False),
 ('KKN_3_ph', True),
 ('KKN_3_Sulfate', True),
 ('KKN_3_Trihalomethanes', False)]
```

4. Обработка атипичного признака

In [115]:

```
df = pd.read_csv('/content/drive/MyDrive/MMO/games.csv')
df[['created_at', 'last_move_at']]
```

Out[115]:

	created_at	last_move_at
0	1.504210e+12	1.504210e+12
1	1.504130e+12	1.504130e+12
2	1.504130e+12	1.504130e+12
3	1.504110e+12	1.504110e+12
4	1.504030e+12	1.504030e+12
...	...	...
20053	1.499791e+12	1.499791e+12
20054	1.499698e+12	1.499699e+12
20055	1.499698e+12	1.499698e+12
20056	1.499696e+12	1.499697e+12
20057	1.499643e+12	1.499644e+12

20058 rows × 2 columns

In [116]:

```
df = df[['created_at', 'last_move_at']]
```

In [117]:

```
import datetime
```

In [118]:

```
df['created_at_str'] = df['created_at'].apply(lambda x: datetime.datetime.fromtimestamp(x/1e3))
df['last_move_at_str'] = df['last_move_at'].apply(lambda x: datetime.datetime.fromtimestamp(x/1e3))
df.drop(['created_at', 'last_move_at'], axis=1)
```

Out[118]:

	created_at_str	last_move_at_str
0	2017-08-31 20:06:40.000	2017-08-31 20:06:40.000
1	2017-08-30 21:53:20.000	2017-08-30 21:53:20.000
2	2017-08-30 21:53:20.000	2017-08-30 21:53:20.000
3	2017-08-30 16:20:00.000	2017-08-30 16:20:00.000
4	2017-08-29 18:06:40.000	2017-08-29 18:06:40.000
...	...	...
20053	2017-07-11 16:35:14.342	2017-07-11 16:40:36.076
20054	2017-07-10 14:48:09.760	2017-07-10 15:00:33.979
20055	2017-07-10 14:44:37.493	2017-07-10 14:47:30.327
20056	2017-07-10 14:15:27.019	2017-07-10 14:31:13.718
20057	2017-07-09 23:32:32.649	2017-07-09 23:44:49.348

20058 rows × 2 columns

In [119]:

```
df['year_start'] = df['created_at_str'].dt.year
df['month_start'] = df['created_at_str'].dt.month
df['day_start'] = df['created_at_str'].dt.day
df['hour_start'] = df['created_at_str'].dt.hour
df['minute_start'] = df['created_at_str'].dt.minute
df['second_start'] = df['created_at_str'].dt.second
df['year_end'] = df['last_move_at_str'].dt.year
df['month_end'] = df['last_move_at_str'].dt.month
df['day_end'] = df['last_move_at_str'].dt.day
df['hour_end'] = df['created_at_str'].dt.hour
df['minute_end'] = df['created_at_str'].dt.minute
df['second_end'] = df['created_at_str'].dt.second
df['game_length'] = df['last_move_at_str'] - df['created_at_str']
df['game_length_sec'] = df['game_length'].apply(lambda x: x.seconds)
df2 = df.iloc[:,4:]
df2
```

Out[119]:

	year_start	month_start	day_start	hour_start	minute_start	second_start	year_end	month_end	day_end	hour_end	minute_e
0	2017	8	31	20	6	40	2017	8	31	20	
1	2017	8	30	21	53	20	2017	8	30	21	
2	2017	8	30	21	53	20	2017	8	30	21	
3	2017	8	30	16	20	0	2017	8	30	16	

	year_start	month_start	day_start	hour_start	minute_start	second_start	year_end	month_end	day_end	hour_end	minute_e
4	2017	8	29	18	6	40	2017	8	29	18	
...	...	...	...	...	...	...	...	...	...	...	
20053	2017	7	11	16	35	14	2017	7	11	16	
20054	2017	7	10	14	48	9	2017	7	10	14	
20055	2017	7	10	14	44	37	2017	7	10	14	
20056	2017	7	10	14	15	27	2017	7	10	14	
20057	2017	7	9	23	32	32	2017	7	9	23	

20058 rows × 14 columns

In [126]:

