In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
```

Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:

- масштабирование признаков (не менее чем тремя способами);
- обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
- обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
- отбор признаков:
  - один метод из группы методов фильтрации **(filter methods);**
  - один метод из группы методов обертывания **(wrapper methods);**
  - один метод из группы методов вложений **(embedded methods).**

In [2]:

```
data = pd.read_csv('/Users/da.karpov/Desktop/МАГА/УЧЕБА/2 сем/ML_MSc_1course/датасеты/top
2018.csv', sep=",")
```

In [3]:

```
data.head()
```

Out[3]:

	id	name	artists	danceability	energy	key	loudness	mode	speechiness	acousticnes
0	6DCZcSspjsKoFjzjrWoCd	God's Plan	Drake	0.754	0.449	7.0	-9.211	1.0	0.1090	0.033
1	3ee8Jmje8o58CHK66QrVC	SAD!	XXXTENTACION	0.740	0.613	8.0	-4.880	1.0	0.1450	0.258
2	0e7ipj03S05BNilyu5bRz	rockstar (feat. 21 Savage)	Post Malone	0.587	0.535	5.0	-6.090	0.0	0.0898	0.117
3	3swc6WTsr7rl9DqQKQA55	Psycho (feat. Ty Dolla $ign)	Post Malone	0.739	0.559	8.0	-8.011	1.0	0.1170	0.580
4	2G7V7zsVDxg1yRsu7Ew9R	In My Feelings	Drake	0.835	0.626	1.0	-5.833	1.0	0.1250	0.058

In [4]:

```
data.describe()
```

Out[4]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness
count	100.00000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
mean	0.71646	0.659060	5.330000	-5.677640	0.590000	0.115569	0.195701	0.001584	0.158302
std	0.13107	0.145067	3.676447	1.777577	0.494311	0.104527	0.220946	0.013449	0.111662
min	0.25800	0.296000	0.000000	-10.109000	0.000000	0.023200	0.000282	0.000000	0.021500
25%	0.63550	0.562000	1.750000	-6.650500	0.000000	0.045350	0.040225	0.000000	0.094675
50%	0.73300	0.678000	5.000000	-5.566500	1.000000	0.074950	0.109000	0.000000	0.118500
75%	0.79825	0.772250	8.250000	-4.363750	1.000000	0.137000	0.247750	0.000031	0.170750
max	0.96400	0.909000	11.000000	-2.384000	1.000000	0.530000	0.934000	0.134000	0.636000

In [5]:

```
X_ALL = data.drop(['id', 'name', 'artists', 'liveness'], axis=1)
```

In [6]:

```
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res
```

Масштабирование признаков

StandardScaler

In [7]:

```
# 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
```

Out[7]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	valence	tempo	du
0	0.287854	-1.455314	0.456531	-1.997753	0.833616	-0.063162	-0.739184	-0.112147	-0.621334	-1.491544	
1	0.180503	-0.319108	0.729903	0.450984	0.833616	0.282982	0.283383	0.159656	-0.055789	-1.566444	
2	-0.992691	-0.859498	-0.090213	-0.233147	-1.199593	-0.247772	-0.357995	-0.113440	-1.679294	1.394085	
3	0.172835	-0.693224	0.729903	-1.319276	0.833616	0.013759	1.748092	-0.118343	-0.221552	0.705712	
4	0.908957	-0.229043	-1.183701	-0.087840	0.833616	0.090680	-0.622280	-0.113859	-0.655462	-1.007767	
...	...	...	...	...	...	...	...	...	...	...	
95	-0.248901	-0.277539	1.276647	-0.750486	0.833616	-0.740065	-0.564510	-0.118343	-0.977238	0.179460	
96	-0.601626	-0.007344	-0.636957	-0.362058	0.833616	-0.672759	0.224249	-0.118061	-0.752970	-0.517533	
97	-1.261069	0.699321	-1.457073	0.549363	0.833616	2.177157	-0.556777	-0.118343	0.753525	0.551376	
98	-3.515443	-1.538451	1.550019	-0.517542	-1.199593	-0.736219	-0.430776	-0.118248	-1.890398	2.098966	
99	-1.253401	-0.506166	1.550019	-0.362623	0.833616	-0.763141	2.280300	-0.118343	-0.202051	0.236629	

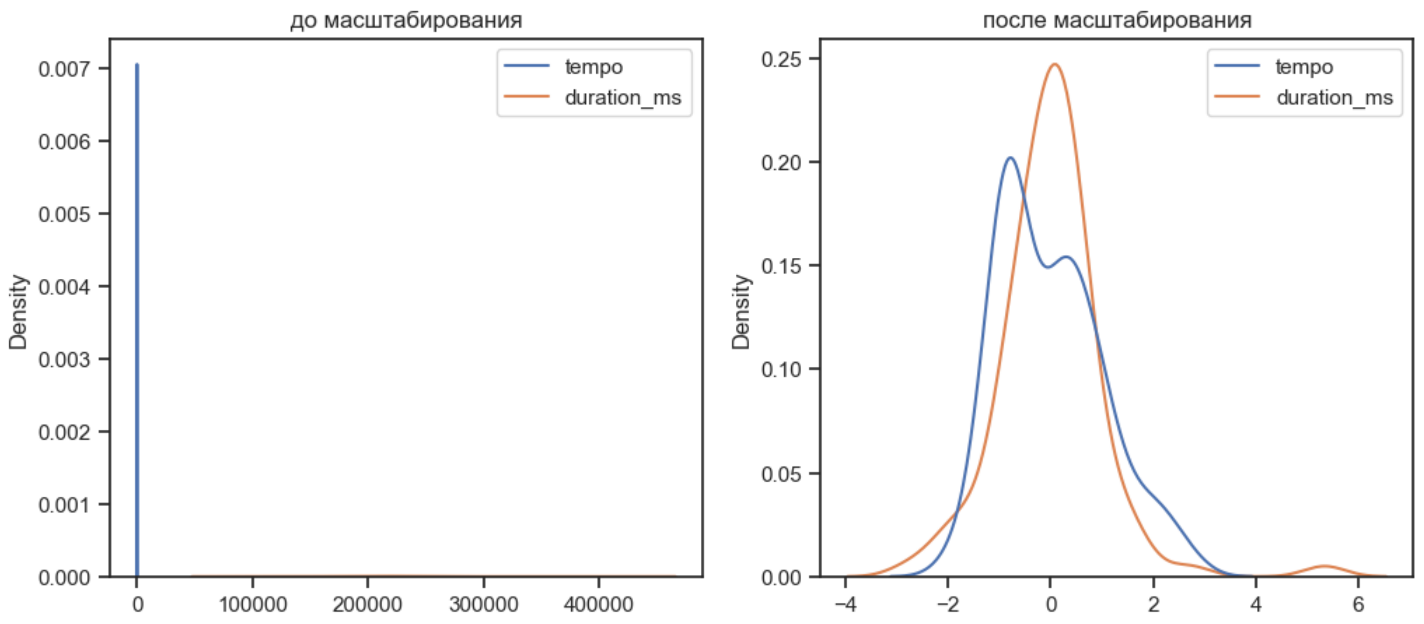
100 rows × 12 columns

In [8]:

```
# 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()
```

In [9]:

```
draw_kde(['tempo', 'duration_ms'], data, data_cs11_scaled, 'до масштабирования', 'после
масштабирования')
```



Масштабирование "Mean Normalisation"

In [10]:

```
# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['liveness'],
                                                    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
```

Out[10]:

```
((80, 12), (20, 12))
```

In [11]:

```
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 [12]:

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

Out[12]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	valence
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
mean	-0.016824	-0.006161	-0.030227	-0.002058	0.002500	-0.007142	0.008788	-0.002752	-0.015016
std	0.185652	0.241376	0.334222	0.231335	0.494311	0.206249	0.250518	0.100364	0.247088
min	-0.666200	-0.610254	-0.514773	-0.578758	-0.587500	-0.189402	-0.212786	-0.014570	-0.500265
25%	-0.131498	-0.167658	-0.355682	-0.128667	-0.587500	-0.145696	-0.167497	-0.014570	-0.186949
50%	0.006604	0.025354	-0.060227	0.012406	0.412500	-0.087290	-0.089517	-0.014570	-0.031729
75%	0.099026	0.182176	0.235227	0.168932	0.412500	0.035145	0.067803	-0.014340	0.173234
max	0.333800	0.409713	0.485227	0.426578	0.412500	0.810598	0.845900	0.985430	0.520231

In [13]:

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

In [14]:

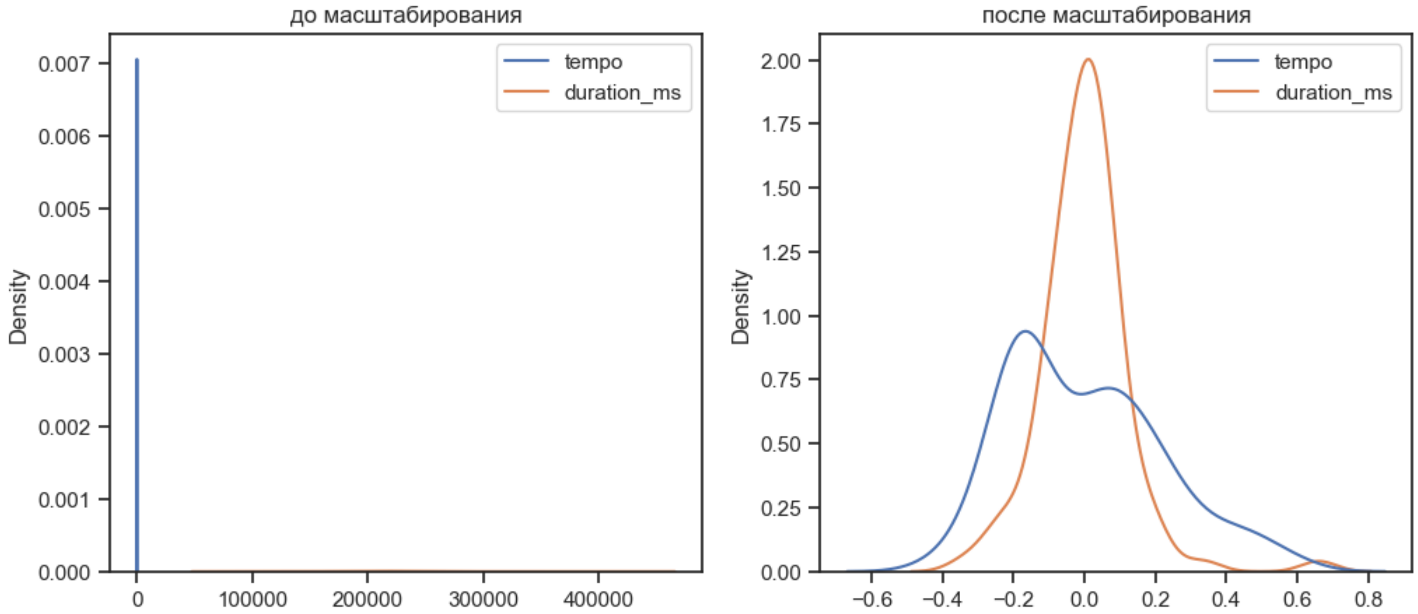
```
data_cs22_scaled_train.describe()
```

