МГТУ им. Н. Э. Баумана, кафедра ИУ5

курс “Методы машинного обучения”

Лабораторная работа №3

«Обработка признаков (часть 2)»

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ПРОВЕРИЛ:

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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:

  1. Масштабирование признаков (не менее чем тремя способами);
  2. Обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
  3. Обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
  4. 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).

- Сформировать отчет и разместить его в своем репозитории на github.

Выполнение работы:

In [55]:

```python
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
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount,
call drive.mount("/content/drive", force_remount=True).
```

In [2]:

```python
data  =  pd.read_csv("/content/drive/MyDrive/data/house_sales.csv")
```

In [3]:

```python
data.head()
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl

5 rows × 81 columns

In [4]:

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

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:   FutureWar
ning: In a future version of pandas all arguments of DataFrame.drop excep
t for the argument 'labels' will be keyword-only
  """Entry point for launching an IPython kernel.
```

Out[4]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	

5 rows × 80 columns

In [ ]:

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

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	Y
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	
mean	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808	
std	42.300571	22.024023	9981.264932	1.382997	1.112799	30.202904	
min	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	
25%	20.000000	60.000000	7553.500000	5.000000	5.000000	1954.000000	
50%	50.000000	70.049958	9478.500000	6.000000	5.000000	1973.000000	
75%	70.000000	79.000000	11601.500000	7.000000	6.000000	2000.000000	
max	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	

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.d
  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['SalePri
                                                    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	YearRemoc
0	0.073375	-0.229372	-0.207142	0.651479	-0.517200	1.050994	0.87
1	-0.872563	0.451936	-0.091886	-0.071836	2.179628	0.156734	-0.42
2	0.073375	-0.093110	0.073480	0.651479	-0.517200	0.984752	0.83
3	0.309859	-0.456474	-0.096897	0.651479	-0.517200	-1.863632	-0.72
4	0.073375	0.633618	0.375148	1.374795	-0.517200	0.951632	0.73
...	...	...	...	...	...	...	
1455	0.073375	-0.365633	-0.260560	-0.071836	-0.517200	0.918511	0.73
1456	-0.872563	0.679039	0.266407	-0.071836	0.381743	0.222975	0.15
1457	0.309859	-0.183951	-0.147810	0.651479	3.078570	-1.002492	1.02
1458	-0.872563	-0.093110	-0.080160	-0.795151	0.381743	-0.704406	0.53
1459	-0.872563	0.224833	-0.058112	-0.795151	0.381743	-0.207594	-0.96

