In [116…

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
import datetime
import  import_ipynb
import pytz
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from IPython.display import Image
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import MaxAbsScaler
import scipy.stats as stats
from sklearn.svm import SVR
from sklearn.svm import LinearSVC
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import mutual_info_classif, mutual_info_regression
from sklearn.feature_selection import SelectKBest, SelectPercentile

from IPython.display import Image
%matplotlib inline
sns.set(style="ticks")

# Будем использовать только обучающую выборку
data = pd.read_csv('test.csv')
data = data.dropna()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             1000 non-null   int64  
 1   battery_power  1000 non-null   int64  
 2   blue           1000 non-null   int64  
 3   clock_speed    1000 non-null   float64
 4   dual_sim       1000 non-null   int64  
 5   fc             1000 non-null   int64  
 6   four_g         1000 non-null   int64  
 7   int_memory     1000 non-null   int64  
 8   m_dep          1000 non-null   float64
 9   mobile_wt      1000 non-null   int64  
 10  n_cores        1000 non-null   int64  
 11  pc             1000 non-null   int64  
 12  px_height      1000 non-null   int64  
 13  px_width       1000 non-null   int64  
 14  ram            1000 non-null   int64  
 15  sc_h           1000 non-null   int64  
 16  sc_w           1000 non-null   int64  
 17  talk_time      1000 non-null   int64  
 18  three_g        1000 non-null   int64  
 19  touch_screen   1000 non-null   int64  
 20  wifi           1000 non-null   int64  
dtypes: float64(2), int64(19)
memory usage: 164.2 KB
```

In [117…

```
# Нужно ли масштабирование
data.describe()
```

Out[117]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000
mean	500.500000	1248.510000	0.516000	1.540900	0.517000	4.593000	0.487000	33.652000	0.517500	139.51100
std	288.819436	432.458227	0.499994	0.829268	0.499961	4.463325	0.500081	18.128694	0.280861	34.85155
min	1.000000	500.000000	0.000000	0.500000	0.000000	0.000000	0.000000	2.000000	0.100000	80.00000
25%	250.750000	895.000000	0.000000	0.700000	0.000000	1.000000	0.000000	18.000000	0.300000	109.75000
50%	500.500000	1246.500000	1.000000	1.500000	1.000000	3.000000	0.000000	34.500000	0.500000	139.00000
75%	750.250000	1629.250000	1.000000	2.300000	1.000000	7.000000	1.000000	49.000000	0.800000	170.00000
max	1000.000000	1999.000000	1.000000	3.000000	1.000000	19.000000	1.000000	64.000000	1.000000	200.00000

8 rows × 21 columns

In [118…
```
# DataFrame не содержащий целевой признак
X_ALL = data.drop(['n_cores','m_dep','ram','wifi'], axis=1)
```

In [119…
```
# Функция для восстановления датафрейма
# на основе масштабированных данных
def arr_to_data(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res
```

In [120…
```
# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['ram'],
                                                    test_size=0.2,
                                                    random_state=1)
# Преобразуем массивы в DataFrame
X_train_df = arr_to_data(X_train)
X_test_df = arr_to_data(X_test)

X_train_df.shape, X_test_df.shape
```

Out[120]: ((800, 17), (200, 17))

In [121…
```
# 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
```

In [122…
```
# 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_data(data_cs11_scaled_temp)
data_cs11_scaled
```

Out[122]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_wt	pc	px_height	px_wi
0	-1.730320	-0.475451	0.968496	0.312601	0.966559	2.108676	-0.974329	-1.581269	1.535535	0.976026	-0.926990	0.3919
1	-1.726856	-0.942782	0.968496	-1.255832	0.966559	-0.132927	1.026347	1.509303	1.478120	0.319433	0.274729	-0.8710
2	-1.723391	1.292077	0.968496	1.519087	-1.034598	-0.805408	-0.974329	-0.367116	1.334582	-0.993754	1.485693	0.2872
3	-1.719927	0.688249	-1.032529	-1.255832	0.966559	3.005317	1.026347	-0.477493	-1.249091	1.632619	-0.767532	1.1656
4	-1.716463	0.429135	-1.032529	-0.169994	-1.034598	1.436195	1.026347	0.847037	-0.904602	1.304323	0.281662	-0.9779
...	...	...	...	...	...	...	...	...	...	...	...	...
995	1.716463	1.044531	0.968496	0.433249	-1.034598	-1.029568	1.026347	1.122981	0.875263	1.140174	0.039007	-0.7435
996	1.719927	-1.479519	-1.032529	0.312601	0.966559	-1.029568	-0.974329	-1.139759	1.334582	-1.322051	1.212995	0.8925
997	1.723391	-0.146932	-1.032529	-0.169994	-1.034598	-0.805408	1.026347	-1.415702	-1.708411	0.319433	-0.346930	-0.9438
998	1.726856	0.658173	0.968496	-1.255832	0.966559	-1.029568	-0.974329	0.902226	0.903970	0.319433	-1.361458	-0.9279
999	1.730320	0.049718	0.968496	-1.255832	-1.034598	-0.132927	1.026347	0.074394	0.014038	1.468471	-0.393150	-1.4376

1000 rows × 17 columns

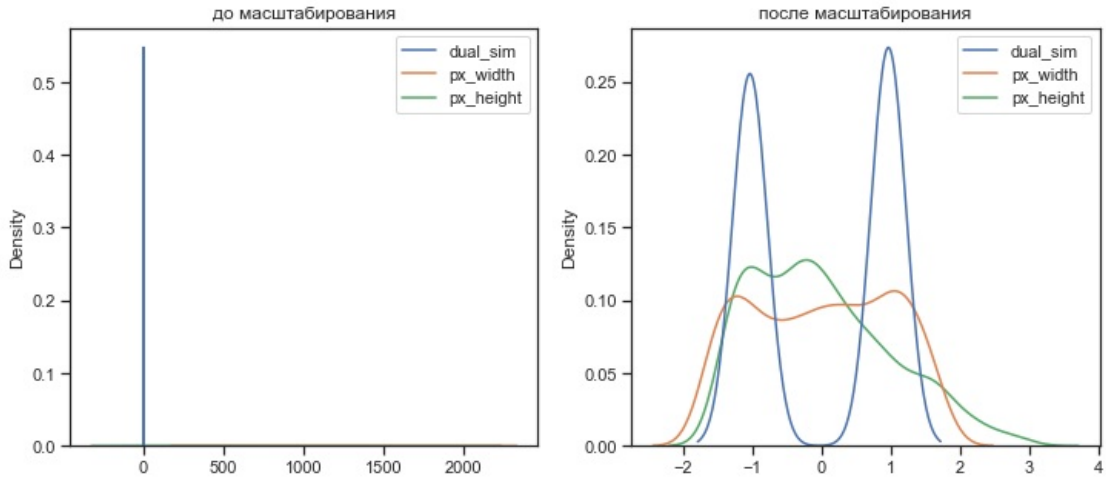
In [123…
```
data_cs11_scaled.describe()
```

Out[123]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_w
count	1.000000e+03	1.000000e+03	1.000000e+03	1.000000e+03	1.000000e+03	1.000000e+03	1.000000e+03	1.000000e+03	1.000000e+03
mean	9.348078e-17	4.998779e-17	-7.660539e-17	-8.570922e-17	-2.013945e-16	-3.966272e-17	-7.194245e-17	-3.178013e-17	1.183931e-16
std	1.000500e+00	1.000500e+00	1.000500e+00	1.000500e+00	1.000500e+00	1.000500e+00	1.000500e+00	1.000500e+00	1.000500e+00
min	-1.730320e+00	-1.731692e+00	-1.032529e+00	-1.255832e+00	-1.034598e+00	-1.029568e+00	-9.743294e-01	-1.746835e+00	-1.708411e+00
25%	-8.651598e-01	-8.178521e-01	-1.032529e+00	-1.014535e+00	-1.034598e+00	-8.054080e-01	-9.743294e-01	-8.638147e-01	-8.543635e-01
50%	0.000000e+00	-4.650173e-03	9.684960e-01	-4.934530e-02	9.665588e-01	-3.570874e-01	-9.743294e-01	4.680008e-02	-1.466953e-02
75%	8.651598e-01	8.808493e-01	9.684960e-01	9.158440e-01	9.665588e-01	5.395539e-01	1.026347e+00	8.470373e-01	8.752625e-01
max	1.730320e+00	1.736273e+00	9.684960e-01	1.760385e+00	9.665588e-01	3.229478e+00	1.026347e+00	1.674869e+00	1.736487e+00

In [124…
```
# Построение плотности распределения
def draw_kde(col_list, data1, data2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    # первый график
    ax1.set_title(label1)
    sns.kdeplot(data=data1[col_list], ax=ax1)
    # второй график
    ax2.set_title(label2)
    sns.kdeplot(data=data2[col_list], ax=ax2)
    plt.show()
```

In [125…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data, data_cs11_scaled, 'до масштабирования', 'после масштабиро
```



In [126…
```
# 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)
```

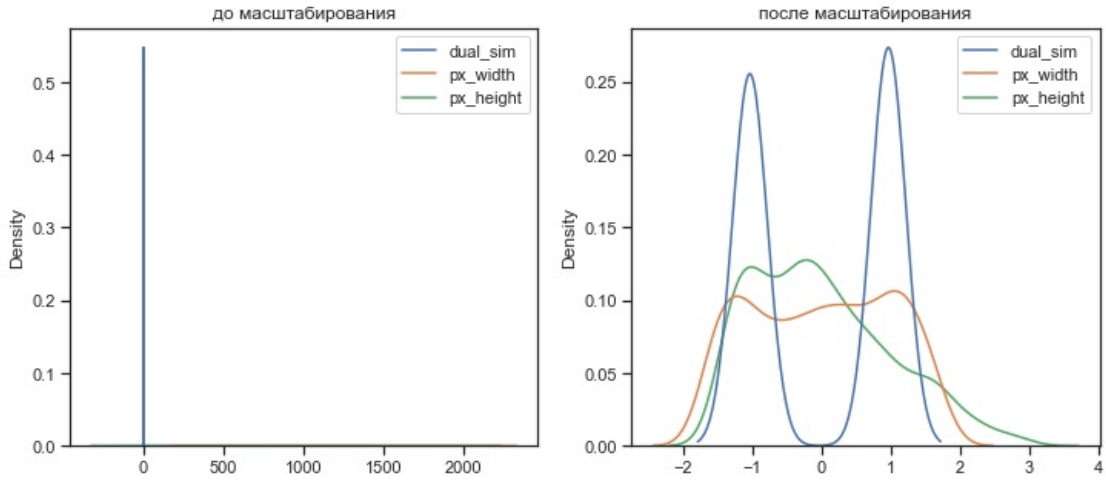
In [127…
```
data_cs12_scaled_train.describe()
```

Out[127]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_w
count	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02
mean	-7.022161e-17	-6.328271e-17	2.847722e-16	-2.875478e-16	2.733924e-16	-4.773959e-17	-2.470246e-16	-8.916479e-17	2.439715e-16
std	1.000626e+00	1.000626e+00	1.000626e+00	1.000626e+00	1.000626e+00	1.000626e+00	1.000626e+00	1.000626e+00	1.000626e+00
min	-1.729672e+00	-1.716841e+00	-1.035635e+00	-1.255733e+00	-1.078036e+00	-1.013195e+00	-9.728679e-01	-1.728332e+00	-1.718799e+00
25%	-8.419447e-01	-8.328932e-01	-1.035635e+00	-1.015344e+00	-1.078036e+00	-7.893462e-01	-9.728679e-01	-9.068816e-01	-8.536682e-01
50%	-2.163997e-02	5.224631e-03	9.655916e-01	-5.378709e-02	9.276126e-01	-3.416490e-01	-9.728679e-01	7.885927e-02	-1.737472e-02
75%	8.781886e-01	8.903183e-01	9.655916e-01	9.077698e-01	9.276126e-01	5.537455e-01	1.027889e+00	8.044740e-01	8.765942e-01
max	1.724425e+00	1.715833e+00	9.655916e-01	1.749132e+00	9.276126e-01	3.239929e+00	1.027889e+00	1.666997e+00	1.741725e+00

In [128…
```
# Построение плотности распределения
def draw_kde(col_list, data1, data2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    # первый график
    ax1.set_title(label1)
    sns.kdeplot(data=data1[col_list], ax=ax1)
    # второй график
    ax2.set_title(label2)
    sns.kdeplot(data=data2[col_list], ax=ax2)
    plt.show()
```

In [129…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data, data_cs11_scaled, 'до масштабирования', 'после масштабиро
```



In [130…
```
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)
```

In [131…
```
sc21 = MeanNormalisation()
data_cs21_scaled = sc21.fit_transform(X_ALL)
data_cs21_scaled.describe()
```

Out[131]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_wt	pc
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	-0.000760	-0.000474	-0.001500	-0.001540	-0.020500	0.003513	0.000750	0.001484	-0.000762	0.002637
std	0.289109	0.288690	0.499994	0.331707	0.499961	0.234912	0.500081	0.292398	0.290430	0.304755
min	-0.500760	-0.500147	-0.517500	-0.417900	-0.537500	-0.238224	-0.486250	-0.509032	-0.496687	-0.500063
25%	-0.250760	-0.236462	-0.517500	-0.337900	-0.537500	-0.185592	-0.486250	-0.250968	-0.248771	-0.250063
50%	-0.000760	-0.001816	0.482500	-0.017900	0.462500	-0.080329	-0.486250	0.015161	-0.005021	-0.000063
75%	0.249240	0.253692	0.482500	0.302100	0.462500	0.130197	0.513750	0.249032	0.253313	0.299937
max	0.499240	0.500521	0.482500	0.582100	0.462500	0.761776	0.513750	0.490968	0.503313	0.499937

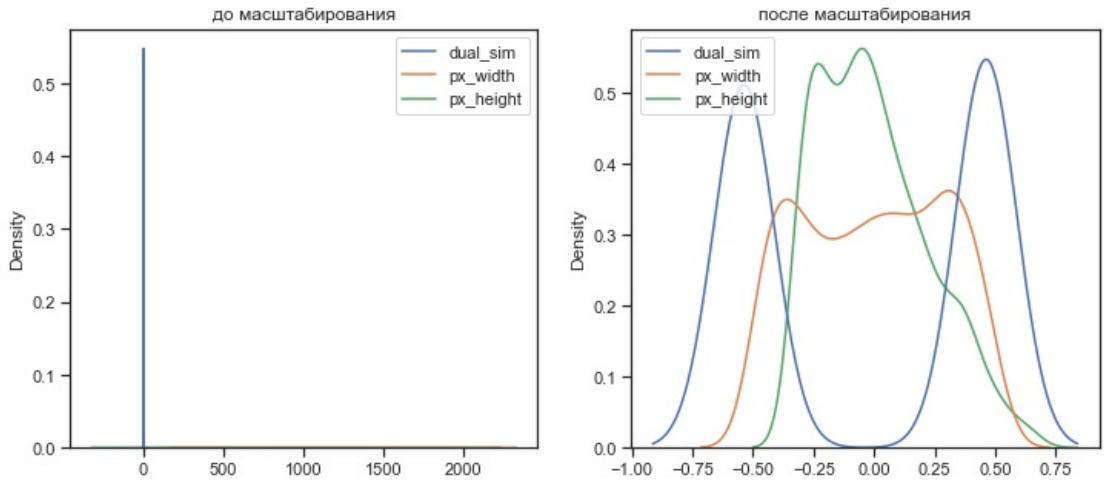
In [132…
```
cs22 = MeanNormalisation()
cs22.fit(X_train)
data_cs22_scaled_train = cs22.transform(X_train)
data_cs22_scaled_test = cs22.transform(X_test)
```

In [133…
```
data_cs22_scaled_train.describe()
```

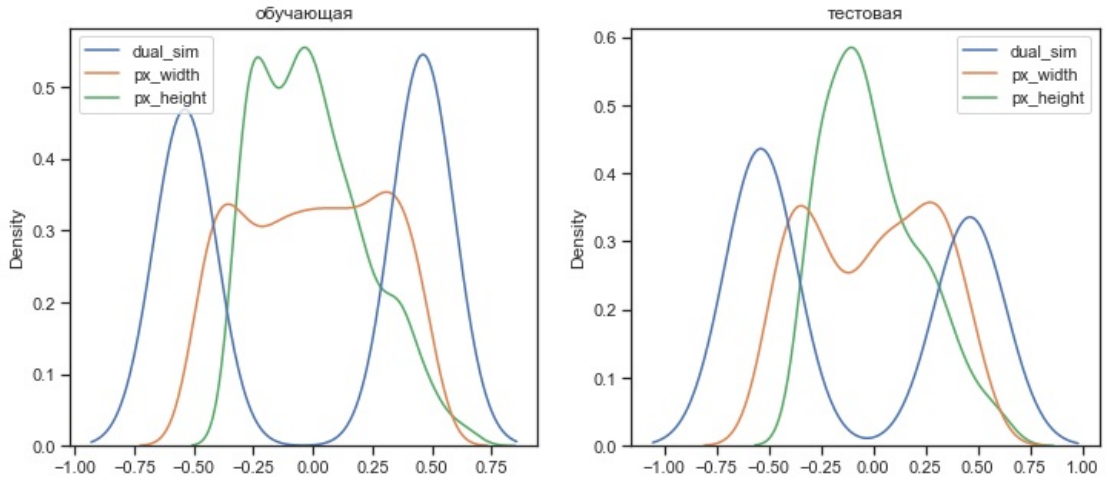
Out[133]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_wt	
count	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.000000e+02	8.(
mean	-2.185752e-17	-2.019218e-17	-4.912737e-17	-2.135098e-16	8.437695e-17	-3.157197e-18	-6.356027e-17	-3.578735e-17	7.178286e-17	
std	2.896924e-01	2.915003e-01	5.000063e-01	3.330018e-01	4.989037e-01	2.352684e-01	5.001236e-01	2.947065e-01	2.891543e-01	3.
min	-5.007595e-01	-5.001469e-01	-5.175000e-01	-4.179000e-01	-5.375000e-01	-2.382237e-01	-4.862500e-01	-5.090323e-01	-4.966875e-01	
25%	-2.437525e-01	-2.426368e-01	-5.175000e-01	-3.379000e-01	-5.375000e-01	-1.855921e-01	-4.862500e-01	-2.670968e-01	-2.466875e-01	
50%	-6.265015e-03	1.522029e-03	4.825000e-01	-1.790000e-02	4.625000e-01	-8.032895e-02	-4.862500e-01	2.322581e-02	-5.020833e-03	
75%	2.542455e-01	2.593658e-01	4.825000e-01	3.021000e-01	4.625000e-01	1.301974e-01	5.137500e-01	2.369355e-01	2.533125e-01	2.
max	4.992405e-01	4.998531e-01	4.825000e-01	5.821000e-01	4.625000e-01	7.617763e-01	5.137500e-01	4.909677e-01	5.033125e-01	4.

In [134…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data, data_cs21_scaled, 'до масштабирования', 'после масштабиро
```



