Лабораторная работа №3

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Задание

Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:

- масштабирование признаков (не менее чем тремя способами);
- обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
- обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
- отбор признаков:
    - один метод из группы методов фильтрации (filter methods);
    - один метод из группы методов обертывания (wrapper methods);
    - один метод из группы методов вложений (embedded methods).

In [ ]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
%matplotlib inline
sns.set(style="ticks")
```

In [ ]:

```
data_loaded = pd.read_csv('solar.csv', sep=",")
```

In [ ]:

```
data_loaded.head()
```

Out[ ]:

	Catalog Number	Unnamed: 1	Time	Delta	Lunationnumber	Sarosnumber	Unnamed: 6	Gamma	Ec
0	1.0	NaN	3:14:51	46438.0	49456.0	5.0	NaN	0.2701	
1	2.0	NaN	23:45:23	46426.0	49457.0	10.0	NaN	0.2702	
2	3.0	NaN	18:09:16	46415.0	49458.0	15.0	NaN	0.2703	

	Catalog Number	Unnamed: 1	Time	Delta	Lunationnumber	Sarosnumber	Unnamed: 6	Gamma	Ec
3	4.0	NaN	5:57:03	46403.0	49459.0	20.0	NaN	0.2704	
4	5.0	NaN	13:19:56	46393.0	49460.0	-13.0	NaN	0.2705	

In [ ]:

```
data_loaded.shape
```

Out[ ]:

```
(32686, 19)
```

In [ ]:

```
data_features = list(zip(
[i for i in data_loaded.columns],
zip(
    #типы колонок
    [str(i) for i in data_loaded.dtypes],
    #проверка, есть ли пропущенные значения
    [i for i in data_loaded.isnull().sum()]
)))
data_features
```

Out[ ]:

```
[('Catalog Number', ('float64', 20788)),
 ('Unnamed: 1', ('float64', 32686)),
 ('Time', ('object', 20788)),
 ('Delta', ('float64', 20788)),
 ('Lunationnumber', ('float64', 20788)),
 ('Sarosnumber', ('float64', 20788)),
 ('Unnamed: 6', ('float64', 32686)),
 ('Gamma', ('float64', 20788)),
 ('Eclipsemagnitude', ('float64', 20788)),
 ('Unnamed: 9', ('float64', 32686)),
 ('Unnamed: 10', ('float64', 32686)),
 ('Sunaltitude', ('float64', 20788)),
 ('Sunazimuth', ('float64', 20788)),
 ('PathWidth (km)', ('float64', 20835)),
 ('Central Duration', ('object', 19672)),
 ('UNIXTime', ('int64', 0)),
 ('WindDirection(Degrees)', ('float64', 0)),
 ('TimeSunRise', ('object', 0)),
 ('TimeSunSet', ('object', 0))]
```

Устранение пропусков в данных

1. **Удаление пропущенных значений**

In [ ]:

```
cols_with_na = ['Time', 'Delta', 'Lunationnumber', 'Sarosnumber', 'Gamma', 'Suna
data_drop = data_loaded[cols_with_na].dropna()
data_drop.shape
```

Out[ ]:

```
(11898, 7)
```

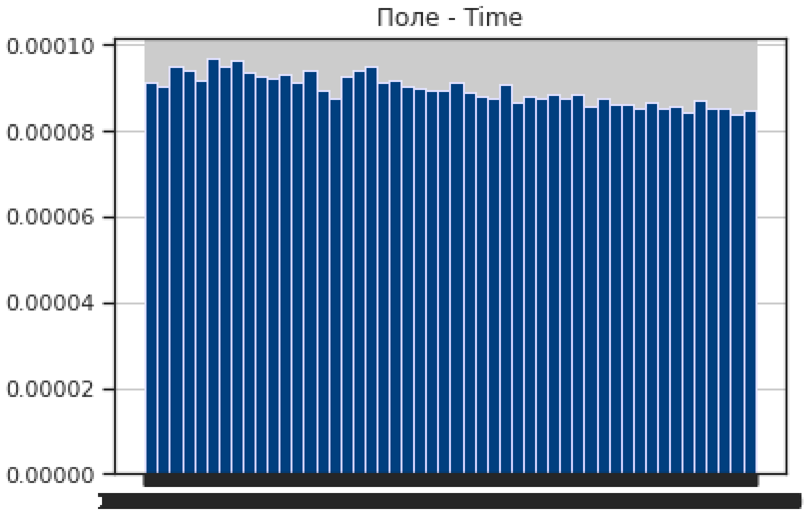
In [ ]:

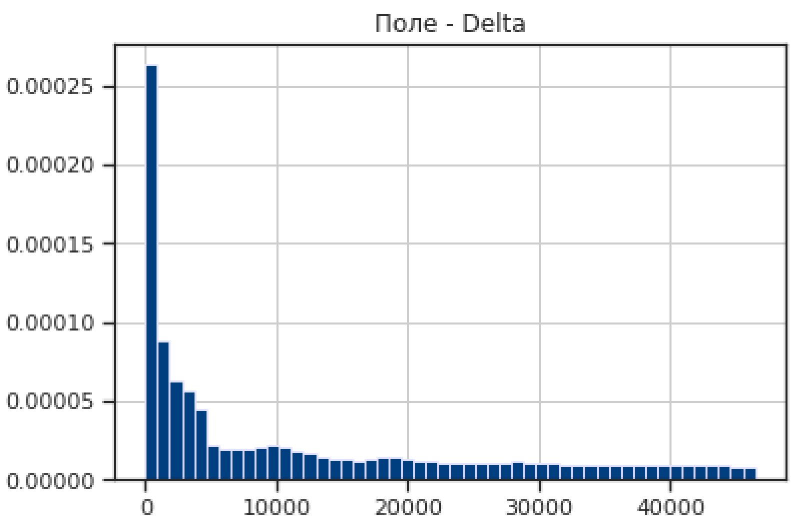
```
def plot_hist_diff(old_ds, new_ds, cols):
    """
    Разница между распределениями до и после устранения пропусков
    """
```

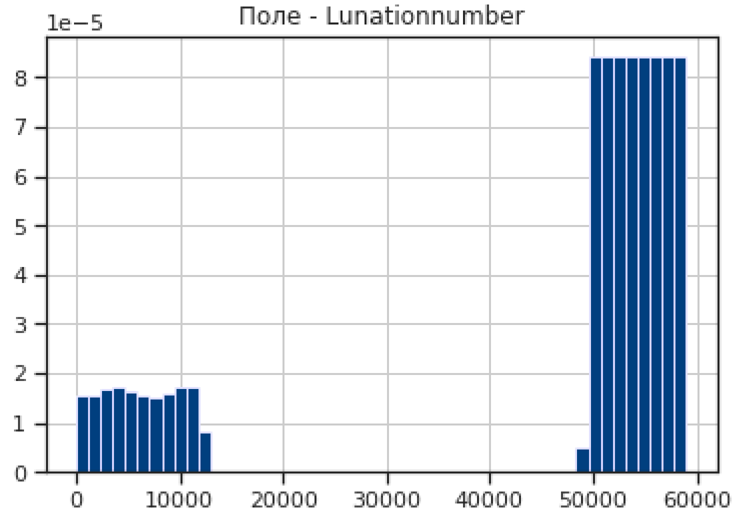
```
    for c in cols:
        fig = plt.figure()
        ax = fig.add_subplot(111)
        ax.title.set_text('Поле - ' + str(c))
        old_ds[c].hist(bins=50, ax=ax, density=True, color='green')
        new_ds[c].hist(bins=50, ax=ax, color='blue', density=True, alpha=0.5)
        plt.show()
```