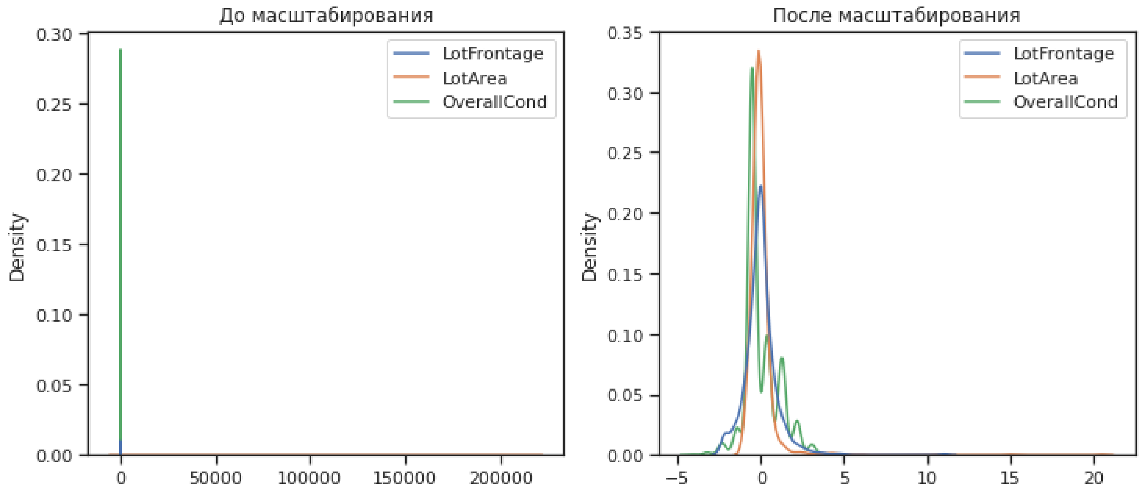
1460 rows × 36 columns

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_scal
```



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['SalePri
                                                    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	Yea
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	
mean	0.000962	-0.000452	-0.000119	-0.003900	-0.003058	-0.003544	
std	0.248827	0.075425	0.046653	0.153666	0.158971	0.218862	
min	-0.216081	-0.168431	-0.043200	-0.570491	-0.656678	-0.722876	

25%	-0.216081	-0.034869	-0.013970	-0.126046	-0.085250	-0.128673
50%	-0.039610	-0.000452	-0.004973	-0.014935	-0.085250	0.009008
75%	0.078037	0.030199	0.004951	0.096176	0.057608	0.204661
max	0.783919	0.831569	0.956800	0.429509	0.486179	0.277124

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()
```

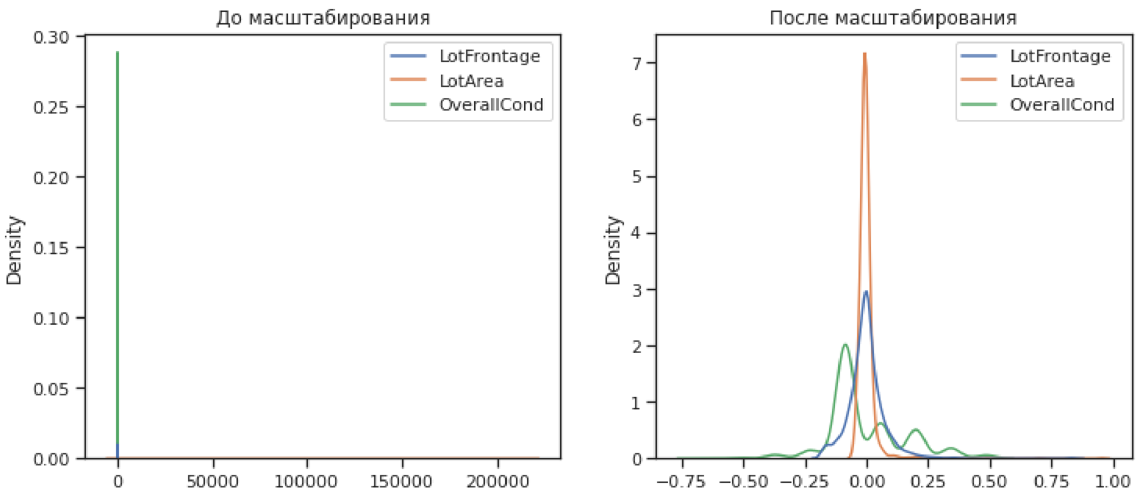
Out[19]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuil
count	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+03	1.168000e+0
mean	-2.932396e-17	6.185596e-17	-2.008002e-18	2.690010e-17	2.934772e-17	7.174151e-1
std	2.475340e-01	7.707084e-02	4.616115e-02	1.522067e-01	1.587482e-01	2.195064e-0
min	-2.160808e-01	-1.684311e-01	-4.319969e-02	-5.704909e-01	-5.138209e-01	-7.228757e0
25%	-2.160808e-01	-3.486947e-02	-1.422028e-02	-1.260464e-01	-8.524951e-02	-1.286728e0
50%	-3.961019e-02	-4.518024e-04	-4.865072e-03	-1.493531e-02	-8.524951e-02	1.625472e-0
75%	7.803687e-02	3.019903e-02	5.045185e-03	9.617580e-02	5.760763e-02	2.119069e-0
max	7.839192e-01	8.315689e-01	9.568003e-01	4.295091e-01	4.861791e-01	2.771243e-0