Out[14]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness
count	8.000000e+01	8.000000e+01	8.000000e+01	8.000000e+01	8.000000e+01	8.000000e+01	8.000000e+01	8.000000e+01
mean	-1.140798e-16	-2.279427e-16	1.457168e-17	-7.181755e-17	1.942890e-17	3.538836e-17	2.706169e-17	6.982262e-18
std	1.742082e-01	2.318961e-01	3.348639e-01	2.281019e-01	4.953901e-01	2.164278e-01	2.333134e-01	1.121774e-01
min	-6.662004e-01	-5.902870e-01	-5.147727e-01	-5.734220e-01	-5.875000e-01	-1.894016e-01	-2.119261e-01	-1.457002e-02
25%	-1.106055e-01	-1.622504e-01	-3.329545e-01	-1.217367e-01	-5.875000e-01	-1.440188e-01	-1.662211e-01	-1.457002e-02
50%	1.226983e-02	2.202579e-02	3.068182e-02	-4.187272e-03	4.125000e-01	-7.860843e-02	-9.972150e-02	-1.457002e-02
75%	1.007967e-01	1.701123e-01	3.034091e-01	1.692575e-01	4.125000e-01	2.823846e-02	6.780310e-02	-1.440976e-02
max	3.337996e-01	4.097130e-01	4.852273e-01	4.265780e-01	4.125000e-01	8.105984e-01	7.880739e-01	9.854300e-01

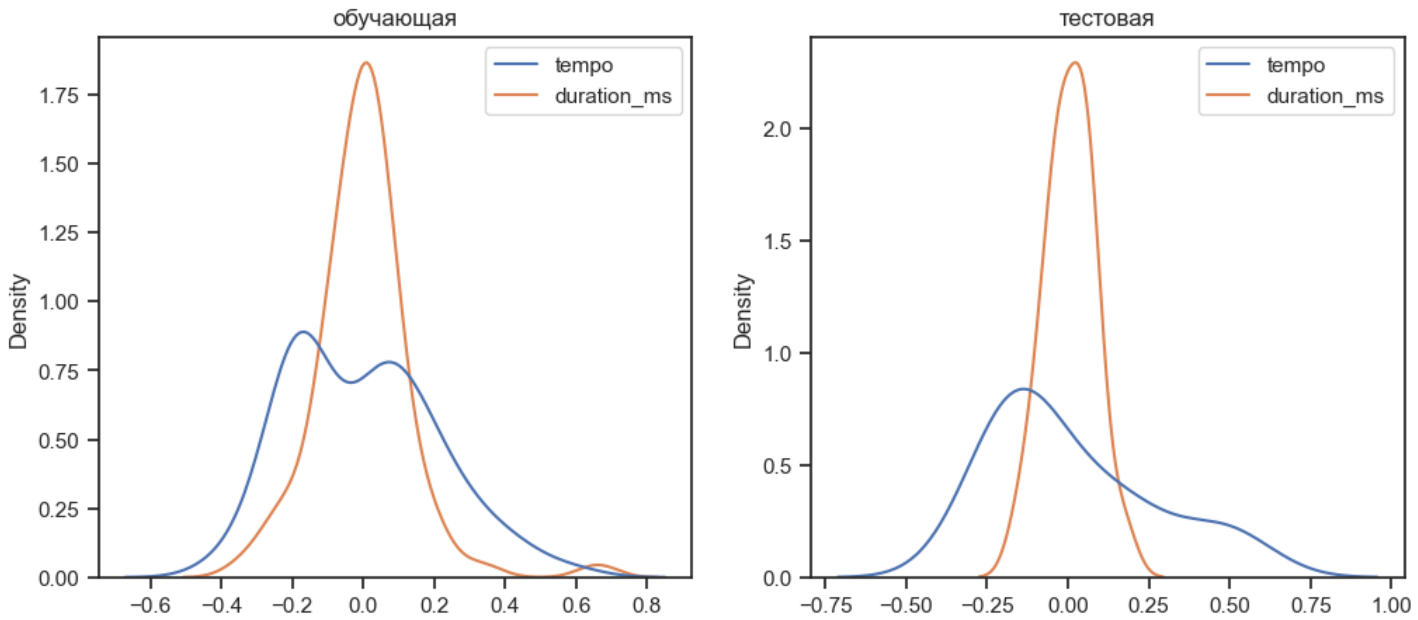
In [15]:

```
draw_kde(['tempo', 'duration_ms'], data, data_cs21_scaled, 'до масштабирования', 'после масштабирования')
```



In [16]:

```
draw_kde(['tempo', 'duration_ms'], data_cs22_scaled_train, data_cs22_scaled_test, 'обуча
ющая', 'тестовая')
```