In [135…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data_cs22_scaled_train, data_cs22_scaled_test, 'обучающая', 'те
```



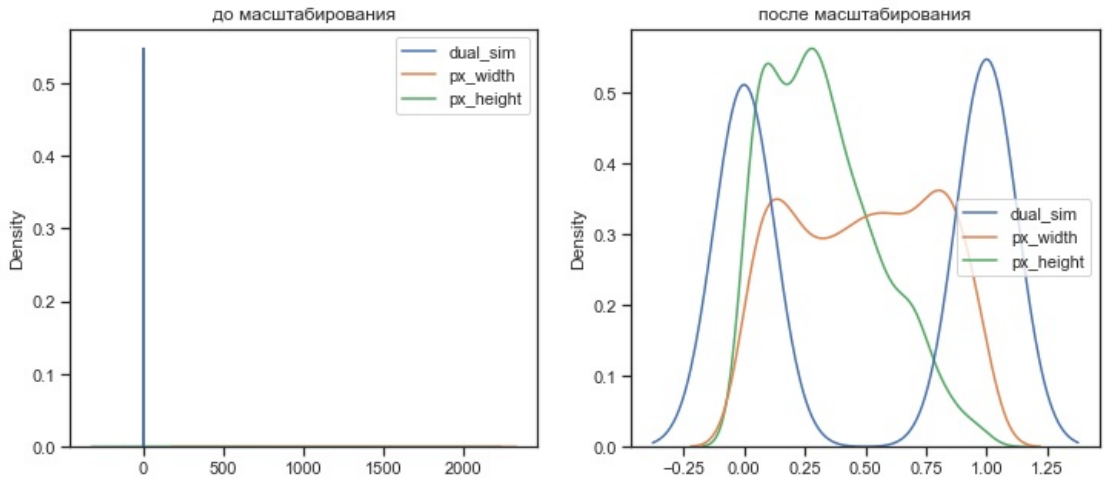
In [136…
```
# Обучаем StandardScaler на всей выборке и масштабируем
cs31 = MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()
```

Out[136]:

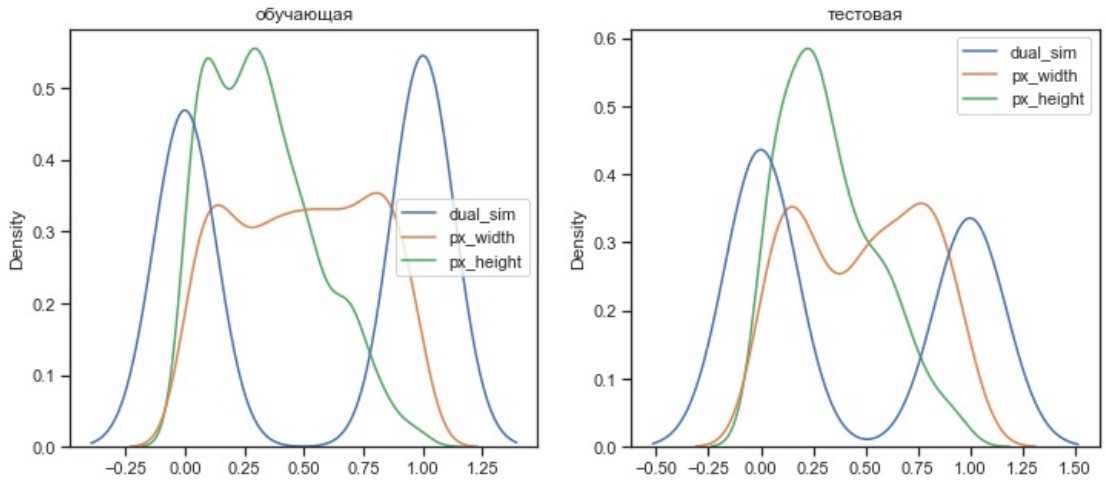
	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_wt	pc
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	0.500000	0.499340	0.516000	0.416360	0.517000	0.241737	0.487000	0.510516	0.495925	0.502700
std	0.289109	0.288498	0.499994	0.331707	0.499961	0.234912	0.500081	0.292398	0.290430	0.304755
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.250000	0.263509	0.000000	0.080000	0.000000	0.052632	0.000000	0.258065	0.247917	0.250000
50%	0.500000	0.497999	1.000000	0.400000	1.000000	0.157895	0.000000	0.524194	0.491667	0.500000
75%	0.750000	0.753336	1.000000	0.720000	1.000000	0.368421	1.000000	0.758065	0.750000	0.800000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [137…
```
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)
```

In [138…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data, data_cs31_scaled, 'до масштабирования', 'после масштабиро
```



In [139…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data_cs32_scaled_train, data_cs32_scaled_test, 'обучающая', 'те
```



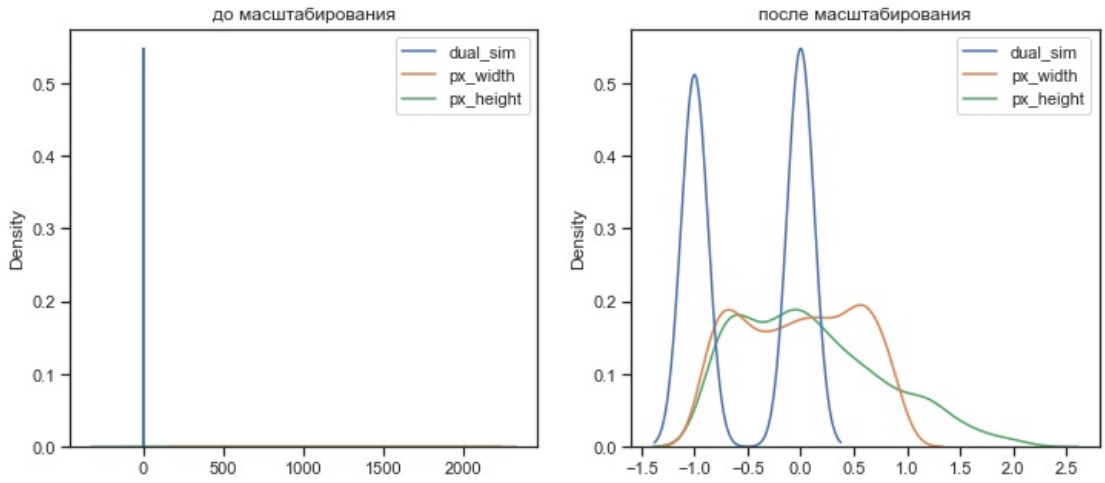
In [140…
```
cs41 = RobustScaler()
data_cs41_scaled_temp = cs41.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs41_scaled = arr_to_df(data_cs41_scaled_temp)
data_cs41_scaled.describe()
```

Out[140]:

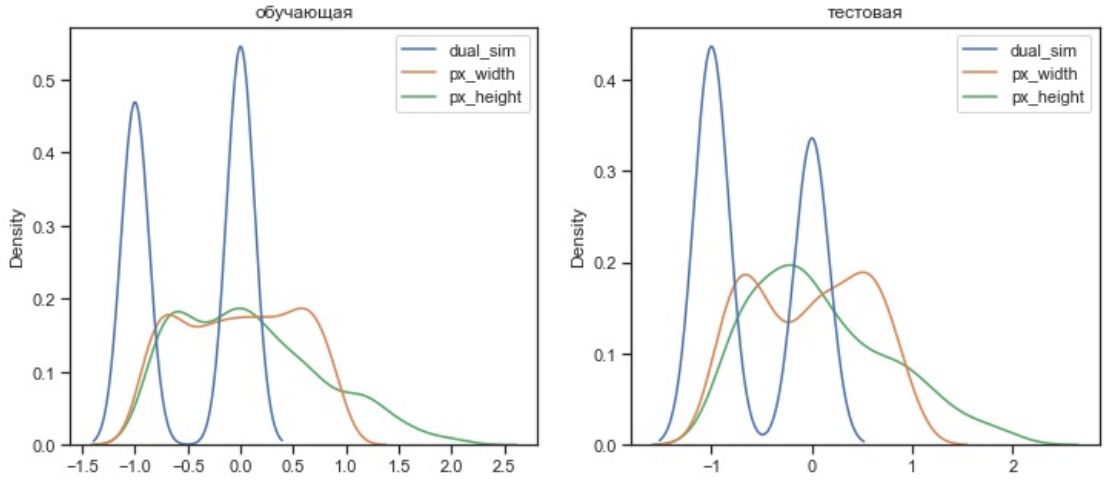
	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_wt	
count	1.000000e+03	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.0000
mean	-5.040413e-17	0.002737	-0.484000	0.025563	-0.483000	0.265500	0.487000	-0.027355	0.008481	0.0049
std	5.782171e-01	0.588980	0.499994	0.518292	0.499961	0.743888	0.500081	0.584797	0.578449	0.5541
min	-1.000000e+00	-1.016684	-1.000000	-0.625000	-1.000000	-0.500000	0.000000	-1.048387	-0.979253	-0.9090
25%	-5.000000e-01	-0.478720	-1.000000	-0.500000	-1.000000	-0.333333	0.000000	-0.532258	-0.485477	-0.4545
50%	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
75%	5.000000e-01	0.521280	0.000000	0.500000	0.000000	0.666667	1.000000	0.467742	0.514523	0.5454
max	1.000000e+00	1.024855	0.000000	0.937500	0.000000	2.666667	1.000000	0.951613	1.012448	0.9090

In [141…
```
cs42 = RobustScaler()
cs42.fit(X_train)
data_cs42_scaled_train_temp = cs42.transform(X_train)
data_cs42_scaled_test_temp = cs42.transform(X_test)
# формируем DataFrame на основе массива
data_cs42_scaled_train = arr_to_df(data_cs42_scaled_train_temp)
data_cs42_scaled_test = arr_to_df(data_cs42_scaled_test_temp)
```

In [142…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data, data_cs41_scaled, 'до масштабирования', 'после масштабиро
```



In [143…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data_cs42_scaled_train, data_cs42_scaled_test, 'обучающая', 'те
```



In [144…
```
cs51 = MaxAbsScaler()
data_cs51_scaled_temp = cs51.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs51_scaled = arr_to_df(data_cs51_scaled_temp)
data_cs51_scaled.describe()
```

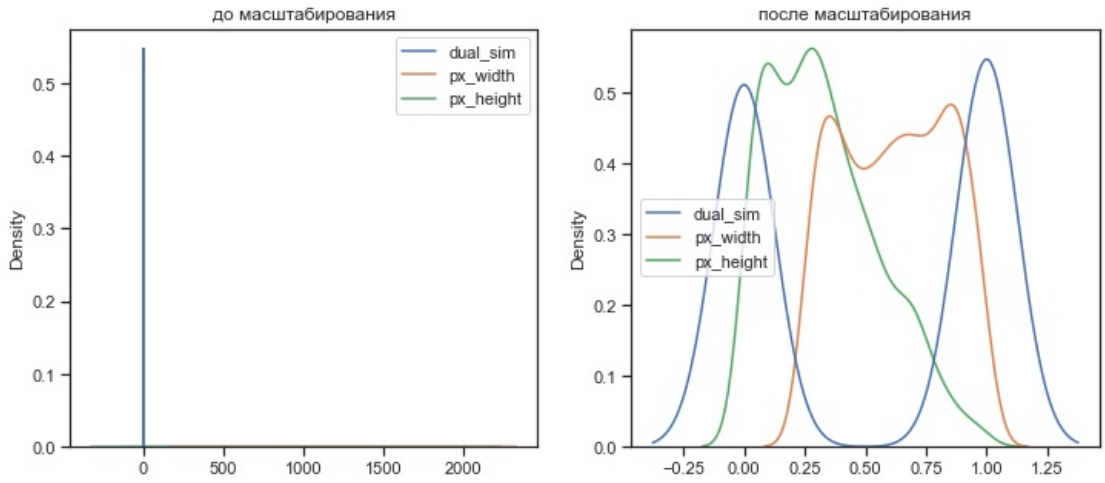
Out[144]:

	id	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	mobile_wt	pc
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	0.500500	0.624567	0.516000	0.513633	0.517000	0.241737	0.487000	0.525813	0.697555	0.502700
std	0.288819	0.216337	0.499994	0.276423	0.499961	0.234912	0.500081	0.283261	0.174258	0.304755
min	0.001000	0.250125	0.000000	0.166667	0.000000	0.000000	0.000000	0.031250	0.400000	0.000000
25%	0.250750	0.447724	0.000000	0.233333	0.000000	0.052632	0.000000	0.281250	0.548750	0.250000
50%	0.500500	0.623562	1.000000	0.500000	1.000000	0.157895	0.000000	0.539062	0.695000	0.500000
75%	0.750250	0.815033	1.000000	0.766667	1.000000	0.368421	1.000000	0.765625	0.850000	0.800000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

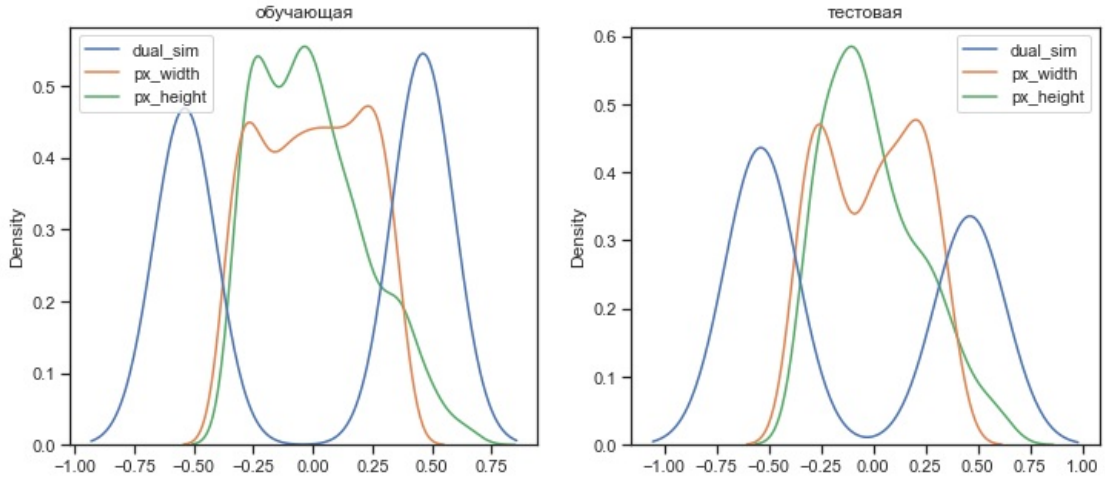
In [145…
```
cs52_mas = MaxAbsScaler()
cs52_mean = StandardScaler(with_mean=True, with_std=False)

cs52_mas.fit(X_train)
cs52_mean.fit(X_train)

data_cs52_scaled_train_temp = cs52_mas.transform(cs52_mean.transform(X_train))
data_cs52_scaled_test_temp = cs52_mas.transform(cs52_mean.transform(X_test))
# формируем DataFrame на основе массива
data_cs52_scaled_train = arr_to_df(data_cs52_scaled_train_temp)
data_cs52_scaled_test = arr_to_df(data_cs52_scaled_test_temp)
```

```
C:\Users\twai1\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature name
s, but MaxAbsScaler was fitted with feature names
  warnings.warn(
C:\Users\twai1\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature name
s, but MaxAbsScaler was fitted with feature names
  warnings.warn(
```

In [146…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data, data_cs51_scaled, 'до масштабирования', 'после масштабиро
```

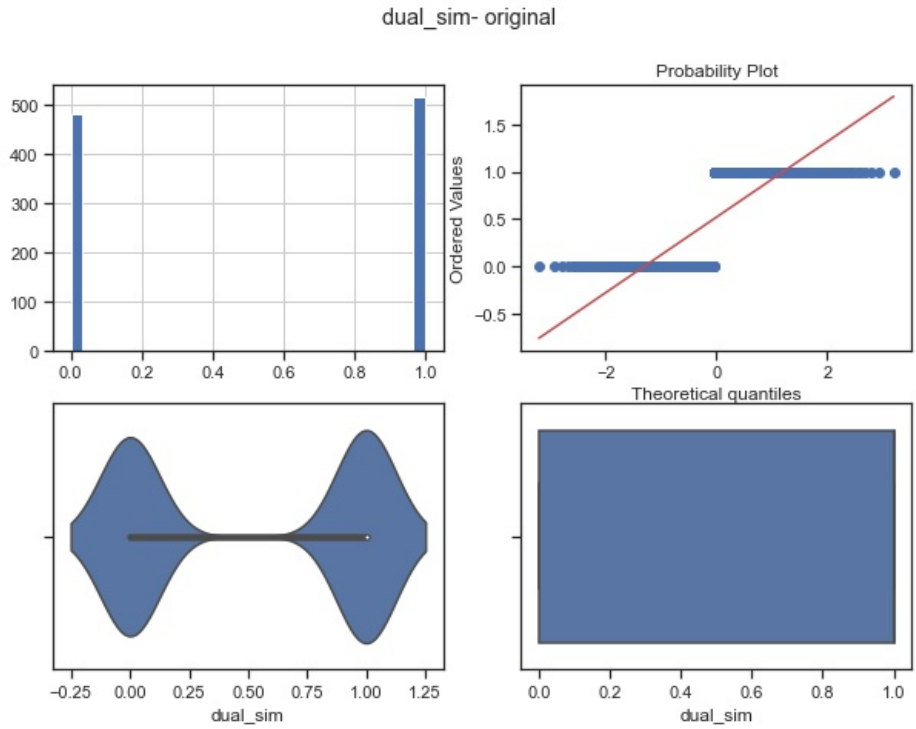


In [147…
```
draw_kde(['dual_sim', 'px_width', 'px_height'], data_cs52_scaled_train, data_cs52_scaled_test, 'обучающая', 'те
```

