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**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:
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подпись, дата

2024 г.

## 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]
```

```
# 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))
```

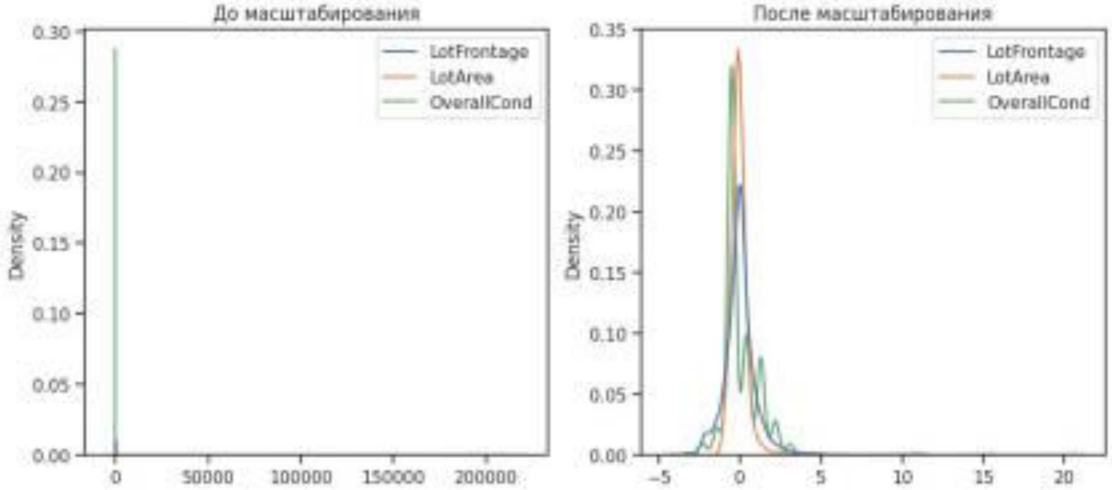
## StandardScaler

```
# 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]
```

```
# 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))
```

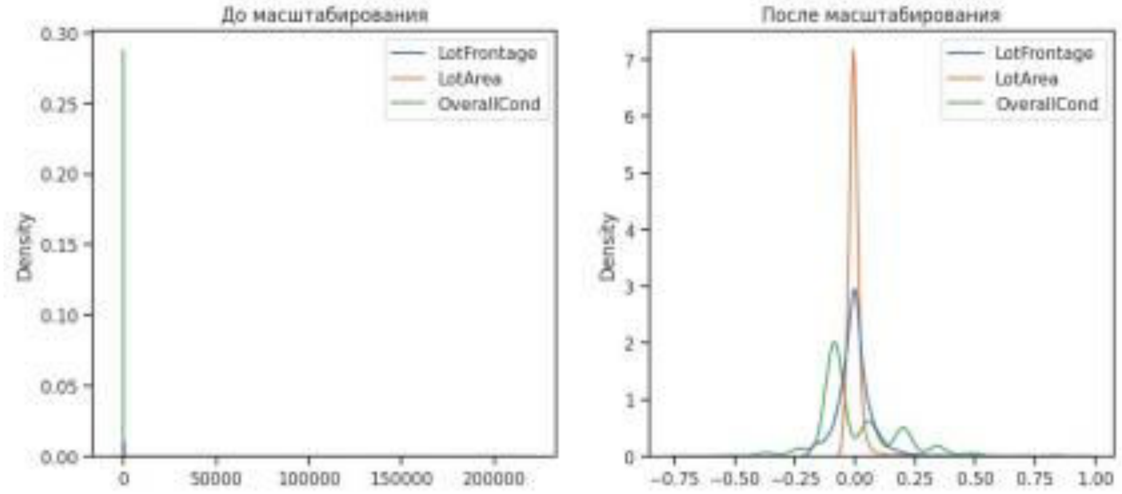
```
class MeanNormalisation:

