Лабораторная работа 3. Выполнил Зоров Владислав Витальевич ИУ5-22м

Задание: Выбрать один или несколько наборов данных (датасетов) для решения следующих задач. Каждая задача может быть решена на отдельном датасете, или несколько задач могут быть решены на одном датасете. Просьба не использовать датасет, на котором данная задача решалась в лекции. 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]:

```
# !pip install scikit-learn
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
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting scikit-learn
  Downloading scikit_learn-1.2.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.wh
l (9.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9.6/9.6 MB 174.2
 kB/s eta 0:00:00m eta 0:00:01[36m0:00:02
Requirement already satisfied: joblib>=1.1.1 in /home/user/.local/lib/python3.10/site-pack
ages (from scikit-learn) (1.2.0)
Requirement already satisfied: numpy>=1.17.3 in /usr/lib/python3/dist-packages (from sciki
t-learn) (1.21.5)
Collecting threadpoolctl>=2.0.0
  Downloading threadpoolctl-3.1.0-py3-none-any.whl (14 kB)
Requirement already satisfied: scipy>=1.3.2 in /usr/lib/python3/dist-packages (from scikit
-learn) (1.8.0)
Installing collected packages: threadpoolctl, scikit-learn
Successfully installed scikit-learn-1.2.2 threadpoolctl-3.1.0
```

In [2]:

```
data = pd.read_csv("data.csv")
```

In [3]:

```
data.head()
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0

5 rows × 81 columns

In [4]:

```
data = data.drop('Id', 1)
data.head()
```

```
<ipython-input-4-c100a8de87ec>:1: FutureWarning: In a future version of pandas all argumen
ts of DataFrame.drop except for the argument 'labels' will be keyword-only.
  data = data.drop('Id', 1)
```

Out[4]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	...	Pc
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside	...	
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2	...	
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside	...	
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner	...	
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2	...	

5 rows × 80 columns

In [5]:

```
# Удаление колонок с высоким процентом пропусков (более 25%)
data.dropna(axis=1, thresh=1095)
```

Out[5]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlop
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gt
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gt
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gt
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gt
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gt
...	...	...	...	...	...	...	...	...	...	.
1455	60	RL	62.0	7917	Pave	Reg	Lvl	AllPub	Inside	Gt
1456	20	RL	85.0	13175	Pave	Reg	Lvl	AllPub	Inside	Gt
1457	70	RL	66.0	9042	Pave	Reg	Lvl	AllPub	Inside	Gt
1458	20	RL	68.0	9717	Pave	Reg	Lvl	AllPub	Inside	Gt
1459	20	RL	75.0	9937	Pave	Reg	Lvl	AllPub	Inside	Gt

1460 rows × 75 columns

In [6]:

```
# Заполним пропуски средними значениями
def impute_na(df, variable, value):
```

```
    df[variable].fillna(value, inplace=True)
impute_na(data, 'LotFrontage', data['LotFrontage'].mean())
```

In [7]:

```
data.describe()
```

Out[7]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrAre
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1452.00000
mean	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808	1984.865753	103.68526
std	42.300571	22.024023	9981.264932	1.382997	1.112799	30.202904	20.645407	181.06620
min	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	1950.000000	0.00000
25%	20.000000	60.000000	7553.500000	5.000000	5.000000	1954.000000	1967.000000	0.00000
50%	50.000000	70.049958	9478.500000	6.000000	5.000000	1973.000000	1994.000000	0.00000
75%	70.000000	79.000000	11601.500000	7.000000	6.000000	2000.000000	2004.000000	166.00000
max	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	2010.000000	1600.00000

8 rows × 37 columns

In [8]:

```
def obj_col(column):
    return column[1] == 'object'

col_names = []
for col in list(filter(obj_col, list(zip(list(data.columns), list(data.dtypes))))):
  col_names.append(col[0])
col_names.append('SalePrice')
```

In [9]:

```
X_ALL = data.drop(col_names, axis=1)
```

In [10]:

```
# 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 [11]:

```
# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['SalePrice'],
                                                    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[11]:

```
((1168, 36), (292, 36))
```

StandardScaler

In [12]:

```
# 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[12]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	Bsmt
0	0.073375	-0.229372	-0.207142	0.651479	-0.517200	1.050994	0.878668	0.510015	0.5
1	-0.872563	0.451936	-0.091886	-0.071836	2.179628	0.156734	-0.429577	-0.572835	1.1
2	0.073375	-0.093110	0.073480	0.651479	-0.517200	0.984752	0.830215	0.322174	0.0
3	0.309859	-0.456474	-0.096897	0.651479	-0.517200	-1.863632	-0.720298	-0.572835	-0.4
4	0.073375	0.633618	0.375148	1.374795	-0.517200	0.951632	0.733308	1.360826	0.4
...	...	...	...	...	...	...	...	...	
1455	0.073375	-0.365633	-0.260560	-0.071836	-0.517200	0.918511	0.733308	-0.572835	-0.9
1456	-0.872563	0.679039	0.266407	-0.071836	0.381743	0.222975	0.151865	0.084610	0.7
1457	0.309859	-0.183951	-0.147810	0.651479	3.078570	-1.002492	1.024029	-0.572835	-0.3
1458	-0.872563	-0.093110	-0.080160	-0.795151	0.381743	-0.704406	0.539493	-0.572835	-0.8
1459	-0.872563	0.224833	-0.058112	-0.795151	0.381743	-0.207594	-0.962566	-0.572835	0.8