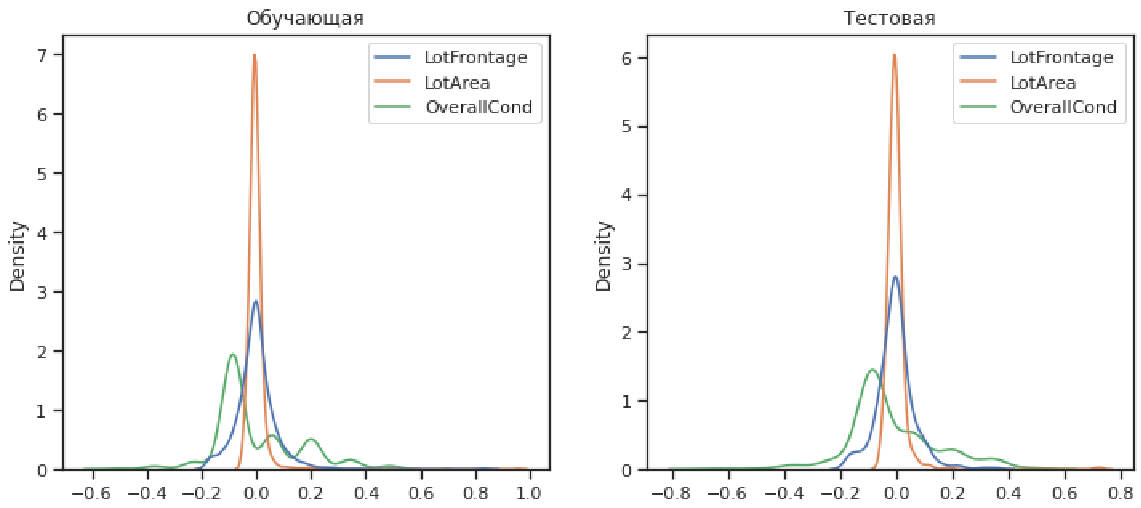
8 rows × 36 columns

In [20]:

```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data, data_cs21_scal
```



In [21]:
```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data_cs22_scaled_tra
```



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()
```

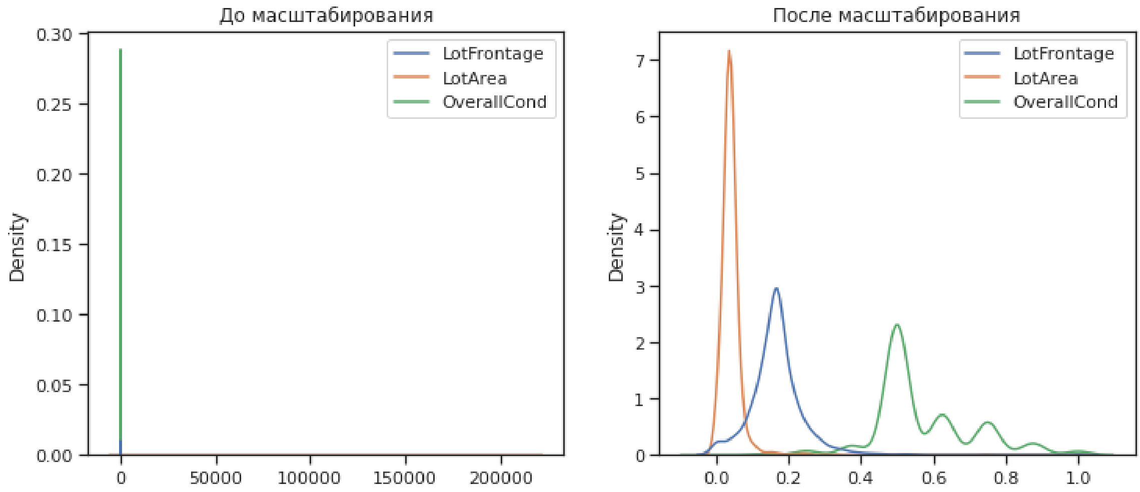
Out[22]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	Yea
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	
mean	0.217043	0.167979	0.043080	0.566591	0.571918	0.719332	
std	0.248827	0.075425	0.046653	0.153666	0.139100	0.218862	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.133562	0.029229	0.444444	0.500000	0.594203	
50%	0.176471	0.167979	0.038227	0.555556	0.500000	0.731884	
75%	0.294118	0.198630	0.048150	0.666667	0.625000	0.927536	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

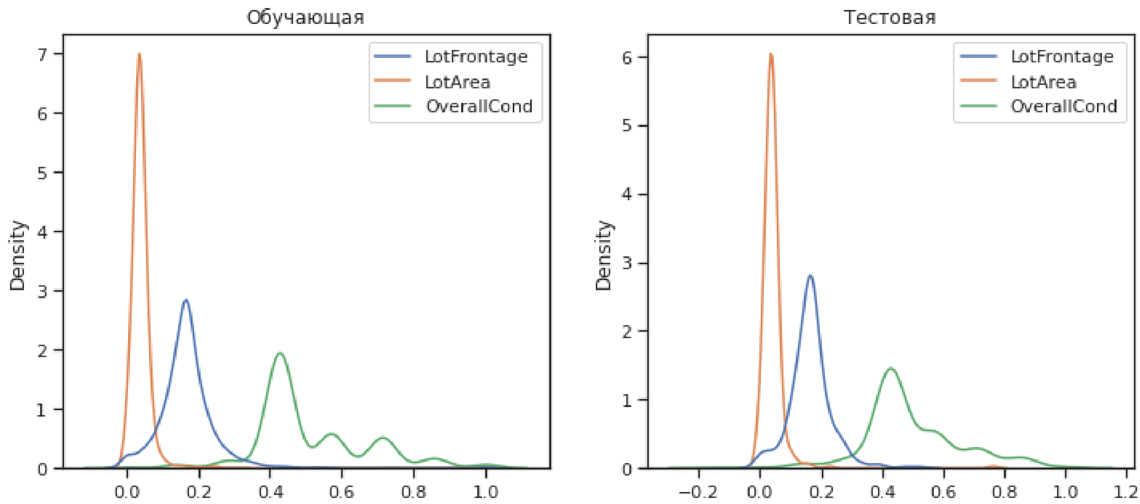
8 rows × 36 columns

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_scal
```