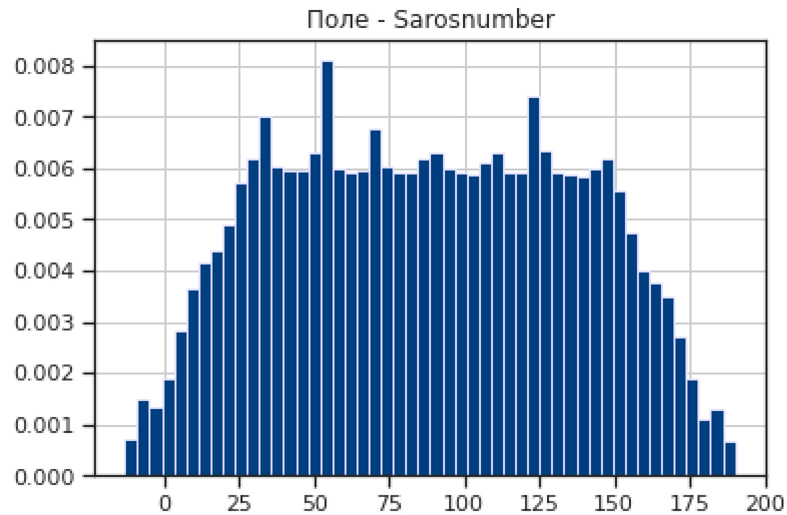
In [ ]:

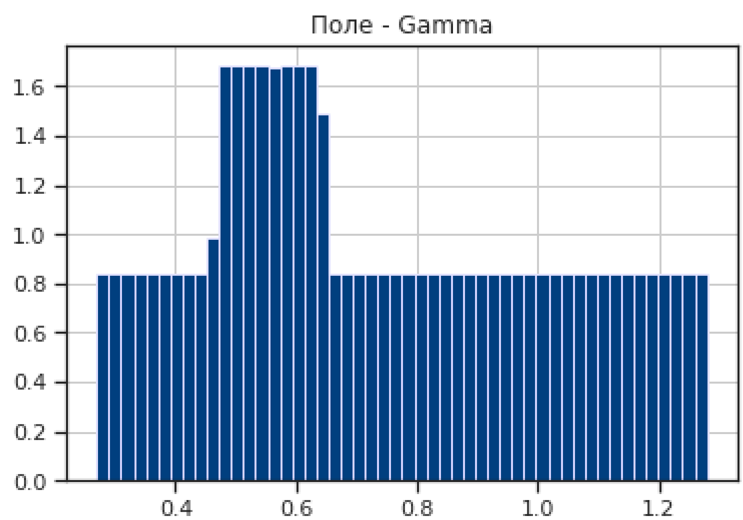
```
plot_hist_diff(data_loaded, data_drop, cols_with_na)
```

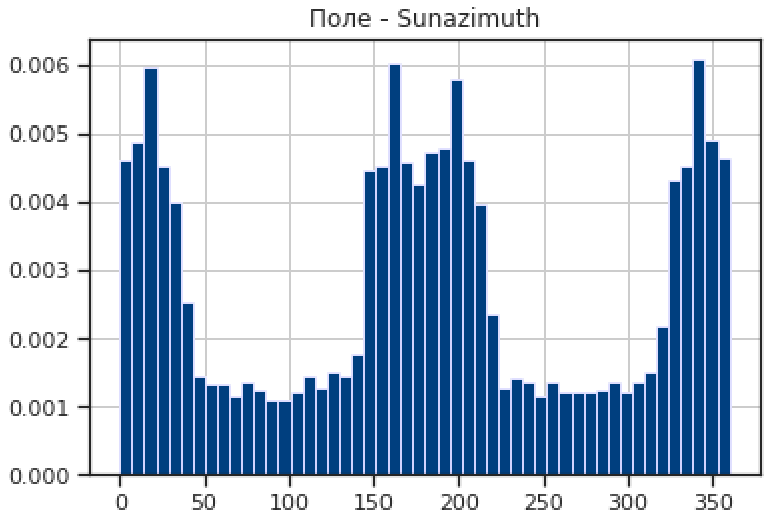


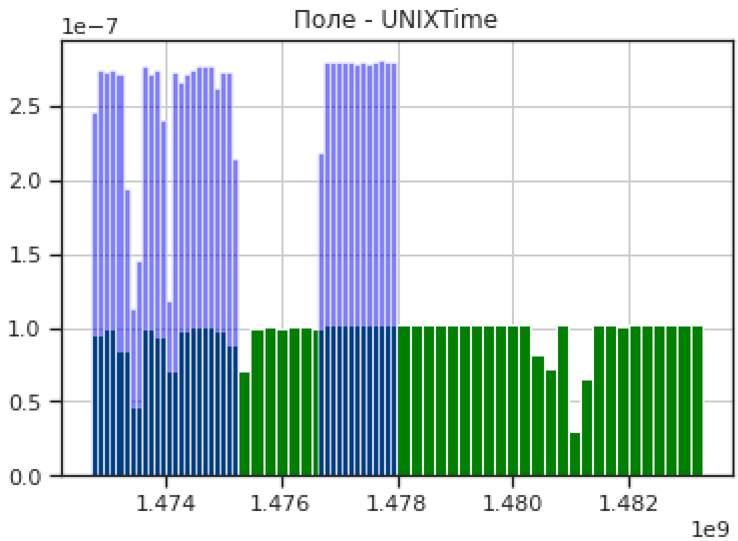



Поле - Lunationnumber
1e−5
0
1
2
3
4
5
6
7
8
0
10000
20000
30000
40000
50000
60000


Поле - Sarosnumber
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0.008
0
25
50
75
100
125
150
175
200


Поле - Gamma
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
0.4
0.6
0.8
1.0
1.2





1. **Заполнение значений для одного признака**

In [ ]:

```
def impute_column(dataset, column, strategy_param, fill_value_param=None):
    """
    Заполнение пропусков в одном признаке
    """
    temp_data = dataset[[column]].values
    size = temp_data.shape[0]

    indicator = MissingIndicator()
    mask_missing_values_only = indicator.fit_transform(temp_data)

    imputer = SimpleImputer(strategy=strategy_param,
                            fill_value=fill_value_param)
    all_data = imputer.fit_transform(temp_data)

    missed_data = temp_data[mask_missing_values_only]
    filled_data = all_data[mask_missing_values_only]

    return all_data.reshape((size,)), filled_data, missed_data
```

In [ ]:

```
#Заполнение показателем центра распределения
all_data, filled_data, missed_data = impute_column(data_loaded, 'UNIXTime', 'mea
```

```
all_data
```

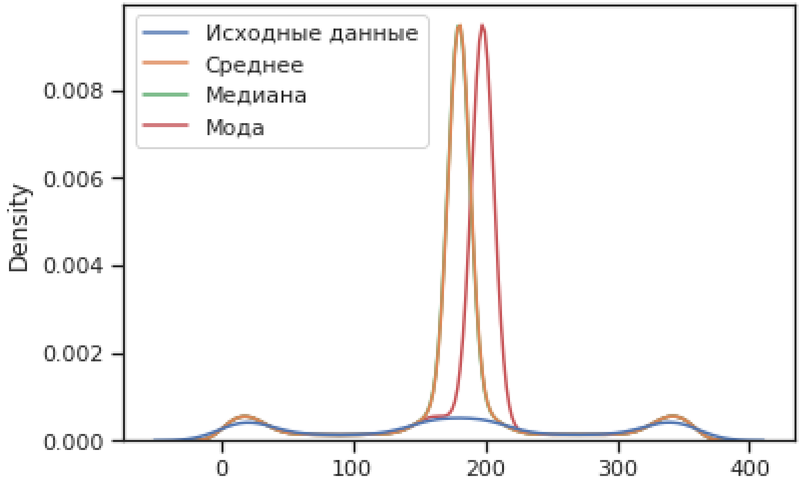
Out[ ]:
```
array([1.47522933e+09, 1.47522902e+09, 1.47522873e+09, ...,
       1.48058700e+09, 1.48058670e+09, 1.48058640e+09])
```

In [ ]:
```
data_loaded['UNIXTime']
```

Out[ ]:
```
0        1475229326
1        1475229023
2        1475228726
3        1475228421
4        1475228124
            ...
32681    1480587604
32682    1480587301
32683    1480587001
32684    1480586702
32685    1480586402
Name: UNIXTime, Length: 32686, dtype: int64
```

In [ ]:
```
def research_impute_numeric_column(dataset, num_column, const_value=None):
    strategy_params = ['mean', 'median', 'most_frequent', 'constant']
    strategy_params_names = ['Среднее', 'Медиана', 'Мода']
    strategy_params_names.append('Константа = ' + str(const_value))

    original_temp_data = dataset[[num_column]].values
    size = original_temp_data.shape[0]
    original_data = original_temp_data.reshape((size,))

    new_df = pd.DataFrame({'Исходные данные':original_data})

    for i in range(len(strategy_params)):
        strategy = strategy_params[i]
        col_name = strategy_params_names[i]
        if (strategy!='constant') or (strategy == 'constant' and const_value!=No
            if strategy == 'constant':
                temp_data, _, _ = impute_column(dataset, num_column, strategy, f
            else:
                temp_data, _, _ = impute_column(dataset, num_column, strategy)
            new_df[col_name] = temp_data