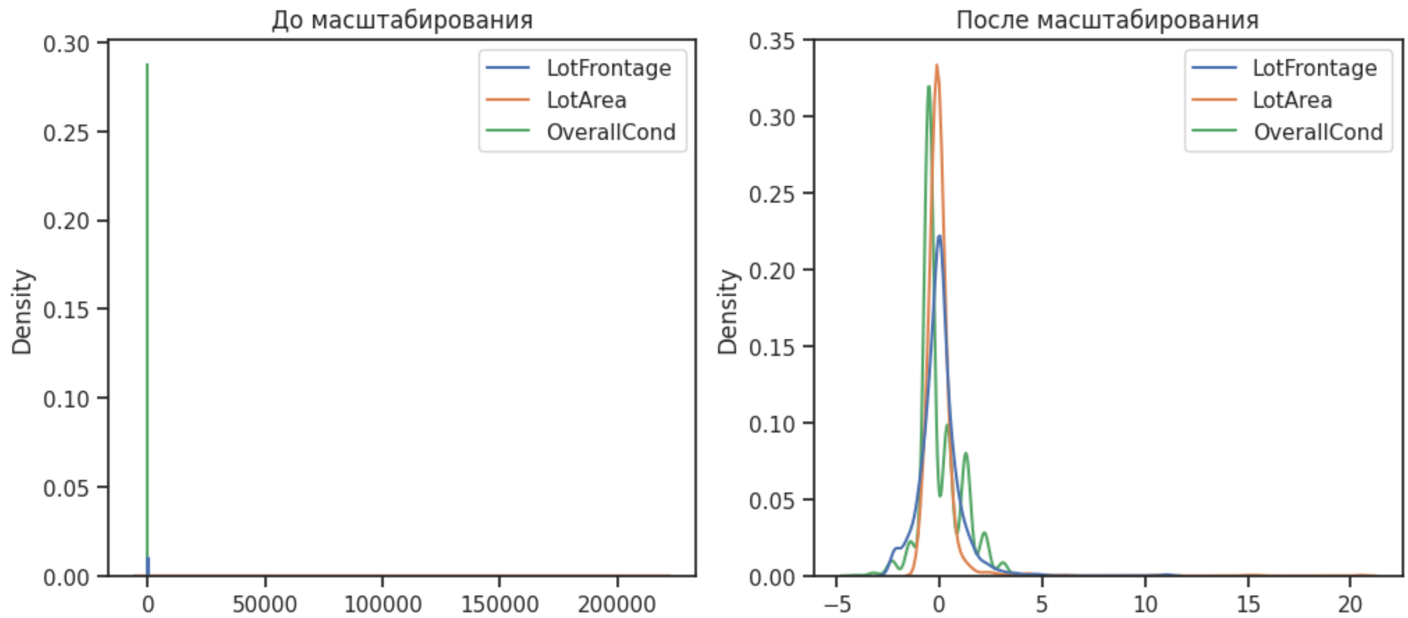
1460 rows × 36 columns

In [13]:

```
# 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 [14]:

```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data, data_cs11_scaled, 'До масштабиро
```



Масштабирование "Mean Normalisation"

In [15]:

```
# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['SalePrice'],
                                                    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[15]:

```
((1168, 36), (292, 36))
```

In [16]:

```
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 [17]:

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

Out[17]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1452.000000
mean	0.000962	-0.000452	-0.000119	-0.003900	-0.003058	-0.003544	-0.008644	-0.000898

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
std	0.248827	0.075425	0.046653	0.153666	0.158971	0.218862	0.344090	0.113166
min	-0.216081	-0.168431	-0.043200	-0.570491	-0.656678	-0.722876	-0.589740	-0.065702
25%	-0.216081	-0.034869	-0.013970	-0.126046	-0.085250	-0.128673	-0.306407	-0.065702
50%	-0.039610	-0.000452	-0.004973	-0.014935	-0.085250	0.009008	0.143593	-0.065702
75%	0.078037	0.030199	0.004951	0.096176	0.057608	0.204661	0.310260	0.038048
max	0.783919	0.831569	0.956800	0.429509	0.486179	0.277124	0.410260	0.934298

8 rows × 36 columns

In [18]:
```
cs22 = MeanNormalisation()
cs22.fit(X_train)
data_cs22_scaled_train = cs22.transform(X_train)
data_cs22_scaled_test = cs22.transform(X_test)
```

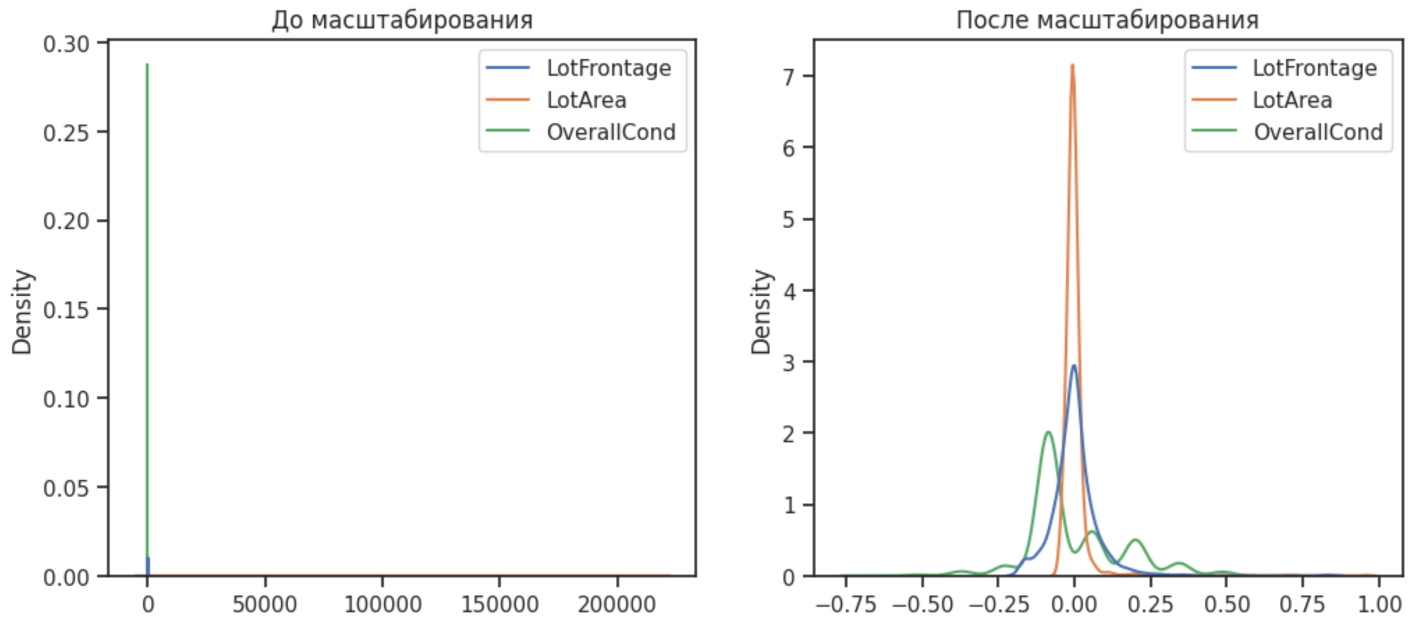
In [19]:
```
data_cs22_scaled_train.describe()
```

Out[19]:

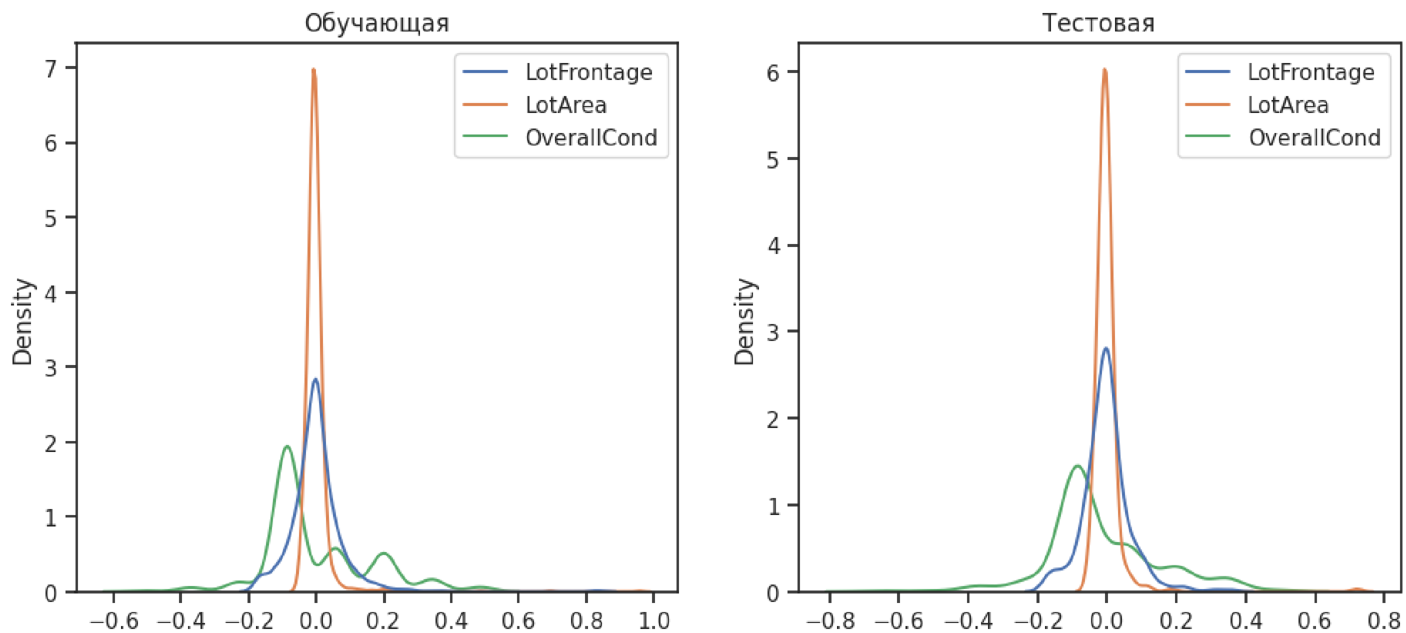
	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	Mas