 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]
```

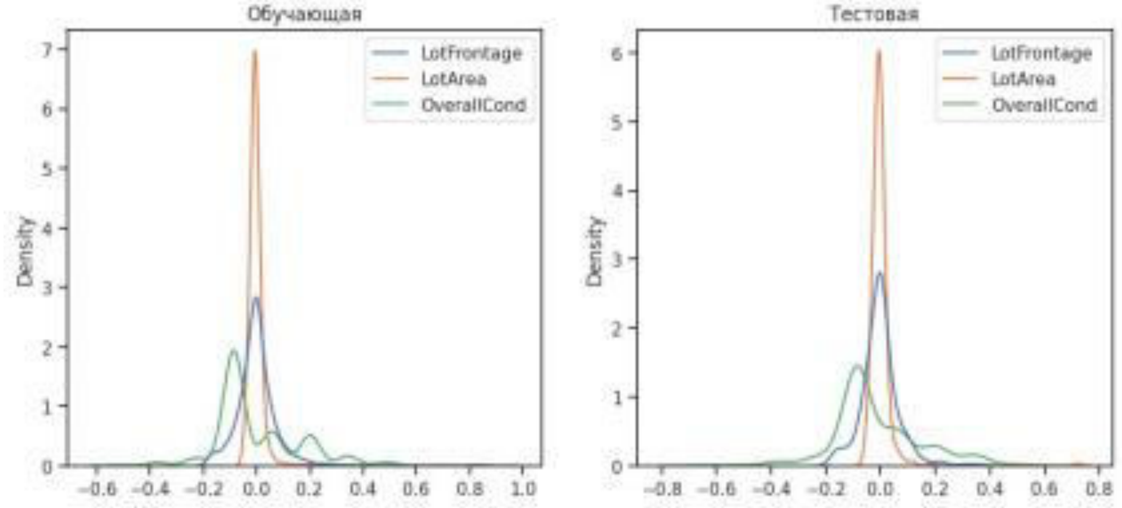
```
cs22 = MeanNormalisation()
cs22.fit(X_train)
data_cs22_scaled_train = cs22.transform(X_train)
data_cs22_scaled_test = cs22.transform(X_test)

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

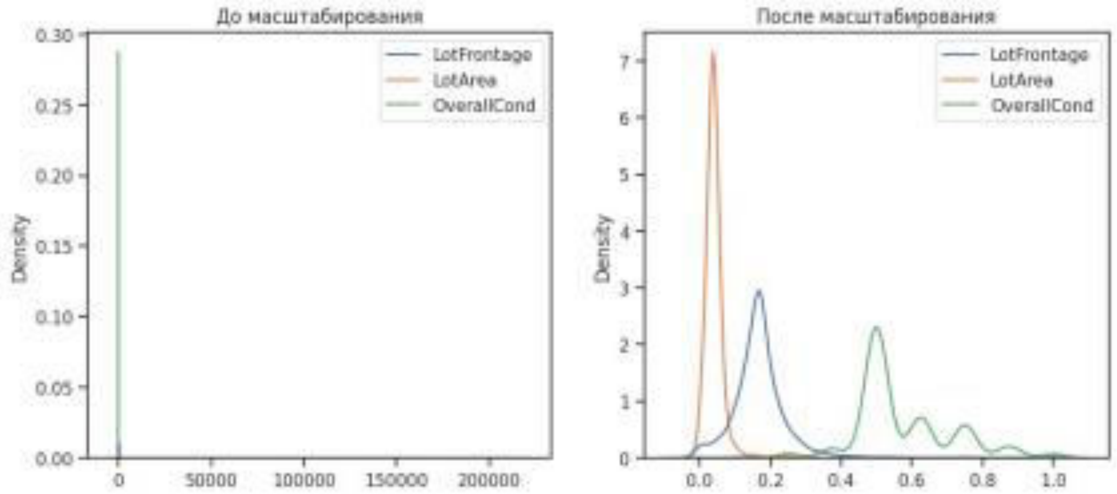
```
# Обучаем StandardScaler на всей выборке и масштабируем cs31 =
MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()

 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
```