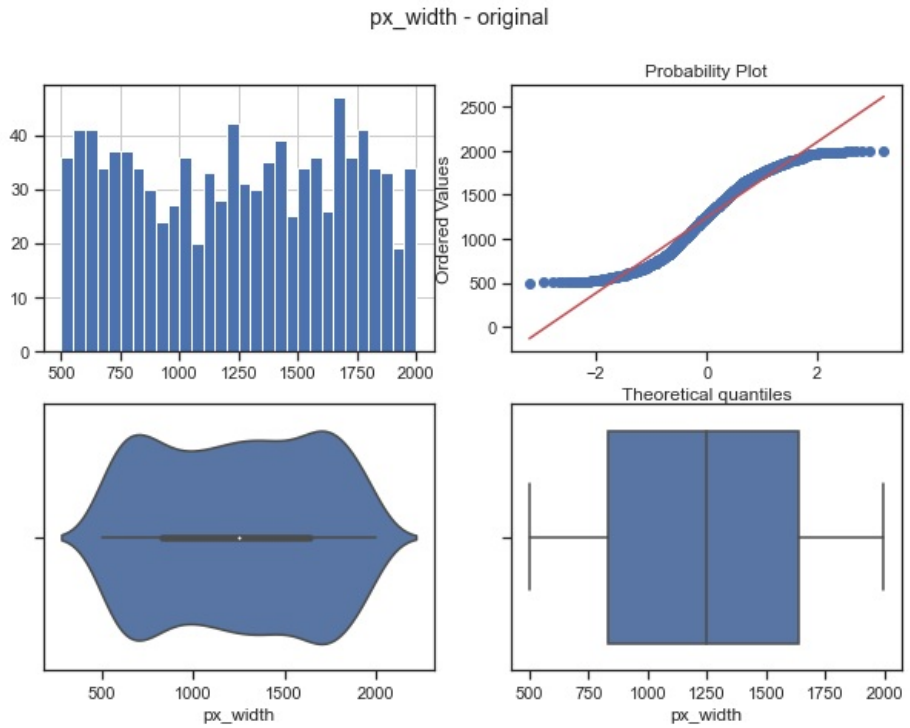


In [148…
```
def diagnostic_plots(df, variable, title):
    fig, ax = plt.subplots(figsize=(10,7))
    # гистограмма
    plt.subplot(2, 2, 1)
    df[variable].hist(bins=30)
    ## Q-Q plot
    plt.subplot(2, 2, 2)
    stats.probplot(df[variable], dist="norm", plot=plt)
    # ящик с усами
    plt.subplot(2, 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()
```

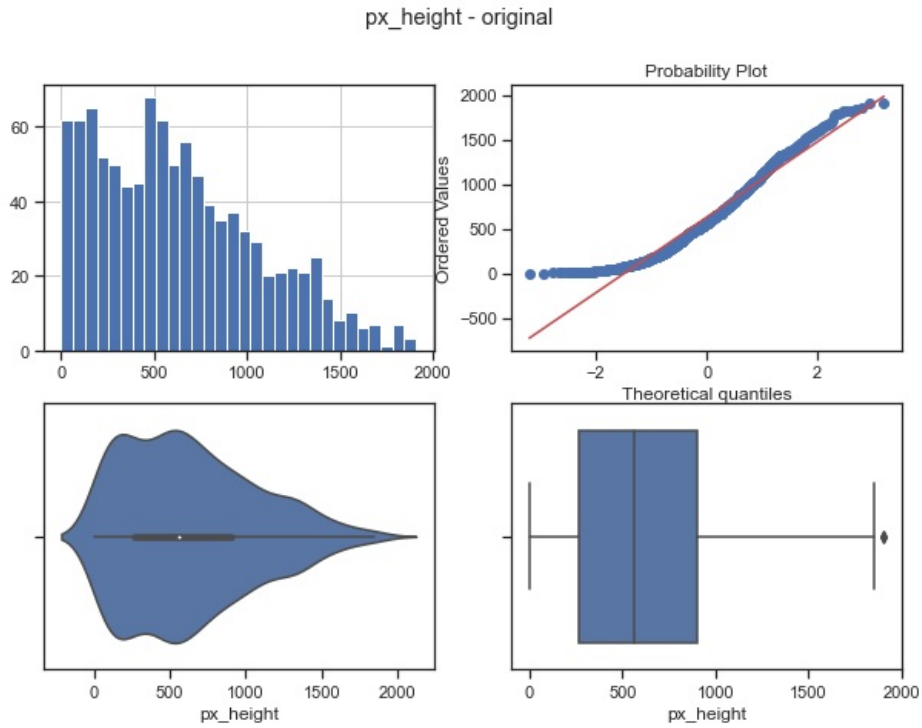
In [149…
```
diagnostic_plots(data, 'dual_sim', 'dual_sim- original')
```



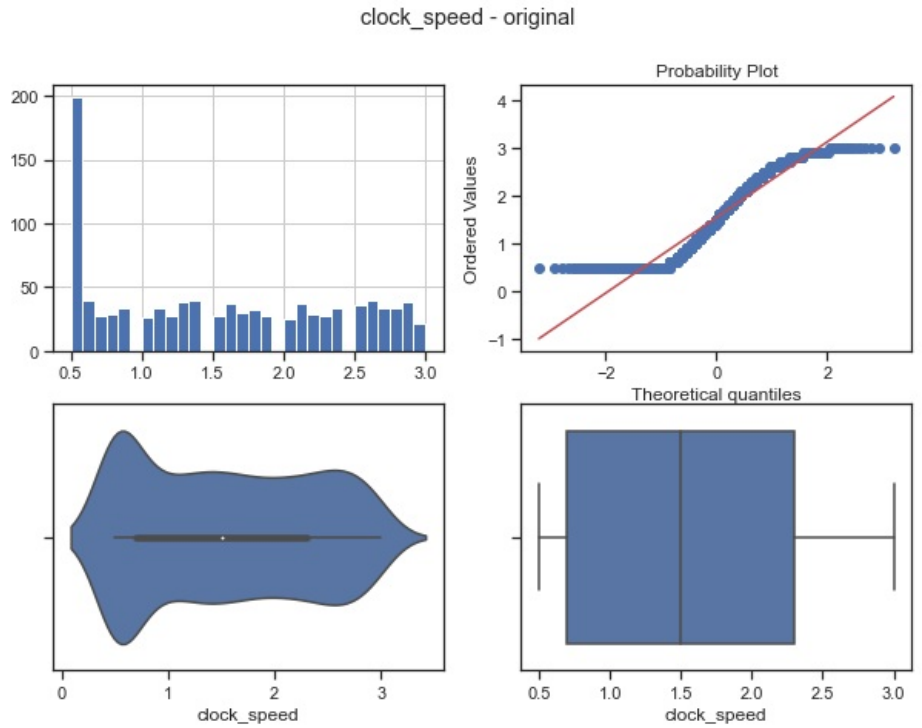
In [150…
```
diagnostic_plots(data, 'px_width', 'px_width - original')
```



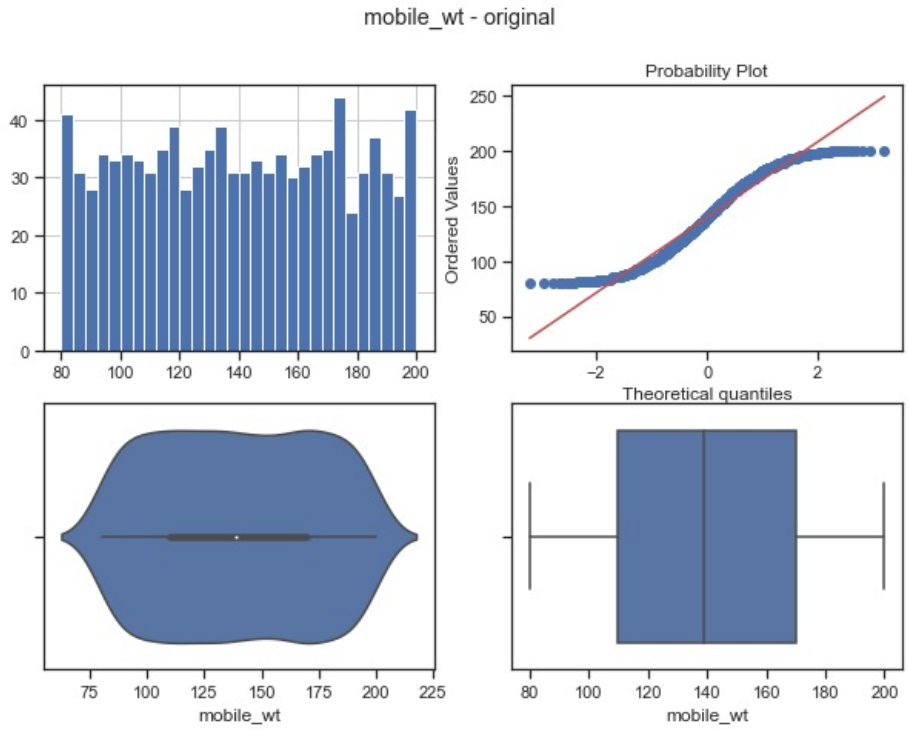
In [151…
```
diagnostic_plots(data, 'px_height', 'px_height - original')
```



In [152…
```
diagnostic_plots(data, 'clock_speed', 'clock_speed - original')
```



In [153…
```
diagnostic_plots(data, 'mobile_wt', 'mobile_wt - original')
```



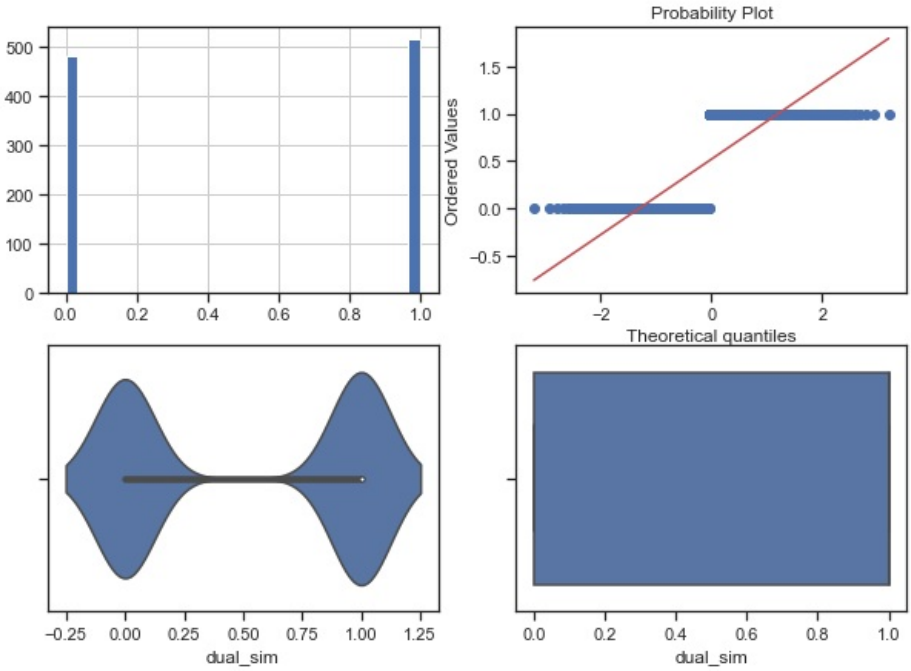
In [154…
```python
# Тип вычисления верхней и нижней границы выбросов
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3

# 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
```

In [155…
```python
data.shape
```

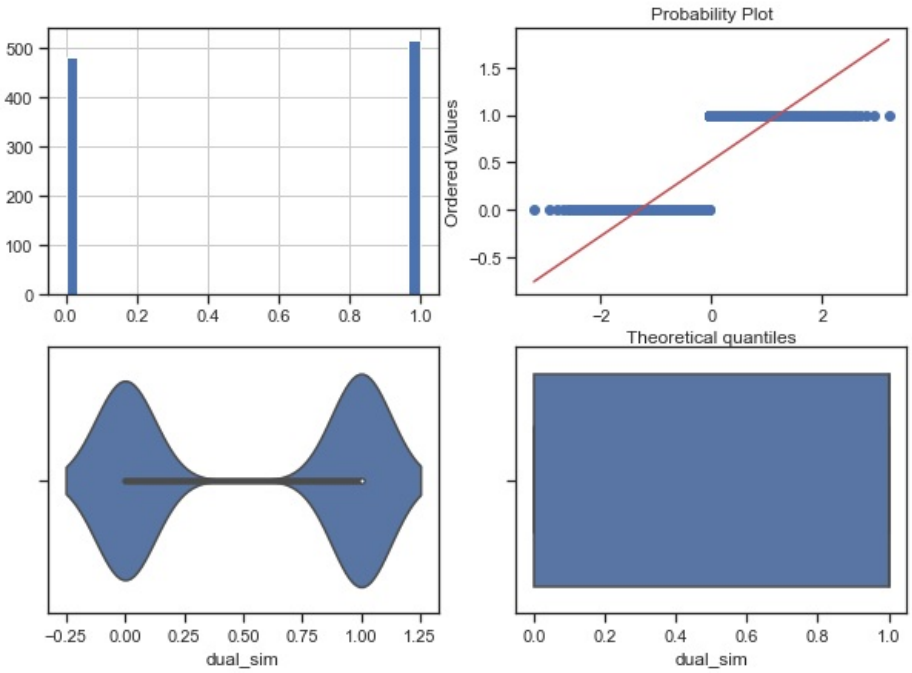
Out[155]:
```
(1000, 21)
```

In [156…
```python
x_col_list=['dual_sim', 'px_height', 'px_width', 'clock_speed', 'mobile_wt']
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)
```

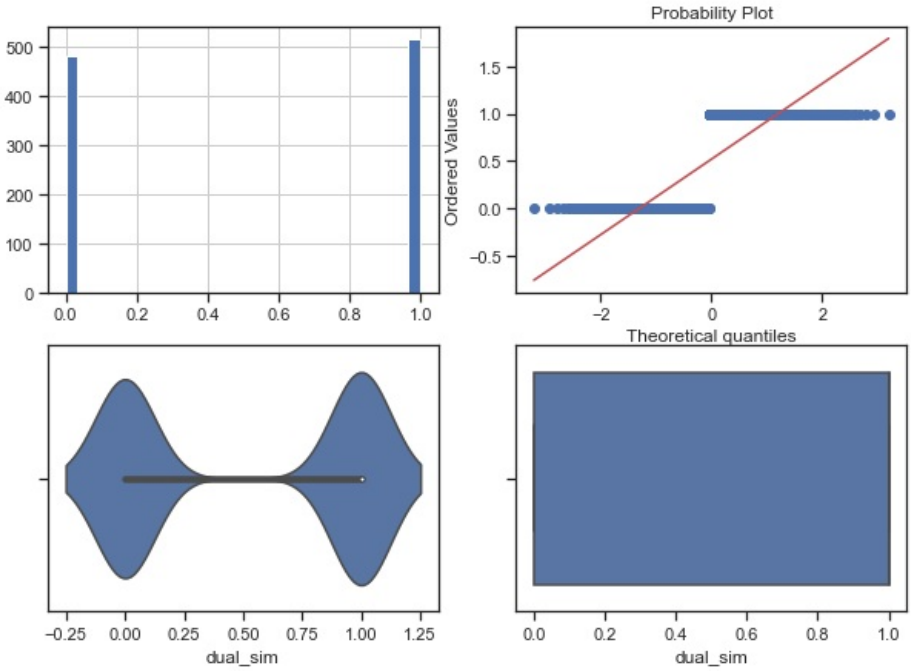
Поле-dual_sim, метод-OutlierBoundaryType.SIGMA, строк-1000



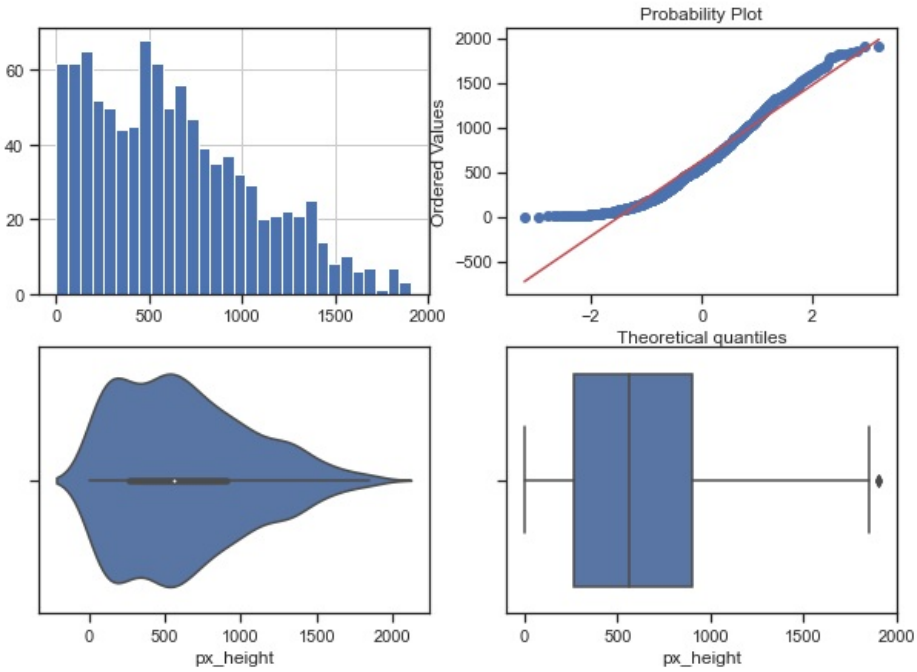
Поле-dual_sim, метод-OutlierBoundaryType.QUANTILE, строк-1000