count	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+03	1.160
mean	-1.672939e-17	1.392531e-17	-1.140640e-18	2.718526e-17	9.125121e-18	7.224054e-16	-1.502508e-15	-2.5
std	2.475340e-01	7.707084e-02	4.616115e-02	1.522067e-01	1.587482e-01	2.195064e-01	3.431316e-01	1.112
min	-2.160808e-01	-1.684311e-01	-4.319969e-02	-5.704909e-01	-5.138209e-01	-7.228757e-01	-5.897403e-01	-6.5
25%	-2.160808e-01	-3.486947e-02	-1.422028e-02	-1.260464e-01	-8.524951e-02	-1.286728e-01	-2.897403e-01	-6.5
50%	-3.961019e-02	-4.518024e-04	-4.865072e-03	-1.493531e-02	-8.524951e-02	1.625472e-02	1.435930e-01	-6.5
75%	7.803687e-02	3.019903e-02	5.045185e-03	9.617580e-02	5.760763e-02	2.119069e-01	3.102597e-01	4.070
max	7.839192e-01	8.315689e-01	9.568003e-01	4.295091e-01	4.861791e-01	2.771243e-01	4.102597e-01	9.342

8 rows × 36 columns

In [20]:
```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data, data_cs21_scaled, 'До масштабиро
```



In [21]:
```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data_cs22_scaled_train, data_cs22_sca
```



MinMax-масштабирование

In [22]:
```
# 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[22]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1452.000000
mean	0.217043	0.167979	0.043080	0.566591	0.571918	0.719332	0.581096	0.064803
std	0.248827	0.075425	0.046653	0.153666	0.139100	0.218862	0.344090	0.113166
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea
25%	0.000000	0.133562	0.029229	0.444444	0.500000	0.594203	0.283333	0.000000
50%	0.176471	0.167979	0.038227	0.555556	0.500000	0.731884	0.733333	0.000000
75%	0.294118	0.198630	0.048150	0.666667	0.625000	0.927536	0.900000	0.103750
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