```
dt_features = list(df2.iloc[:,:-2].columns)
dt_features.remove('year_start')
dt_features.remove('year_end')
dt_features
```

Out[126]:

```
['month_start',
 'day_start',
 'hour_start',
 'minute_start',
 'second_start',
 'month_end',
 'day_end',
 'hour_end',
 'minute_end',
 'second_end']
```

In [127]:

```
df2
```

Out[127]:

	year_start	month_start	day_start	hour_start	minute_start	second_start	year_end	month_end	day_end	hour_end	minute_e
0	2017	8	31	20	6	40	2017	8	31	20	
1	2017	8	30	21	53	20	2017	8	30	21	
2	2017	8	30	21	53	20	2017	8	30	21	
3	2017	8	30	16	20	0	2017	8	30	16	
4	2017	8	29	18	6	40	2017	8	29	18	
...	...	...	...	...	...	...	...	...	...	...	
20053	2017	7	11	16	35	14	2017	7	11	16	
20054	2017	7	10	14	48	9	2017	7	10	14	
20055	2017	7	10	14	44	37	2017	7	10	14	
20056	2017	7	10	14	15	27	2017	7	10	14	
20057	2017	7	9	23	32	32	2017	7	9	23	

20058 rows × 14 columns

In [133]:

```
def cosine_encode(v, T, cos=True):
  x = 2*np.pi*v/T
  if cos:
    return np.cos(x)
  else:
    return np.sin(x)
```

In [128]:

```
for f in dt_features:
    print(f, df2[f].min(), df2[f].max())
```

```
month_start 1 12
day_start 1 31
hour_start 0 23
minute_start 0 59
second_start 0 59
month_end 1 12
day_end 1 31
hour_end 0 23
minute_end 0 59
second_end 0 59
```

In [129]:

```
dt_features_periods = [12, 31, 24, 60, 60, 12, 31, 24, 60, 60]
```

In [134]:

```
dt_features_cosine = []
for f,p in zip(dt_features, dt_features_periods):
  f_cos = str(f + '_cos')
  f_sin = str(f + '_sin')
  df2[f_cos] = df2.apply(lambda x: cosine_encode(x[f], p), axis=1)
  df2[f_sin] = df2.apply(lambda x: cosine_encode(x[f], p, False), axis=1)
  dt_features_cosine.append(f_cos)
  dt_features_cosine.append(f_sin)
dt_features_cosine
```

Out[134]:

```
['month_start_cos',
 'month_start_sin',
 'day_start_cos',
 'day_start_sin',
 'hour_start_cos',
 'hour_start_sin',
 'minute_start_cos',
 'minute_start_sin',
 'second_start_cos',
 'second_start_sin',
 'month_end_cos',
 'month_end_sin',
 'day_end_cos',
 'day_end_sin',
 'hour_end_cos',
 'hour_end_sin',
 'minute_end_cos',
 'minute_end_sin',
 'second_end_cos',
 'second_end_sin']
```

In [135]:

```
df2
```

Out[135]:

	year_start	month_start	day_start	hour_start	minute_start	second_start	year_end	month_end	day_end	hour_end	...	mont
0	2017	8	31	20	6	40	2017	8	31	20	...	
1	2017	8	30	21	53	20	2017	8	30	21	...	
2	2017	8	30	21	53	20	2017	8	30	21	...	
3	2017	8	30	16	20	0	2017	8	30	16	...	
4	2017	8	29	18	6	40	2017	8	29	18	...	
...	...	...	...	...	...	...	...	...	...	...	...	
20053	2017	7	11	16	35	14	2017	7	11	16	...	
20054	2017	7	10	14	48	9	2017	7	10	14	...	
20055	2017	7	10	14	44	37	2017	7	10	14	...	
20056	2017	7	10	14	15	27	2017	7	10	14	...	
20057	2017	7	9	23	32	32	2017	7	9	23	...	

20058 rows × 34 columns