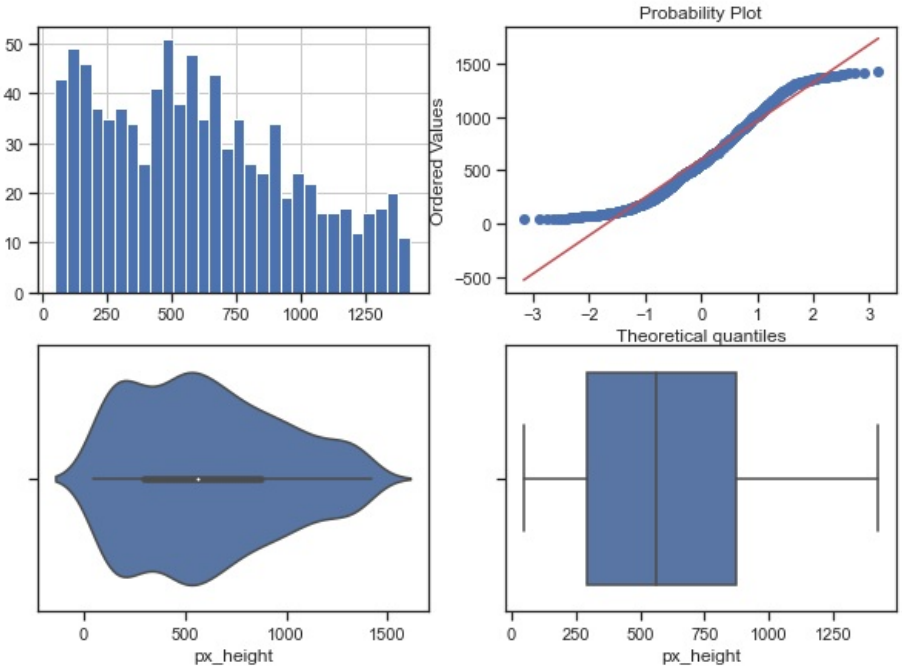
Поле-dual_sim, метод-OutlierBoundaryType.IRQ, строк-1000



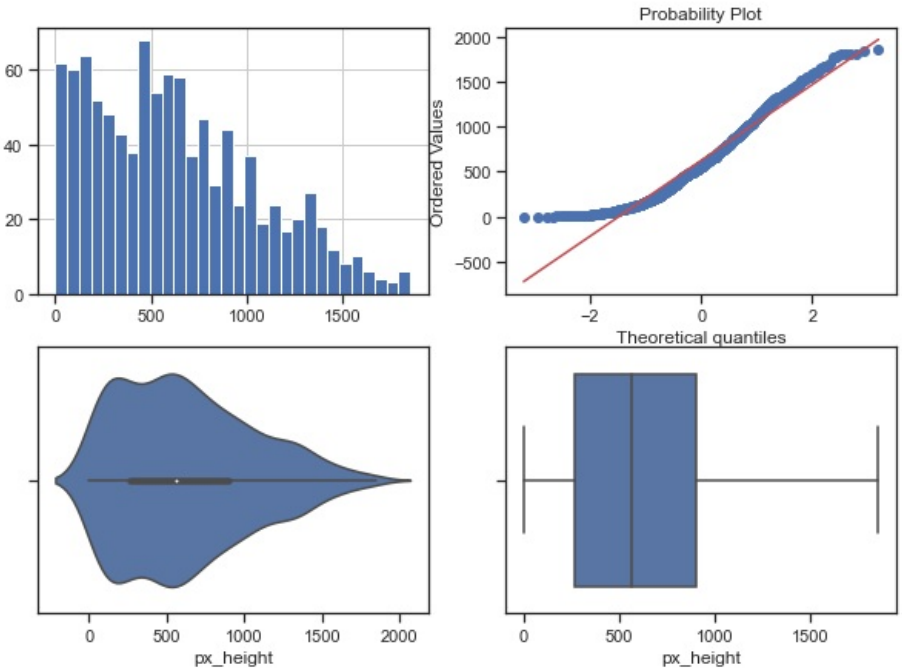
Поле-px_height, метод-OutlierBoundaryType.SIGMA, строк-1000



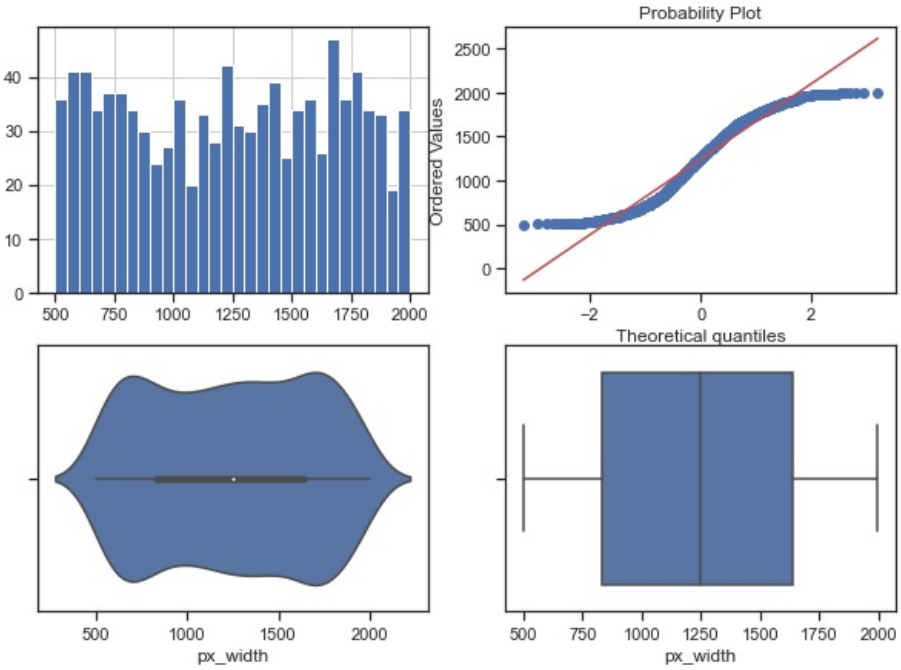
Поле-px_height, метод-OutlierBoundaryType.QUANTILE, строк-902



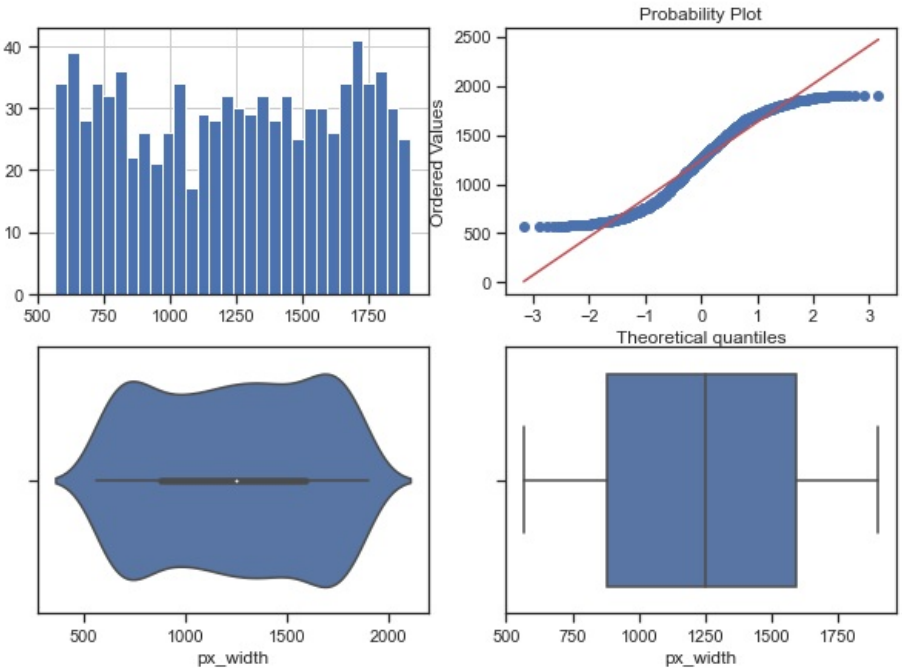
Поле-px_height, метод-OutlierBoundaryType.IRQ, строк-998



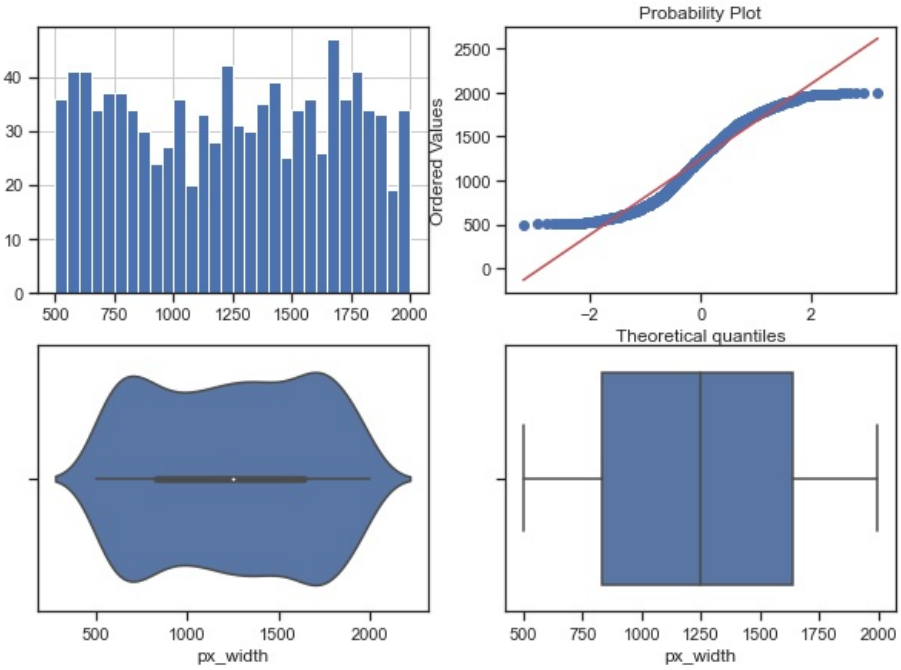
Поле-px_width, метод-OutlierBoundaryType.SIGMA, строк-1000



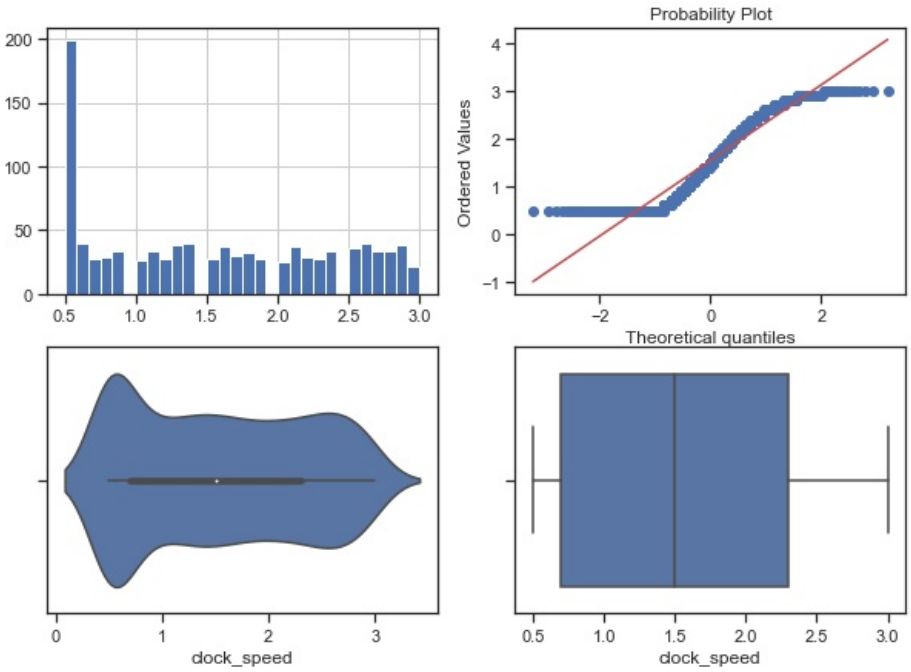
Поле-px_width, метод-OutlierBoundaryType.QUANTILE, строк-900



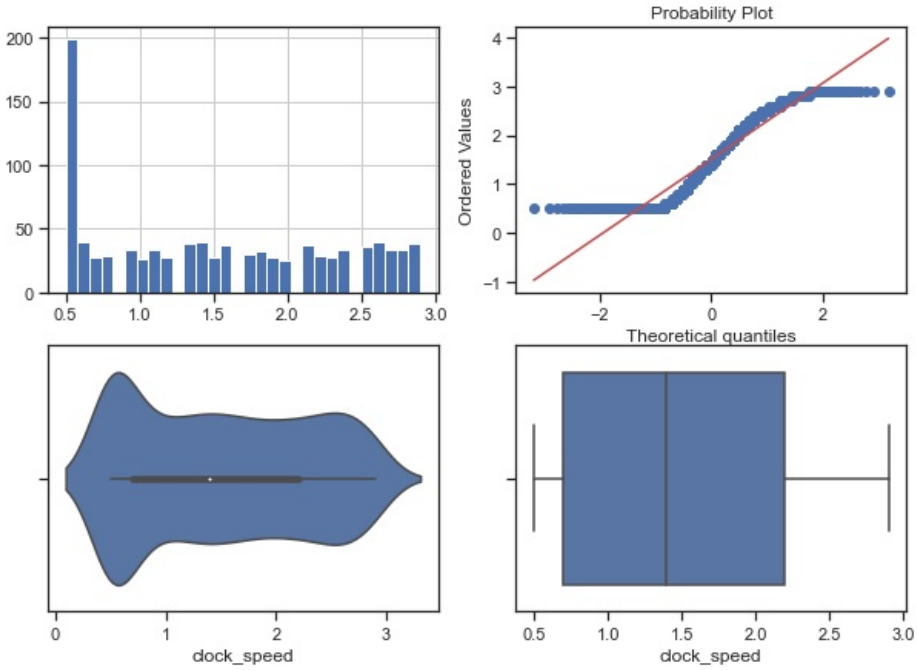
Поле-px_width, метод-OutlierBoundaryType.IRQ, строк-1000



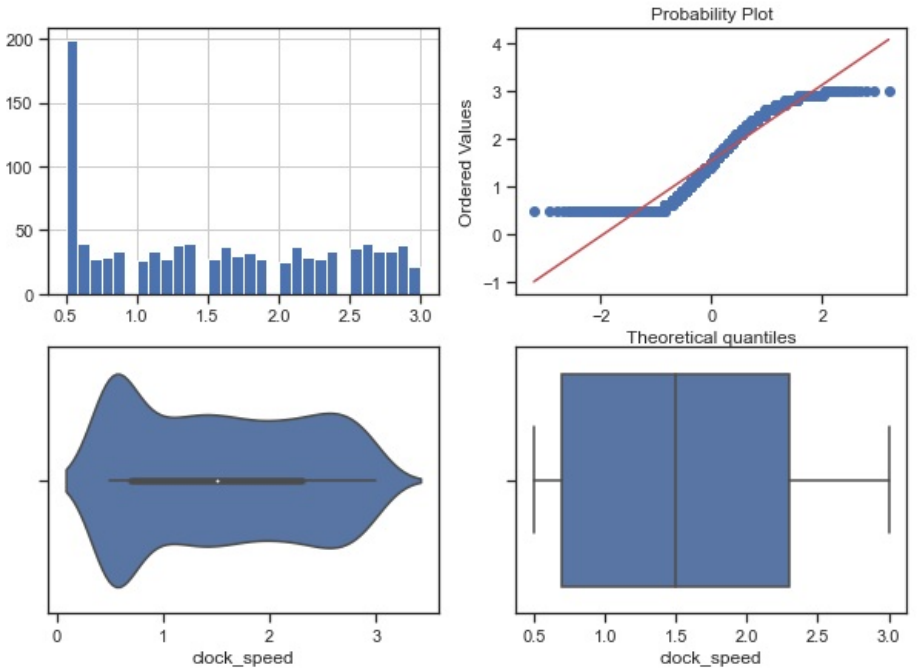
Поле-clock_speed, метод-OutlierBoundaryType.SIGMA, строк-1000



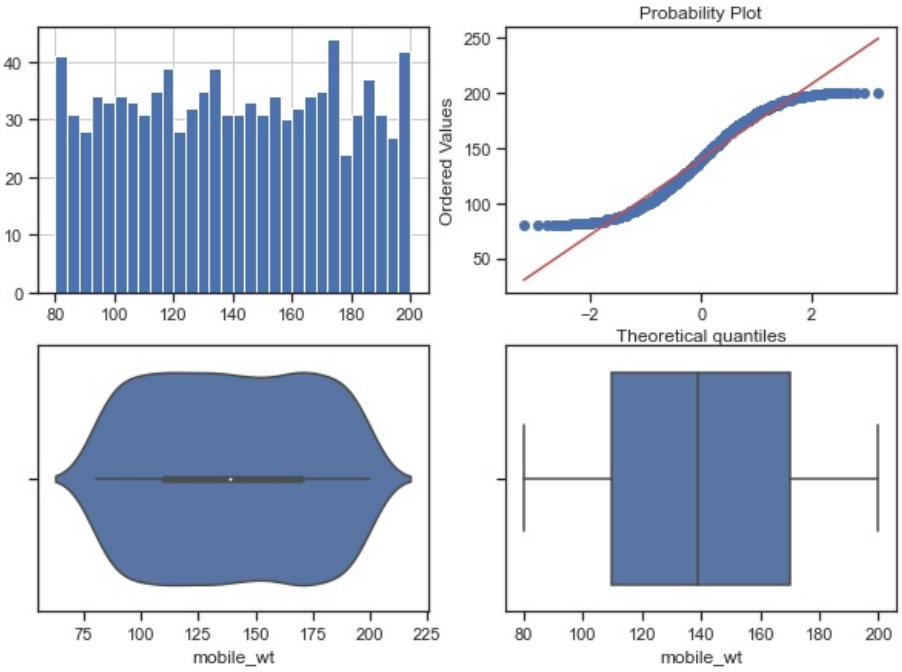
Поле-clock_speed, метод-OutlierBoundaryType.QUANTILE, строк-979



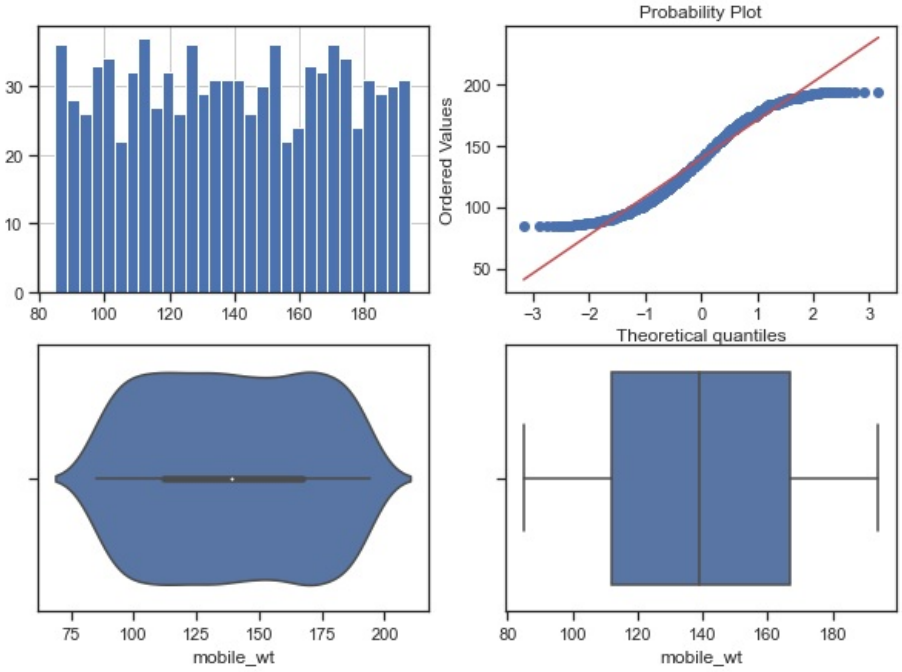
Поле-clock_speed, метод-OutlierBoundaryType.IRQ, строк-1000