In [25]:
```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data_cs32_scaled_tra
```



Обработка выбросов для числовых признаков

In [26]:
```
data2 = pd.read_csv("/content/drive/MyDrive/data/Car_sales.csv")
```

In [27]:
```
data2.head()
```

Out[27]:

	Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	Price_in_th
0	Acura	Integra	16.919	16.360	Passenger	
1	Acura	TL	39.384	19.875	Passenger	
2	Acura	CL	14.114	18.225	Passenger	
3	Acura	RL	8.588	29.725	Passenger	
4	Audi	A4	20.397	22.255	Passenger	

In [28]:
```
data2.describe()
```

Out[28]:

	Sales_in_thousands	__year_resale_value	Price_in_thousands	Engine_size	Horsepow
count	157.000000	121.000000	155.000000	156.000000	156.0000

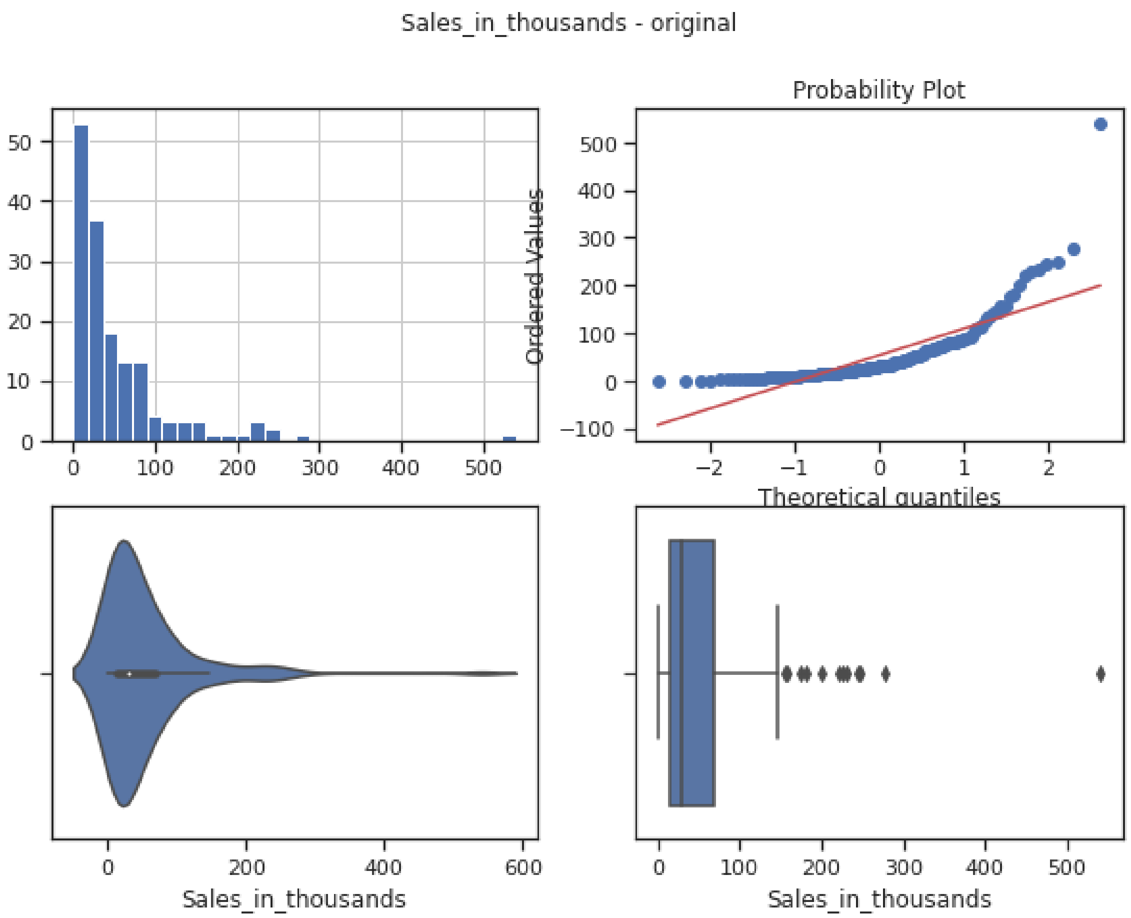
mean	52.998076	18.072975	27.390755	3.060897	185.9487
std	68.029422	11.453384	14.351653	1.044653	56.7003
min	0.110000	5.160000	9.235000	1.000000	55.0000
25%	14.114000	11.260000	18.017500	2.300000	149.5000
50%	29.450000	14.180000	22.799000	3.000000	177.5000
75%	67.956000	19.875000	31.947500	3.575000	215.0000
max	540.561000	67.550000	85.500000	8.000000	450.0000