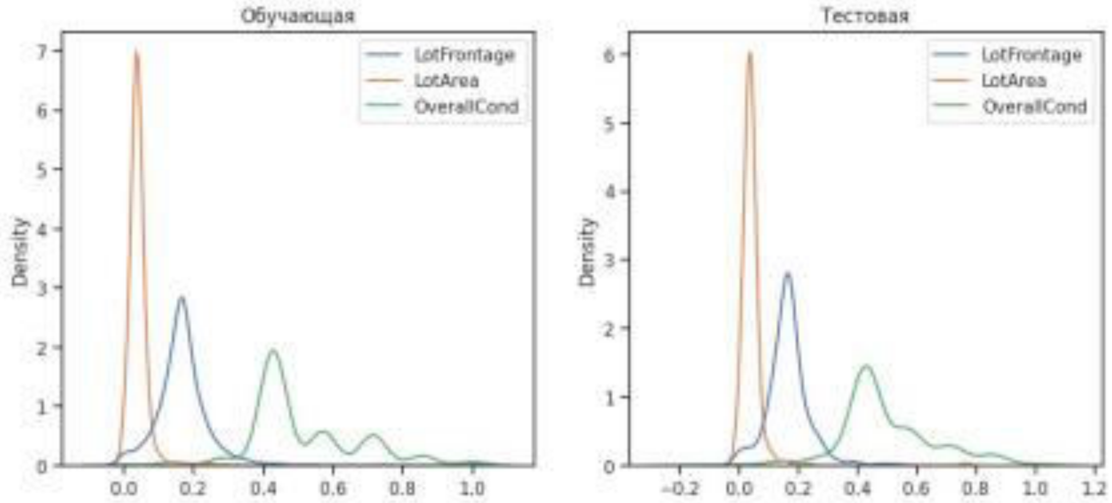
```
 YearBuilt YearRemodAdd MasVnrArea BsmtFinSF1  BsmtFinSF2 ... \
count 1460.000000 1460.000000 1452.000000 1460.000000  1460.000000 ...
mean 0.719332 0.581096 0.064803 0.078604  0.031580 ...
std 0.218862 0.344090 0.113166 0.080811  0.109443 ...
min 0.000000 0.000000 0.000000 0.000000  0.000000 ...
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
```

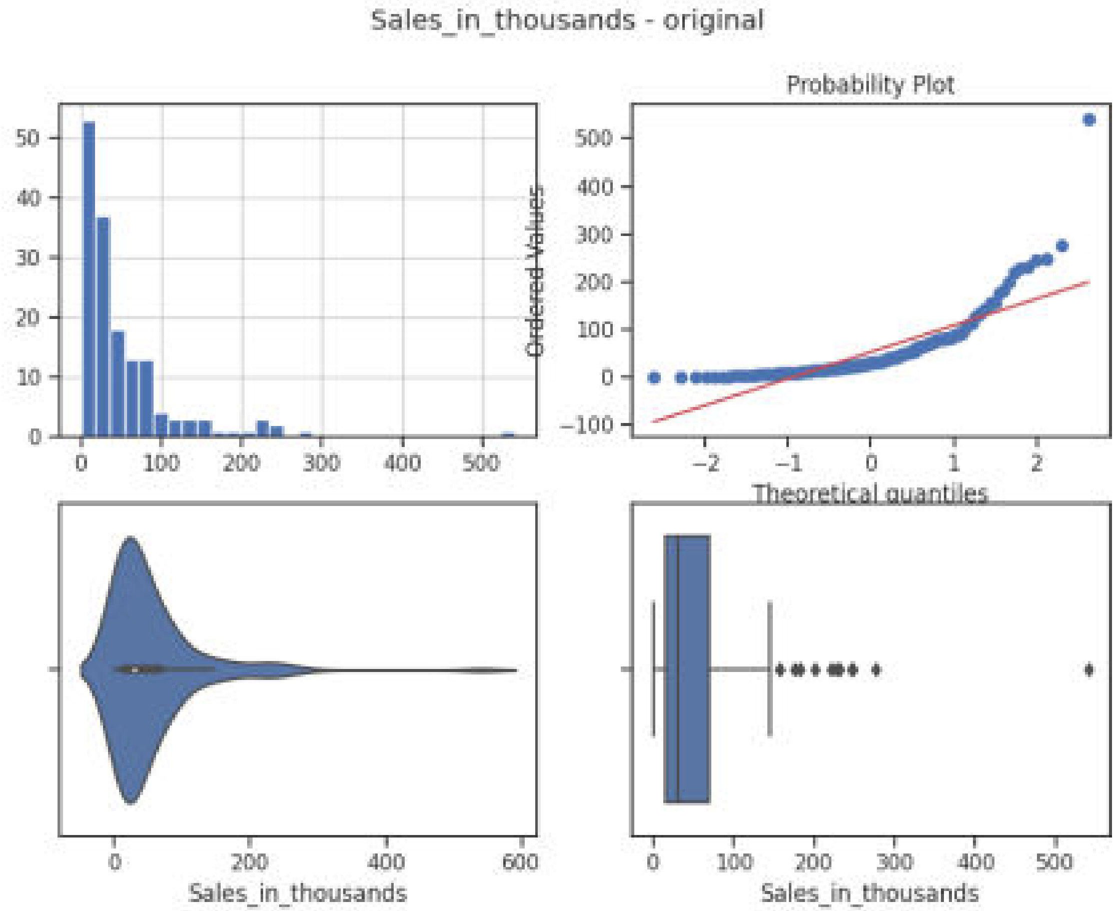
data2.describe()

```
 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()
```

