**Министерство науки и высшего образования Российской Федерации**
**Федеральное государственное бюджетное образовательное учреждение**
**высшего образования**
**«Московский государственный технический университет**
**имени Н.Э. Баумана**
**(национальный исследовательский университет)»**
**(МГТУ им. Н.Э. Баумана)**

**Факультет «Информатика и системы управления»**

**Кафедра ИУ5 «Системы обработки информации и управления»**

# Отчет по лабораторной работе №3

по дисциплине «Методы машинного обучения»

по теме «Обработка признаков (часть 2)»

Выполнил:
студент группы № ИУ5-21М
Камалов М.Р.
подпись, дата

Проверил:
Балашов А.М.
подпись, дата

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## Задание:

1. 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.
2. Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
   i. масштабирование признаков (не менее чем тремя способами);
   ii. обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
   iii. обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
   iv. 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).

```
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
```

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

```
data.head()
```

```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape
\
0   1          60       RL         65.0     8450   Pave   NaN      Reg

1   2          20       RL         80.0     9600   Pave   NaN      Reg

2   3          60       RL         68.0    11250   Pave   NaN      IR1

3   4          70       RL         60.0     9550   Pave   NaN      IR1

4   5          60       RL         84.0    14260   Pave   NaN      IR1


  LandContour Utilities  ... PoolArea PoolQC Fence MiscFeature MiscVal
MoSold  \
0         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
2
1         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
5
2         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
9
3         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
2
4         Lvl    AllPub  ...        0    NaN   NaN         NaN       0
12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
```

```
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

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

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

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

  LandContour Utilities LotConfig  ... PoolArea PoolQC Fence
MiscFeature  \
0         Lvl    AllPub    Inside  ...        0    NaN   NaN
NaN
1         Lvl    AllPub       FR2  ...        0    NaN   NaN
NaN
2         Lvl    AllPub    Inside  ...        0    NaN   NaN
NaN
3         Lvl    AllPub    Corner  ...        0    NaN   NaN
NaN
4         Lvl    AllPub       FR2  ...        0    NaN   NaN
NaN

  MiscVal MoSold  YrSold  SaleType  SaleCondition  SalePrice
0       0      2    2008        WD         Normal     208500
1       0      5    2007        WD         Normal     181500
2       0      9    2008        WD         Normal     223500
3       0      2    2006        WD        Abnorml     140000
4       0     12    2008        WD         Normal     250000

[5 rows x 80 columns]
```

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

```
      MSSubClass MSZoning  LotFrontage  LotArea Street LotShape
LandContour  \
0             60       RL         65.0     8450   Pave      Reg
Lvl
1             20       RL         80.0     9600   Pave      Reg
Lvl
```

```
2             60       RL         68.0    11250   Pave      IR1
Lvl
3             70       RL         60.0     9550   Pave      IR1
Lvl
4             60       RL         84.0    14260   Pave      IR1
Lvl
...          ...      ...          ...      ...    ...      ...
...
1455          60       RL         62.0     7917   Pave      Reg
Lvl
1456          20       RL         85.0    13175   Pave      Reg
Lvl
1457          70       RL         66.0     9042   Pave      Reg
Lvl
1458          20       RL         68.0     9717   Pave      Reg
Lvl
1459          20       RL         75.0     9937   Pave      Reg
Lvl

     Utilities LotConfig LandSlope  ... EnclosedPorch 3SsnPorch
ScreenPorch  \
0       AllPub    Inside       Gtl  ...             0         0
0
1       AllPub       FR2       Gtl  ...             0         0
0
2       AllPub    Inside       Gtl  ...             0         0
0
3       AllPub    Corner       Gtl  ...           272         0
0
4       AllPub       FR2       Gtl  ...             0         0
0
...        ...       ...       ...  ...           ...       ...
...
1455    AllPub    Inside       Gtl  ...             0         0
0
1456    AllPub    Inside       Gtl  ...             0         0
0
1457    AllPub    Inside       Gtl  ...             0         0
0
1458    AllPub    Inside       Gtl  ...           112         0
0
1459    AllPub    Inside       Gtl  ...             0         0
0

     PoolArea MiscVal  MoSold  YrSold  SaleType  SaleCondition
SalePrice
0           0       0       2    2008        WD         Normal
208500
1           0       0       5    2007        WD         Normal
181500
```

```
2             0       0       9    2008        WD        Normal
223500
3             0       0       2    2006        WD       Abnorml
140000
4             0       0      12    2008        WD        Normal
250000
...         ...     ...     ...     ...       ...           ...       .
..
1455          0       0       8    2007        WD        Normal
175000
1456          0       0       2    2010        WD        Normal
210000
1457          0    2500       5    2010        WD        Normal
266500
1458          0       0       4    2010        WD        Normal
142125
1459          0       0       6    2008        WD        Normal
147500

[1460 rows x 75 columns]
```

```python
# Заполним пропуски средними значениями
def impute_na(df, variable, value):
    df[variable].fillna(value, inplace=True)
impute_na(data, 'LotFrontage', data['LotFrontage'].mean())

data.describe()
```

```
        MSSubClass  LotFrontage        LotArea  OverallQual
OverallCond  \
count  1460.000000  1460.000000    1460.000000  1460.000000
1460.000000
mean     56.897260    70.049958   10516.828082     6.099315
5.575342
std      42.300571    22.024023    9981.264932     1.382997
1.112799
min      20.000000    21.000000    1300.000000     1.000000
1.000000
25%      20.000000    60.000000    7553.500000     5.000000
5.000000
50%      50.000000    70.049958    9478.500000     6.000000
5.000000
75%      70.000000    79.000000   11601.500000     7.000000
6.000000
max     190.000000   313.000000  215245.000000    10.000000
9.000000

         YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1
BsmtFinSF2  ...  \
count  1460.000000   1460.000000  1452.000000  1460.000000
1460.000000  ...
```

```
mean   1971.267808   1984.865753   103.685262   443.639726
46.549315  ...
std      30.202904     20.645407   181.066207   456.098091
161.319273  ...
min    1872.000000   1950.000000     0.000000     0.000000
0.000000  ...
25%    1954.000000   1967.000000     0.000000     0.000000
0.000000  ...
50%    1973.000000   1994.000000     0.000000   383.500000
0.000000  ...
75%    2000.000000   2004.000000   166.000000   712.250000
0.000000  ...
max    2010.000000   2010.000000  1600.000000  5644.000000
1474.000000  ...

        WoodDeckSF  OpenPorchSF  EnclosedPorch    3SsnPorch
ScreenPorch  \
count  1460.000000  1460.000000    1460.000000  1460.000000
1460.000000
mean     94.244521    46.660274      21.954110     3.409589
15.060959
std     125.338794    66.256028      61.119149    29.317331
55.757415
min       0.000000     0.000000       0.000000     0.000000
0.000000
25%       0.000000     0.000000       0.000000     0.000000
0.000000
50%       0.000000    25.000000       0.000000     0.000000
0.000000
75%     168.000000    68.000000       0.000000     0.000000
0.000000
max     857.000000   547.000000     552.000000   508.000000
480.000000

          PoolArea       MiscVal       MoSold       YrSold
SalePrice
count  1460.000000   1460.000000  1460.000000  1460.000000
1460.000000
mean      2.758904     43.489041     6.321918  2007.815753
180921.195890
std      40.177307    496.123024     2.703626     1.328095
79442.502883
min       0.000000      0.000000     1.000000  2006.000000
34900.000000
25%       0.000000      0.000000     5.000000  2007.000000
129975.000000
50%       0.000000      0.000000     6.000000  2008.000000
163000.000000
75%       0.000000      0.000000     8.000000  2009.000000
214000.000000
```

```
max     738.000000  15500.000000    12.000000  2010.000000
755000.000000

[8 rows x 37 columns]
```

```
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')

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

# 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

# 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
```

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

## StandardScaler

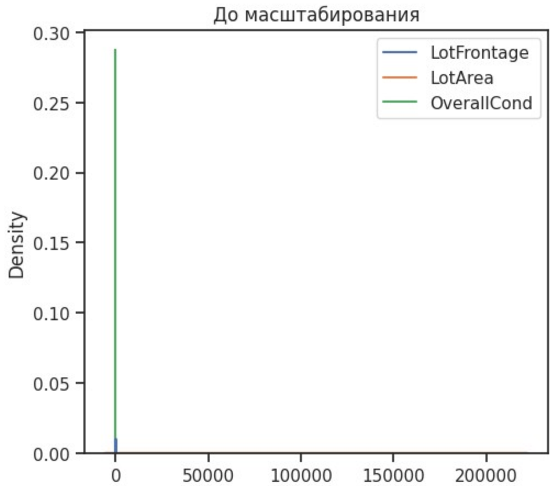
```
# Обучаем StandardScaler на всей выборке и масштабируем
cs11 = StandardScaler()
data_cs11_scaled_temp = cs11.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs11_scaled =  arr_to_df(data_cs11_scaled_temp)
data_cs11_scaled
```

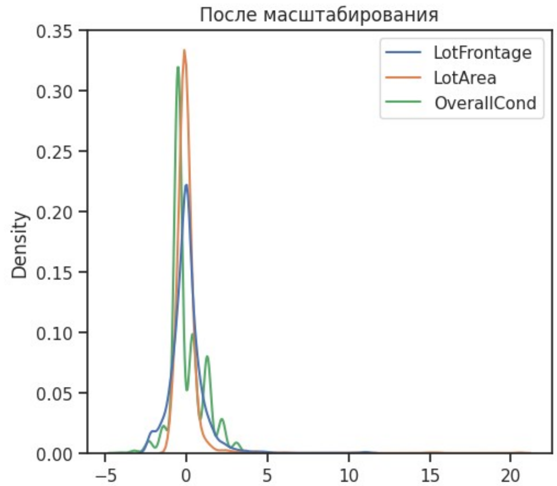
```
      MSSubClass  LotFrontage   LotArea  OverallQual  OverallCond
YearBuilt  \
0       0.073375    -0.229372 -0.207142     0.651479    -0.517200
1.050994
1      -0.872563     0.451936 -0.091886    -0.071836     2.179628
0.156734
2       0.073375    -0.093110  0.073480     0.651479    -0.517200
0.984752
```

```
3       0.309859    -0.456474 -0.096897     0.651479    -0.517200  -
1.863632
4       0.073375     0.633618  0.375148     1.374795    -0.517200
0.951632
...          ...          ...       ...          ...          ...
...
1455    0.073375    -0.365633 -0.260560    -0.071836    -0.517200
0.918511
1456   -0.872563     0.679039  0.266407    -0.071836     0.381743
0.222975
1457    0.309859    -0.183951 -0.147810     0.651479     3.078570  -
1.002492
1458   -0.872563    -0.093110 -0.080160    -0.795151     0.381743  -
0.704406
1459   -0.872563     0.224833 -0.058112    -0.795151     0.381743  -
0.207594

      YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  ...
GarageArea  \
0         0.878668    0.510015    0.575425   -0.288653  ...
0.351000
1        -0.429577   -0.572835    1.171992   -0.288653  ...   -
0.060731
2         0.830215    0.322174    0.092907   -0.288653  ...
0.631726
3        -0.720298   -0.572835   -0.499274   -0.288653  ...
0.790804
4         0.733308    1.360826    0.463568   -0.288653  ...
1.698485
...            ...         ...         ...         ...  ...         ..
.
1455      0.733308   -0.572835   -0.973018   -0.288653  ...   -
0.060731
1456      0.151865    0.084610    0.759659    0.722112  ...
0.126420
1457      1.024029   -0.572835   -0.369871   -0.288653  ...   -
1.033914
1458      0.539493   -0.572835   -0.865548    6.092188  ...   -
1.090059
1459     -0.962566   -0.572835    0.847389    1.509640  ...   -
0.921624

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch
ScreenPorch  \
0      -0.752176     0.216503      -0.359325  -0.116339    -0.270208

1       1.626195    -0.704483      -0.359325  -0.116339    -0.270208

2      -0.752176    -0.070361      -0.359325  -0.116339    -0.270208
```

```
3      -0.752176    -0.176048       4.092524  -0.116339    -0.270208

4       0.780197     0.563760      -0.359325  -0.116339    -0.270208

...          ...          ...            ...        ...          ...

1455   -0.752176    -0.100558      -0.359325  -0.116339    -0.270208

1456    2.033231    -0.704483      -0.359325  -0.116339    -0.270208

1457   -0.752176     0.201405      -0.359325  -0.116339    -0.270208

1458    2.168910    -0.704483       1.473789  -0.116339    -0.270208

1459    5.121921     0.322190      -0.359325  -0.116339    -0.270208


      PoolArea   MiscVal    MoSold    YrSold
0    -0.068692 -0.087688 -1.599111  0.138777
1    -0.068692 -0.087688 -0.489110 -0.614439
2    -0.068692 -0.087688  0.990891  0.138777
3    -0.068692 -0.087688 -1.599111 -1.367655
4    -0.068692 -0.087688  2.100892  0.138777
...        ...       ...       ...       ...
1455 -0.068692 -0.087688  0.620891 -0.614439
1456 -0.068692 -0.087688 -1.599111  1.645210
1457 -0.068692  4.953112 -0.489110  1.645210
1458 -0.068692 -0.087688 -0.859110  1.645210
1459 -0.068692 -0.087688 -0.119110  0.138777

[1460 rows x 36 columns]
```

```python
# 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()

draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data,
data_cs11_scaled, 'До масштабирования', 'После масштабирования')
```




## Масштабирование "Mean Normalisation"

```
# 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
```

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

```
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)

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

```
        MSSubClass  LotFrontage      LotArea  OverallQual  OverallCond
\
count  1460.000000  1460.000000  1460.000000  1460.000000  1460.000000

mean      0.000962    -0.000452    -0.000119    -0.003900    -0.003058

std       0.248827     0.075425     0.046653     0.153666     0.158971

min      -0.216081    -0.168431    -0.043200    -0.570491    -0.656678

25%      -0.216081    -0.034869    -0.013970    -0.126046    -0.085250

50%      -0.039610    -0.000452    -0.004973    -0.014935    -0.085250

75%       0.078037     0.030199     0.004951     0.096176     0.057608

max       0.783919     0.831569     0.956800     0.429509     0.486179


         YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1
BsmtFinSF2  ...  \
count  1460.000000   1460.000000  1452.000000  1460.000000
1460.000000  ...
mean     -0.003544     -0.008644    -0.000898    -0.001612
0.001276  ...
std       0.218862      0.344090     0.113166     0.080811
0.109443  ...
min      -0.722876     -0.589740    -0.065702    -0.080216    -
0.030304  ...
25%      -0.128673     -0.306407    -0.065702    -0.080216    -
0.030304  ...
50%       0.009008      0.143593    -0.065702    -0.012267    -
0.030304  ...
75%       0.204661      0.310260     0.038048     0.045980    -
0.030304  ...
max       0.277124      0.410260     0.934298     0.919784
0.969696  ...

        GarageArea   WoodDeckSF  OpenPorchSF  EnclosedPorch
3SsnPorch  \
count  1460.000000  1460.000000  1460.000000    1460.000000
1460.000000
mean     -0.000804    -0.000560    -0.001199      -0.001448    -
0.000481
std       0.150779     0.170297     0.121126       0.110723
0.057711
min      -0.334359    -0.128610    -0.086501      -0.041220    -
0.007193
25%      -0.098463    -0.128610    -0.086501      -0.041220    -
```

```
0.007193
50%       0.004146    -0.128610    -0.040797      -0.041220    -
0.007193
75%       0.071847     0.099651     0.037814      -0.041220    -
0.007193
max       0.665641     1.035793     0.913499       0.958780
0.992807

       ScreenPorch     PoolArea      MiscVal       MoSold       YrSold

count  1460.000000  1460.000000  1460.000000  1460.000000  1460.000000

mean     -0.002194     0.000461    -0.000417     0.002802    -0.001969

std       0.116161     0.054441     0.032008     0.245784     0.332024

min      -0.033571    -0.003277    -0.003222    -0.481009    -0.455908

25%      -0.033571    -0.003277    -0.003222    -0.117372    -0.205908

50%      -0.033571    -0.003277    -0.003222    -0.026463     0.044092

75%      -0.033571    -0.003277    -0.003222     0.155355     0.294092

max       0.966429     0.996723     0.996778     0.518991     0.544092


[8 rows x 36 columns]
```

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

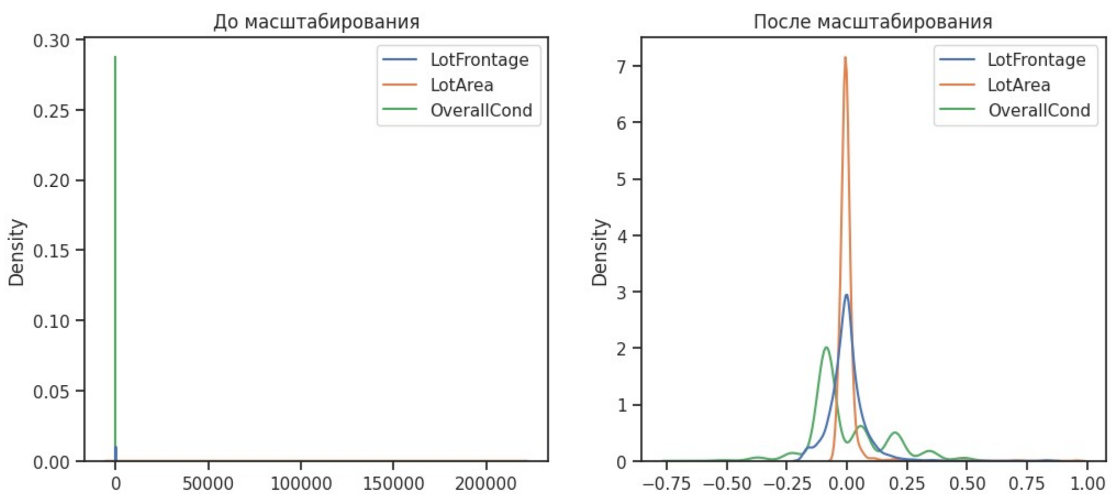
```
data_cs22_scaled_train.describe()
```

```
         MSSubClass   LotFrontage       LotArea   OverallQual
OverallCond  \
count  1.168000e+03  1.168000e+03  1.168000e+03  1.168000e+03
1.168000e+03
mean  -1.672939e-17  1.392531e-17 -1.140640e-18  2.718526e-17
9.125121e-18
std    2.475340e-01  7.707084e-02  4.616115e-02  1.522067e-01
1.587482e-01
min   -2.160808e-01 -1.684311e-01 -4.319969e-02 -5.704909e-01 -
5.138209e-01
25%   -2.160808e-01 -3.486947e-02 -1.422028e-02 -1.260464e-01 -
8.524951e-02
50%   -3.961019e-02 -4.518024e-04 -4.865072e-03 -1.493531e-02 -
8.524951e-02
```

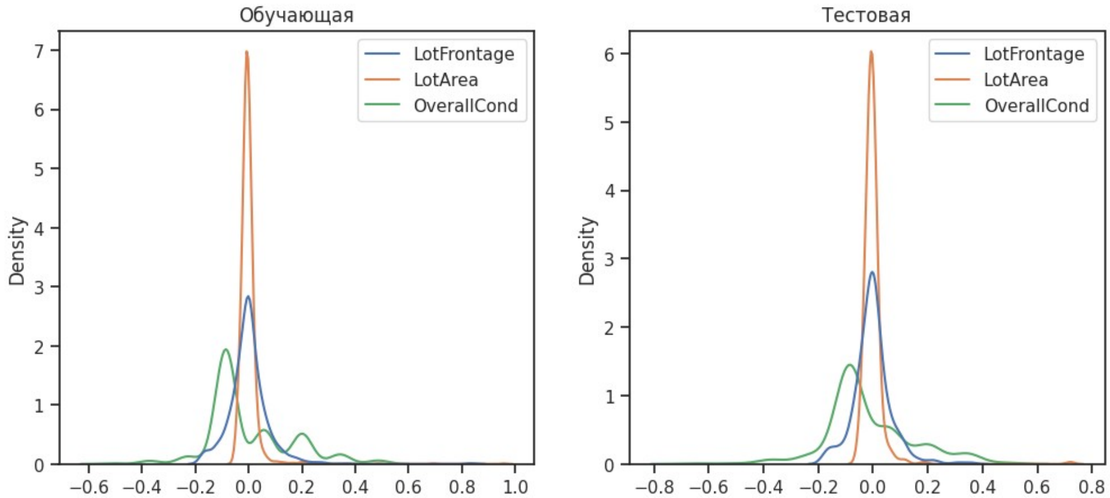
```
75%    7.803687e-02  3.019903e-02  5.045185e-03  9.617580e-02
5.760763e-02
max    7.839192e-01  8.315689e-01  9.568003e-01  4.295091e-01
4.861791e-01

          YearBuilt  YearRemodAdd    MasVnrArea    BsmtFinSF1
BsmtFinSF2  \
count  1.168000e+03  1.168000e+03  1.160000e+03  1.168000e+03
1.168000e+03
mean   7.224054e-16 -1.502508e-15 -2.584140e-18  5.322987e-18 -
2.471387e-18
std    2.195064e-01  3.431316e-01  1.112988e-01  8.212989e-02
1.098439e-01
min   -7.228757e-01 -5.897403e-01 -6.570151e-02 -8.021550e-02 -
3.030380e-02
25%   -1.286728e-01 -2.897403e-01 -6.570151e-02 -8.021550e-02 -
3.030380e-02
50%    1.625472e-02  1.435930e-01 -6.570151e-02 -9.609550e-03 -
3.030380e-02
75%    2.119069e-01  3.102597e-01  4.070474e-02  4.890392e-02 -
3.030380e-02
max    2.771243e-01  4.102597e-01  9.342985e-01  9.197845e-01
9.696962e-01

       ...    GarageArea    WoodDeckSF   OpenPorchSF  EnclosedPorch  \
count  ...  1.168000e+03  1.168000e+03  1.168000e+03   1.168000e+03
mean   ... -2.281280e-18  1.330747e-17 -2.471387e-18   3.897187e-18
std    ...  1.486998e-01  1.659810e-01  1.237650e-01   1.136065e-01
min    ... -3.343588e-01 -1.286096e-01 -8.650078e-02  -4.121997e-02
25%    ... -9.740530e-02 -1.286096e-01 -8.650078e-02  -4.121997e-02
50%    ...  4.146178e-03 -1.286096e-01 -3.714063e-02  -4.121997e-02
75%    ...  7.184717e-02  9.965125e-02  3.781367e-02  -4.121997e-02
max    ...  6.656412e-01  8.713904e-01  9.134992e-01   9.587800e-01

          3SsnPorch   ScreenPorch      PoolArea       MiscVal
MoSold  \
count  1.168000e+03  1.168000e+03  1.168000e+03  1.168000e+03
1.168000e+03
mean  -1.140640e-18  1.121629e-17  7.129001e-19  9.505334e-20
2.927643e-17
std    6.122720e-02  1.203524e-01  5.066415e-02  3.560991e-02
2.444658e-01
min   -7.193129e-03 -3.357056e-02 -3.277323e-03 -3.222492e-03 -
4.810087e-01
25%   -7.193129e-03 -3.357056e-02 -3.277323e-03 -3.222492e-03 -
1.173724e-01
50%   -7.193129e-03 -3.357056e-02 -3.277323e-03 -3.222492e-03 -
2.646326e-02
75%   -7.193129e-03 -3.357056e-02 -3.277323e-03 -3.222492e-03
1.553549e-01
```

```
max    9.928069e-01  9.664294e-01  9.967227e-01  9.967775e-01
5.189913e-01

             YrSold
count  1.168000e+03
mean  -1.635222e-14
std    3.313190e-01
min   -4.559075e-01
25%   -2.059075e-01
50%    4.409247e-02
75%    2.940925e-01
max    5.440925e-01

[8 rows x 36 columns]
```

```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data,
data_cs21_scaled, 'До масштабирования', 'После масштабирования')
```




```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'],
data_cs22_scaled_train, data_cs22_scaled_test, 'Обучающая',
'Тестовая')
```



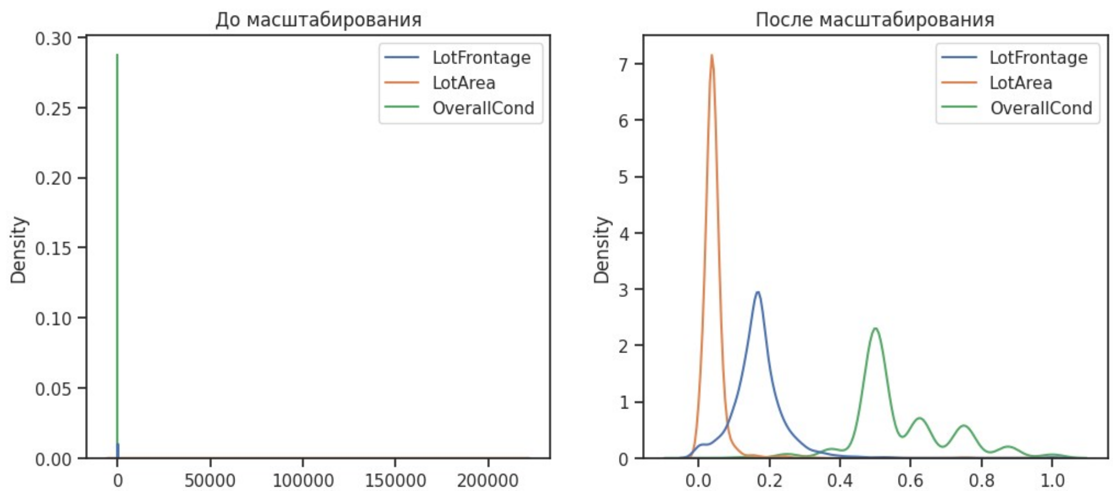

### MinMax-масштабирование

```
# 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()
```

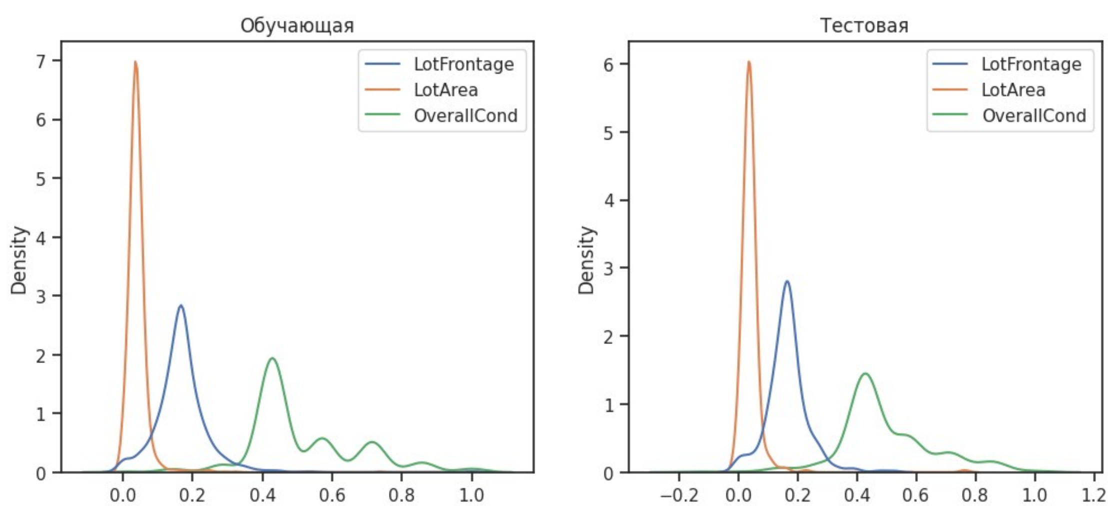
```
        MSSubClass  LotFrontage      LotArea  OverallQual  OverallCond
\
count  1460.000000  1460.000000  1460.000000  1460.000000  1460.000000

mean      0.217043     0.167979     0.043080     0.566591     0.571918

std       0.248827     0.075425     0.046653     0.153666     0.139100

min       0.000000     0.000000     0.000000     0.000000     0.000000

25%       0.000000     0.133562     0.029229     0.444444     0.500000

50%       0.176471     0.167979     0.038227     0.555556     0.500000

75%       0.294118     0.198630     0.048150     0.666667     0.625000

max       1.000000     1.000000     1.000000     1.000000     1.000000


         YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1
BsmtFinSF2  ...  \
count  1460.000000   1460.000000  1452.000000  1460.000000
1460.000000  ...
mean      0.719332      0.581096     0.064803     0.078604
0.031580  ...
```

```
std       0.218862      0.344090     0.113166     0.080811
0.109443  ...
min       0.000000      0.000000     0.000000     0.000000
0.000000  ...
25%       0.594203      0.283333     0.000000     0.000000
0.000000  ...
50%       0.731884      0.733333     0.000000     0.067948
0.000000  ...
75%       0.927536      0.900000     0.103750     0.126196
0.000000  ...
max       1.000000      1.000000     1.000000     1.000000
1.000000  ...

        GarageArea   WoodDeckSF  OpenPorchSF  EnclosedPorch
3SsnPorch  \
count  1460.000000  1460.000000  1460.000000    1460.000000
1460.000000
mean      0.333554     0.109970     0.085302       0.039772
0.006712
std       0.150779     0.146253     0.121126       0.110723
0.057711
min       0.000000     0.000000     0.000000       0.000000
0.000000
25%       0.235896     0.000000     0.000000       0.000000
0.000000
50%       0.338505     0.000000     0.045704       0.000000
0.000000
75%       0.406206     0.196033     0.124314       0.000000
0.000000
max       1.000000     1.000000     1.000000       1.000000
1.000000

       ScreenPorch     PoolArea      MiscVal       MoSold       YrSold

count  1460.000000  1460.000000  1460.000000  1460.000000  1460.000000

mean      0.031377     0.003738     0.002806     0.483811     0.453938

std       0.116161     0.054441     0.032008     0.245784     0.332024

min       0.000000     0.000000     0.000000     0.000000     0.000000

25%       0.000000     0.000000     0.000000     0.363636     0.250000

50%       0.000000     0.000000     0.000000     0.454545     0.500000

75%       0.000000     0.000000     0.000000     0.636364     0.750000

max       1.000000     1.000000     1.000000     1.000000     1.000000
```

```
[8 rows x 36 columns]

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)

draw_kde(['LotFrontage', 'LotArea', 'OverallCond'], data,
data_cs31_scaled, 'До масштабирования', 'После масштабирования')
```




```
draw_kde(['LotFrontage', 'LotArea', 'OverallCond'],
data_cs32_scaled_train, data_cs32_scaled_test, 'Обучающая',
'Тестовая')
```



### Обработка выбросов для числовых признаков

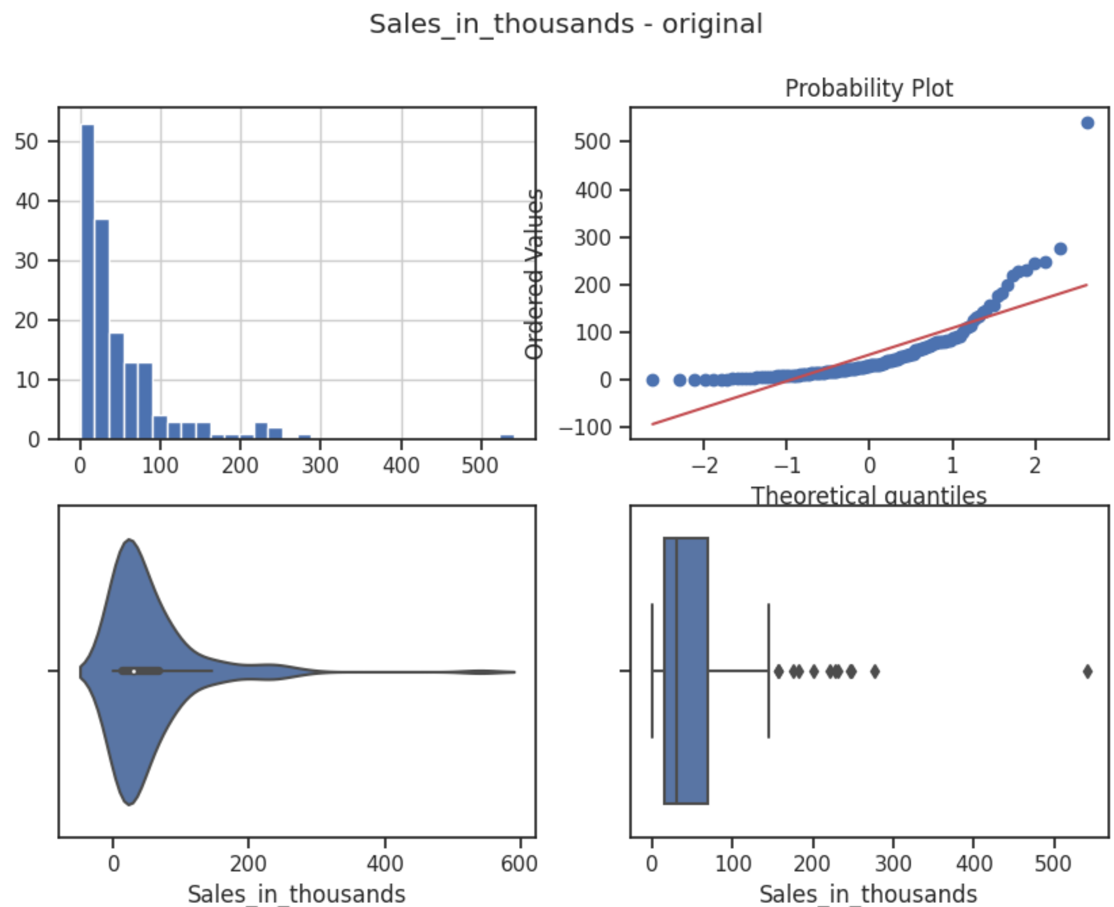
```
data2 = pd.read_csv("Car_sales.csv")

data2.head()

  Manufacturer    Model  Sales_in_thousands  __year_resale_value
Vehicle_type  \
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

   Price_in_thousands  Engine_size  Horsepower  Wheelbase  Width
Length  \
0               21.50          1.8       140.0      101.2   67.3
172.4
1               28.40          3.2       225.0      108.1   70.3
192.9
2                 NaN          3.2       225.0      106.9   70.6
192.0
3               42.00          3.5       210.0      114.6   71.4
196.6
4               23.99          1.8       150.0      102.6   68.2
178.0

   Curb_weight  Fuel_capacity  Fuel_efficiency Latest_Launch  \
0        2.639           13.2             28.0      2/2/2012
1        3.517           17.2             25.0      6/3/2011
2        3.470           17.2             26.0      1/4/2012
3        3.850           18.0             22.0     3/10/2011
4        2.998           16.4             27.0     10/8/2011

   Power_perf_factor
0          58.280150
1          91.370778
2                NaN
3          91.389779
4          62.777639

data2.describe()

       Sales_in_thousands  __year_resale_value  Price_in_thousands  \
count          157.000000           121.000000          155.000000
mean            52.998076            18.072975           27.390755
```

```
std            68.029422           11.453384          14.351653
min             0.110000            5.160000           9.235000
25%            14.114000           11.260000          18.017500
50%            29.450000           14.180000          22.799000
75%            67.956000           19.875000          31.947500
max           540.561000           67.550000          85.500000

       Engine_size  Horsepower   Wheelbase       Width      Length  \
count   156.000000  156.000000  156.000000  156.000000  156.000000   
mean      3.060897  185.948718  107.487179   71.150000  187.343590   
std       1.044653   56.700321    7.641303    3.451872   13.431754   
min       1.000000   55.000000   92.600000   62.600000  149.400000   
25%       2.300000  149.500000  103.000000   68.400000  177.575000   
50%       3.000000  177.500000  107.000000   70.550000  187.900000   
75%       3.575000  215.000000  112.200000   73.425000  196.125000   
max       8.000000  450.000000  138.700000   79.900000  224.500000   

       Curb_weight  Fuel_capacity  Fuel_efficiency  Power_perf_factor  

count   155.000000     156.000000       154.000000         155.000000  

mean      3.378026      17.951923        23.844156          77.043591  

std       0.630502       3.887921         4.282706          25.142664  

min       1.895000      10.300000        15.000000          23.276272  

25%       2.971000      15.800000        21.000000          60.407707  

50%       3.342000      17.200000        24.000000          72.030917  

75%       3.799500      19.575000        26.000000          89.414878  

max       5.572000      32.000000        45.000000         188.144323  
```

```python
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])
```

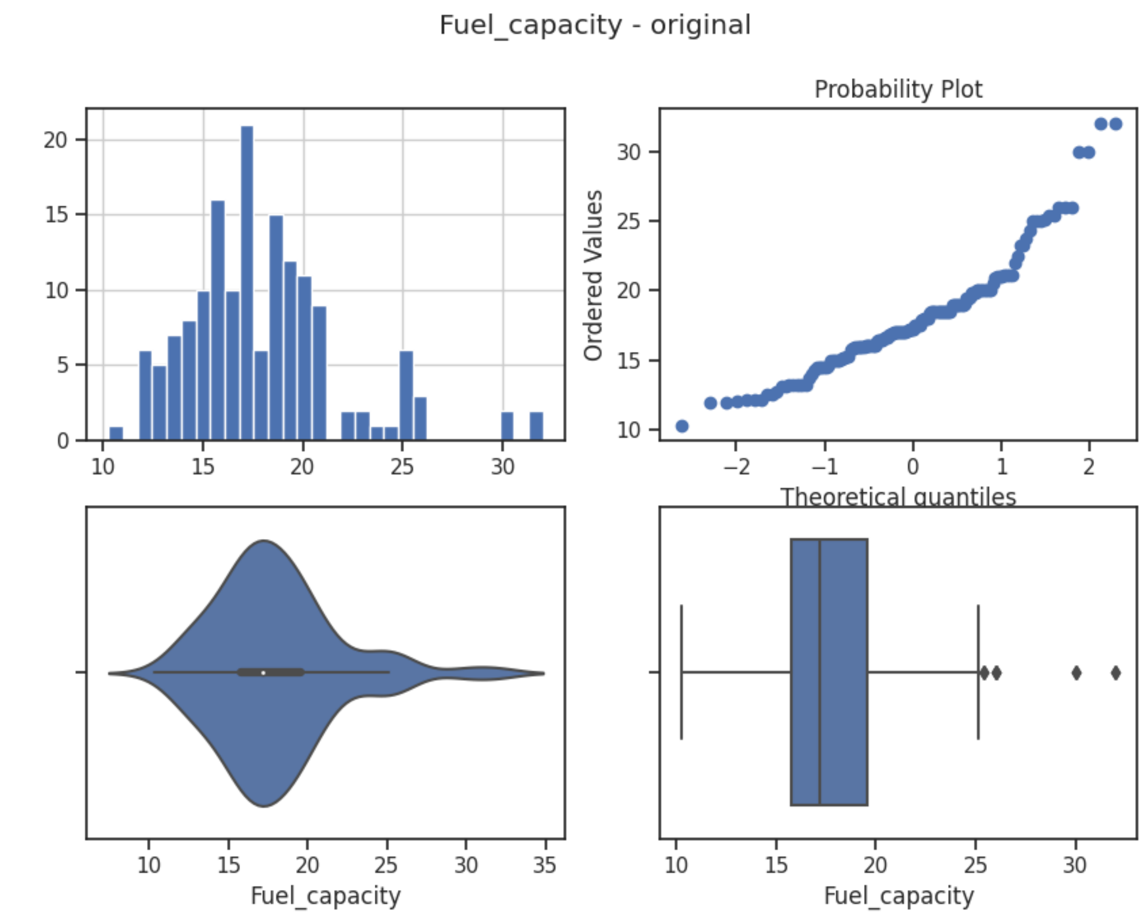
```
    fig.suptitle(title)
    plt.show()

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

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




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

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



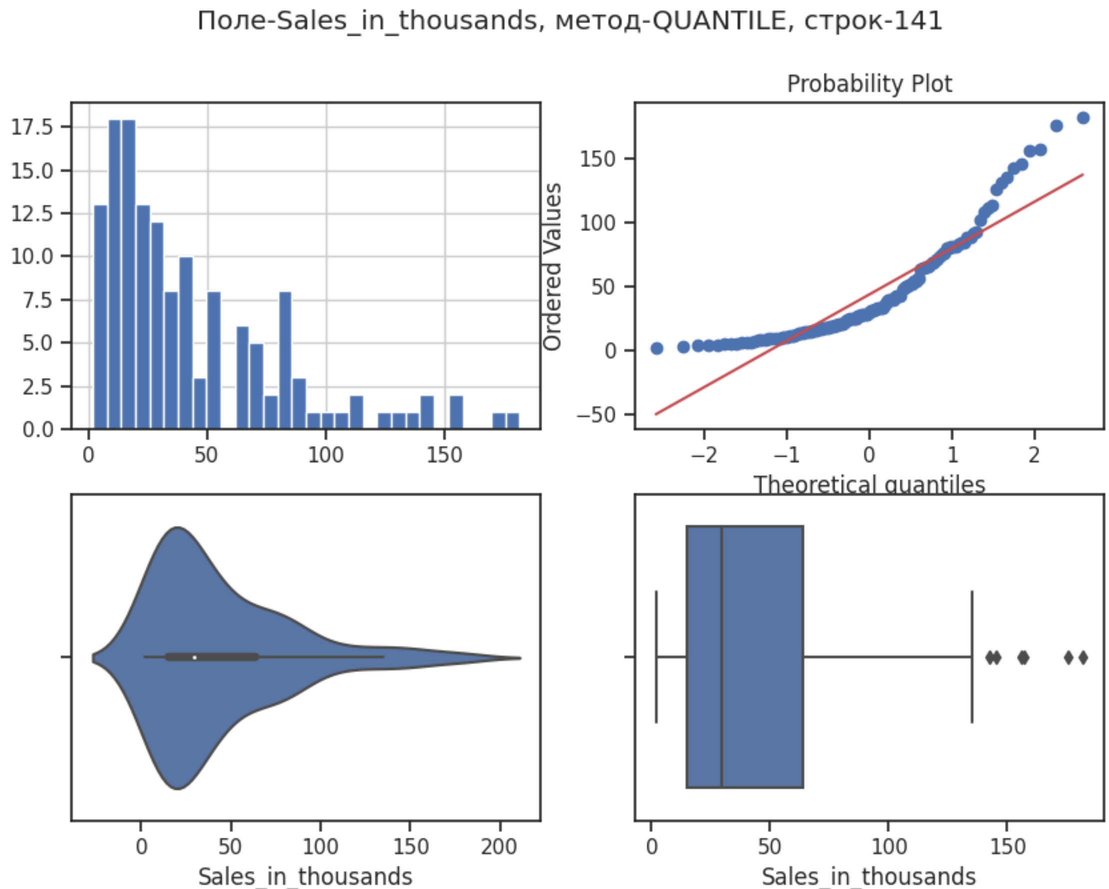

```
# Тип вычисления верхней и нижней границы выбросов
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3

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

### Удаление выбросов (number_of_reviews)

```
# 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, False))
# Удаление данных на основе флага
```

```
data_trimmed = data2.loc[~(outliers_temp), ]
title = 'Поле-{}, метод-{}, строк-{}'.format("Sales_in_thousands",
"QUANTILE", data_trimmed.shape[0])
diagnostic_plots(data_trimmed, "Sales_in_thousands", title)
```

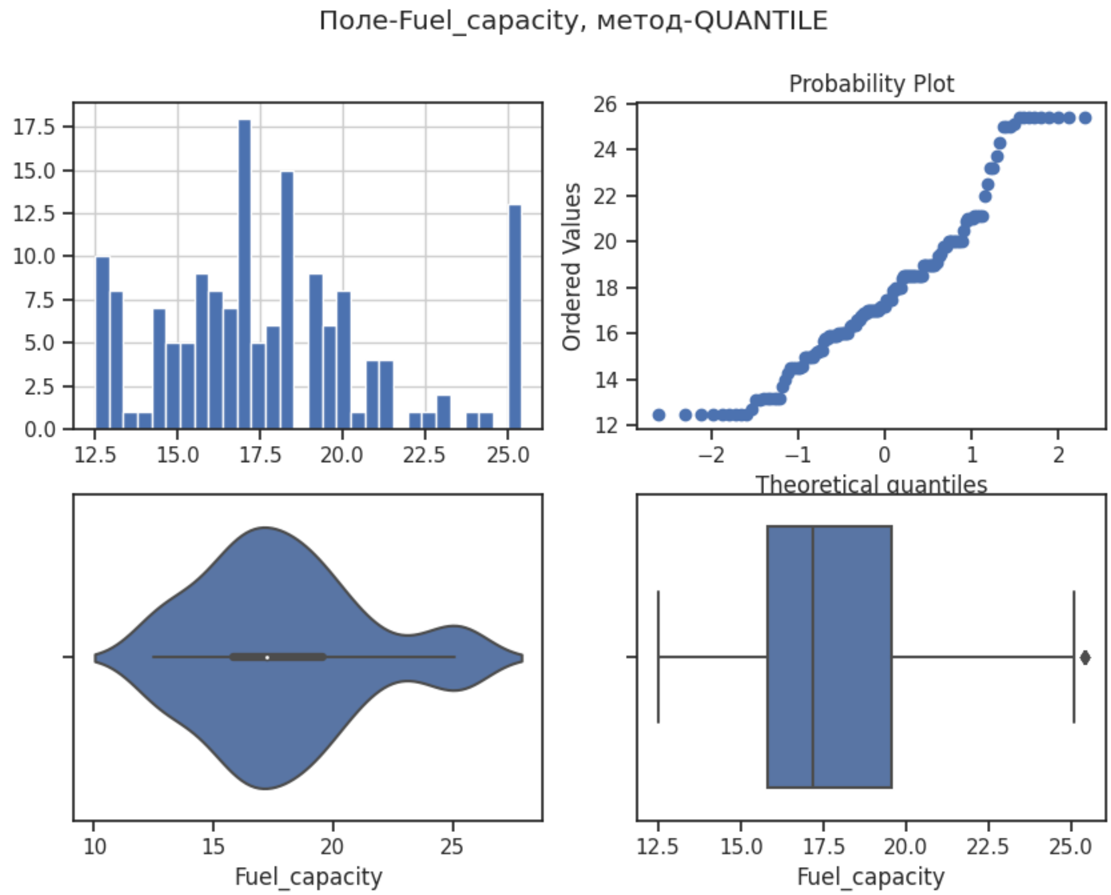
```
<ipython-input-29-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-
removal of overlapping axes is deprecated since 3.6 and will be
removed two minor releases later; explicitly call ax.remove() as
needed.
  plt.subplot(2, 2, 1)
```




### Замена выбросов

```
# 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, data2["Fuel_capacity"]))
title = 'Поле-{}, метод-{}'.format("Fuel_capacity", "QUANTILE")
diagnostic_plots(data2, "Fuel_capacity", title)
```

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




## Обработка нестандартного признака

```
data2.dtypes

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
```

```python
# Сконвертируем дату и время в нужный формат
data2["Latest_Launch_Date"] = data2.apply(lambda x:
pd.to_datetime(x["Latest_Launch"], format='%m/%d/%Y'), axis=1)

data2.head(5)
```

```
  Manufacturer    Model  Sales_in_thousands  __year_resale_value
Vehicle_type  \
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

   Price_in_thousands  Engine_size  Horsepower  Wheelbase  Width
Length  \
0               21.50          1.8       140.0      101.2   67.3
172.4
1               28.40          3.2       225.0      108.1   70.3
192.9
2                 NaN          3.2       225.0      106.9   70.6
192.0
3               42.00          3.5       210.0      114.6   71.4
196.6
4               23.99          1.8       150.0      102.6   68.2
178.0

   Curb_weight  Fuel_capacity  Fuel_efficiency Latest_Launch  \
0        2.639           13.2             28.0      2/2/2012
1        3.517           17.2             25.0      6/3/2011
2        3.470           17.2             26.0      1/4/2012
3        3.850           18.0             22.0     3/10/2011
4        2.998           16.4             27.0     10/8/2011

   Power_perf_factor Latest_Launch_Date
0          58.280150         2012-02-02
1          91.370778         2011-06-03
2                NaN         2012-01-04
3          91.389779         2011-03-10
4          62.777639         2011-10-08
```

```python
data2.dtypes
```

```
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
```

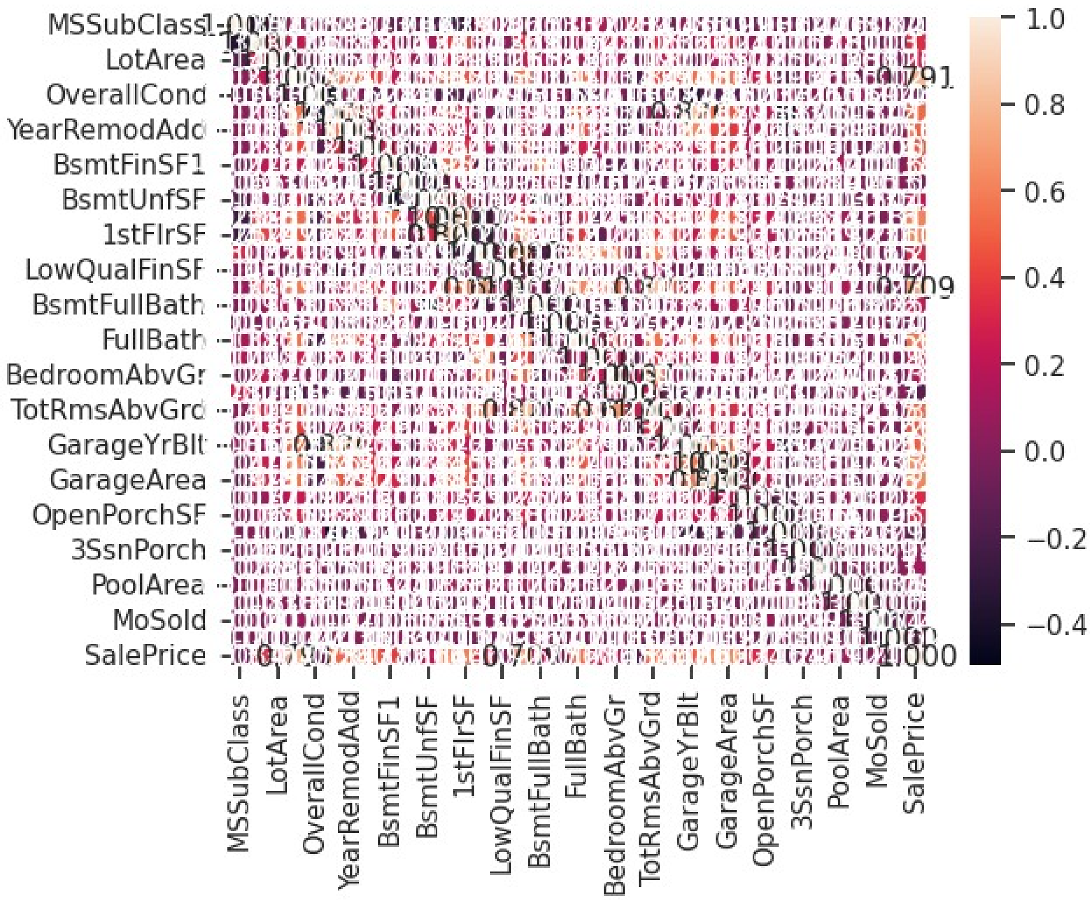
```
# День
data2['Latest_Launch_Day'] = data2['Latest_Launch_Date'].dt.day
# Месяц
data2['Latest_Launch_Month'] = data2['Latest_Launch_Date'].dt.month
# Год
data2['Latest_Launch_Year'] = data2['Latest_Launch_Date'].dt.year
```

## Отбор признаков

### Метод фильтрации (Корреляция признаков)

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

```
<Axes: >
```




```
# 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

# 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

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

```
[['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

```
data3 = pd.read_csv("WineQT.csv", sep=",")
```

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

# 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)

# Используем L1-регуляризацию
e_lr1 = LogisticRegression(C=1000, solver='liblinear', penalty='l1',
max_iter=500, random_state=1)
e_lr1.fit(X3_train, y3_train)
# Коэффициенты регрессии
e_lr1.coef_
```

```
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]])
```

```
# 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()
```

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

```
e_lr2 = LinearSVC(C=0.01, penalty="l1", max_iter=2000, dual=False)
e_lr2.fit(X3_train, y3_train)
```

```python
# Коэффициенты регрессии
e_lr2.coef_
```

```
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]])
```

```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()
```

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