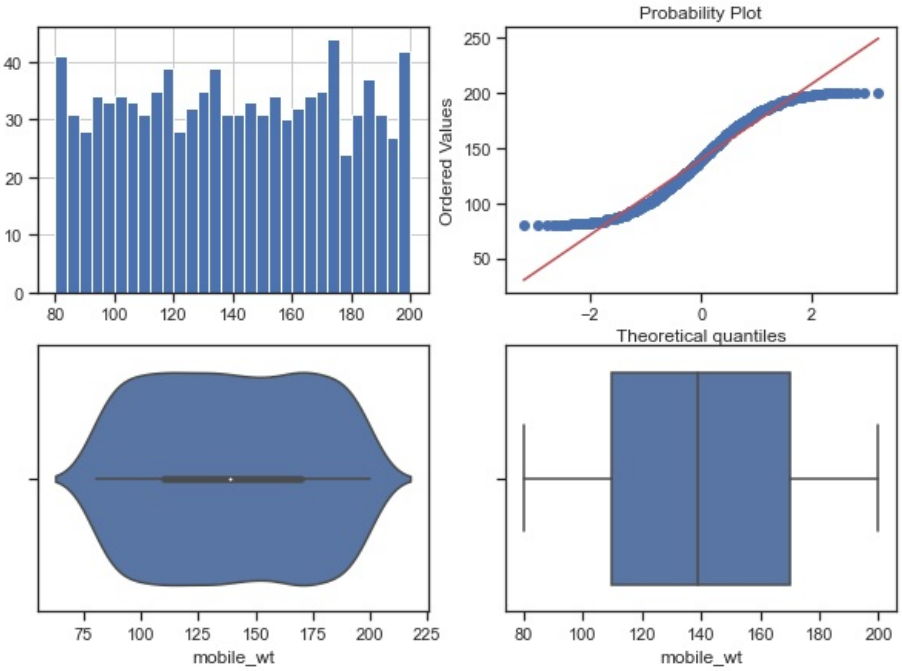
Поле-mobile_wt, метод-OutlierBoundaryType.SIGMA, строк-1000



Поле-mobile_wt, метод-OutlierBoundaryType.QUANTILE, строк-909



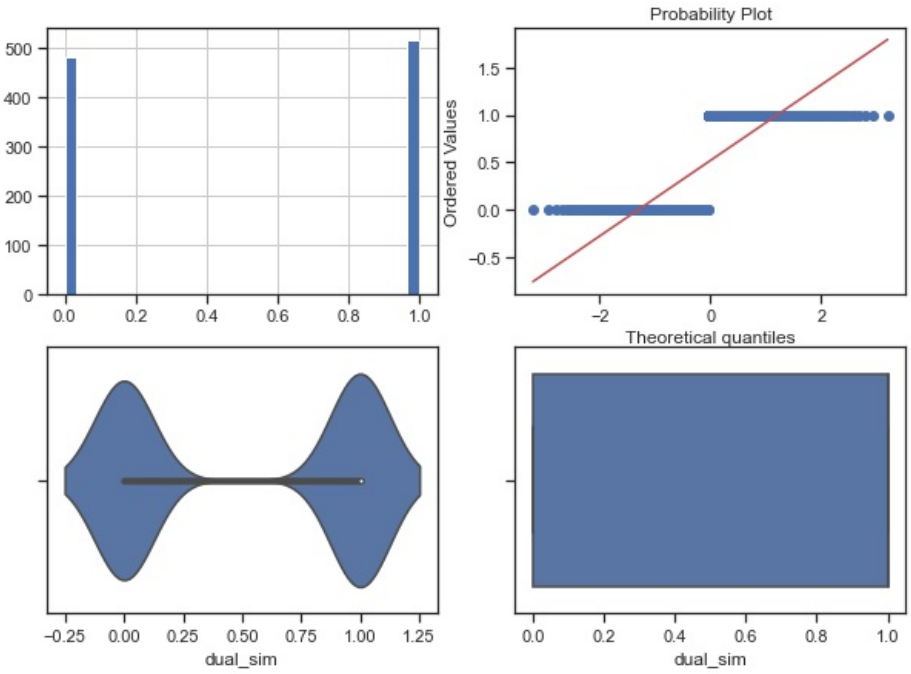
Поле-mobile_wt, метод-OutlierBoundaryType.IRQ, строк-1000



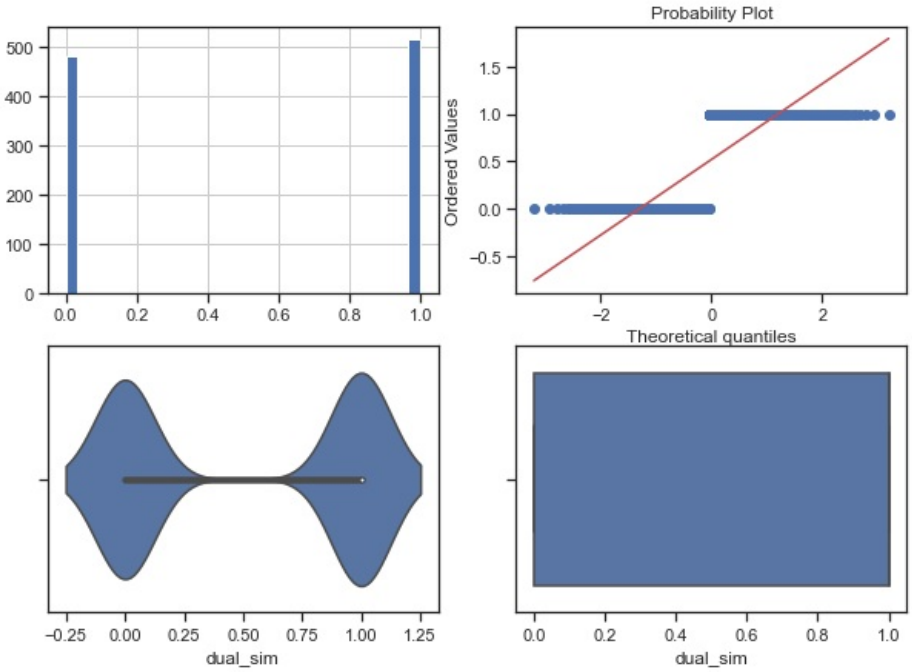
In [157…

```
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)
```

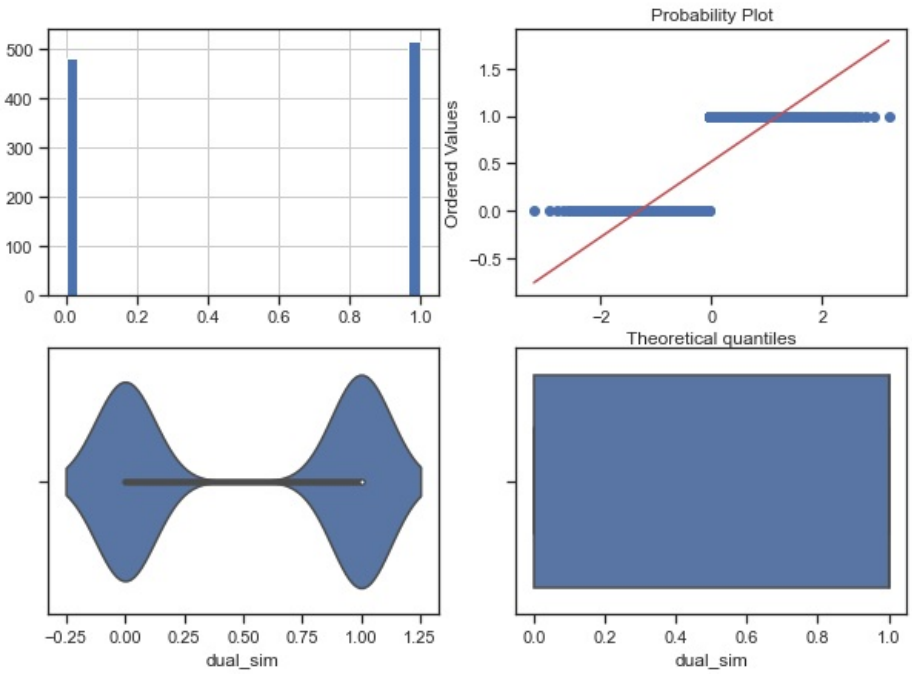
Поле-dual_sim, метод-OutlierBoundaryType.SIGMA



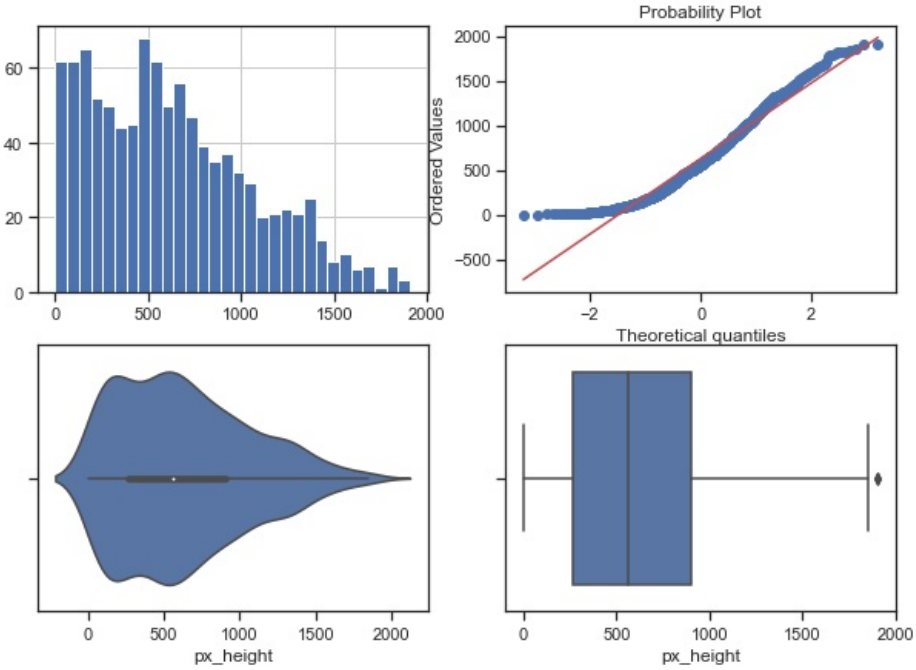
Поле-dual_sim, метод-OutlierBoundaryType.QUANTILE



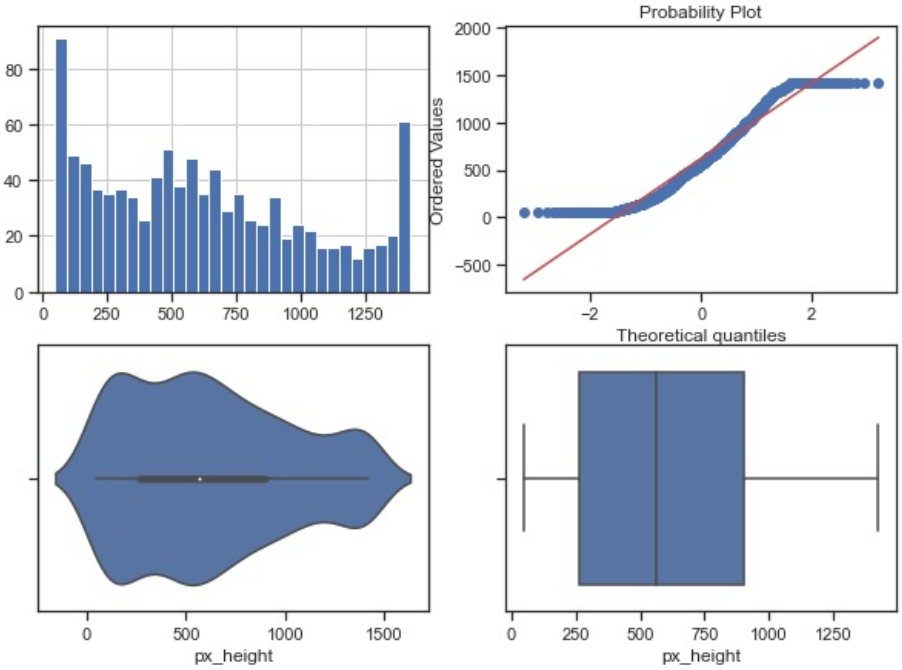
Поле-dual_sim, метод-OutlierBoundaryType.IRQ



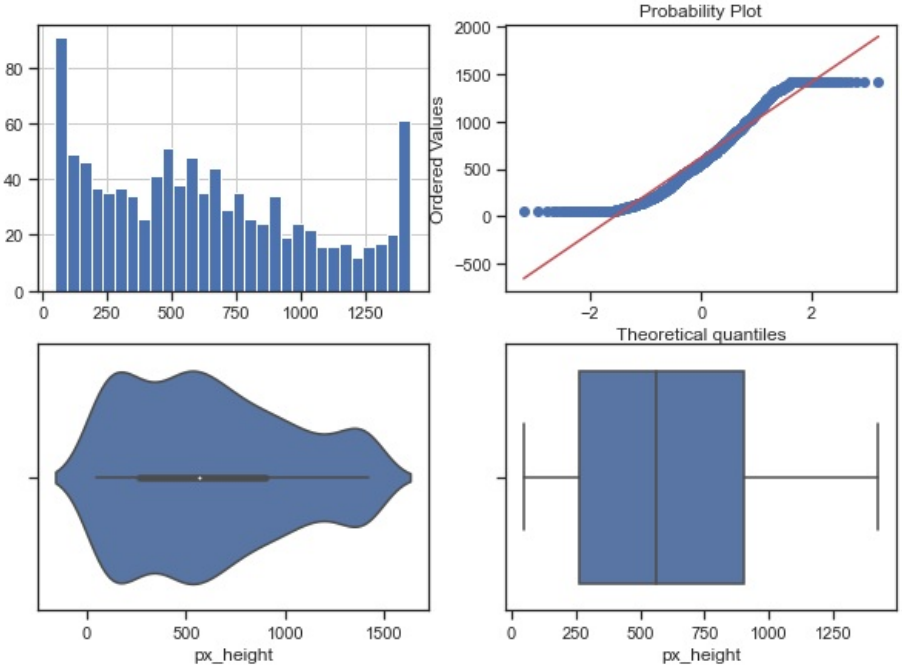
Поле-px_height, метод-OutlierBoundaryType.SIGMA



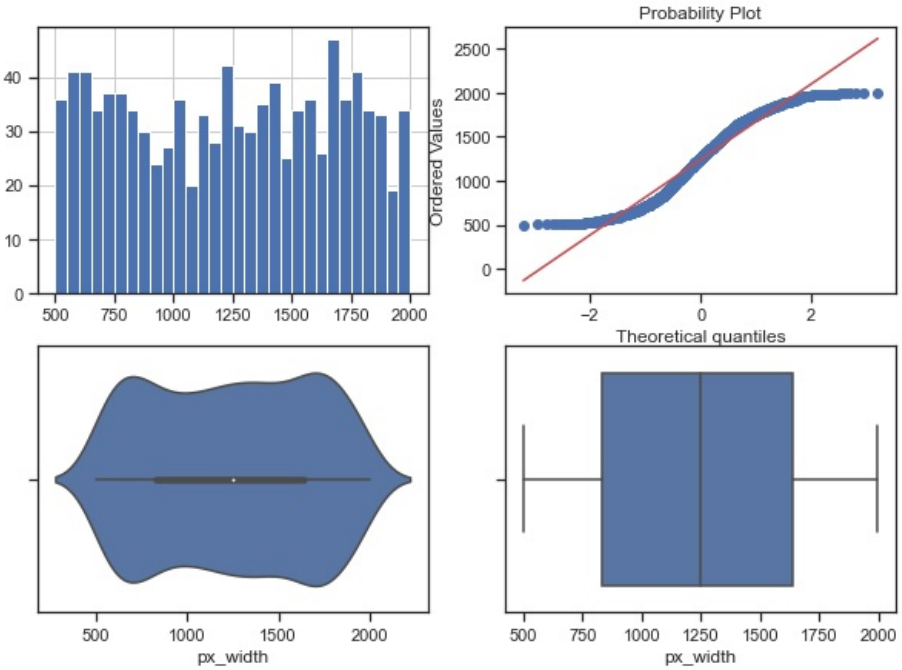
Поле-px_height, метод-OutlierBoundaryType.QUANTILE



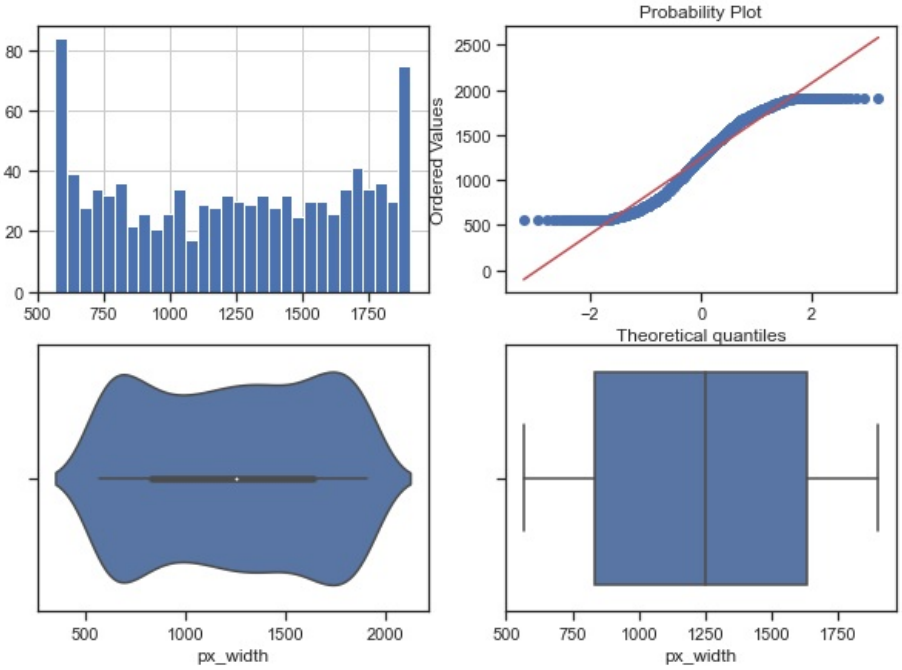
Поле-px_height, метод-OutlierBoundaryType.IRQ