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)
    # 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()
```

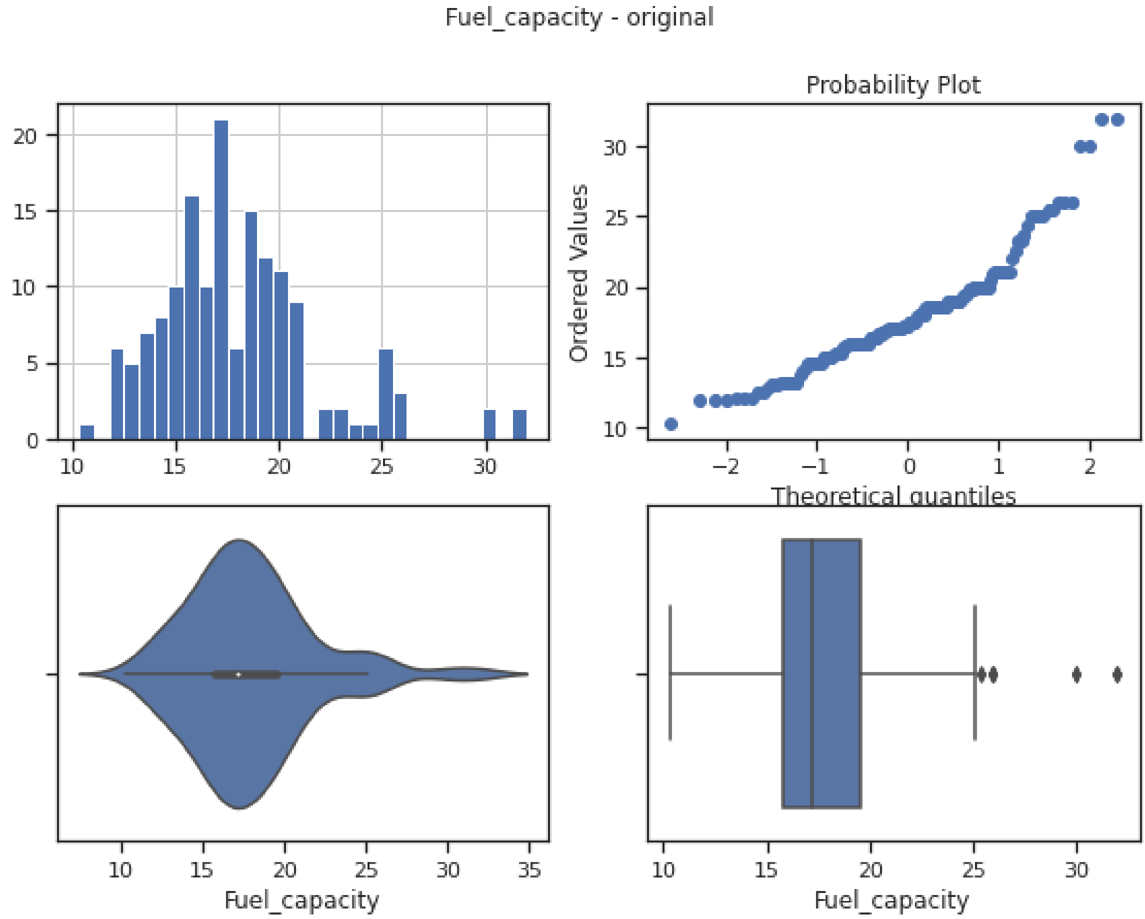
In [30]:

```
diagnostic_plots(data2, 'Sales_in_thousands', 'Sales_in_thousands - orig
```



In [31]:

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



In [32]:

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

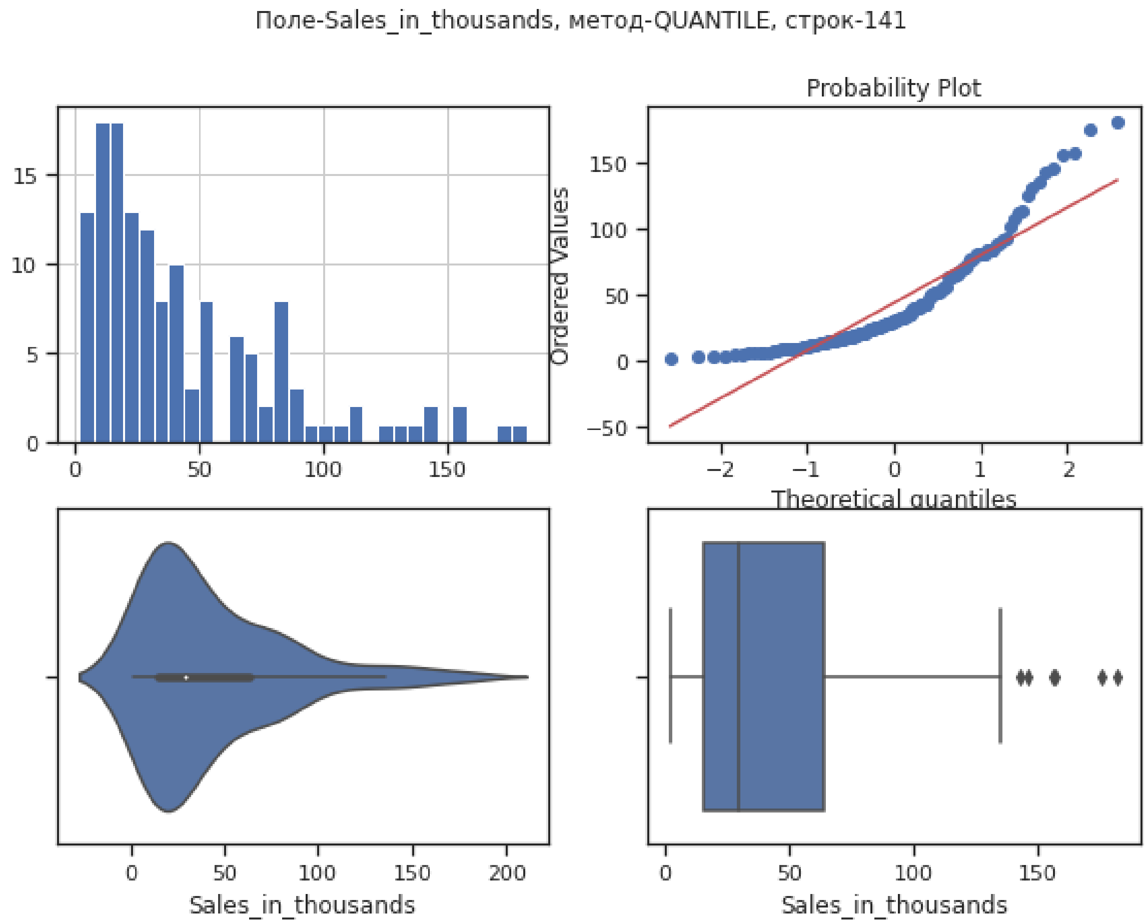
In [33]:

```
# 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]:

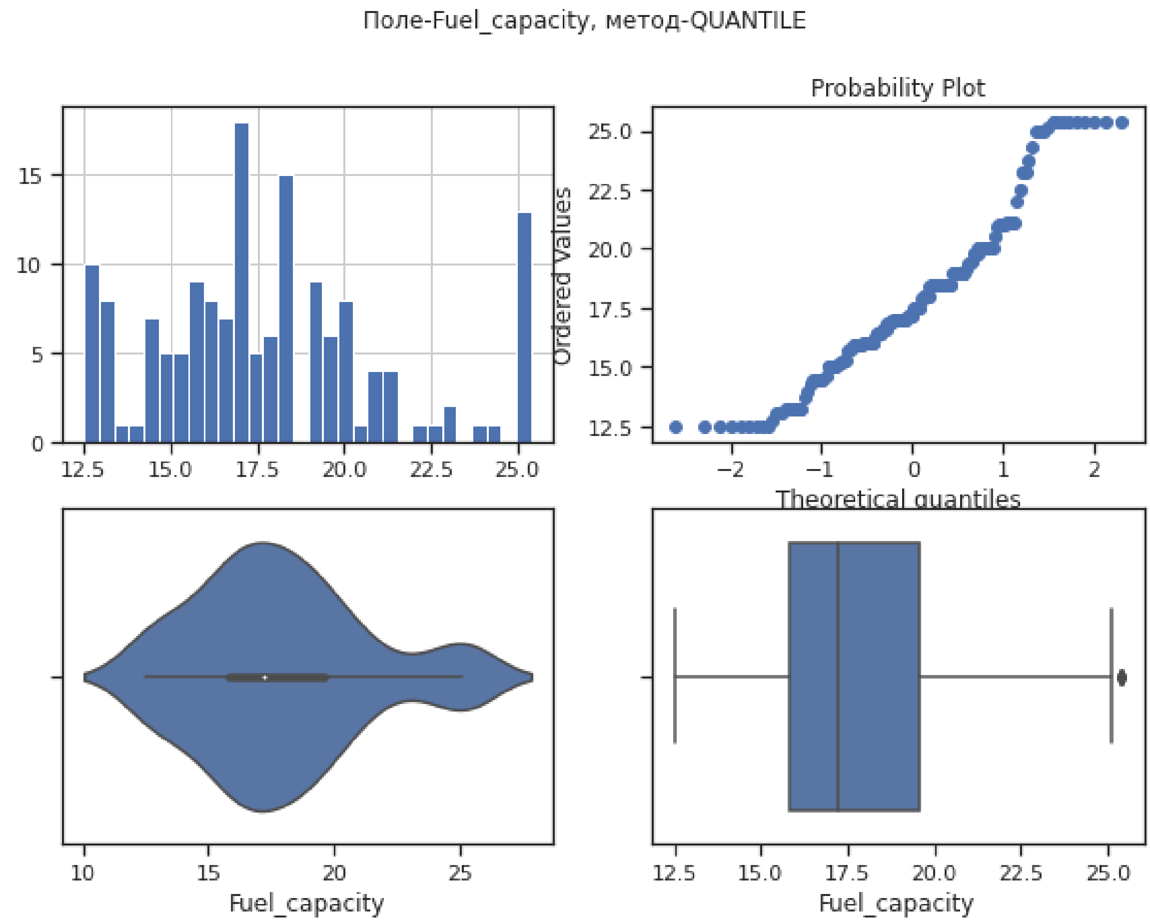
```
# Вычисление верхней и нижней границы
lower_boundary, upper_boundary = get_outlier_boundaries(data2, "Sales_in
# Флаги для удаления выбросов
outliers_temp = np.where(data2["Sales_in_thousands"] > upper_boundary, T
                         np.where(data2["Sales_in_thousands"] < lower_bo
# Удаление данных на основе флага
data_trimmed = data2.loc[~(outliers_temp), ]
title = 'Поле-{}, метод-{}, строк-{}'.format("Sales_in_thousands", "QUAN
diagnostic_plots(data_trimmed, "Sales_in_thousands", title)
```



Замена выбросов

In [35]:

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



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["La
```

In [38]:

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

Out[38]:

Manufacturer	Model	Sales_in_thousands	__year_resale_value	Vehicle_type	Price_in_th

0	Acura	Integra	16.919	16.360	Passenger
1	Acura	TL	39.384	19.875	Passenger
2	Acura	CL	14.114	18.225	Passenger
3	Acura	RL	8.588	29.725	Passenger
4	Audi	A4	20.397	22.255	Passenger

In [41]:

```
data2.dtypes
```

Out[41]:

```
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]
Latest_Launch_Day              int64
Latest_Launch_Month            int64
Latest_Launch_Year             int64
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