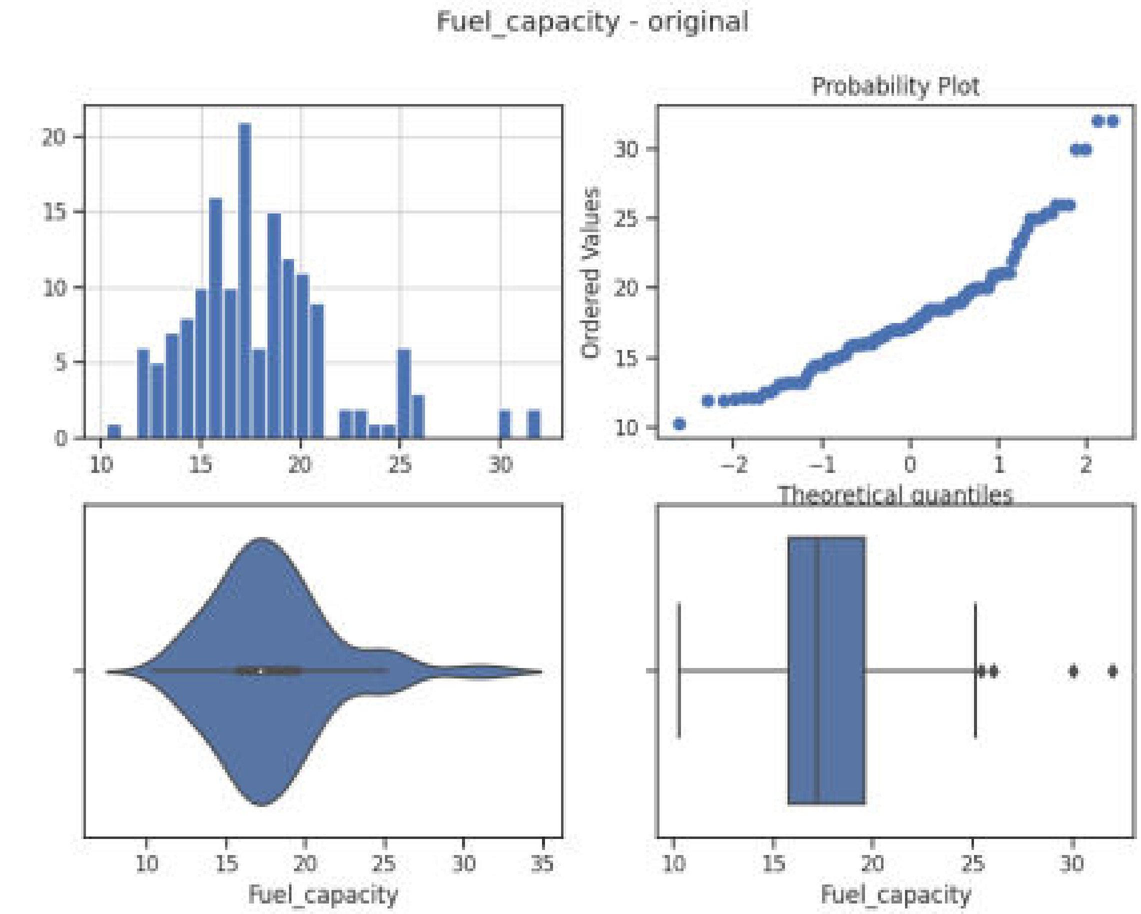
```
diagnostic_plots(data2, 'Sales_in_thousands', 'Sales_in_thousands -  original')
```

```
<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)
```