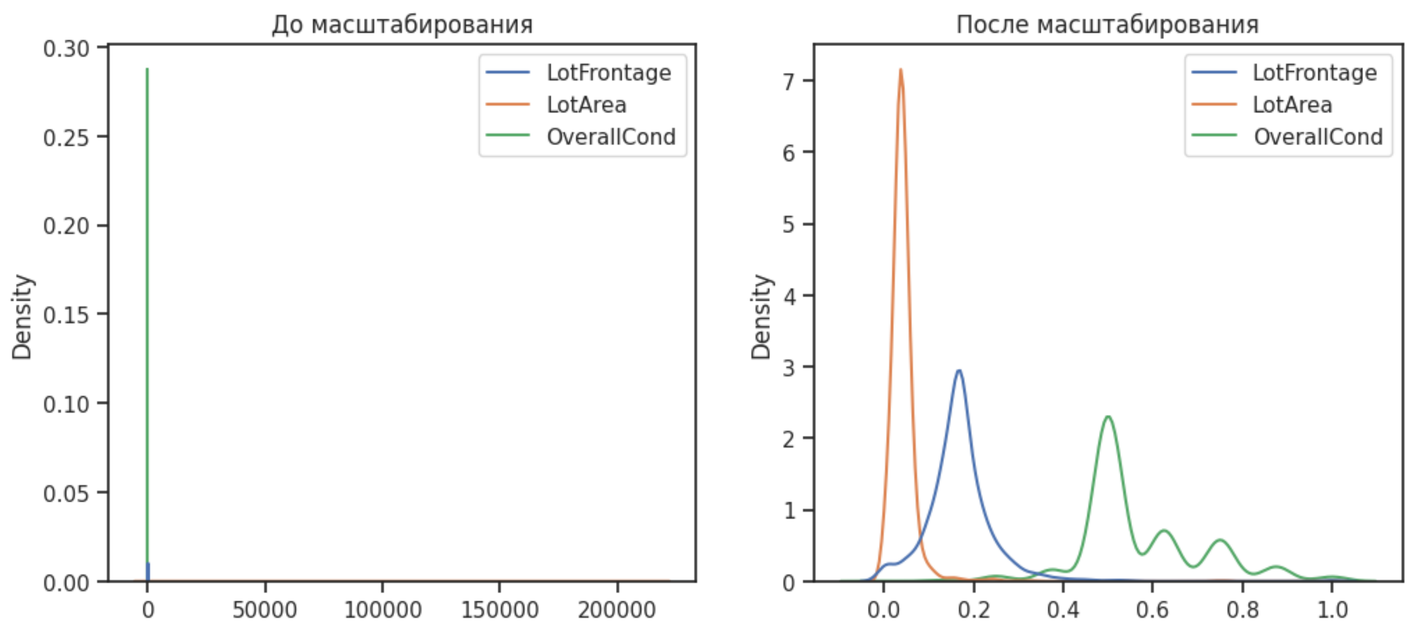
8 rows × 36 columns

In [23]:

```
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)
```

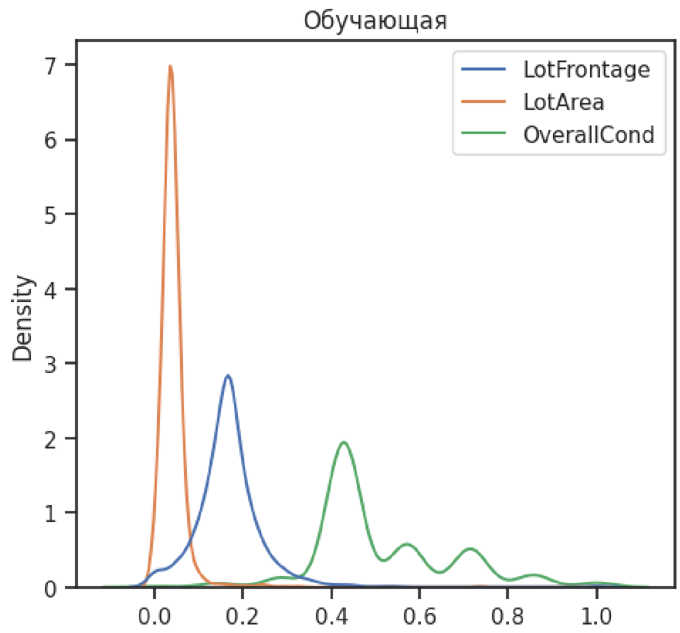
In [24]:

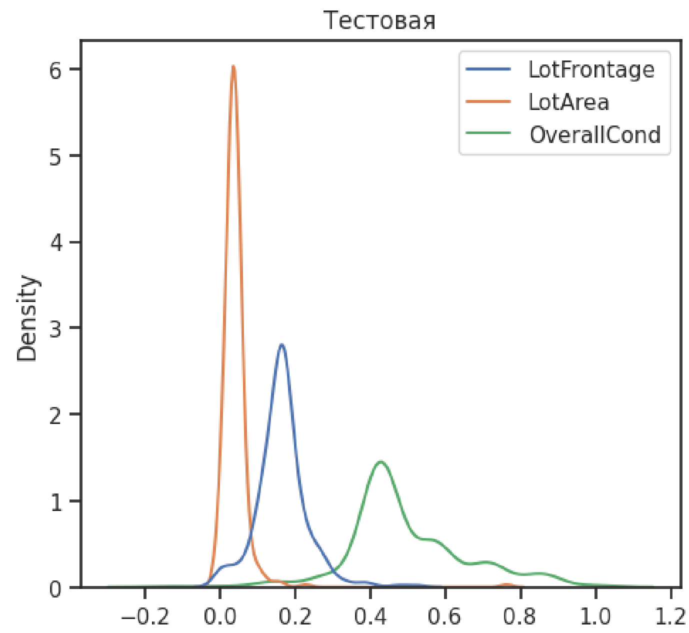
```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data, data_cs31_scaled, 'До масштабиро
```



In [25]:

```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data_cs32_scaled_train, data_cs32_scal
```





Обработка выбросов для числовых признаков

In [26]:

```
data2 = pd.read_csv("Car_sales.csv")
```

In [27]:

```
data2.head()
```

Out[27]:

	Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	Price_in_thousands	Engine_size	Hors
0	Acura	Integra	16.919	16.360	Passenger	21.50	1.8	
1	Acura	TL	39.384	19.875	Passenger	28.40	3.2	
2	Acura	CL	14.114	18.225	Passenger	NaN	3.2	
3	Acura	RL	8.588	29.725	Passenger	42.00	3.5	
4	Audi	A4	20.397	22.255	Passenger	23.99	1.8	

In [28]:

```
data2.describe()
```

Out[28]:

	Sales_in_thousands	__year_resale_value	Price_in_thousands	Engine_size	Horsepower	Wheelbase	Width
count	157.000000	121.000000	155.000000	156.000000	156.000000	156.000000	156.000000
mean	52.998076	18.072975	27.390755	3.060897	185.948718	107.487179	71.150000
std	68.029422	11.453384	14.351653	1.044653	56.700321	7.641303	3.451872
min	0.110000	5.160000	9.235000	1.000000	55.000000	92.600000	62.600000
25%	14.114000	11.260000	18.017500	2.300000	149.500000	103.000000	68.400000
50%	29.450000	14.180000	22.799000	3.000000	177.500000	107.000000	70.550000
75%	67.956000	19.875000	31.947500	3.575000	215.000000	112.200000	73.425000
max	540.561000	67.550000	85.500000	8.000000	450.000000	138.700000	79.900000

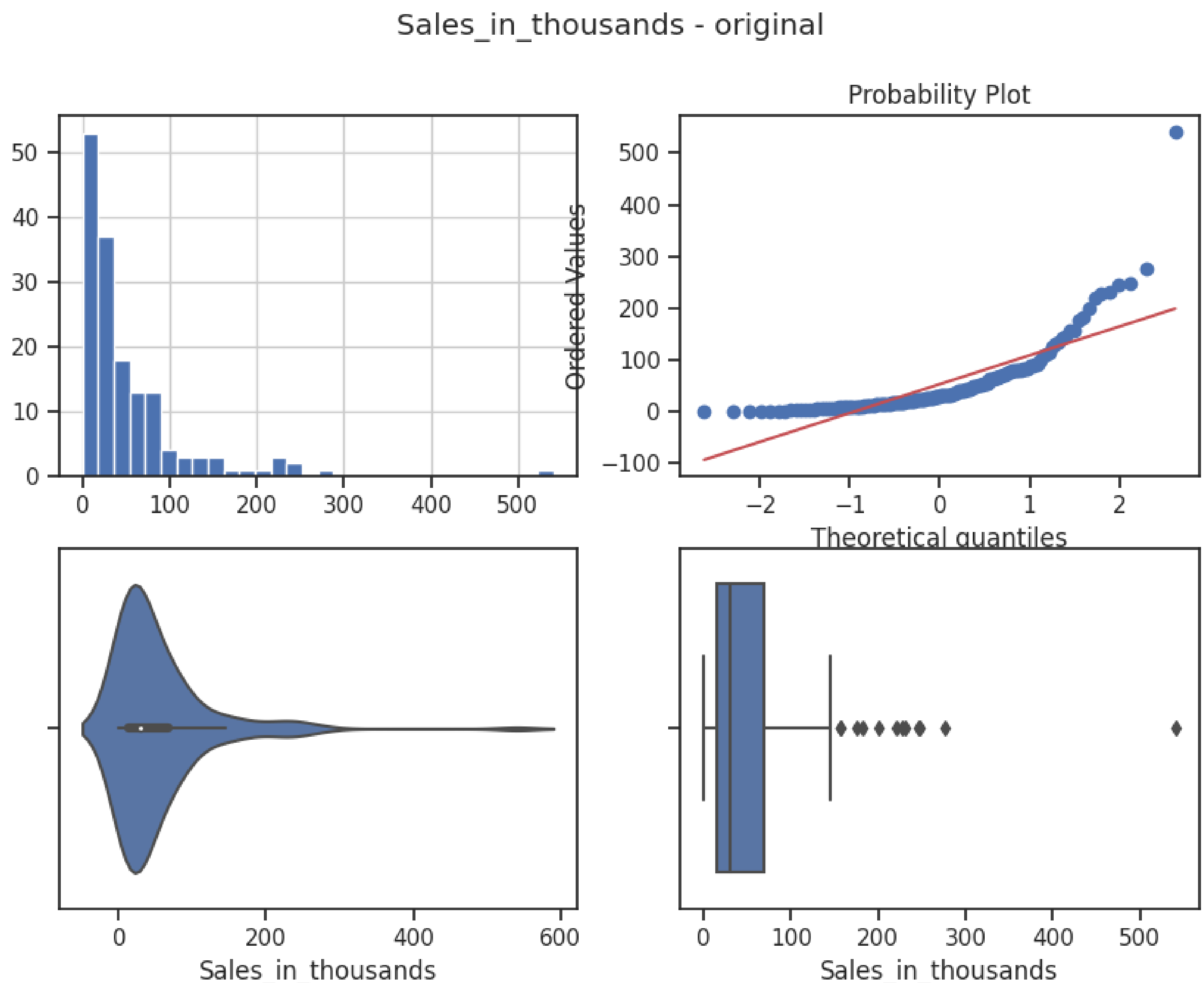
In [29]:

```
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)
    # violinplot
    plt.subplot(2, 2, 3)
    sns.violinplot(x=df[variable])
    # boxplot
    plt.subplot(2, 2, 4)
    sns.boxplot(x=df[variable])
    fig.suptitle(title)
    plt.show()
```