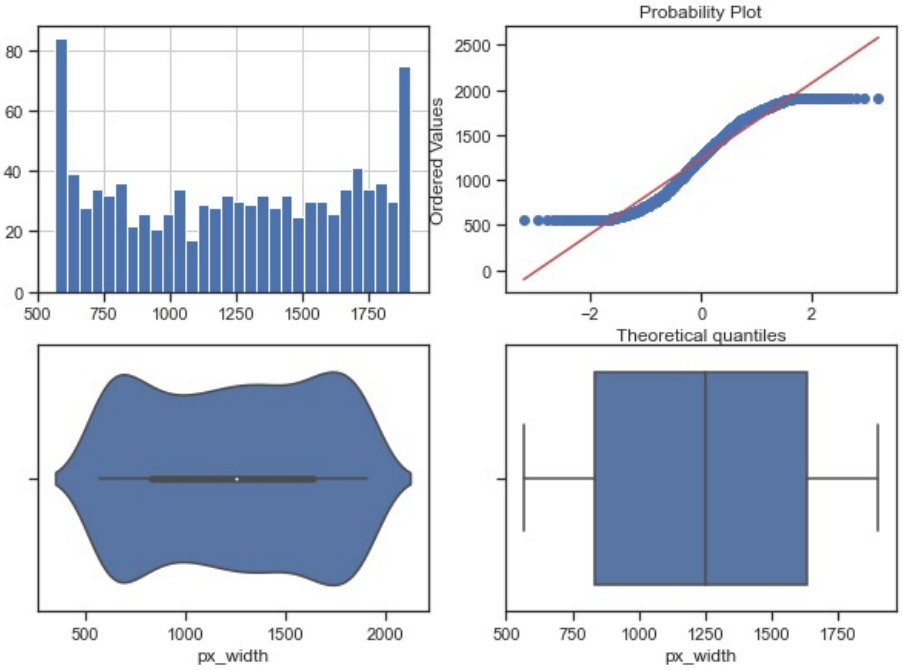
Поле-px_width, метод-OutlierBoundaryType.SIGMA



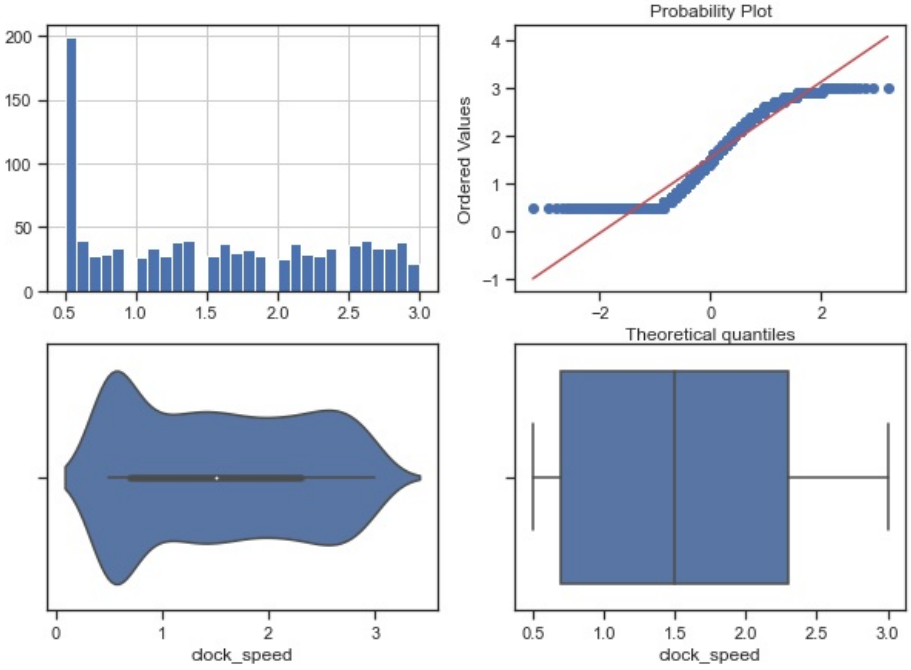
Поле-px_width, метод-OutlierBoundaryType.QUANTILE



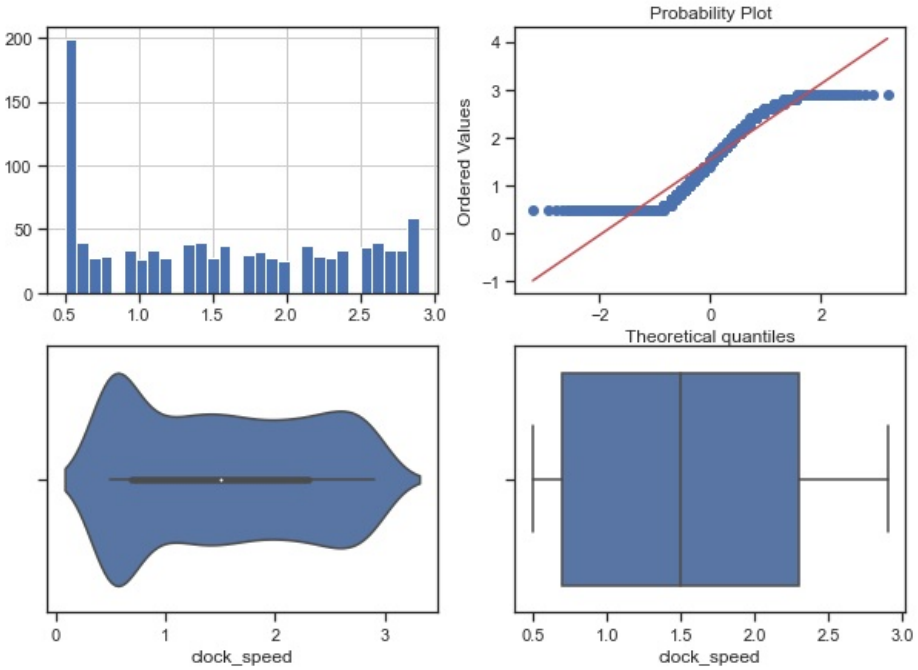
Поле-px_width, метод-OutlierBoundaryType.IRQ



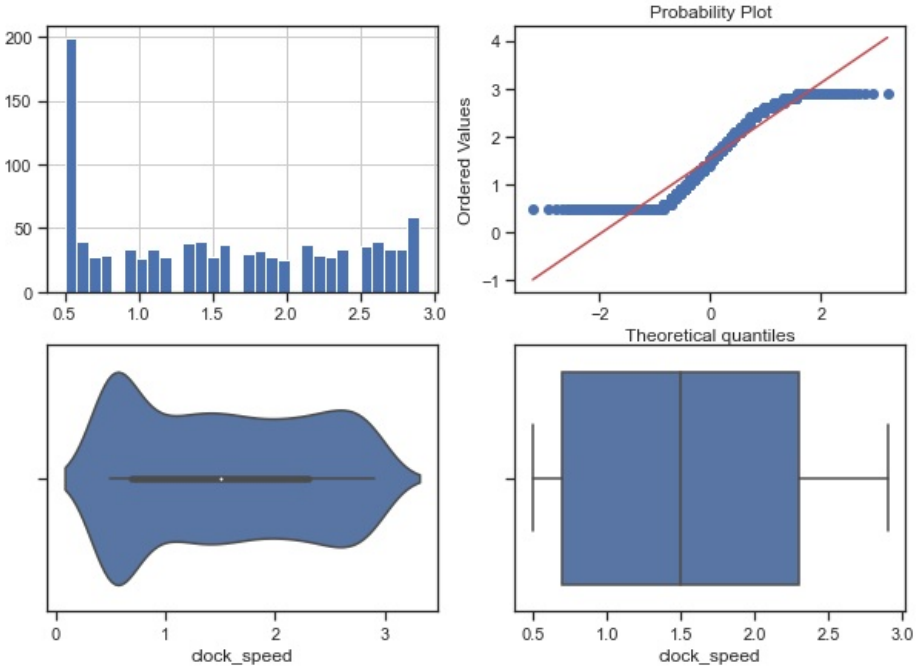
Поле-clock_speed, метод-OutlierBoundaryType.SIGMA



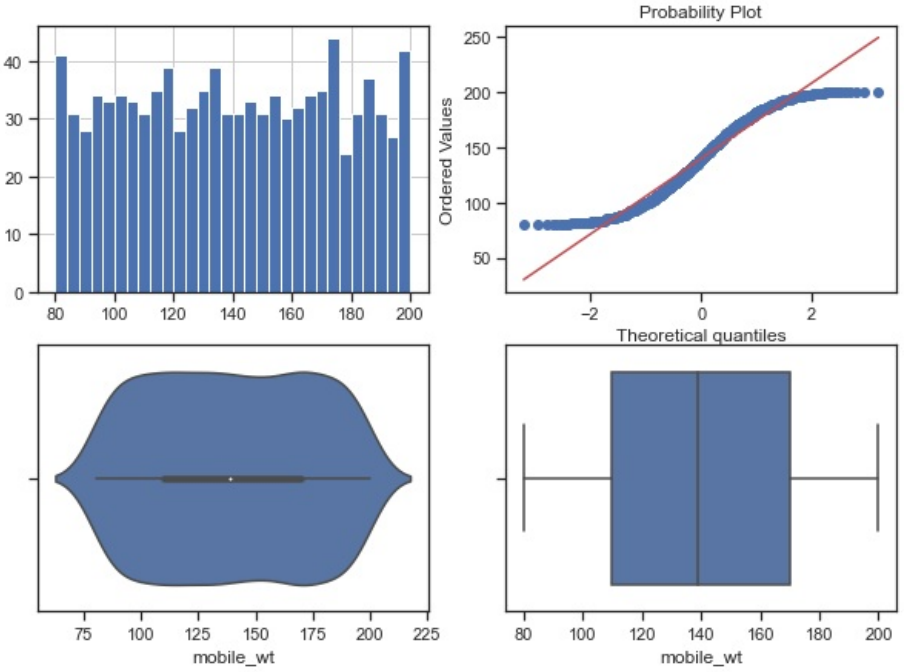
Поле-clock_speed, метод-OutlierBoundaryType.QUANTILE



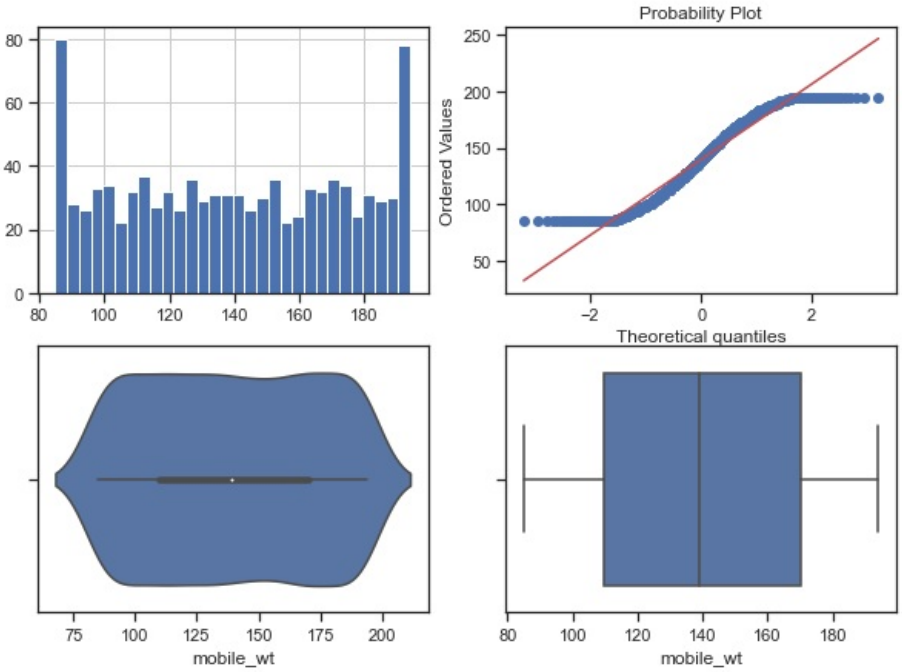
Поле-clock_speed, метод-OutlierBoundaryType.IRQ



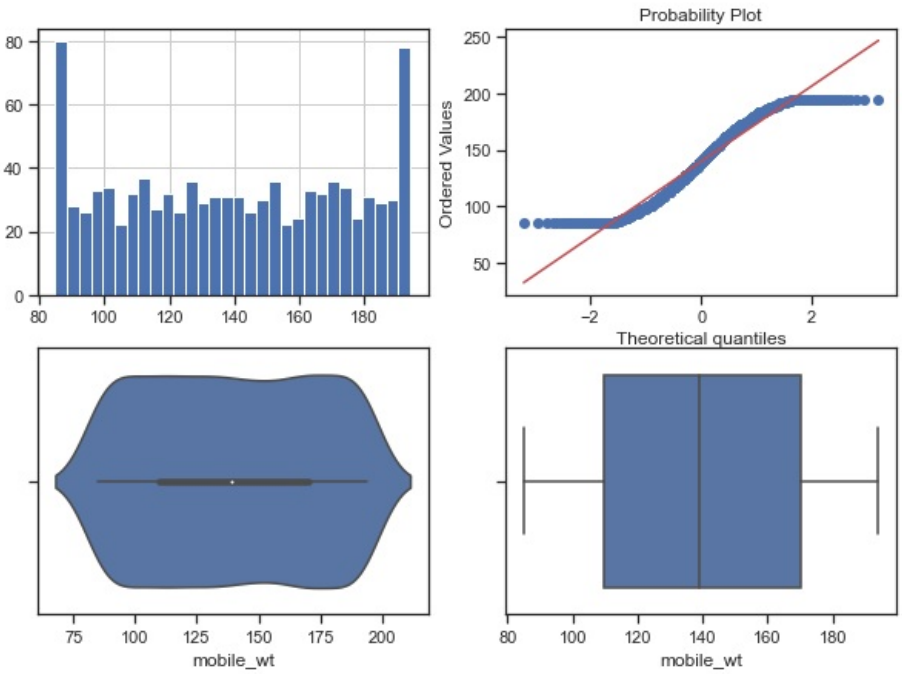
Поле-mobile_wt, метод-OutlierBoundaryType.SIGMA



Поле-mobile_wt, метод-OutlierBoundaryType.QUANTILE



Поле-mobile_wt, метод-OutlierBoundaryType.IRQ



In [158…

```
# Будем использовать только обучающую выборку
df = pd.read_csv('1429_1.csv', delimiter=',')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34660 entries, 0 to 34659
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    34660 non-null  object
 1   name                  27900 non-null  object
 2   asins                 34658 non-null  object
 3   brand                 34660 non-null  object
 4   categories            34660 non-null  object
 5   keys                  34660 non-null  object
 6   manufacturer          34660 non-null  object
 7   reviews.date          34621 non-null  object
 8   reviews.dateAdded     24039 non-null  object
 9   reviews.dateSeen      34660 non-null  object
 10  reviews.didPurchase   1 non-null      object
 11  reviews.doRecommend   34066 non-null  object
 12  reviews.id            1 non-null      float64
 13  reviews.numHelpful    34131 non-null  float64
 14  reviews.rating        34627 non-null  float64
 15  reviews.sourceURLs    34660 non-null  object
 16  reviews.text          34659 non-null  object
 17  reviews.title         34655 non-null  object
 18  reviews.userCity      0 non-null      float64
 19  reviews.userProvince  0 non-null      float64
 20  reviews.username      34658 non-null  object
dtypes: float64(5), object(16)
memory usage: 5.6+ MB
```

```
C:\Users\twai1\AppData\Local\Temp\ipykernel_1924\3722640383.py:2: DtypeWarning: Columns (1,10) have mixed types
. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('1429_1.csv', delimiter=',')
```

In [159…
```
df.head()
```

Out[159]:

	id	name	asins	brand	categories	keys	manufacturer	
0	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	13
1	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	13
2	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	13
3	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	13
4	AVqkIhwDv8e3D1O-lebb	All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi,...	B01AHB9CN2	Amazon	Electronics,iPad & Tablets,All Tablets,Fire Ta...	841667104676,amazon/53004484,amazon/b01ahb9cn2...	Amazon	12

5 rows × 21 columns

In [160…
```
df = df[['reviews.date','reviews.dateAdded']]
df = df.dropna()
# Сконвертируем дату и время в нужный формат
df['reviews_time'] = df.apply(lambda x: pd.to_datetime(x['reviews.date'], format='%Y-%m-%dT%H:%M:%S'), axis=1)
df['reviews_time_added'] = df.apply(lambda x: pd.to_datetime(x['reviews.dateAdded'], format='%Y-%m-%dT%H:%M:%S'
```

In [161…
```
#df[['reviews_time','reviews_time_added']].head()
df.head()
```

Out[161]:

	reviews.date	reviews.dateAdded	reviews_time	reviews_time_added
0	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00
1	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00
2	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00
3	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00
4	2017-01-12T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-12 00:00:00+00:00	2017-07-03 23:33:15+00:00

In [162…
```
df.dtypes
```

Out[162]:
```
reviews.date                      object
reviews.dateAdded                 object
reviews_time          datetime64[ns, UTC]
reviews_time_added    datetime64[ns, UTC]
dtype: object
```