MinMax-масштабирование

In [17]:

```
# 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[17]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	valence
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
mean	0.649377	0.592268	0.484545	0.573639	0.590000	0.182259	0.209292	0.011818	0.475503
std	0.185652	0.236651	0.334222	0.230107	0.494311	0.206249	0.236631	0.100364	0.242125
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.534703	0.433931	0.159091	0.447702	0.000000	0.043706	0.042778	0.000000	0.307024

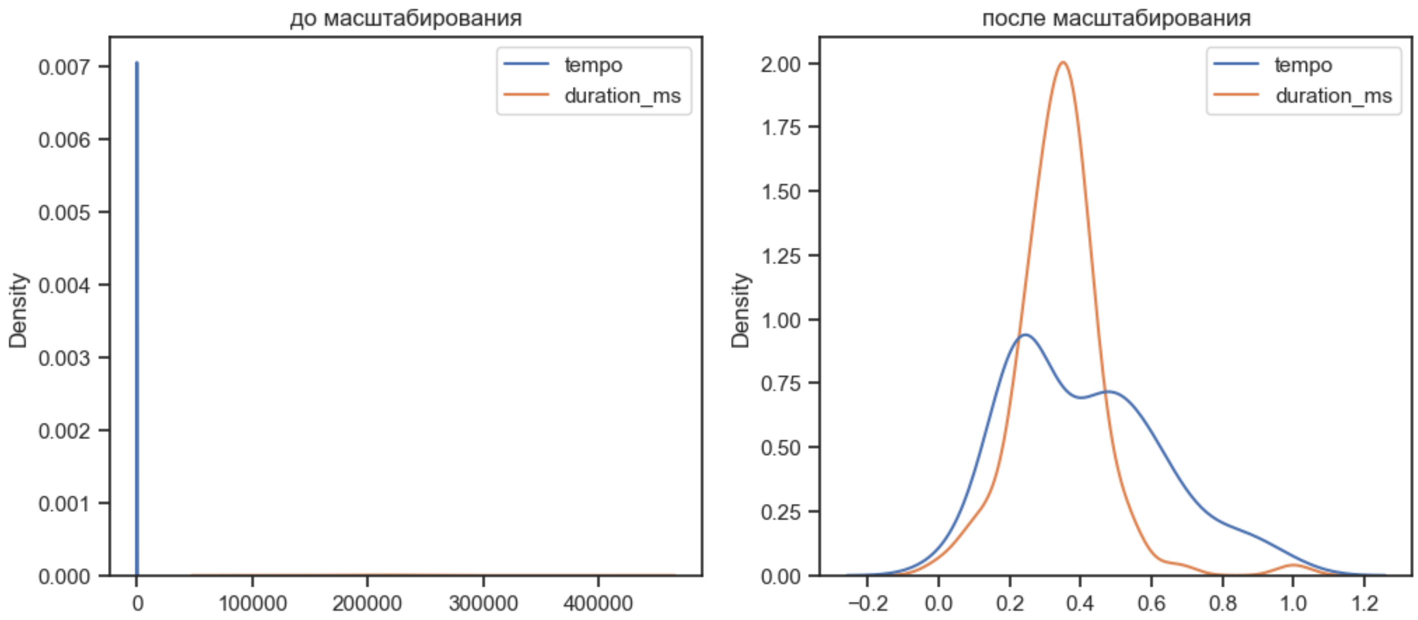
	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	valence
50%	0.672805	0.623165	0.454545	0.588026	1.000000	0.102111	0.116436	0.000000	0.459126
75%	0.765227	0.776917	0.750000	0.743722	1.000000	0.224546	0.265035	0.000230	0.659972
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [18]:

```
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)
```

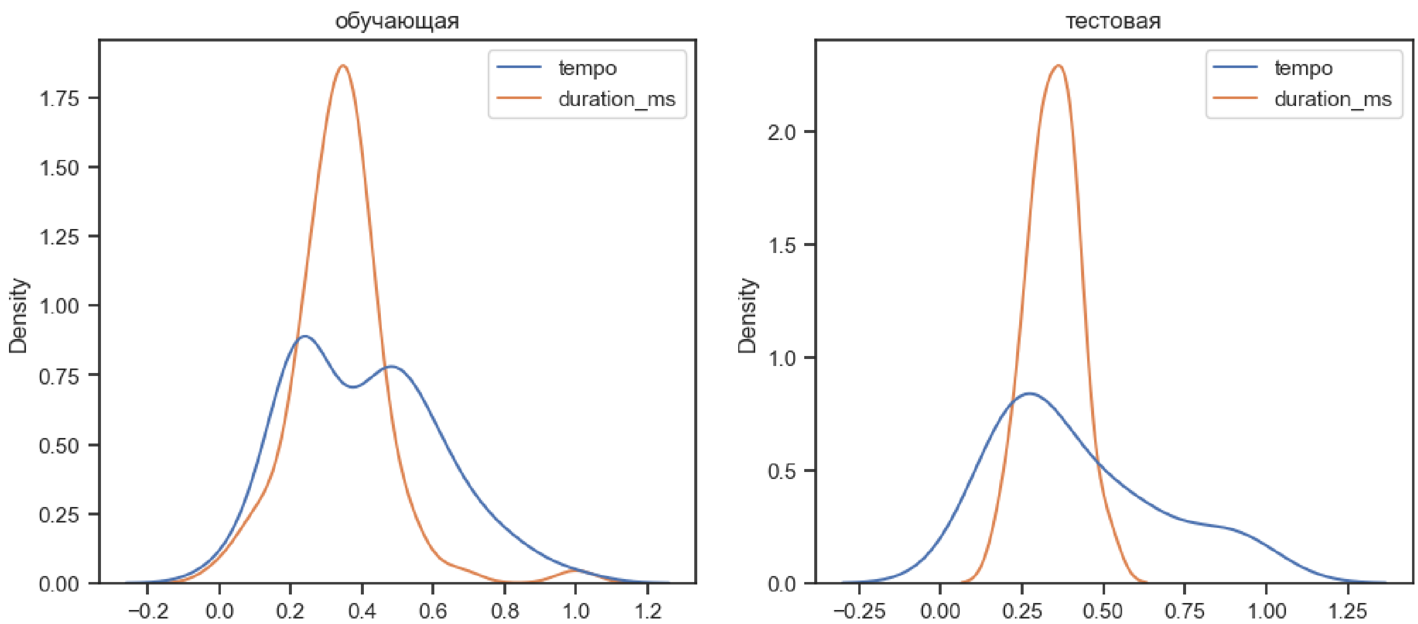
In [19]:

```
draw_kde(['tempo', 'duration_ms'], data, data_cs31_scaled, 'до масштабирования', 'после масштабирования')
```



In [20]:

```
draw_kde(['tempo', 'duration_ms'], data_cs32_scaled_train, data_cs32_scaled_test, 'обучающая', 'тестовая')
```



Обработка выбросов для числовых признаков

In [21]:

```
data2 = pd.read_csv('/Users/da.karpov/Desktop/МАГА/УЧЕБА/2 сем/ML_MSc_1course/датасеты/AB
_NYC_2019.csv')
```

In [22]:

```
data2.head()
```

Out[22]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80

In [23]:

```
data2.describe()
```

Out[23]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_|
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	388
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	

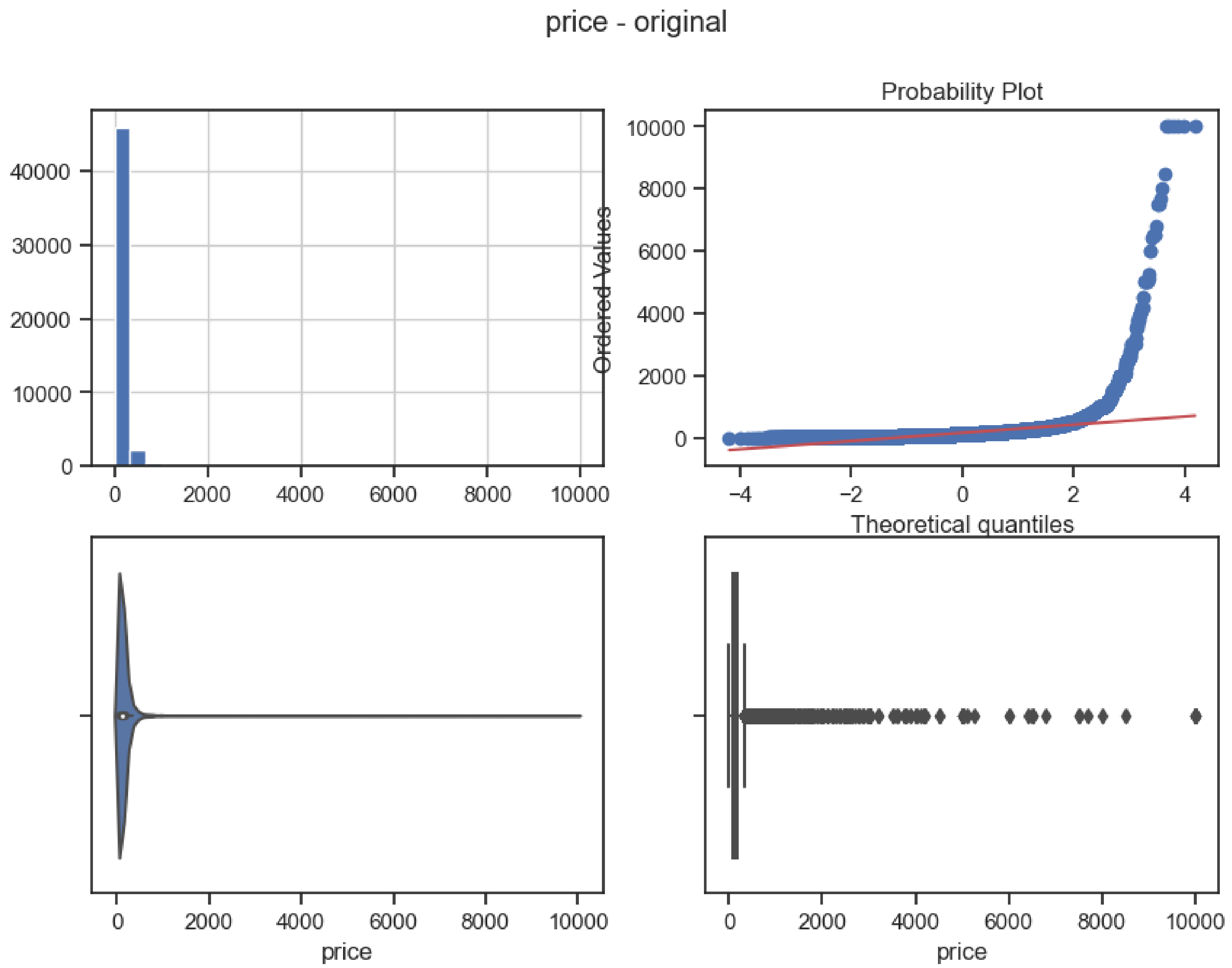
In [24]:

```
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()
```

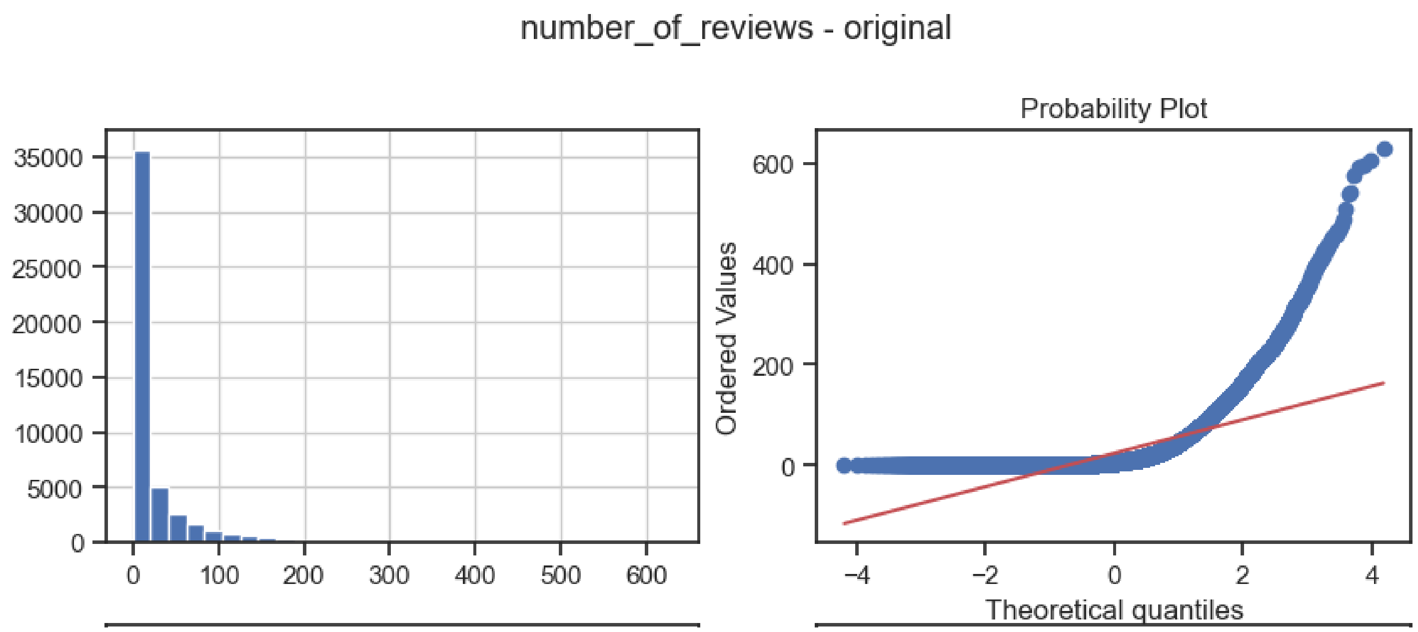
In [25]:

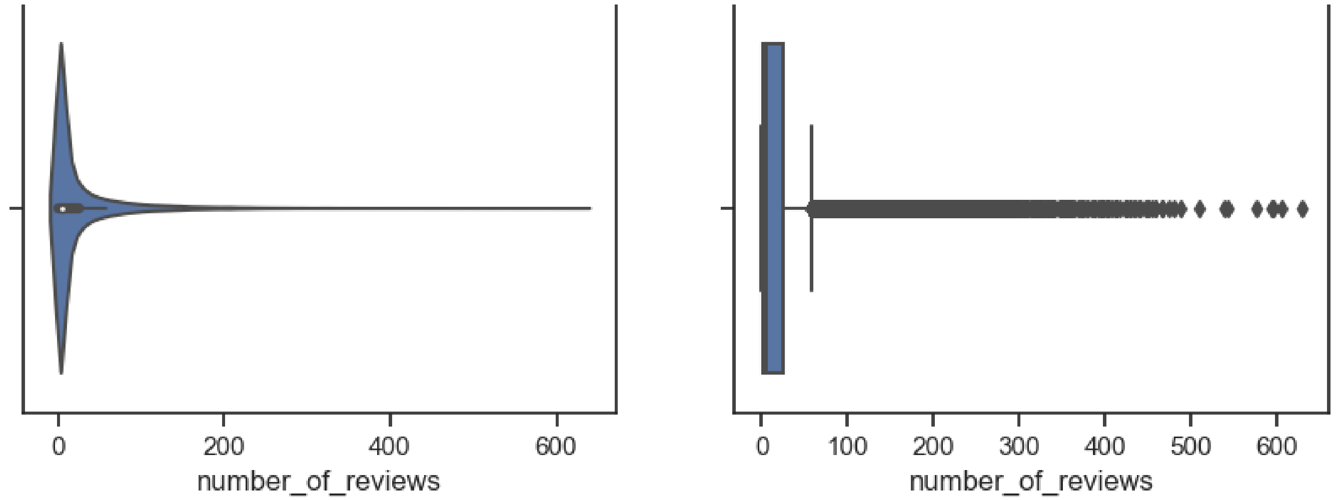
```
diagnostic_plots(data2, 'price', 'price - original')
```



In [26]:

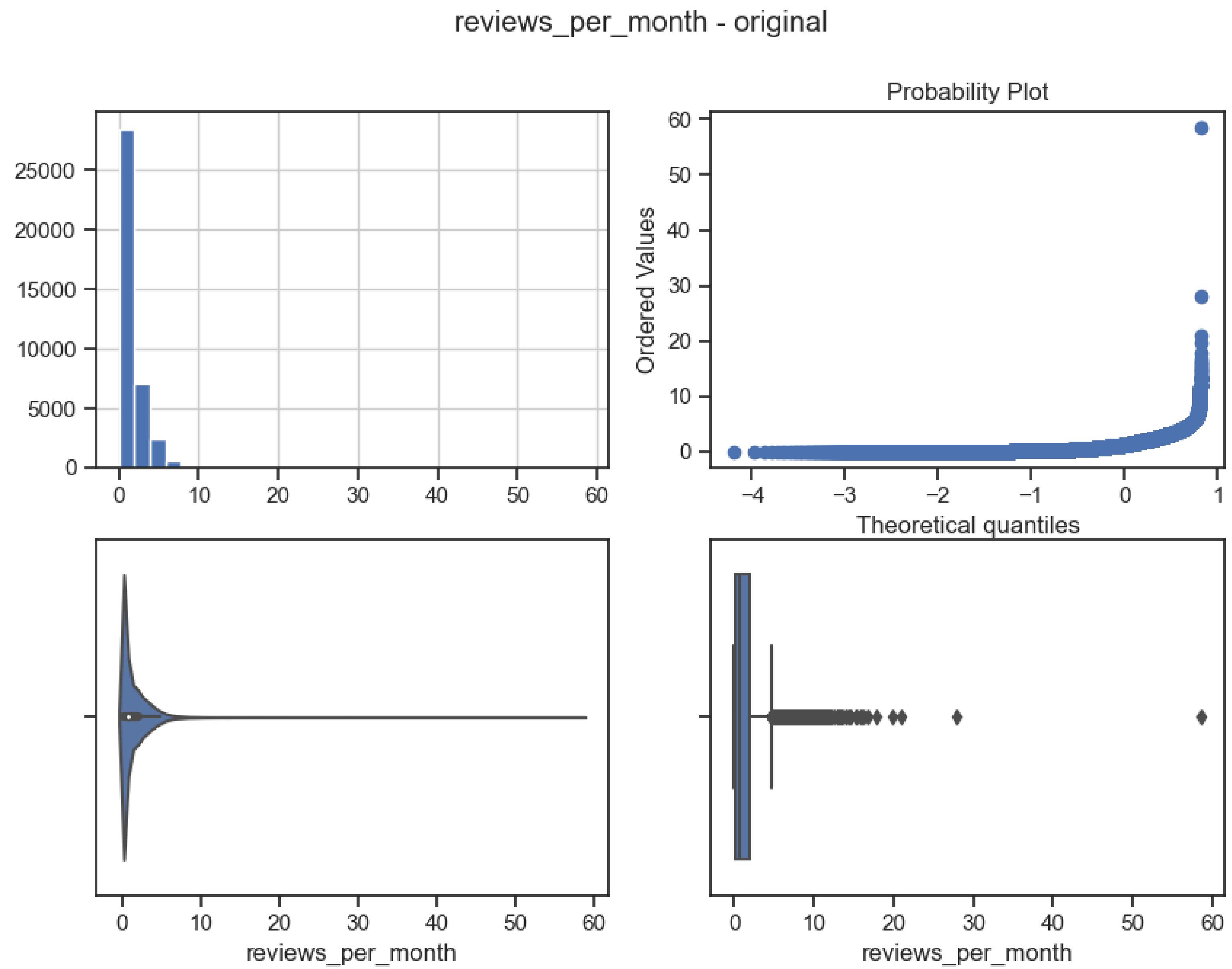
```
diagnostic_plots(data2, 'number_of_reviews', 'number_of_reviews - original')
```





In [27]:

```
diagnostic_plots(data2, 'reviews_per_month', 'reviews_per_month - original')
```



Явно заметны выбросы на полях**: number_of_reviews, reviews_per_month, price**

In [28]:

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

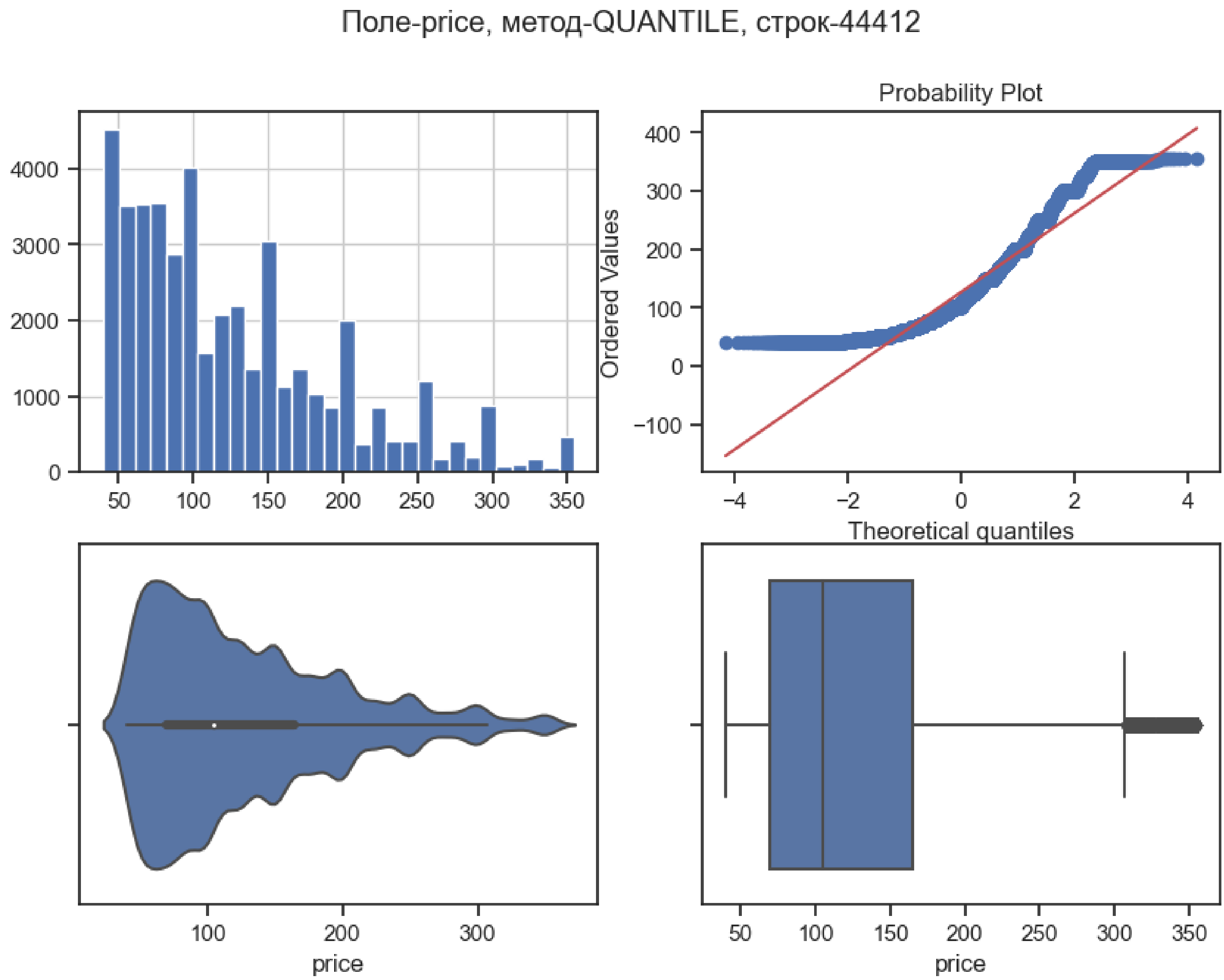
In [29]:

```
# Функция вычисления верхней и нижней границы выбросов
def get_outlier_boundaries(df, col):
    lower_boundary = df[col].quantile(0.05)
    upper_boundary = df[col].quantile(0.95)
    return lower_boundary, upper_boundary
```

Удаление выбросов (**number_of_reviews**)

In [30]:

```
# Вычисление верхней и нижней границы
lower_boundary, upper_boundary = get_outlier_boundaries(data2, "price")
# Флаги для удаления выбросов
outliers_temp = np.where(data2["price"] > upper_boundary, True,
                         np.where(data2["price"] < lower_boundary, True, False))
# Удаление данных на основе флага
data_trimmed = data2.loc[~(outliers_temp), ]
title = 'Поле-{}, метод-{}, строк-{}'.format("price", "QUANTILE", data_trimmed.shape[0])
diagnostic_plots(data_trimmed, "price", title)
```

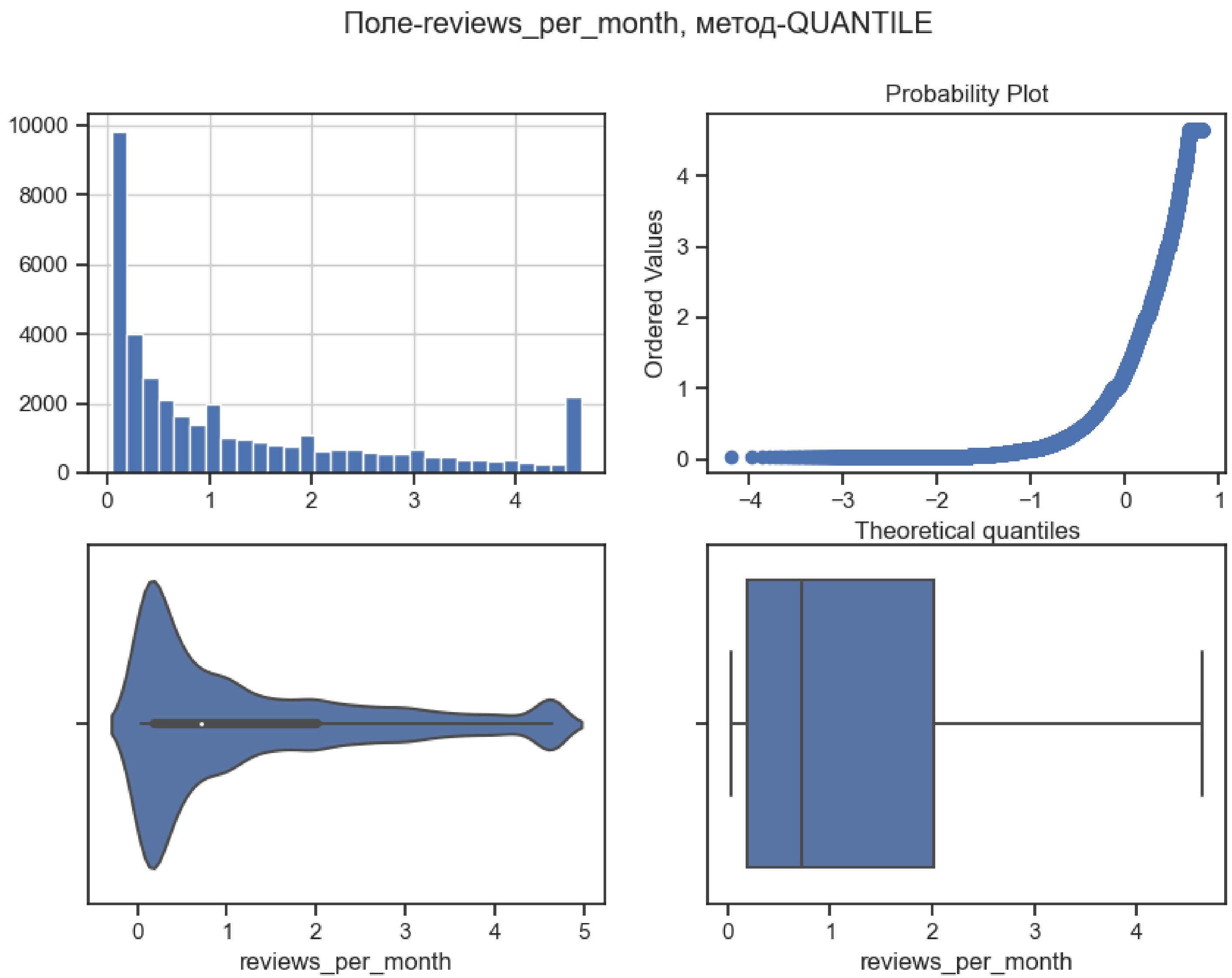


Замена выбросов

In [31]:

```
# Вычисление верхней и нижней границы
lower_boundary, upper_boundary = get_outlier_boundaries(data2, "reviews_per_month")
# Изменение данных
data2["reviews_per_month"] = np.where(data2["reviews_per_month"] > upper_boundary, upper
_boundary,
```

```
                    np.where(data2["reviews_per_month"] < lower_boundary, lower_boundar
y, data2["reviews_per_month"]))
title = 'Поле-{}, метод-{}'.format("reviews_per_month", "QUANTILE")
diagnostic_plots(data2, "reviews_per_month", title)
```



Обработка нестандартного признака

In [32]:

```
data2.dtypes
```

Out[32]:

```
id                                  int64
name                               object
host_id                             int64
host_name                          object
neighbourhood_group                object
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
price                               int64
minimum_nights                      int64
number_of_reviews                   int64
last_review                        object
reviews_per_month                 float64
calculated_host_listings_count      int64
availability_365                    int64
dtype: object
```

In [33]:

```
# Сконвертируем дату и время в нужный формат
data2["last_review_date"] = data2.apply(lambda x: pd.to_datetime(x["last_review"], forma
t='%Y/%m/%d'), axis=1)
```

In [34]:

```
data2.head(5)
```

Out[34]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80

In [35]:

```
data2.dtypes
```

Out[35]:

```
id                                           int64
name                                        object
host_id                                      int64
host_name                                   object
neighbourhood_group                         object
neighbourhood                               object
latitude                                   float64
longitude                                  float64
room_type                                   object
price                                        int64
minimum_nights                               int64
number_of_reviews                            int64
last_review                                 object
reviews_per_month                          float64
calculated_host_listings_count               int64
availability_365                             int64
last_review_date                    datetime64[ns]
dtype: object
```

In [36]:

```
# День
data2['last_review_day'] = data2['last_review_date'].dt.day
# Месяц
data2['last_review_month'] = data2['last_review_date'].dt.month
# Год
data2['last_review_year'] = data2['last_review_date'].dt.year
```

In [37]:

```
data2.head(5)
```

Out[37]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80