In [30]:
```
diagnostic_plots(data2, 'Sales_in_thousands', 'Sales_in_thousands - original')
```

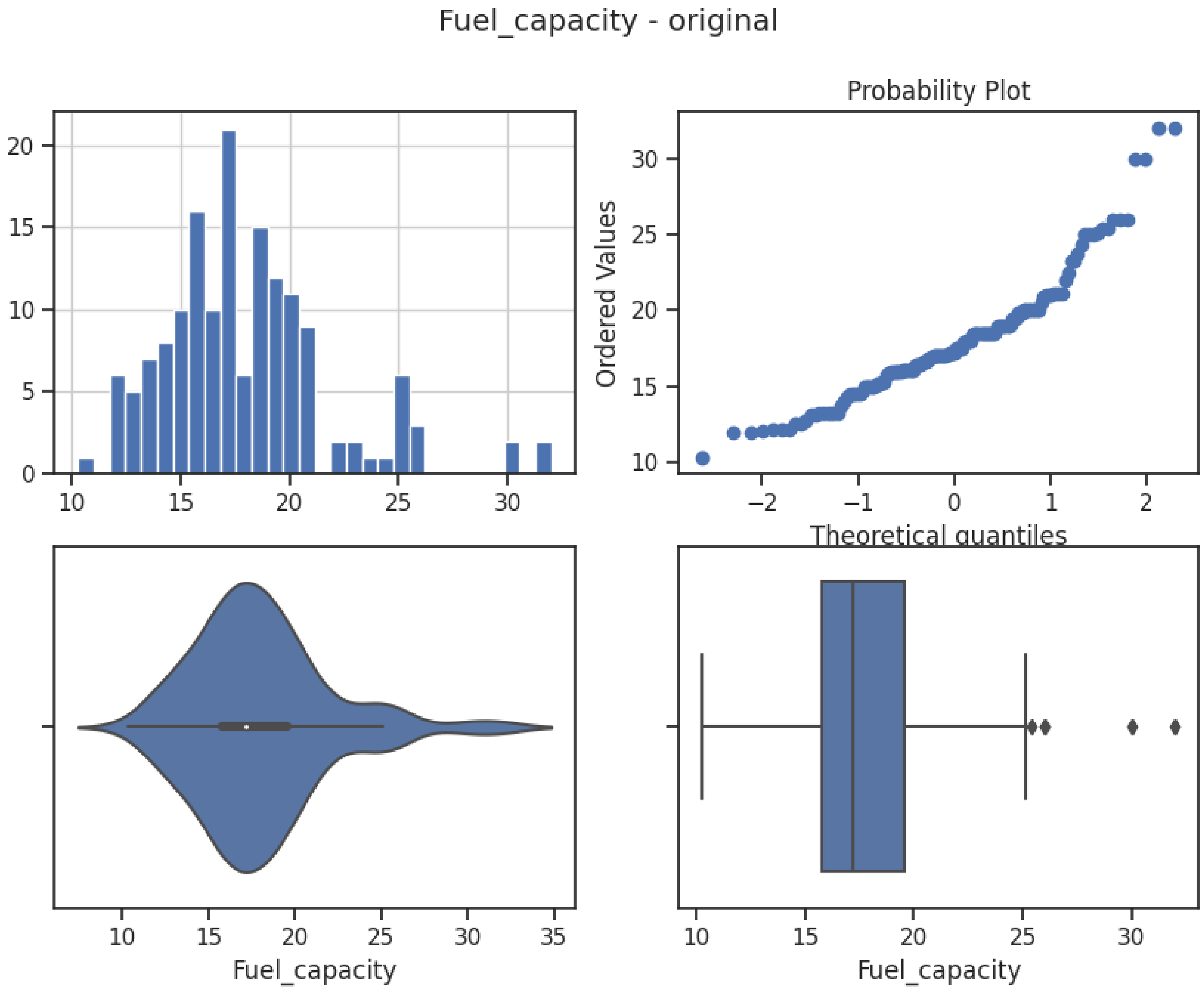
```
<ipython-input-29-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlappi
ng axes is deprecated since 3.6 and will be removed two minor releases later; explicitly c
all ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



In [31]:
```
diagnostic_plots(data2, 'Fuel_capacity', 'Fuel_capacity - original')
```

```
<ipython-input-29-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlappi
```

```
ng axes is deprecated since 3.6 and will be removed two minor releases later; explicitly c
all ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



In [32]:

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

In [33]:

```
# 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
```

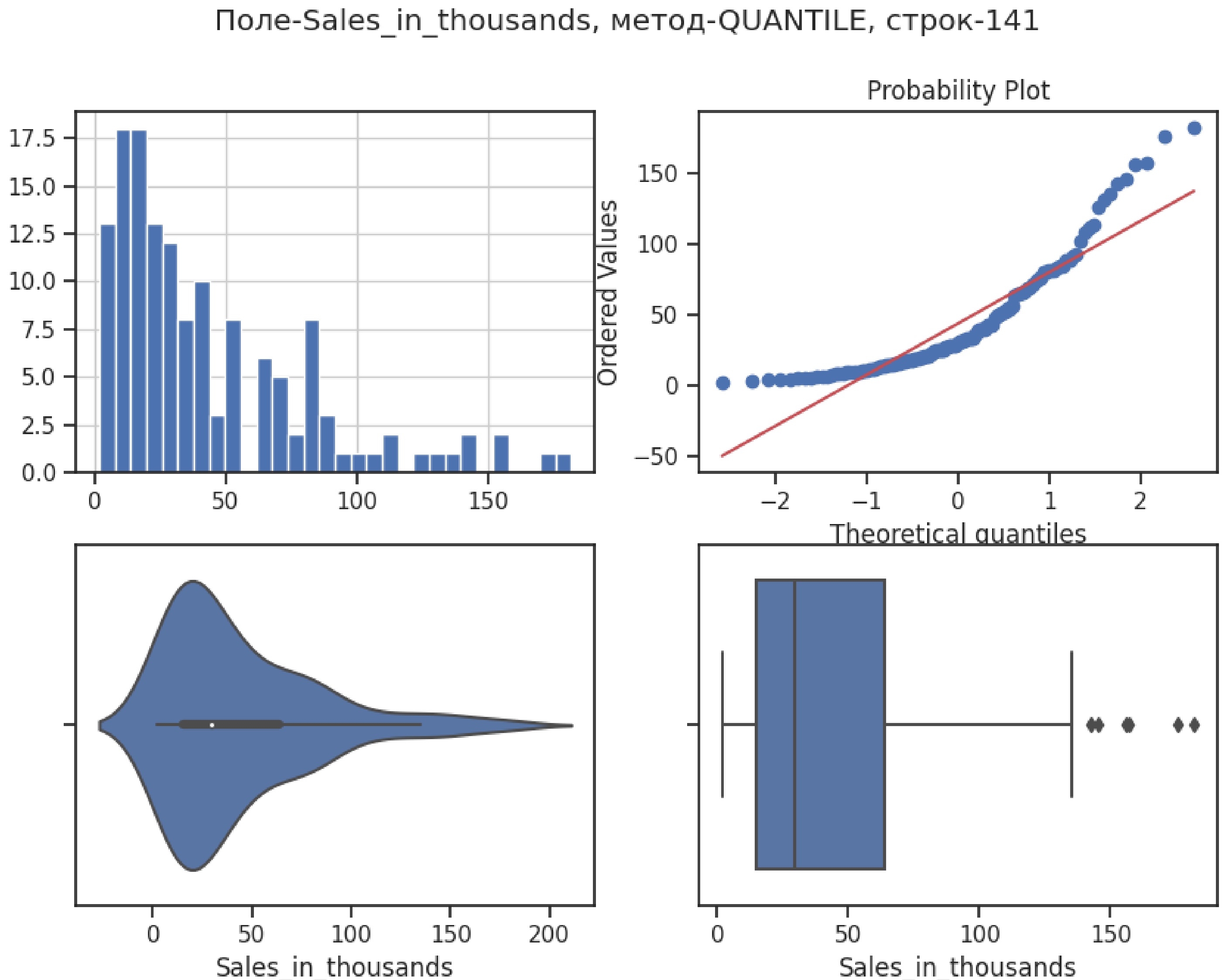
Удаление выбросов (number_of_reviews)

In [34]:

```
# Вычисление верхней и нижней границы
lower_boundary, upper_boundary = get_outlier_boundaries(data2, "Sales_in_thousands")
# Флаги для удаления выбросов
outliers_temp = np.where(data2["Sales_in_thousands"] > upper_boundary, True,
                         np.where(data2["Sales_in_thousands"] < lower_boundary, True, Fals
```

```
# Удаление данных на основе флага
data_trimmed = data2.loc[~(outliers_temp), ]
title = 'Поле-{}, метод-{}, строк-{}'.format("Sales_in_thousands", "QUANTILE", data_trimme
diagnostic_plots(data_trimmed, "Sales_in_thousands", title)
```

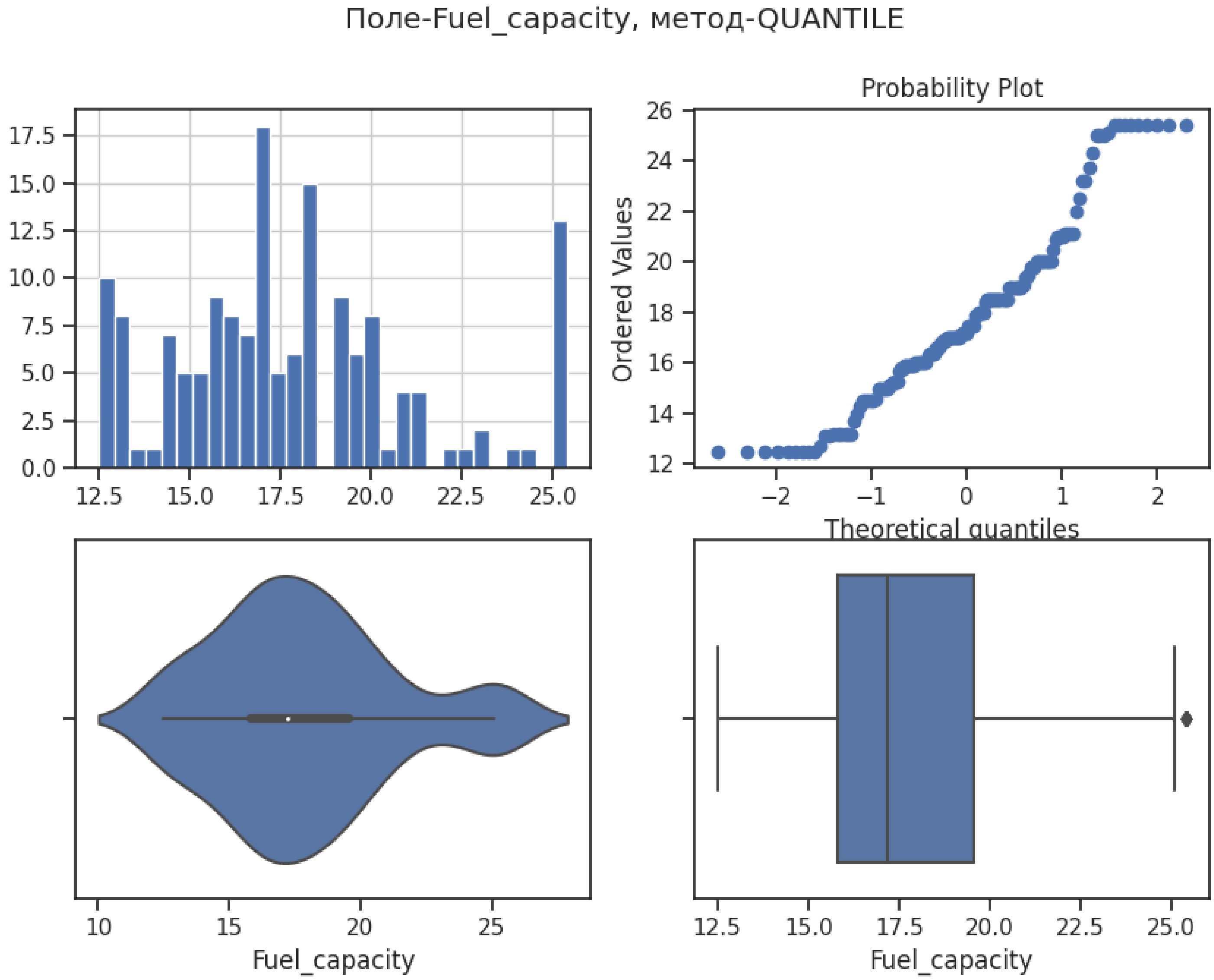
```
<ipython-input-29-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlappi
ng axes is deprecated since 3.6 and will be removed two minor releases later; explicitly c
all ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



Замена выбросов

In [35]:
```
# Вычисление верхней и нижней границы
lower_boundary, upper_boundary = get_outlier_boundaries(data2, "Fuel_capacity")
# Изменение данных
data2["Fuel_capacity"] = np.where(data2["Fuel_capacity"] > upper_boundary, upper_boundary,
                         np.where(data2["Fuel_capacity"] < lower_boundary, lower_boundary, dat
title = 'Поле-{}, метод-{}'.format("Fuel_capacity", "QUANTILE")
diagnostic_plots(data2, "Fuel_capacity", title)
```