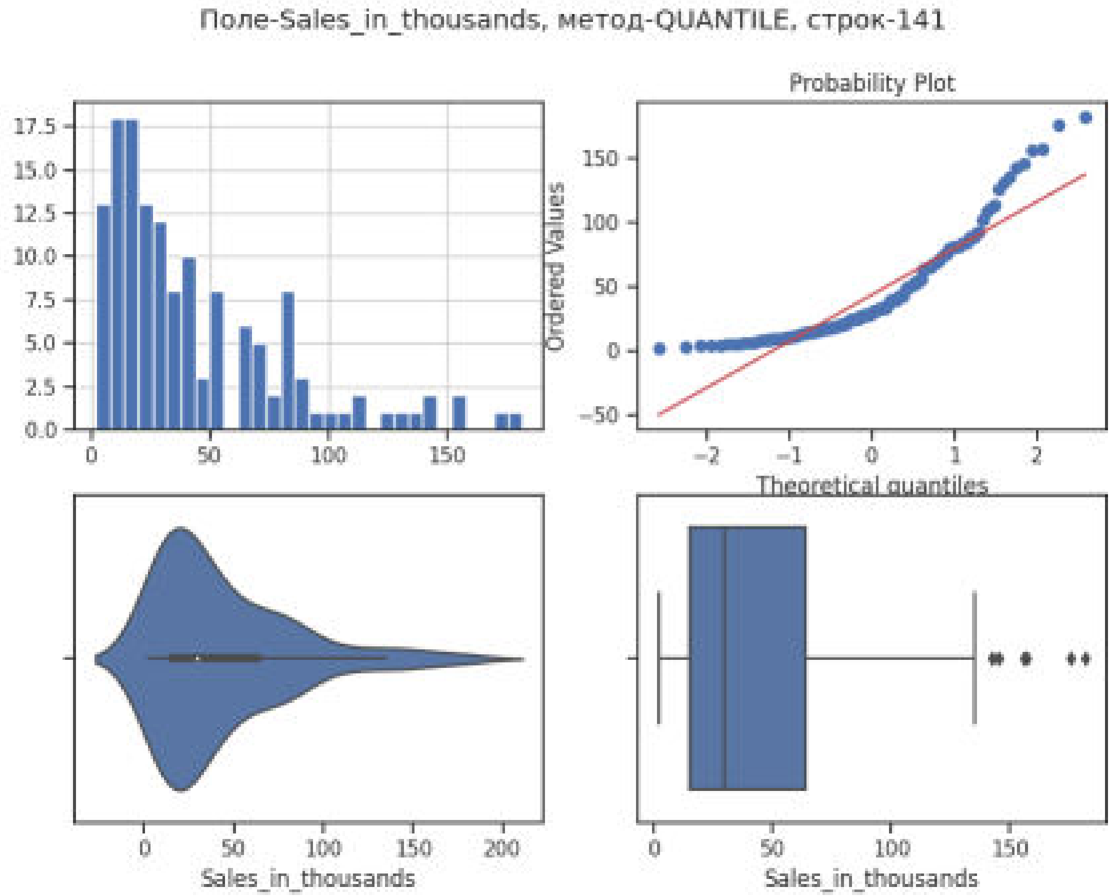


```
# Тип вычисления верхней и нижней границы выбросов
from enum import Enum
class OutlierBoundaryType(Enum):
 SIGMA = 1
 QUANTILE = 2
 IRQ = 3

# 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)
```