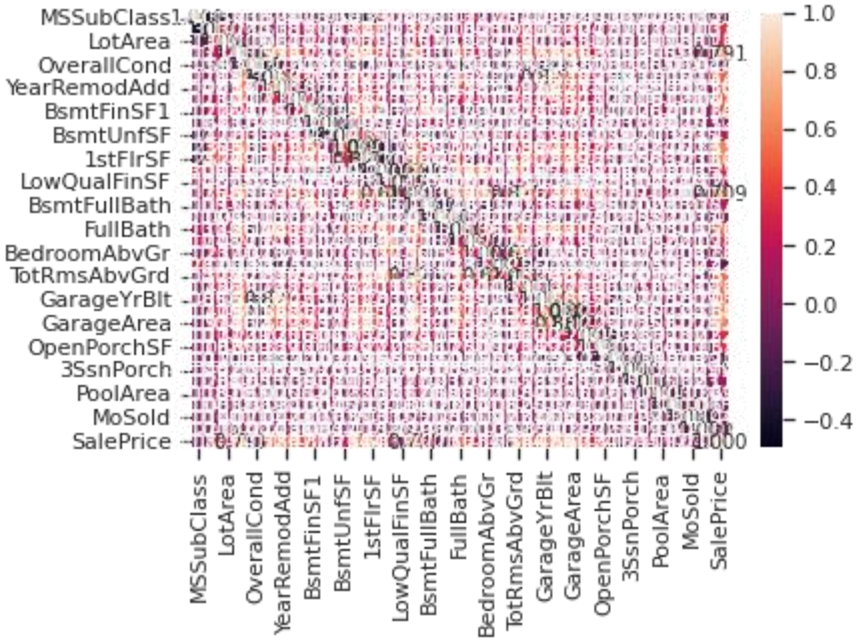
Метод фильтрации (Корреляция признаков)

In [42]:

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

Out[42]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffafc4f1f50>
```



In [43]:
```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 [44]:
```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 [45]:
```python
# Группы коррелирующих признаков
corr_groups(make_corr_df(data))
```

Out[45]:
```
[['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 [46]:

```
data3 = pd.read_csv("/content/drive/MyDrive/data/WineQT.csv", sep=",")
```

In [49]:

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

In [51]:

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

In [52]:

```
# Используем L1-регуляризацию
e_lr1 = LogisticRegression(C=1000, solver='liblinear', penalty='l1', max
e_lr1.fit(X3_train, y3_train)
# Коэффициенты регрессии
e_lr1.coef_
```

Out[52]:

```
array([[ 8.12685010e-01,  1.13666762e+01,  7.82623669e+00,
         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 [54]:

```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[54]:

```
array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True])
```

In [56]:

```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[56]:

```
array([[ 0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,   0.00000000e+00,   0.00000000e+00,
        -4.11590915e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00, -8.74405380e-02,  2.16195308e-05],
       [-3.25634884e-02,   0.00000000e+00,   0.00000000e+00,
         0.00000000e+00,   0.00000000e+00,   0.00000000e+00,
        -1.53903186e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00, -5.09600420e-02, -7.57538218e-05],
       [ 5.38464273e-03,   0.00000000e+00,   0.00000000e+00,
         0.00000000e+00,   0.00000000e+00,  -1.01450282e-02,
         9.75002480e-03,   0.00000000e+00,   2.68720467e-01,
         0.00000000e+00, -1.39098820e-01,   6.67270806e-05],
       [-3.23150714e-03,   0.00000000e+00,   0.00000000e+00,
        -3.14484287e-03,   0.00000000e+00,   8.03406641e-03,
        -6.31251948e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00,   0.00000000e+00,   1.50594009e-05],
       [-3.14935119e-03,   0.00000000e+00,   0.00000000e+00,
         0.00000000e+00,   0.00000000e+00,   3.10845849e-03,
        -4.09632766e-03,  0.00000000e+00, -2.53401927e-01,
         0.00000000e+00,  3.23326792e-02, -8.18790120e-05],
       [-3.58500393e-02,   0.00000000e+00,   0.00000000e+00,
         0.00000000e+00,   0.00000000e+00,   0.00000000e+00,
        -3.69158731e-03,  0.00000000e+00,  0.00000000e+00,
         0.00000000e+00, -4.94195235e-02, -5.74388942e-05]])
```

In [58]:

```python
# Признаки с флагом False д.б. исключены
sel_e_lr2 = SelectFromModel(e_lr2)
sel_e_lr2.fit(X3_train, y3_train)
sel_e_lr2.get_support()
```

Out[58]:
```
array([ True, False, False,  True, False,  True,  True, False,  True,
        False,  True,  True])
```