In [163…
```
# День
df['day'] = df['reviews_time_added'].dt.day
# Месяц
df['month'] = df['reviews_time_added'].dt.month
# Год
df['year'] = df['reviews_time_added'].dt.year
# Часы
df['hour'] = df['reviews_time_added'].dt.hour
#Минуты
df['minute'] = df['reviews_time_added'].dt.minute
#Секунды
df['second'] = df['reviews_time_added'].dt.second
#Неделя года
df['week'] = df['reviews_time_added'].dt.isocalendar().week
#Квартал
df['quarter'] = df['reviews_time_added'].dt.quarter
#День недели
df['dayofweek'] = df['reviews_time_added'].dt.dayofweek
#Выходной день
df['day_name'] = df['reviews_time_added'].dt.day_name()
df['is_holiday'] = df.apply(lambda x: 1 if x['reviews_time_added'].dayofweek in [5,6] else 0, axis=1)
```

In [164…
```
df.head()
```

Out[164]:

	reviews.date	reviews.dateAdded	reviews_time	reviews_time_added	day	month	year	hour	minute	second	week	quarter	dayo
0	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	27	3	
1	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	27	3	
2	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	27	3	
3	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	27	3	
4	2017-01-12T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-12 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	27	3	

In [165…
```
# Создадим масштабируемые признаки для дальнейших экспериментов
dt_features = ['year', 'day', 'month', 'hour', 'minute', 'second', 'week', 'quarter', 'dayofweek']
dt_features_scaled = []
for f in dt_features:
    f_new = str(f + '_scaled')
    dt_features_scaled.append(f_new)
    df[f_new] = MinMaxScaler().fit_transform(df[[f]])
dt_features_scaled
```

Out[165]:
```
['year_scaled',
 'day_scaled',
 'month_scaled',
 'hour_scaled',
 'minute_scaled',
 'second_scaled',
 'week_scaled',
 'quarter_scaled',
 'dayofweek_scaled']
```

In [166…
```
df.head()
```

Out[166]:

	reviews.date	reviews.dateAdded	reviews_time	reviews_time_added	day	month	year	hour	minute	second	...	is_holiday	year_
0	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0	
1	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0	
2	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0	
3	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0	
4	2017-01-12T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-12 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0	

5 rows × 24 columns

In [167…

```
# Разница между датами
utc=pytz.UTC
df['now'] = datetime.datetime.now(tz=utc)
df['diff'] = df['now'] - df['reviews_time']
df.dtypes
df['diff']
```

Out[167]:

```
0       1970 days 14:12:03.614920
1       1970 days 14:12:03.614920
2       1970 days 14:12:03.614920
3       1970 days 14:12:03.614920
4       1971 days 14:12:03.614920
                   ...
34622   2221 days 14:12:03.614920
34623   2162 days 14:12:03.614920
34624   2377 days 14:12:03.614920
34626   2098 days 14:12:03.614920
34628   2427 days 14:12:03.614920
Name: diff, Length: 24037, dtype: timedelta64[ns]
```

In [168…

```
# Чтобы получить разницу между датами в заданных единицах
# (минутах, днях и т.д.) нужно разделить timedelta64 на длительность
df['diff_days']=df['diff']/np.timedelta64(1,'D')
df.dtypes
```

Out[168]:

```
reviews.date                        object
reviews.dateAdded                   object
reviews_time          datetime64[ns, UTC]
reviews_time_added    datetime64[ns, UTC]
day                                 int64
month                               int64
year                                int64
hour                                int64
minute                              int64
second                              int64
week                               UInt32
quarter                             int64
dayofweek                           int64
day_name                           object
is_holiday                          int64
year_scaled                       float64
day_scaled                        float64
month_scaled                      float64
hour_scaled                       float64
minute_scaled                     float64
second_scaled                     float64
week_scaled                       float64
quarter_scaled                    float64
dayofweek_scaled                  float64
now                   datetime64[ns, UTC]
diff                      timedelta64[ns]
diff_days                         float64
dtype: object
```

In [169…

```
df.head()
```

Out[169]:

	reviews.date	reviews.dateAdded	reviews_time	reviews_time_added	day	month	year	hour	minute	second	...	month_scaled	h
0	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0.444444	
1	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0.444444	
2	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0.444444	
3	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0.444444	
4	2017-01-12T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-12 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	0.444444	

5 rows × 27 columns

In [170…

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

# Опередемим периоды для признаков
for f in dt_features:
    print(f, df[f].min(), df[f].max())
```

```
year 2016 2017
day 2 29
month 3 12
hour 0 23
minute 0 59
second 0 59
week 10 50
quarter 1 4
dayofweek 0 6
```

In [171…

```
# периоды для признаков
dt_features_periods = [0, 31, 12, 24, 60, 60, 52, 4, 7]
```

In [172…

```
df['year_round'] = df.apply(lambda x: 1 if x['year']==2017 else 0, axis=1)
dt_features_round = ['year_round']

df.head()
```

Out[172]:

	reviews.date	reviews.dateAdded	reviews_time	reviews_time_added	day	month	year	hour	minute	second	...	hour_scaled	min
0	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	1.0	
1	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	1.0	
2	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	1.0	
3	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	1.0	
4	2017-01-12T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-12 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	1.0	

5 rows × 28 columns

In [173…

```
%%time
# Построим отображение признаков на круг, год пропускаем
for f,p in zip(dt_features[1:], dt_features_periods[1:]):
    f_cos = str(f + '_cos')
    f_sin = str(f + '_sin')
    df[f_cos] = df.apply(lambda x: round_code(x[f], p), axis=1)
    df[f_sin] = df.apply(lambda x: round_code(x[f], p, False), axis=1)
    dt_features_round.append(f_cos)
    dt_features_round.append(f_sin)
dt_features_round
```

```
CPU times: total: 8.41 s
Wall time: 8.42 s
```

Out[173]:
```
['year_round',
 'day_cos',
 'day_sin',
 'month_cos',
 'month_sin',
 'hour_cos',
 'hour_sin',
 'minute_cos',
 'minute_sin',
 'second_cos',
 'second_sin',
 'week_cos',
 'week_sin',
 'quarter_cos',
 'quarter_sin',
 'dayofweek_cos',
 'dayofweek_sin']
```

In [174…
```
df.head()
```

Out[174]:

	reviews.date	reviews.dateAdded	reviews_time	reviews_time_added	day	month	year	hour	minute	second	...	minute_cos	minu
0	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	-0.951057	-0.
1	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	-0.951057	-0.
2	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	-0.951057	-0.
3	2017-01-13T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-13 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	-0.951057	-0.
4	2017-01-12T00:00:00.000Z	2017-07-03T23:33:15Z	2017-01-12 00:00:00+00:00	2017-07-03 23:33:15+00:00	3	7	2017	23	33	15	...	-0.951057	-0.

5 rows × 44 columns

In [175…
```
data_select = data_cs42_scaled_train
selector_1211 = VarianceThreshold(threshold=0.15)
selector_1211.fit(data_select)
# Значения дисперсий для каждого признака
selector_1211.variances_
```

Out[175]:
```
array([0.33796816, 0.33676181, 0.24969375, 0.27038962, 0.24859375,
       0.55435586, 0.24981094, 0.34144399, 0.33402278, 0.31116734,
       0.45168858, 0.30294255, 0.30060312, 0.49480486, 0.37855432,
       0.18624375, 0.24999844])
```

In [176…
```
# Константный и псевдоконстантный признаки удалены
selector_1211.transform(data_select)
```

Out[176]:
```
array([[-0.22512563, -0.94348404,  0.        , ..., -0.77777778,
         0.        ,  1.        ],
       [ 1.00502513, -0.41954787,  0.        , ...,  0.11111111,
         0.        ,  1.        ],
       [ 0.98090452,  0.99268617,  0.        , ..., -0.22222222,
         0.        ,  0.        ],
       ...,
       [ 0.8321608 ,  0.53922872, -1.        , ...,  0.11111111,
         0.        ,  1.        ],
       [-0.52060302,  0.35571809, -1.        , ..., -0.44444444,
        -1.        ,  1.        ],
       [-0.91859296,  0.61635638, -1.        , ...,  0.11111111,
         0.        ,  0.        ]])
```

In [177…
```
def get_duplicates(X):
    """
    Поиск дубликатов в колонках
    X - DataFrame
    """

    pairs = {}
    dups = []

    # Перебор всех колонок (внешний)
    for i in range(X.shape[1]):

        # текущая колонка
        feat_outer = X.columns[i]

        # если текущая колонка не является дублем
        if feat_outer not in dups:

            # создаем запись в словаре, колонка является ключом
            pairs[feat_outer] = []

            # Перебор оставшихся колонок (внутренний)
```

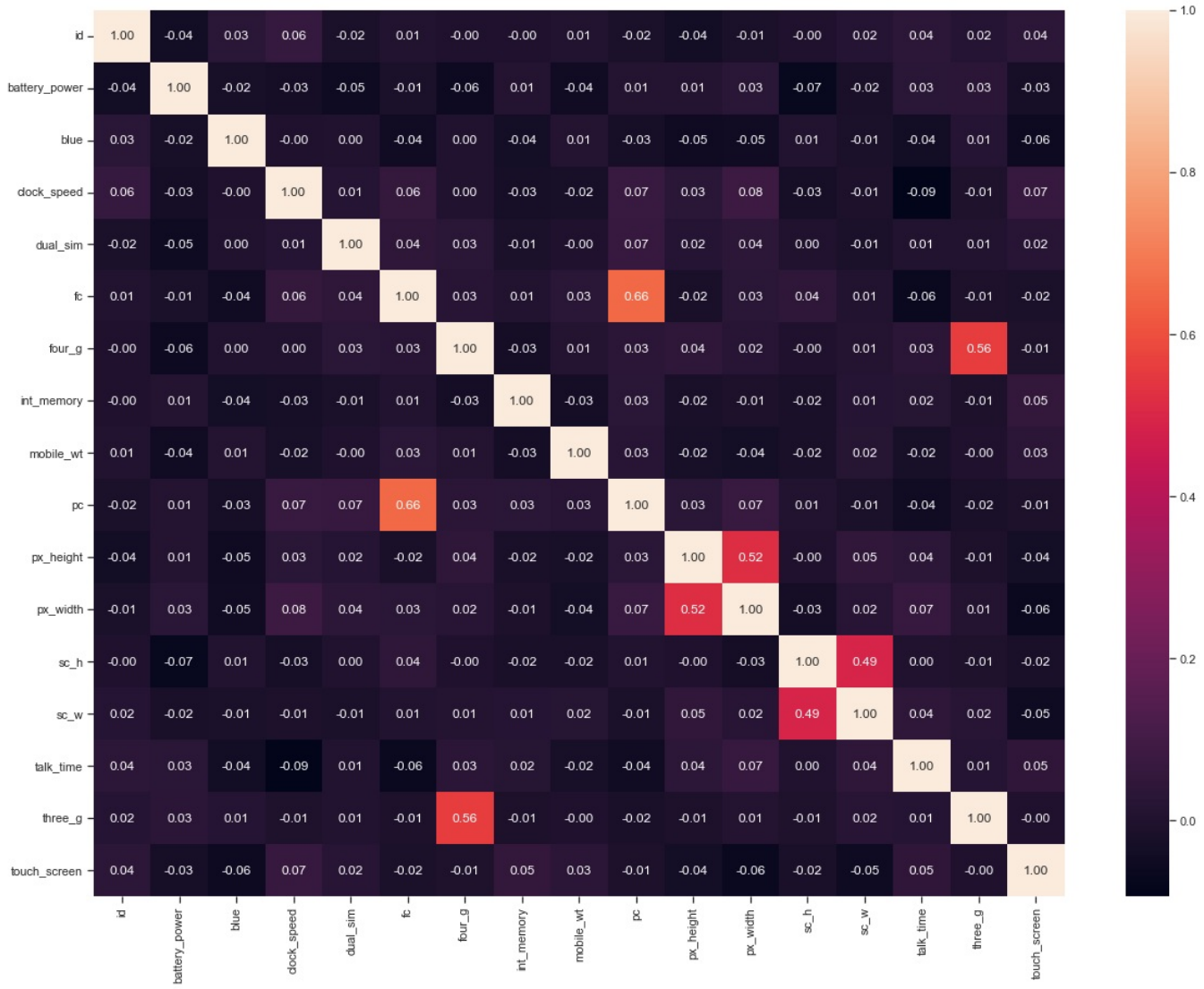
```
            for feat_inner in X.columns[i + 1:]:

                # Если колонки идентичны
                if X[feat_outer].equals(X[feat_inner]):

                    # добавление в словарь и список дубликатов
                    pairs[feat_outer].append(feat_inner)
                    dups.append(feat_inner)

    return pairs
```

In [178…
```
get_duplicates(data_select)
```

Out[178]:
```
{'id': [],
 'battery_power': [],
 'blue': [],
 'clock_speed': [],
 'dual_sim': [],
 'fc': [],
 'four_g': [],
 'int_memory': [],
 'mobile_wt': [],
 'pc': [],
 'px_height': [],
 'px_width': [],
 'sc_h': [],
 'sc_w': [],
 'talk_time': [],
 'three_g': [],
 'touch_screen': []}
```

In [179…
```
fig, ax = plt.subplots(figsize=(20,15))
sns.heatmap(data_select.corr(), annot=True, fmt='.2f',ax=ax)
```

Out[179]: <AxesSubplot:>



In [180…
```
# 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 >= 0.8]
    cr = cr[cr < 1]
```

```
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']
    return cr

# 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
```

In [181…
```
make_corr_df(data_select)
```

Out[181]:

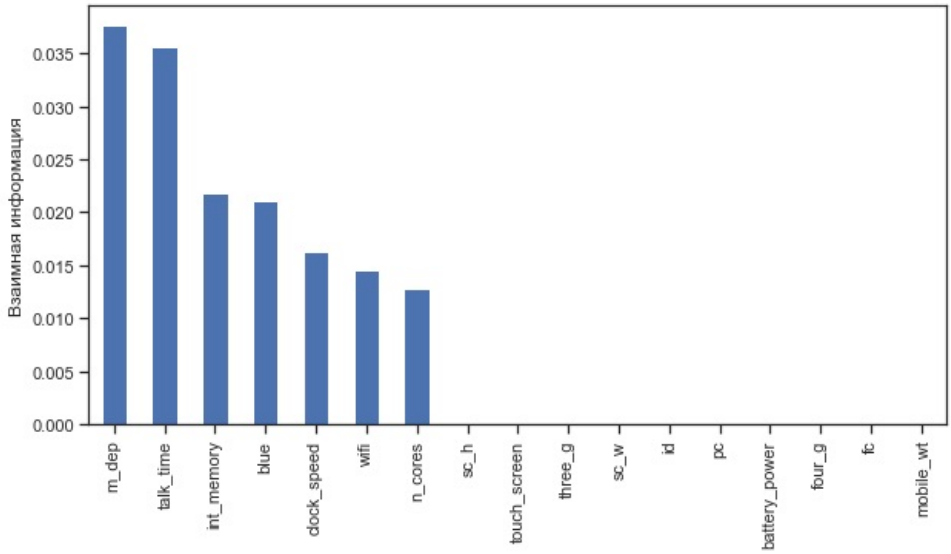
	f1	f2	corr

In [182…
```
# Группы коррелирующих признаков
corr_groups(make_corr_df(data))
```

Out[182]:
```
[]
```

In [183…
```
# DataFrame не содержащий целевой признак
data_select = data.drop(['dual_sim','px_width','px_height'], axis=1)
data_select = data_select.dropna()
selectX = data_select.drop(['ram'],axis=1)
Y = data_select['ram']
mi = mutual_info_regression(selectX, Y)
mi = pd.Series(mi)
mi.index = selectX.columns
mi.sort_values(ascending=False).plot.bar(figsize=(10,5))
plt.ylabel('Взаимная информация')
```

Out[183]:
```
Text(0, 0.5, 'Взаимная информация')
```



In [184…
```
sel_mi = SelectKBest(mutual_info_regression, k=5).fit(selectX, Y)

list(zip(selectX.columns, sel_mi.get_support()))
```

Out[184]:
```
[('id', False),
 ('battery_power', False),
 ('blue', True),
 ('clock_speed', True),
 ('fc', False),
 ('four_g', False),
 ('int_memory', True),
 ('m_dep', True),
 ('mobile_wt', False),
 ('n_cores', False),
 ('pc', False),
 ('sc_h', False),
 ('sc_w', False),
 ('talk_time', True),
 ('three_g', False),
 ('touch_screen', False),
 ('wifi', False)]
```

In [185…
```
selectX.columns[sel_mi.get_support()]
```

Out[185]:
```
Index(['blue', 'clock_speed', 'int_memory', 'm_dep', 'talk_time'], dtype='object')
```

In [186…
```
import  import_ipynb
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS

knn = KNeighborsClassifier(n_neighbors=3)
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Input In [186], in <cell line: 2>()
      1 import  import_ipynb
----> 2 from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
      4 knn = KNeighborsClassifier(n_neighbors=3)

ModuleNotFoundError: No module named 'mlxtend'
```

In [187…
```
efs1 = EFS(knn,
           min_features=2,
           max_features=4,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs1 = efs1.fit(selectX[:200], Y[:200], custom_feature_names=selectX.columns)

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

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Input In [187], in <cell line: 1>()
----> 1 efs1 = EFS(knn,
      2            min_features=2,
      3            max_features=4,
      4            scoring='accuracy',
      5            print_progress=True,
      6            cv=5)
      8 efs1 = efs1.fit(selectX[:200], Y[:200], custom_feature_names=selectX.columns)
     10 print('Best accuracy score: %.2f' % efs1.best_score_)

NameError: name 'EFS' is not defined
```

In [188…
```
efs2 = EFS(knn,
           min_features=1,
           max_features=2,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs2 = efs2.fit(selectX, Y, custom_feature_names=selectX.columns)

print('Best accuracy score: %.2f' % efs2.best_score_)
print('Best subset (indices):', efs2.best_idx_)
print('Best subset (corresponding names):', efs2.best_feature_names_)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Input In [188], in <cell line: 1>()
----> 1 efs2 = EFS(knn,
      2            min_features=1,
      3            max_features=2,
      4            scoring='accuracy',
      5            print_progress=True,
      6            cv=5)
      8 efs2 = efs2.fit(selectX, Y, custom_feature_names=selectX.columns)
     10 print('Best accuracy score: %.2f' % efs2.best_score_)