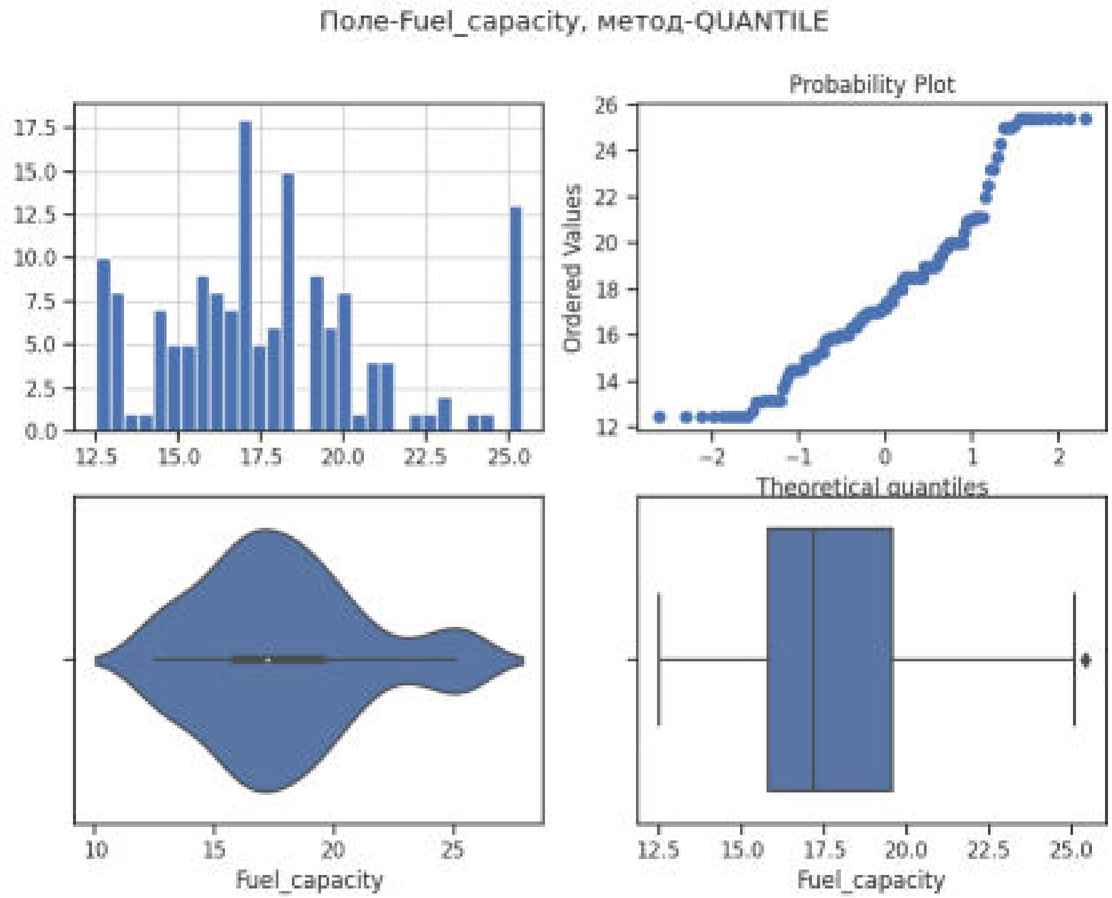
```
<ipython-input-29-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto removal of
overlapping axes is deprecated since 3.6 and will be  removed two minor releases later;
explicitly call ax.remove() as  needed.
 plt.subplot(2, 2, 1)
```



## 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
```

```
# 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
```

```
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
```

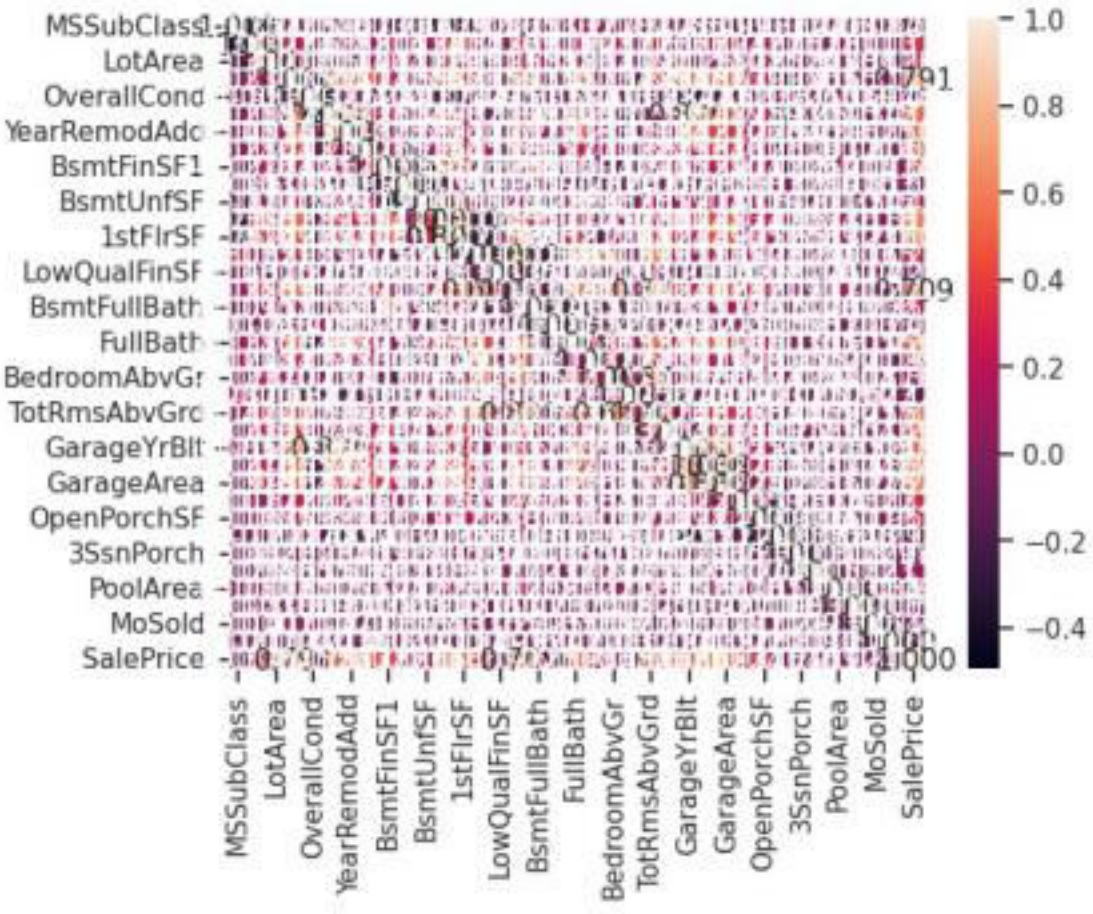
```
# День
data2['Latest_Launch_Day'] = data2['Latest_Launch_Date'].dt.day # Месяц
data2['Latest_Launch_Month'] = data2['Latest_Launch_Date'].dt.month # Год
data2['Latest_Launch_Year'] = data2['Latest_Launch_Date'].dt.year
```

## 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)
# 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]])
```

```
# 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])
```