```
<ipython-input-29-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlappi
ng axes is deprecated since 3.6 and will be removed two minor releases later; explicitly c
all ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



Обработка нестандартного признака

In [36]:
```
data2.dtypes
```

Out[36]:
```
Manufacturer            object
Model                   object
Sales_in_thousands     float64
__year_resale_value    float64
Vehicle_type            object
Price_in_thousands     float64
Engine_size            float64
Horsepower             float64
Wheelbase              float64
Width                  float64
Length                 float64
Curb_weight            float64
Fuel_capacity          float64
Fuel_efficiency        float64
Latest_Launch           object
Power_perf_factor      float64
dtype: object
```

In [37]:
```
# Сконвертируем дату и время в нужный формат
data2["Latest_Launch_Date"] = data2.apply(lambda x: pd.to_datetime(x["Latest_Launch"], for
```

In [38]:
```
data2.head(5)
```

Out[38]:

	Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	Price_in_thousands	Engine_size	Hors
0	Acura	Integra	16.919	16.360	Passenger	21.50	1.8	
1	Acura	TL	39.384	19.875	Passenger	28.40	3.2	
2	Acura	CL	14.114	18.225	Passenger	NaN	3.2	
3	Acura	RL	8.588	29.725	Passenger	42.00	3.5	
4	Audi	A4	20.397	22.255	Passenger	23.99	1.8	

In [39]:
```
data2.dtypes
```

Out[39]:
```
Manufacturer                    object
Model                           object
Sales_in_thousands             float64
__year_resale_value            float64
Vehicle_type                    object
Price_in_thousands             float64
Engine_size                    float64
Horsepower                     float64
Wheelbase                      float64
Width                          float64
Length                         float64
Curb_weight                    float64
Fuel_capacity                  float64
Fuel_efficiency                float64
Latest_Launch                   object
Power_perf_factor              float64
Latest_Launch_Date      datetime64[ns]
dtype: object
```

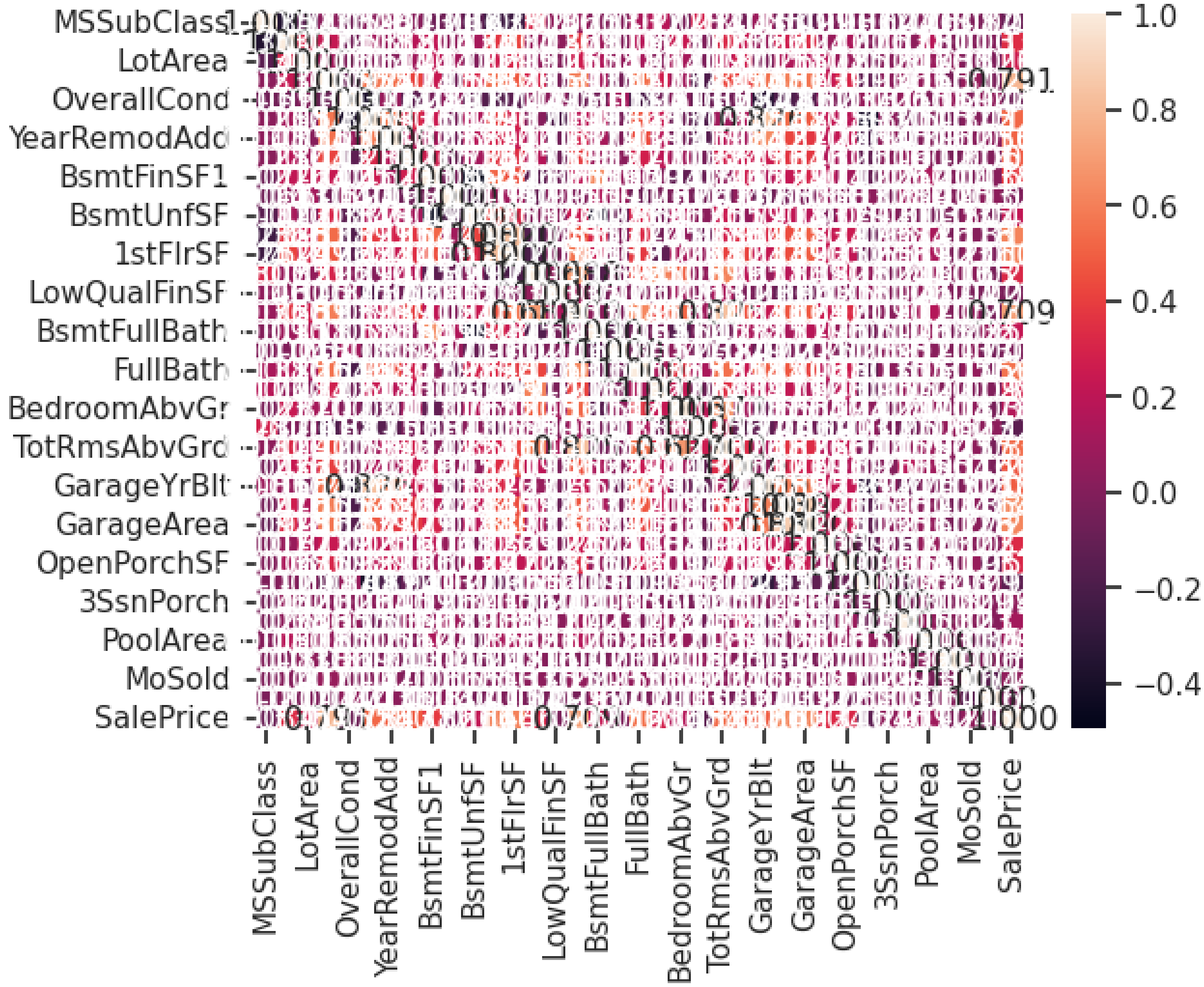
In [40]:
```
# День
data2['Latest_Launch_Day'] = data2['Latest_Launch_Date'].dt.day
# Месяц
data2['Latest_Launch_Month'] = data2['Latest_Launch_Date'].dt.month
# Год
data2['Latest_Launch_Year'] = data2['Latest_Launch_Date'].dt.year
```

Отбор признаков

Метод фильтрации (Корреляция признаков)

In [41]:
```
sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

Out[41]:
```
<Axes: >
```



In [42]:

```python
# Формирование DataFrame с сильными корреляциями
def make_corr_df(df):
    cr = data.corr()
    cr = cr.abs().unstack()
    cr = cr.sort_values(ascending=False)
    cr = cr[cr >= 0.3]
    cr = cr[cr < 1]
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']
    return cr
```

In [43]:

```python
# 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 [44]:

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

Out[44]:
```
[['GarageArea',
  'SalePrice',
  'OverallQual',
  'GarageYrBlt',
  'YearBuilt',
  'FullBath',
  'GrLivArea',
  '1stFlrSF',
  'TotalBsmtSF',
  'YearRemodAdd',
  'MasVnrArea',
  'TotRmsAbvGrd',
  'Fireplaces',
  'GarageCars'],
 ['GrLivArea',
  'TotRmsAbvGrd',
  'HalfBath',
  'BedroomAbvGr',
  'FullBath',
  'SalePrice',
  'MSSubClass',
  '2ndFlrSF'],
 ['BsmtFullBath',
  'TotalBsmtSF',
  'BsmtUnfSF',
  '1stFlrSF',
  'SalePrice',
  'BsmtFinSF1'],
 ['1stFlrSF',
  'GrLivArea',
  'TotalBsmtSF',
  'MSSubClass',
  'SalePrice',
  'GarageArea',
  'TotRmsAbvGrd',
  'LotArea',
  'LotFrontage'],
 ['YearBuilt', 'EnclosedPorch'],
 ['YearBuilt', 'GarageYrBlt', 'OverallCond'],
 ['GrLivArea', 'SalePrice', 'OverallQual', 'OpenPorchSF'],
 ['SalePrice', 'WoodDeckSF']]
```

Метод из группы методов вложений

In [45]:
```
data3 = pd.read_csv("WineQT.csv", sep=",")
```

In [46]:
```
X3_ALL = data3.drop(['quality'], axis=1)
```

In [47]:
```
# Разделим выборку на обучающую и тестовую
X3_train, X3_test, y3_train, y3_test = train_test_split(X3_ALL, data3['quality'],
                                                        test_size=0.2,
                                                        random_state=1)
```

In [48]:
```
# Используем L1-регуляризацию
e_lr1 = LogisticRegression(C=1000, solver='liblinear', penalty='l1', max_iter=500, random_
e_lr1.fit(X3_train, y3_train)
# Коэффициенты регрессии
e_lr1.coef_
```

```
array([[ 8.12685010e-01,  1.13666762e+01,  7.82623669e+00,
```

Out[48]:
```
         2.73003859e-01,  2.20854445e+00, -8.14499398e-02,
        -6.07359291e-02, -9.71364320e+00,  1.05928330e+01,
        -3.02935401e+00, -3.49793957e+00,  4.48070237e-03],
       [-1.70947991e-02,  3.42135554e+00, -1.21007833e-01,
         8.32452278e-02,  3.20689559e+00,  1.03669460e-02,
        -1.25693925e-02, -5.18479271e+00,  2.46658035e+00,
         9.88462824e-01, -2.04766665e-01, -4.73535890e-04],
       [-1.50633685e-01,  1.93721323e+00,  1.12321685e+00,
         1.01141678e-02,  1.55206374e+00, -1.74615115e-02,
         1.48826890e-02,  5.10001726e+00, -2.81228295e-02,
        -2.62509731e+00, -9.26899115e-01,  5.26799951e-05],
       [ 1.90322225e-01, -1.79843954e+00, -2.04300613e+00,
        -4.72955643e-02,  2.58455381e+00,  1.21352411e-02,
        -7.83754176e-03, -2.99949432e+00,  9.79232831e-01,
         8.78802257e-01,  2.38635326e-01,  1.63131072e-04],
       [-2.89452663e-02, -3.07001091e+00,  1.47490514e+00,
         7.64831115e-02, -1.76133253e+01,  2.58137752e-02,
        -2.04458316e-02, -3.51585085e+00, -1.28269840e+00,
         2.73049298e+00,  8.81957513e-01, -5.47347256e-04],
       [-5.95096357e-01,  3.04283371e+00,  3.41733495e+00,
        -1.83182731e-01, -3.51167880e+01, -2.83696795e-02,
        -2.51328328e-02,  7.93053290e+00, -9.85694602e+00,
         3.86988223e+00,  1.26366792e+00,  6.15531404e-04]])
```

In [49]:
```python
# Все признаки являются "хорошими"
from sklearn.feature_selection import SelectFromModel
sel_e_lr1 = SelectFromModel(e_lr1)
sel_e_lr1.fit(X3_train, y3_train)
sel_e_lr1.get_support()
```

Out[49]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True])
```

In [50]:
```python
e_lr2 = LinearSVC(C=0.01, penalty="l1", max_iter=2000, dual=False)
e_lr2.fit(X3_train, y3_train)
# Коэффициенты регрессии
e_lr2.coef_
```

Out[50]:
```
array([[ 0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        -4.12130029e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00, -8.74167991e-02,  2.15055368e-05],
       [-3.25687798e-02,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        -1.53909186e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00, -5.09548206e-02, -7.57658974e-05],
       [ 5.37963884e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,  0.00000000e+00, -1.01448829e-02,
         9.74948422e-03,  0.00000000e+00,  2.68713702e-01,
         0.00000000e+00, -1.39086322e-01,  6.67062423e-05],
       [-3.23477532e-03,  0.00000000e+00,  0.00000000e+00,
        -3.13809898e-03,  0.00000000e+00,  8.03447243e-03,
        -6.31263148e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,  0.00000000e+00,  1.50668477e-05],
       [-3.14912831e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,  0.00000000e+00,  3.10838096e-03,
        -4.09583482e-03,  0.00000000e+00, -2.53569087e-01,
         0.00000000e+00,  3.23836792e-02, -8.18803137e-05],
       [-3.58432219e-02,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        -3.69134838e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00, -4.94265352e-02, -5.74247806e-05]])
```

In [51]:
```python
# Признаки с флагом False д.б. исключены
```

```python
sel_e_lr2 = SelectFromModel(e_lr2)
sel_e_lr2.fit(X3_train, y3_train)
sel_e_lr2.get_support()
```

Out[51]:
```
array([ True, False, False,  True, False,  True,  True, False,  True,
       False,  True,  True])
```