NameError: name 'EFS' is not defined
```

In [189…
```
# Используем L1-регуляризацию
e_lr1 = LogisticRegression(C=1000, solver='liblinear', penalty='l1', max_iter=500, random_state=1)
e_lr1.fit(selectX, Y)
# Коэффициенты регрессии
e_lr1.coef_
```

Out[189]:
```
array([[-2.53023342e-02, -5.80166474e-03,  4.43186154e+00, ...,
         0.00000000e+00, -5.72126818e+00,  0.00000000e+00],
       [ 1.03561434e-03, -5.20402055e-03, -5.48987666e+00, ...,
         0.00000000e+00,  0.00000000e+00,  2.95600783e+00],
       [ 1.50480145e-02, -2.16817799e-04,  7.42681376e+00, ...,
         0.00000000e+00,  4.52255680e+00, -7.76326135e+00],
       ...,
       [-8.69332344e-02, -2.02068290e-02,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [ 5.71631539e-03, -1.02398280e-02,  3.86405166e+00, ...,
         0.00000000e+00, -1.20990677e+01, -6.19171698e+00],
       [-7.99424623e-03,  1.74447731e-02, -5.72297873e+00, ...,
        -1.61411263e+01,  3.01455851e+00, -1.76131659e+01]])
```

In [190…
```
sel_e_lr1 = SelectFromModel(e_lr1)
sel_e_lr1.fit(selectX, Y)
sel_e_lr1.get_support()
```

Out[190]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True])
```

In [191…
```
e_lr2 = LinearSVC(C=0.01, penalty="l1", max_iter=5000, dual=False)
e_lr2.fit(selectX, Y)
# Коэффициенты регрессии
e_lr2.coef_
```

Out[191]:
```
array([[-5.18411161e-04, -3.89616837e-04,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-1.61874964e-04, -1.73318797e-04,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-3.14312837e-05, -1.57150551e-04,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       ...,
       [-8.33902076e-04, -1.32394637e-03,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-1.73067061e-04, -6.17747443e-04,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-4.85969299e-05,  7.66990955e-06,  0.00000000e+00, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00]])
```

In [192…
```
sel_e_lr2 = SelectFromModel(e_lr2)
sel_e_lr2.fit(selectX, Y)
sel_e_lr2.get_support()
```

Out[192]:
```
array([ True,  True, False, False, False, False,  True, False,  True,
       False,  True,  True,  True,  True, False, False, False])
```

In [193…
```
# Используем L1-регуляризацию
e_ls1 = Lasso(random_state=1)
e_ls1.fit(selectX, Y)
# Коэффициенты регрессии
list(zip(selectX.columns, e_ls1.coef_))
```

Out[193]:
```
[('id', -0.17009662120857336),
 ('battery_power', -0.06866374656168905),
 ('blue', 106.69980516168043),
 ('clock_speed', 0.0),
 ('fc', -8.999056176316834),
 ('four_g', 47.53849791144925),
 ('int_memory', -0.20358767802549568),
 ('m_dep', 68.49577168439173),
 ('mobile_wt', 0.9456418003862929),
 ('n_cores', -20.790295272320712),
 ('pc', -3.9497812569221002),
 ('sc_h', 2.456596668068263),
 ('sc_w', 6.252941927107051),
 ('talk_time', -0.5646335964563717),
 ('three_g', 47.94958681151395),
 ('touch_screen', -83.42821544017599),
 ('wifi', -82.84041936629959)]
```

In [194…
```
sel_e_ls1 = SelectFromModel(e_ls1)
sel_e_ls1.fit(selectX, Y)
list(zip(selectX.columns, sel_e_ls1.get_support()))
```

Out[194]:
```
[('id', True),
 ('battery_power', True),
 ('blue', True),
 ('clock_speed', False),
 ('fc', True),
 ('four_g', True),
 ('int_memory', True),
 ('m_dep', True),
 ('mobile_wt', True),
 ('n_cores', True),
 ('pc', True),
 ('sc_h', True),
 ('sc_w', True),
 ('talk_time', True),
 ('three_g', True),
 ('touch_screen', True),
 ('wifi', True)]
```

In [ ]:
```
dtc1 = DecisionTreeClassifier()
rfc1 = RandomForestClassifier()
gbc1 = GradientBoostingClassifier()
dtc1.fit(selectX, Y)
rfc1.fit(selectX, Y)
gbc1.fit(selectX, Y)

# Важность признаков
dtc1.feature_importances_, sum(dtc1.feature_importances_)
```

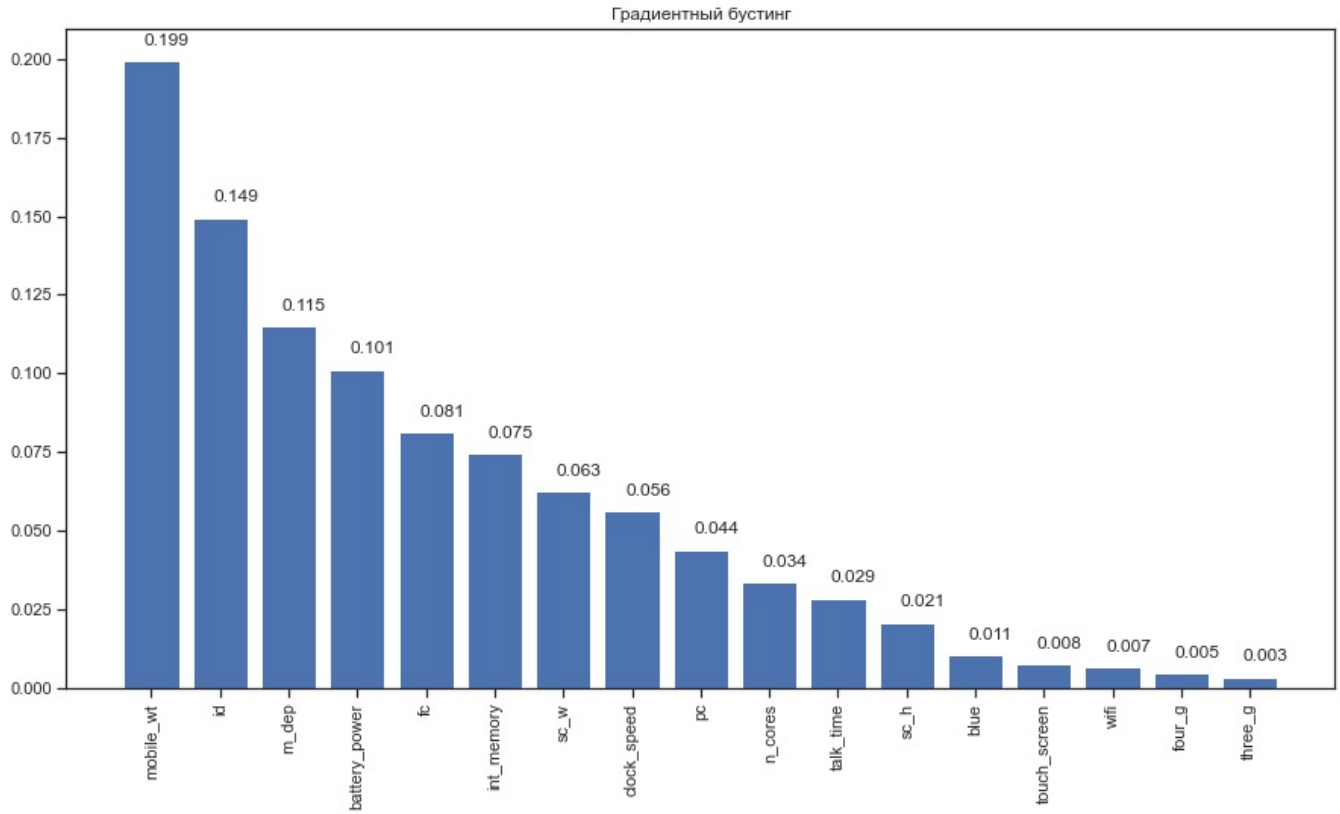
In [ ]:
```
from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, title, figsize=(7,4)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.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=figsize)
    ax.set_title(title)
    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()
    return labels, data
```

In [ ]:
```
_,_=draw_feature_importances(dtc1, selectX, 'Решающее дерево',figsize=(15,8))
```

In [107…
```
list(zip(selectX.columns, SelectFromModel(dtc1).fit(selectX, Y).get_support()))
```

Out[107]:
```
[('id', True),
 ('battery_power', True),
 ('blue', False),
 ('clock_speed', True),
 ('fc', False),
 ('four_g', False),
 ('int_memory', True),
 ('m_dep', True),
 ('mobile_wt', True),
 ('n_cores', False),
 ('pc', True),
 ('sc_h', True),
 ('sc_w', True),
 ('talk_time', True),
 ('three_g', False),
 ('touch_screen', False),
 ('wifi', False)]
```

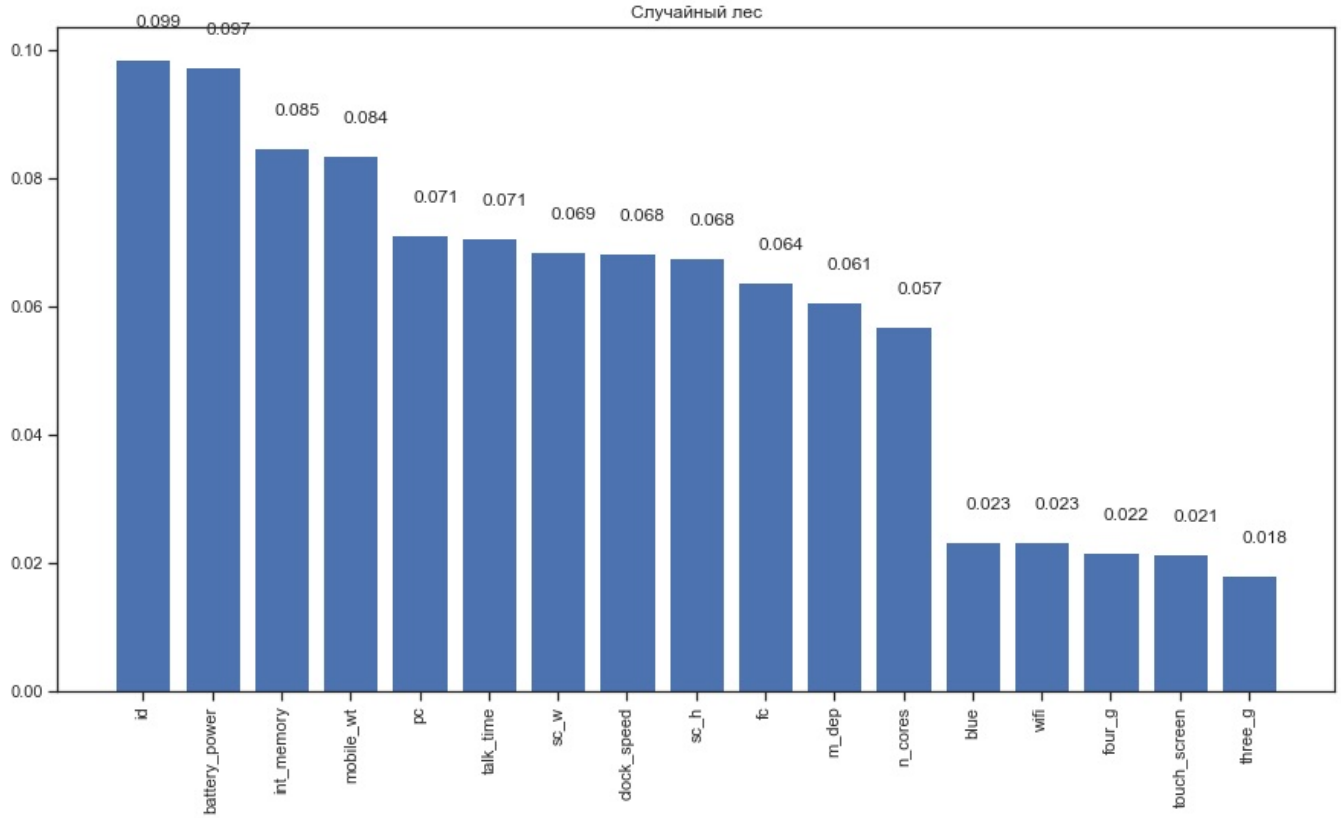
In [108…
```
_,_=draw_feature_importances(gbc1, selectX, 'Градиентный бустинг',figsize=(15,8))
```



In [109…
```
list(zip(selectX.columns, SelectFromModel(gbc1).fit(selectX, Y).get_support()))
```

Out[109]:
```
[('id', True),
 ('battery_power', True),
 ('blue', False),
 ('clock_speed', False),
 ('fc', True),
 ('four_g', False),
 ('int_memory', True),
 ('m_dep', True),
 ('mobile_wt', True),
 ('n_cores', False),
 ('pc', False),
 ('sc_h', False),
 ('sc_w', False),
 ('talk_time', False),
 ('three_g', False),
 ('touch_screen', False),
 ('wifi', False)]
```

In [110…
```
_,_=draw_feature_importances(rfc1, selectX, 'Случайный лес',figsize=(15,8))
```



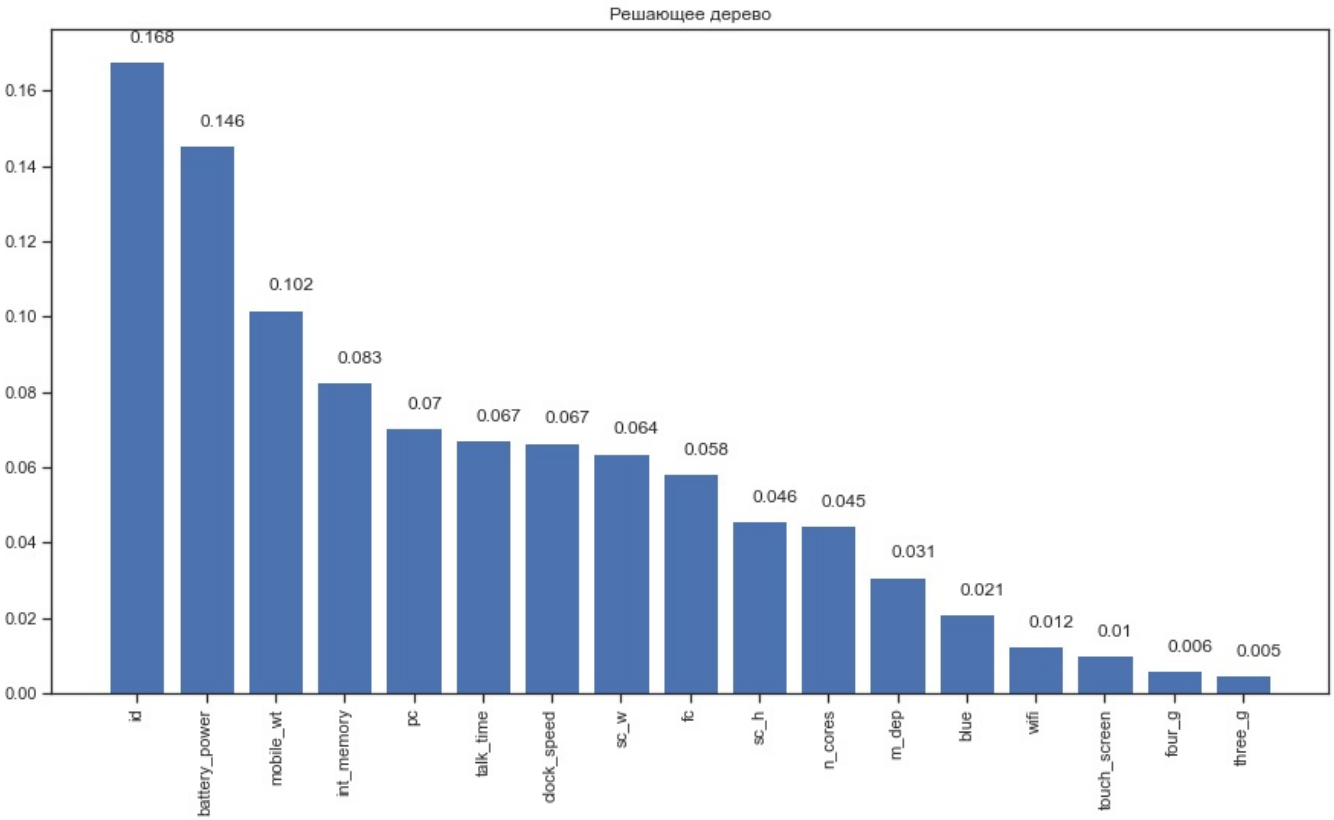
In [111…
```
list(zip(selectX.columns, SelectFromModel(rfc1).fit(selectX, Y).get_support()))
```

Out[111]:
```
[('id', True),
 ('battery_power', True),
 ('blue', False),
 ('clock_speed', True),
 ('fc', True),
 ('four_g', False),
 ('int_memory', True),
 ('m_dep', True),
 ('mobile_wt', True),
 ('n_cores', False),
 ('pc', True),
 ('sc_h', True),
 ('sc_w', True),
 ('talk_time', True),
 ('three_g', False),
 ('touch_screen', False),
 ('wifi', False)]
```

In [112…
```
dtr1 = DecisionTreeRegressor()
rfr1 = RandomForestRegressor()
gbr1 = GradientBoostingRegressor()
dtr1.fit(selectX, Y)
rfr1.fit(selectX, Y)
gbr1.fit(selectX, Y)

# Важность признаков
dtr1.feature_importances_, sum(dtr1.feature_importances_)
```

Out[112]:
```
(array([0.16780876, 0.14550247, 0.02110927, 0.06665835, 0.05841739,
        0.00604376, 0.08260701, 0.03090996, 0.10184624, 0.0445999 ,
        0.0703989 , 0.04587579, 0.06379226, 0.06714511, 0.00469101,
        0.01016348, 0.01243033]),
 1.0)
```

In [113…
```
_,_=draw_feature_importances(dtr1, selectX, 'Решающее дерево', figsize=(15,8))
```



In [114…
```
list(zip(selectX.columns, SelectFromModel(dtr1).fit(selectX, Y).get_support()))
```

Out[114]:
```
[('id', True),
 ('battery_power', True),
 ('blue', False),
 ('clock_speed', True),
 ('fc', True),
 ('four_g', False),
 ('int_memory', True),
 ('m_dep', False),
 ('mobile_wt', True),
 ('n_cores', False),
 ('pc', True),
 ('sc_h', False),
 ('sc_w', False),
 ('talk_time', False),
 ('three_g', False),
 ('touch_screen', False),
 ('wifi', False)]
```

In [ ]:
```
_,_=draw_feature_importances(gbr1, selectX, 'Градиентный бустинг', figsize=(15,8))
```

In [ ]:
```
list(zip(selectX.columns, SelectFromModel(gbr1).fit(selectX, Y).get_support()))
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: