1. Цель лабораторной работы:

изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

2. 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: 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).

3. Ход выполнения работы

Импорт библиотек

In [2]:

```
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
```

In [3]:

```
data = pd.read_csv(r'C:\Users\asus\Desktop\iu5\MMO\lab3\data.csv')
```

In [4]:

```
data.head()
```

Out[4]:

	Row	Id	Surname	Score	Nationality	Gender	Age	Tenure	Balance	Products	C
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	

In [5]:

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

```
C:\Users\asus\AppData\Local\Temp/ipykernel_22008/222650945.py:1: FutureWarning: In a
future version of pandas all arguments of DataFrame.drop except for the argument 'la
bels' will be keyword-only
  data = data.drop('Id', 1)
```

Out[5]:

	Row	Surname	Score	Nationality	Gender	Age	Tenure	Balance	Products	Card	Active
0	1	Hargrave	619	France	Female	42	2	0.00	1	1	1
1	2	Hill	608	Spain	Female	41	1	83807.86	1	0	1
2	3	Onio	502	France	Female	42	8	159660.80	3	1	(
3	4	Boni	699	France	Female	39	1	0.00	2	0	(
4	5	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1

In [6]:

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

Out[6]:

	Row	Surname	Score	Nationality	Gender	Age	Tenure	Balance	Products	Card
0	1	Hargrave	619	France	Female	42	2	0.00	1	1
1	2	Hill	608	Spain	Female	41	1	83807.86	1	0
2	3	Onio	502	France	Female	42	8	159660.80	3	1
3	4	Boni	699	France	Female	39	1	0.00	2	0
4	5	Mitchell	850	Spain	Female	43	2	125510.82	1	1
...	...	...	...	...	...	...	...	...	...	...
9995	9996	Obijiaku	771	France	Male	39	5	0.00	2	1
9996	9997	Johnstone	516	France	Male	35	10	57369.61	1	1
9997	9998	Liu	709	France	Female	36	7	0.00	1	0
9998	9999	Sabbatini	772	Germany	Male	42	3	75075.31	2	1
9999	10000	Walker	792	France	Female	28	4	130142.79	1	1

10000 rows × 13 columns

In [7]:

```
data.describe()
```

Out[7]:

	Row	Score	Age	Tenure	Balance	Products
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	5000.50000	650.528800	38.921800	5.012800	76485.889288	1.530200
std	2886.89568	96.653299	10.487806	2.892174	62397.405202	0.581654
min	1.00000	350.000000	18.000000	0.000000	0.000000	1.000000
25%	2500.75000	584.000000	32.000000	3.000000	0.000000	1.000000
50%	5000.50000	652.000000	37.000000	5.000000	97198.540000	1.000000
75%	7500.25000	718.000000	44.000000	7.000000	127644.240000	2.000000
max	10000.00000	850.000000	92.000000	10.000000	250898.090000	4.000000

In [8]:

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

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

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['Salary'],
                                                    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]:

((8000, 9), (2000, 9))

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]:

	Row	Score	Age	Tenure	Balance	Products	Card	Active	
0	-1.731878	-0.326221	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	1.
1	-1.731531	-0.440036	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	-0.
2	-1.731185	-1.536794	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	1.
3	-1.730838	0.501521	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.
4	-1.730492	2.063884	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.
...	...	...	...	...	...	...	...	...	
9995	1.730492	1.246488	0.007457	-0.004426	-1.225848	0.807737	0.646092	-1.030670	-0.
9996	1.730838	-1.391939	-0.373958	1.724464	-0.306379	-0.911583	0.646092	0.970243	-0.
9997	1.731185	0.604988	-0.278604	0.687130	-1.225848	-0.911583	-1.547768	0.970243	1.
9998	1.731531	1.256835	0.293517	-0.695982	-0.022608	0.807737	0.646092	-1.030670	1.
9999	1.731878	1.463771	-1.041433	-0.350204	0.859965	-0.911583	0.646092	-1.030670	-0.

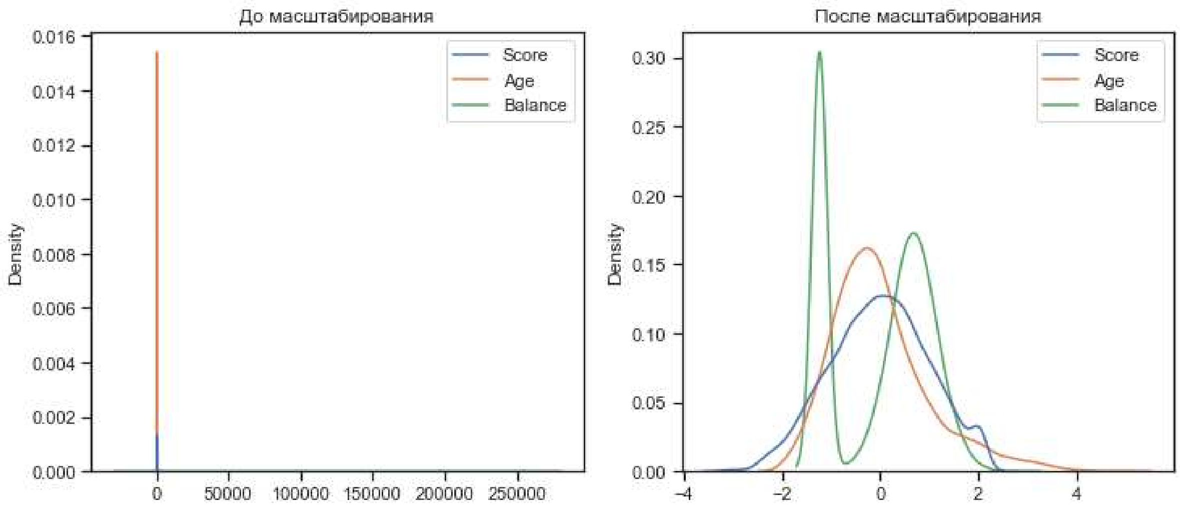
10000 rows × 9 columns

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(['Score', 'Age', 'Balance'], data, data_cs11_scaled, 'До масштабирования',
```



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['Salary'],
                                                    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]:

```
((8000, 9), (2000, 9))
```

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]:

	Row	Score	Age	Tenure	Balance	Products	
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	1C
mean	-0.001795	0.000430	0.000467	-0.001220	0.000089	-0.000558	
std	0.288718	0.193307	0.141727	0.289217	0.248696	0.193885	
min	-0.501795	-0.600627	-0.282260	-0.502500	-0.304759	-0.177292	
25%	-0.251795	-0.132627	-0.093071	-0.202500	-0.304759	-0.177292	
50%	-0.001795	0.003373	-0.025503	-0.002500	0.082644	-0.177292	
75%	0.248205	0.135373	0.069091	0.197500	0.203990	0.156042	
max	0.498205	0.399373	0.717740	0.497500	0.695241	0.822708	

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]:

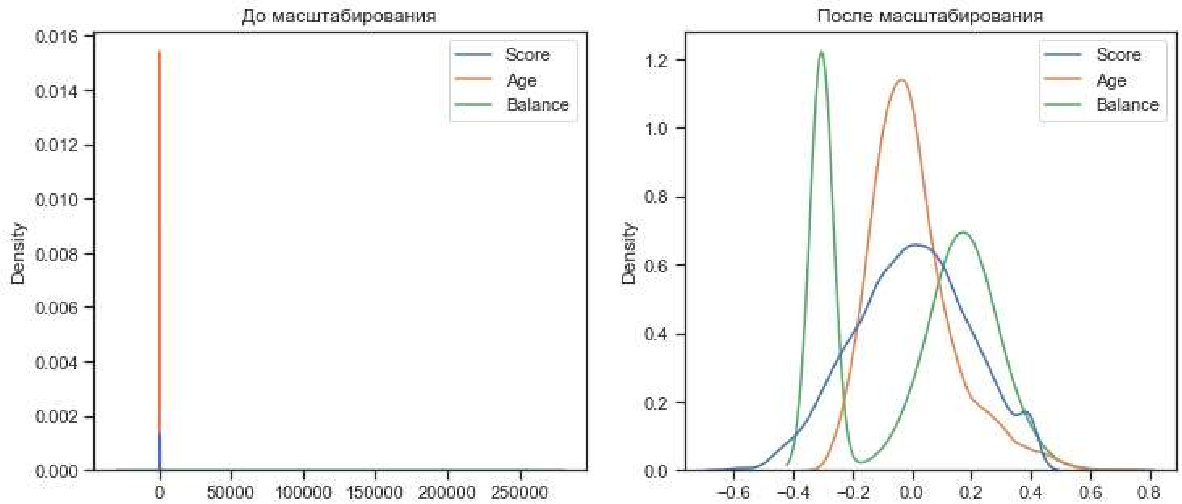
```
data_cs22_scaled_train.describe()
```

Out[19]:

	Row	Score	Age	Tenure	Balance	Products	
count	8.000000e+03	8.000000e+03	8.000000e+03	8.000000e+03	8.000000e+03	8.000000e+03	8
mean	-2.884498e-17	-1.356207e-17	-2.579534e-17	1.474341e-17	-1.079838e-15	-7.000303e-17	
std	2.885589e-01	1.933540e-01	1.414715e-01	2.885856e-01	2.485971e-01	1.945155e-01	4
min	-5.017945e-01	-6.006273e-01	-2.822601e-01	-5.025000e-01	-3.047590e-01	-1.772917e-01	
25%	-2.485942e-01	-1.346273e-01	-9.307095e-02	-2.025000e-01	-3.047590e-01	-1.772917e-01	
50%	8.057306e-04	1.372750e-03	-2.550338e-02	-2.500000e-03	8.207197e-02	-1.772917e-01	2
75%	2.500307e-01	1.353727e-01	6.909122e-02	1.975000e-01	2.039710e-01	1.560417e-01	2
max	4.982055e-01	3.993727e-01	7.177399e-01	4.975000e-01	6.952410e-01	8.227083e-01	2

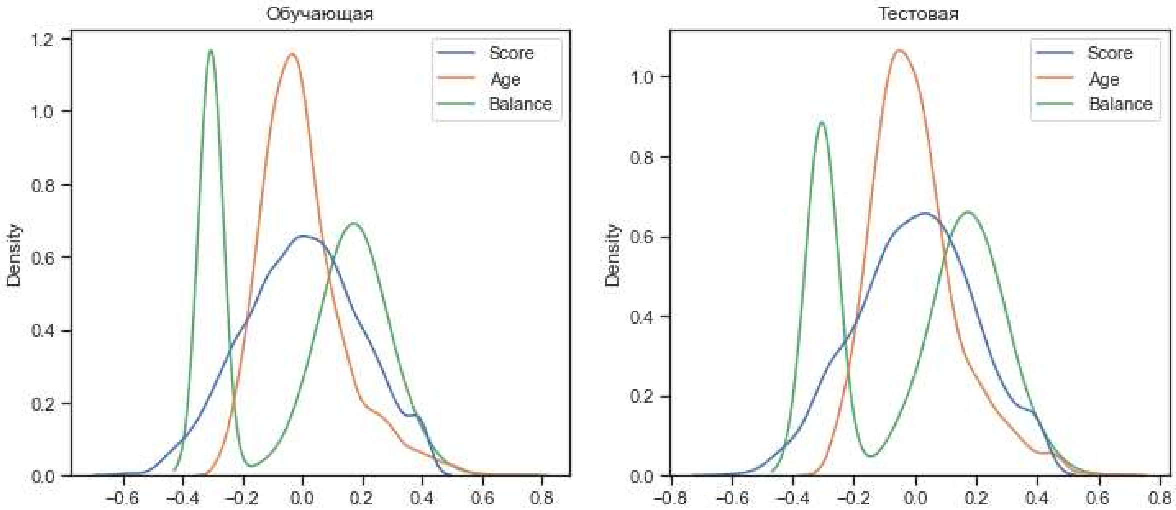
In [20]:

```
draw_kde(['Score', 'Age', 'Balance'], data, data_cs21_scaled, 'До масштабирования',
```



In [21]:

```
draw_kde(['Score', 'Age', 'Balance'], data_cs22_scaled_train, data_cs22_scaled_test, 'Обучающ
```



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]:

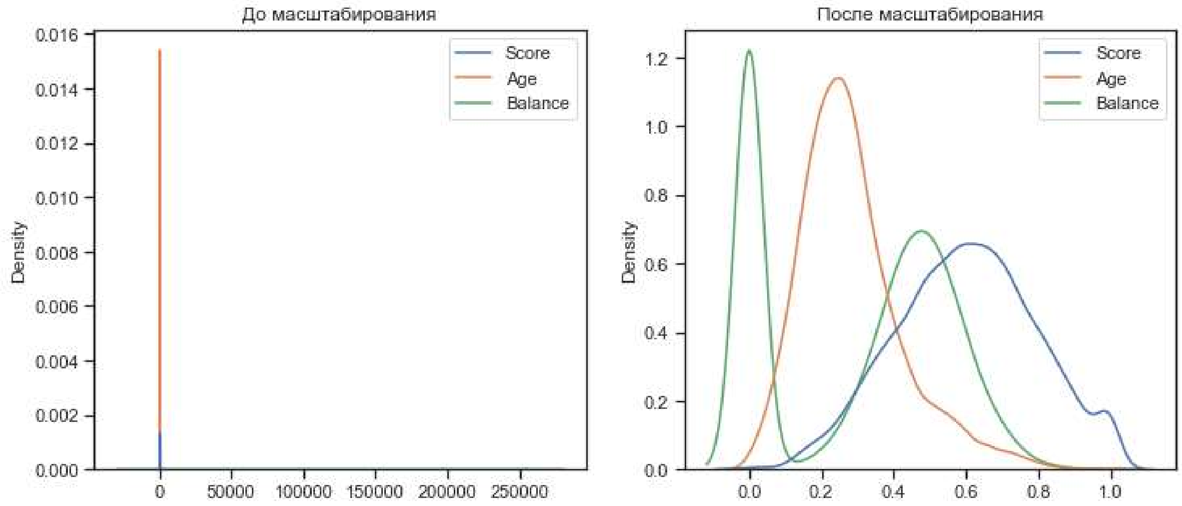
	Row	Score	Age	Tenure	Balance	Products	
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	1(
mean	0.500000	0.601058	0.282727	0.501280	0.304848	0.176733	
std	0.288718	0.193307	0.141727	0.289217	0.248696	0.193885	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.250000	0.468000	0.189189	0.300000	0.000000	0.000000	
50%	0.500000	0.604000	0.256757	0.500000	0.387402	0.000000	
75%	0.750000	0.736000	0.351351	0.700000	0.508749	0.333333	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

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)
```

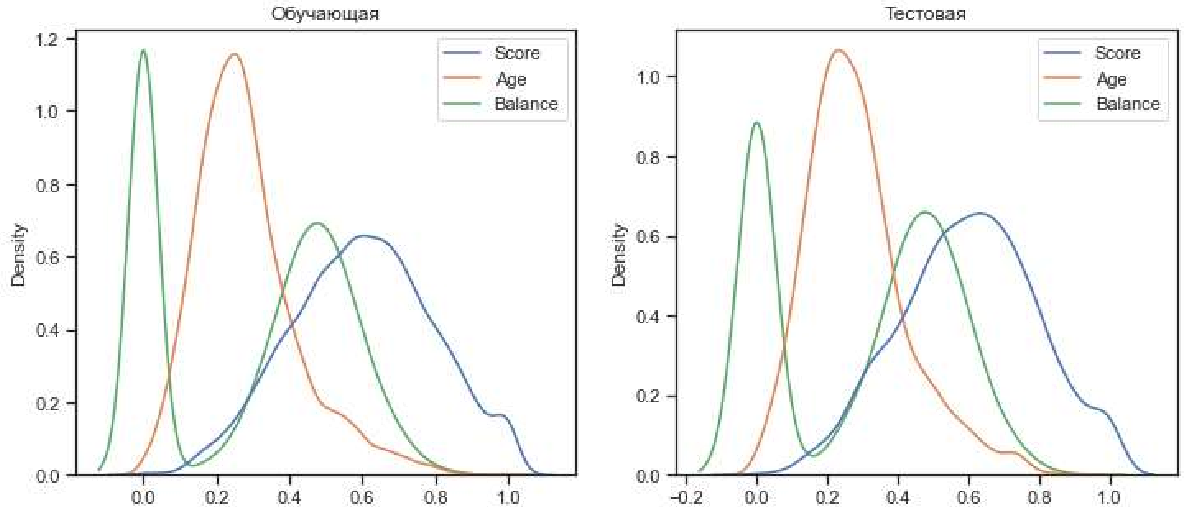
In [24]:

```
draw_kde(['Score', 'Age', 'Balance'], data, data_cs31_scaled, 'До масштабирования',
```



In [25]:

```
draw_kde(['Score', 'Age', 'Balance'], data_cs32_scaled_train, data_cs32_scaled_test, 'Обучающ
```



Обработка выбросов для числовых признаков

In [26]:

```
data2 = pd.read_csv(r"C:\Users\asus\Desktop\iu5\MMO\lab3\Air_Traffic_Cargo_Statistics.csv")
```

In [27]:

```
data2.head()
```

Out[27]:

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Cargo Type Code	
0	200507	ABX Air	GB	ABX Air	GB	Domestic	US	Deplaned	Cargo	
1	200507	ABX Air	GB	ABX Air	GB	Domestic	US	Enplaned	Cargo	
2	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Deplaned	Cargo	P
3	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Deplaned	Mail	P
4	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Enplaned	Cargo	P

In [28]:

```
data2.describe()
```

Out[28]:

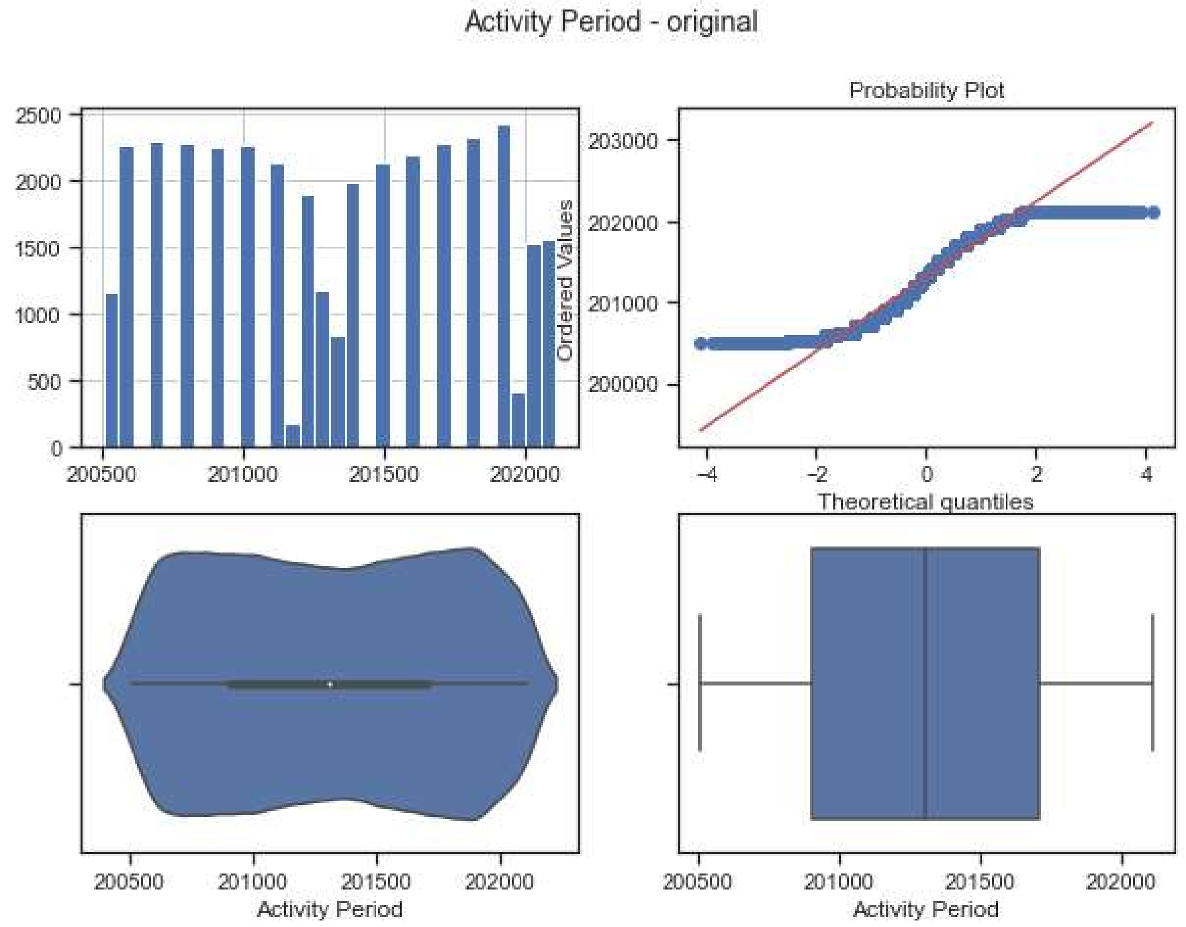
	Activity Period	Cargo Weight LBS	Cargo Metric TONS
count	35599.000000	3.559900e+04	35599.000000
mean	201311.369449	4.799115e+05	217.687856
std	473.480500	9.509778e+05	431.363548
min	200507.000000	1.000000e+00	0.000000
25%	200905.000000	1.839650e+04	8.344500
50%	201307.000000	1.329570e+05	60.309000
75%	201709.000000	5.469705e+05	248.106000
max	202109.000000	2.381234e+07	10801.278000

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()
```

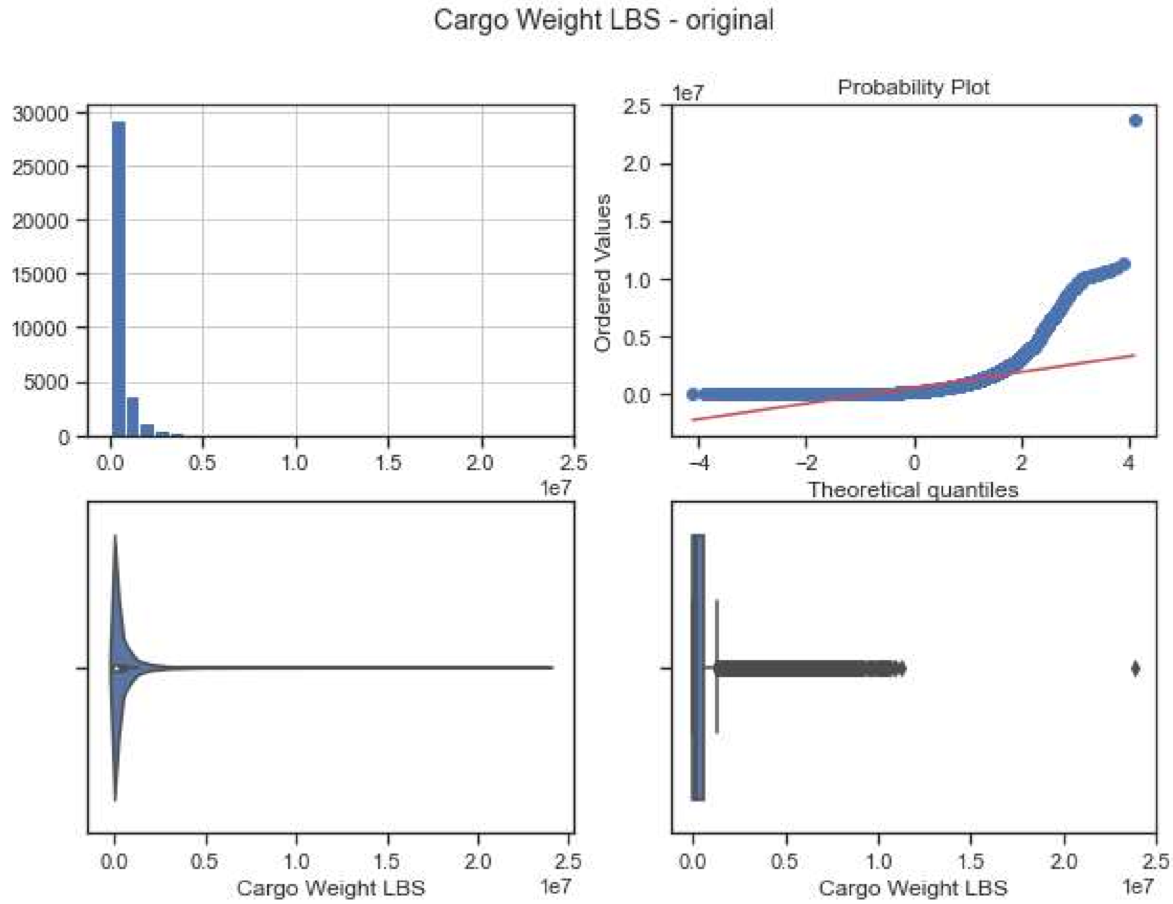
In [34]:

```
diagnostic_plots(data2, 'Activity Period', 'Activity Period - original')
```



In [36]:

```
diagnostic_plots(data2, 'Cargo Weight LBS', 'Cargo Weight LBS - original')
```



In [37]:

```
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3
```

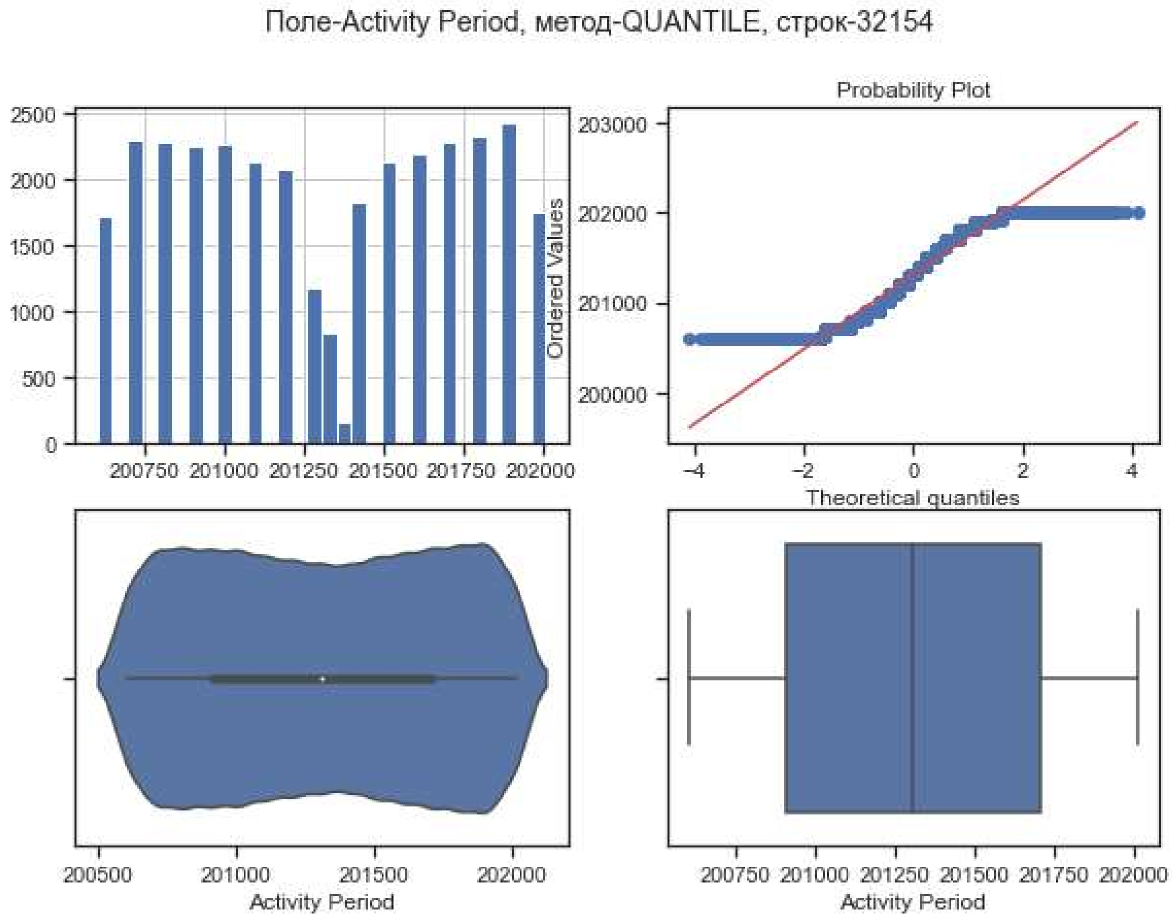
In [38]:

```
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 [39]:

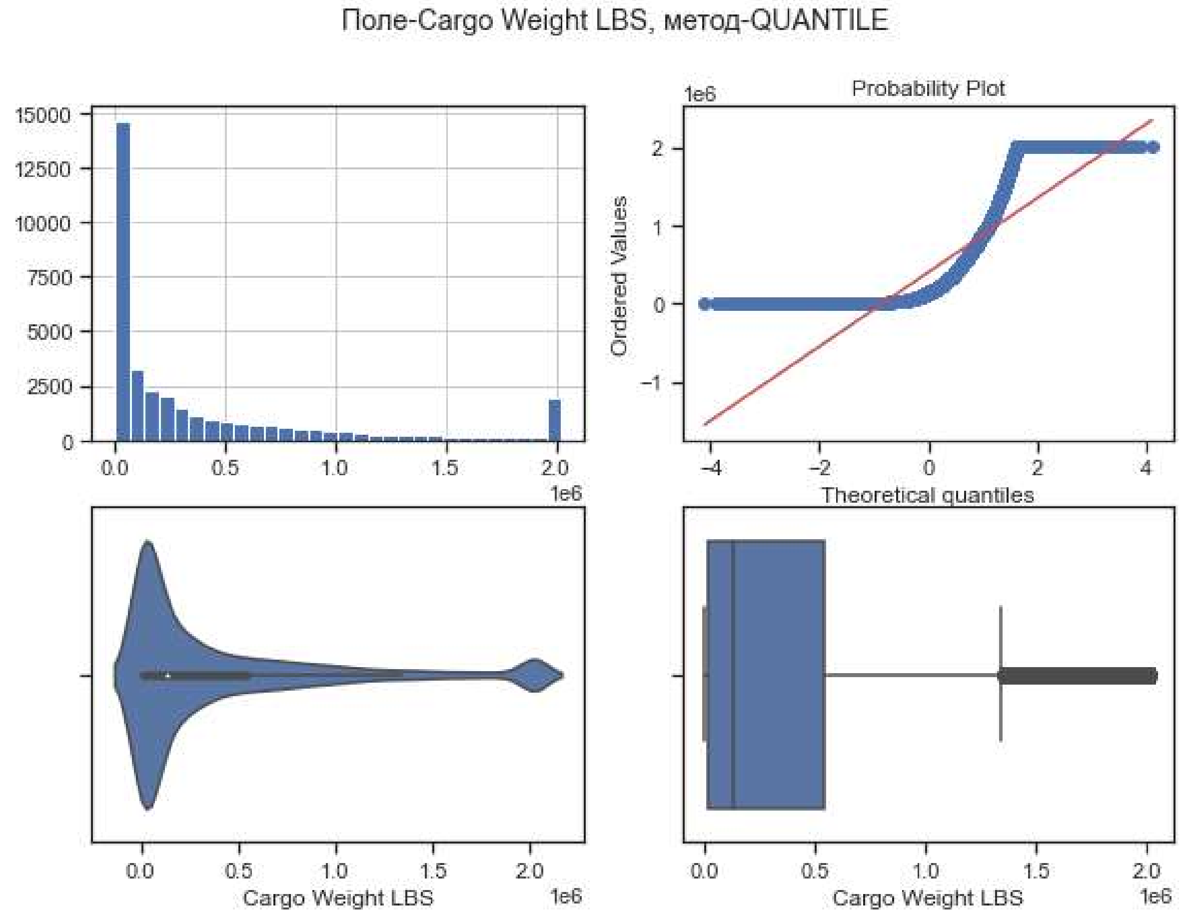
```
# Вычисление верхней и нижней границы
lower_boundary, upper_boundary = get_outlier_boundaries(data2, "Activity Period")
# Флаги для удаления выбросов
outliers_temp = np.where(data2["Activity Period"] > upper_boundary, True,
                         np.where(data2["Activity Period"] < lower_boundary,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



Замена выбросов

In [41]:

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



Обработка нестандартного признака

In [42]:

```
data2.dtypes
```

Out[42]:

```
Activity Period                  int64
Operating Airline               object
Operating Airline IATA Code     object
Published Airline               object
Published Airline IATA Code     object
GEO Summary                     object
GEO Region                      object
Activity Type Code              object
Cargo Type Code                 object
Cargo Aircraft Type             object
Cargo Weight LBS               float64
Cargo Metric TONS              float64
dtype: object
```

Отбор признаков

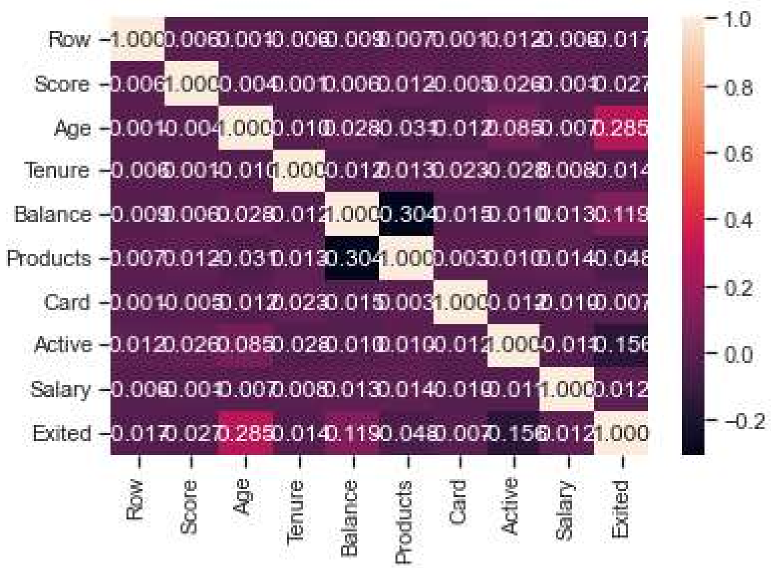
Метод фильтрации (Корреляция признаков)

In [45]:

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

Out[45]:

<AxesSubplot:>



In [46]:

```
# 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 [47]:

```
# 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 [48]:

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

Out[48]:

```
[['Products', 'Balance']]
```

Метод из группы методов вложений

In [49]:

```
data3 = pd.read_csv(r"C:\Users\asus\Desktop\iu5\MMO\lab3\waste water treatment.csv", sep=",")
```

In [51]:

```
data3.head(5)
```

Out[51]:

	Variable	VariableDescription	Country	Year	PercentageValue
0	TOTPUBSEW	Total public sewerage (% of resident populatio...	Australia	2010	92.79
1	TOTPUBSEW	Total public sewerage (% of resident populatio...	Australia	2011	93.84
2	TOTPUBSEW	Total public sewerage (% of resident populatio...	Australia	2012	94.10
3	TOTPUBSEW	Total public sewerage (% of resident populatio...	Australia	2013	94.08
4	TOTPUBSEW	Total public sewerage (% of resident populatio...	Australia	2014	92.57

In [52]:

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

In [54]:

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

In [ ]:

```

```

In [ ]:

```

```