    sns.kdeplot(data=new_df)
```

In [ ]:
```
#Сравнение заполнения различными показателями распределения
research_impute_numeric_column(data_loaded, 'Sunazimuth')
```



In [ ]:
```
#Заполнение наиболее распросттраненным значением категории
data_cat_cols = ['Sunazimuth', 'UNIXTime', 'Gamma']
data_cat_new = data_loaded[data_cat_cols].copy()
```

In [ ]:
```
data_cat_new
```

Out[ ]:

	Sunazimuth	UNIXTime	Gamma
0	344.0	1475229326	0.2701
1	21.0	1475229023	0.2702
2	151.0	1475228726	0.2703
3	74.0	1475228421	0.2704
4	281.0	1475228124	0.2705
...	...	...	...
32681	NaN	1480587604	NaN
32682	NaN	1480587301	NaN
32683	NaN	1480587001	NaN
32684	NaN	1480586702	NaN
32685	NaN	1480586402	NaN

32686 rows × 3 columns

In [ ]:
```
data_loaded.loc[data_loaded.loc[:, 'Sunazimuth'] == 'Новозыбков']
```

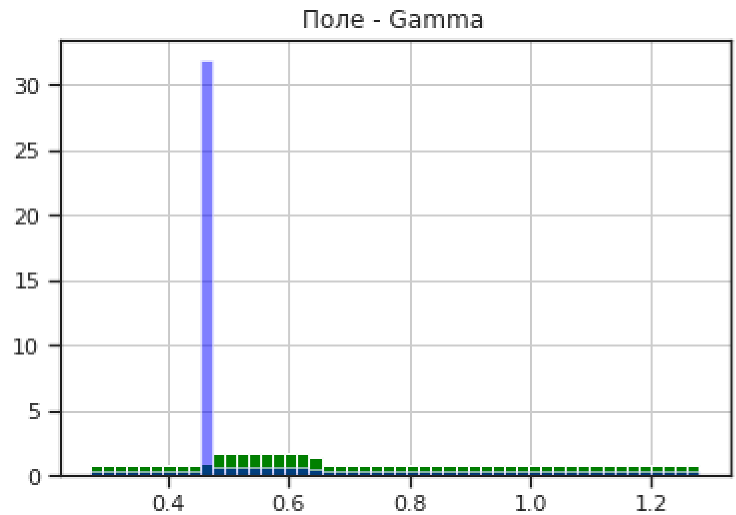
Out[ ]:

Catalog Number	Unnamed: 1	Time	Delta	Lunationnumber	Sarosnumber	Unnamed: 6	Gamma	Eclipsema

In [ ]:
```
Sunazimuth_cat_new, _, _ = impute_column(data_cat_new, 'Sunazimuth', 'most_frequ
UNIXTime_cat_new, _, _ = impute_column(data_cat_new, 'UNIXTime', 'most_frequent'
Gamma_cat_new, _, _ = impute_column(data_cat_new, 'Gamma', 'most_frequent')
```

In [ ]:
```
data_cat_new['Sunazimuth'] = Sunazimuth_cat_new
data_cat_new['UNIXTime'] = UNIXTime_cat_new
data_cat_new['Gamma'] = Gamma_cat_new
```

In [ ]:
```
plot_hist_diff(data_loaded, data_cat_new, ['Gamma'])
```



Кодирование категориальных признаков

1. **Label Encoding**

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
```

In [ ]:
```
data = data_loaded.copy()
data['Gamma']
```

Out[ ]:
```
0        0.2701
1        0.2702
2        0.2703
3        0.2704
4        0.2705
          ...
32681       NaN
32682       NaN
32683       NaN
32684       NaN
32685       NaN
Name: Gamma, Length: 32686, dtype: float64
```

In [ ]:
```
data['Gamma'] = data_cat_new['Gamma']
data['Gamma']
```

Out[ ]:
```
0        0.2701
1        0.2702
2        0.2703
3        0.2704
4        0.2705
```

```
            ...
32681    0.4686
32682    0.4686
32683    0.4686
32684    0.4686
32685    0.4686
Name: Gamma, Length: 32686, dtype: float64
```

In [ ]:
```
data_loaded['Gamma']
```

Out[ ]:
```
0        0.2701
1        0.2702
2        0.2703
3        0.2704
4        0.2705
          ...
32681       NaN
32682       NaN
32683       NaN
32684       NaN
32685       NaN
Name: Gamma, Length: 32686, dtype: float64
```

In [ ]:
```
le = LabelEncoder()
cat_enc_le = le.fit_transform(data['Gamma'])
cat_enc_le
```

Out[ ]:
```
array([   0,    1,    2, ..., 1985, 1985, 1985])
```

In [ ]:
```
data['Gamma'].unique()
```

Out[ ]:
```
array([0.2701, 0.2702, 0.2703, ..., 1.2792, 1.2793, 1.2794])
```

In [ ]:
```
np.unique(cat_enc_le)
```

Out[ ]:
```
array([    0,     1,     2, ..., 10091, 10092, 10093])
```

In [ ]:
```
le.inverse_transform([0, 1, 2, 3, 4, 5, 6, 7, 8])
```

Out[ ]:
```
array([0.2701, 0.2702, 0.2703, 0.2704, 0.2705, 0.2706, 0.2707, 0.2708,
       0.2709])
```

1. **One-Hot Encoding**

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder
```

In [ ]:
```
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(data[['Gamma']])
cat_enc_ohe
```

Out[ ]:
```
<32686x10094 sparse matrix of type '<class 'numpy.float64'>'
	with 32686 stored elements in Compressed Sparse Row format>
```

In [ ]:
```
cat_enc_ohe.todense()[0:10]
```

Out[ ]:
```
matrix([[1., 0., 0., ..., 0., 0., 0.],
        [0., 1., 0., ..., 0., 0., 0.],
        [0., 0., 1., ..., 0., 0., 0.],
        ...,
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.]])
```

In [ ]:
```
# one-hot encoding с помощью pd.get_dummies()
pd.get_dummies(data[['Gamma']]).head()
```

Out[ ]:

	Gamma
0	0.2701
1	0.2702
2	0.2703
3	0.2704
4	0.2705

In [ ]:
```
# с добавлением отдельной колонки - признака пустых значений
pd.get_dummies(data_loaded[['Gamma']], dummy_na=True).head()
```

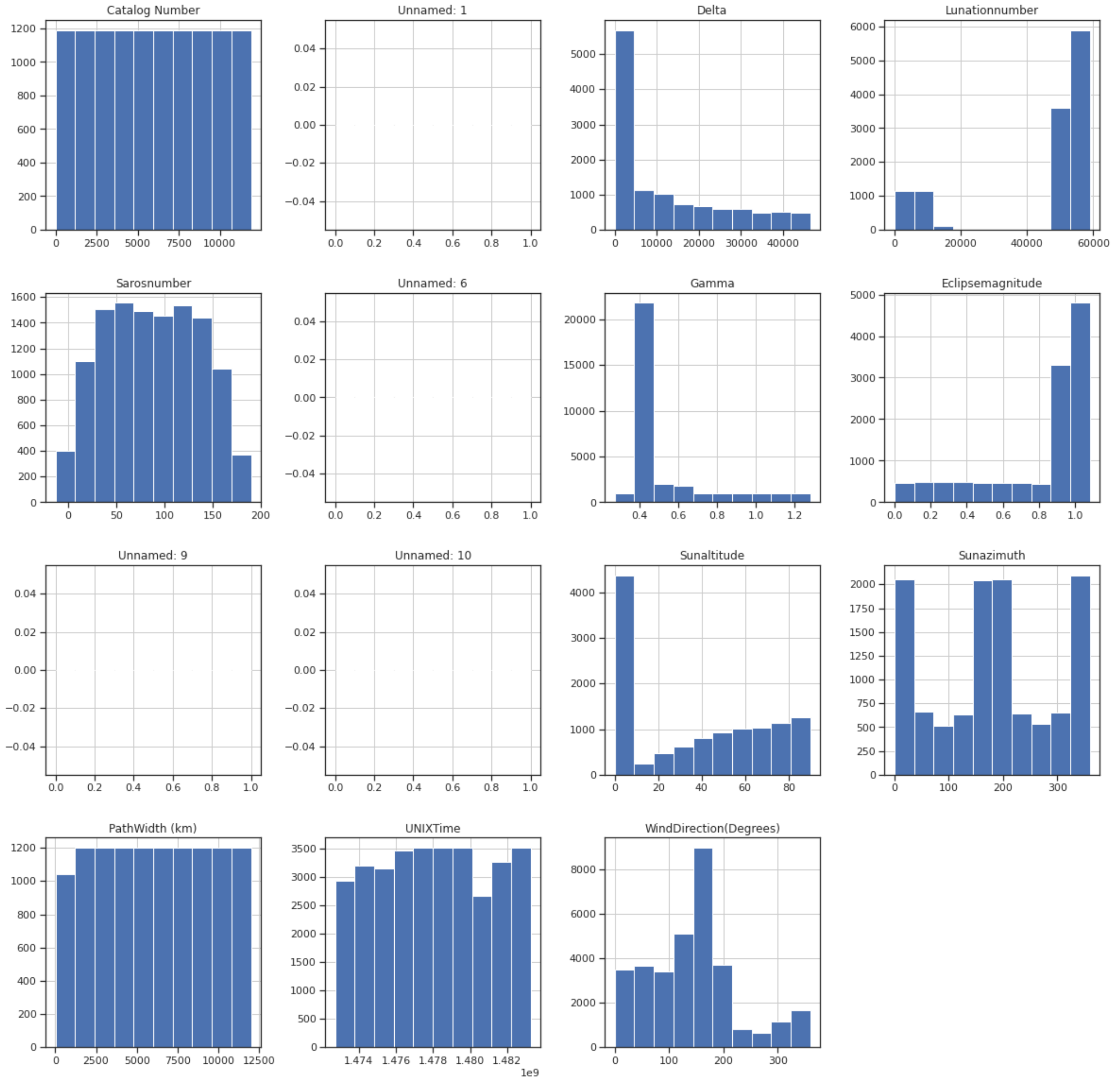
Out[ ]:

	Gamma
0	0.2701
1	0.2702
2	0.2703
3	0.2704
4	0.2705

Нормализация числовых признаков

In [ ]:
```
import scipy.stats as stats
```

In [ ]:
```
data.hist(figsize=(20,20))
plt.show()
```

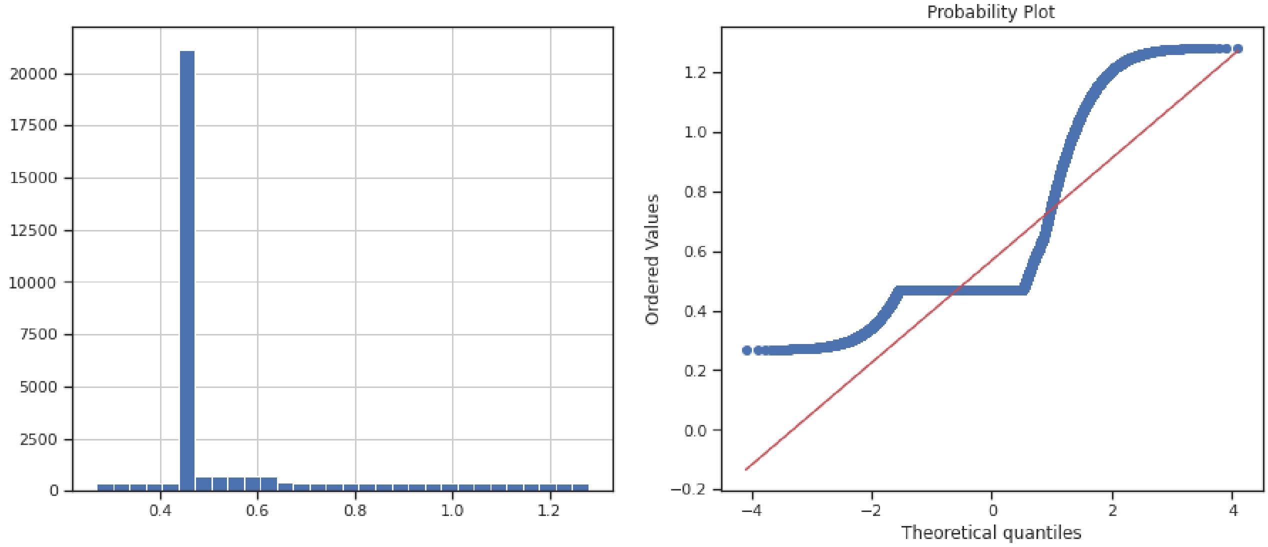


In [ ]:

```
def diagnostic_plots(df, variable):
    plt.figure(figsize=(15,6))
    # гистограмма
    plt.subplot(1, 2, 1)
    df[variable].hist(bins=30)
    ## Q-Q plot
    plt.subplot(1, 2, 2)
    stats.probplot(df[variable], dist="norm", plot=plt)
    plt.show()
```

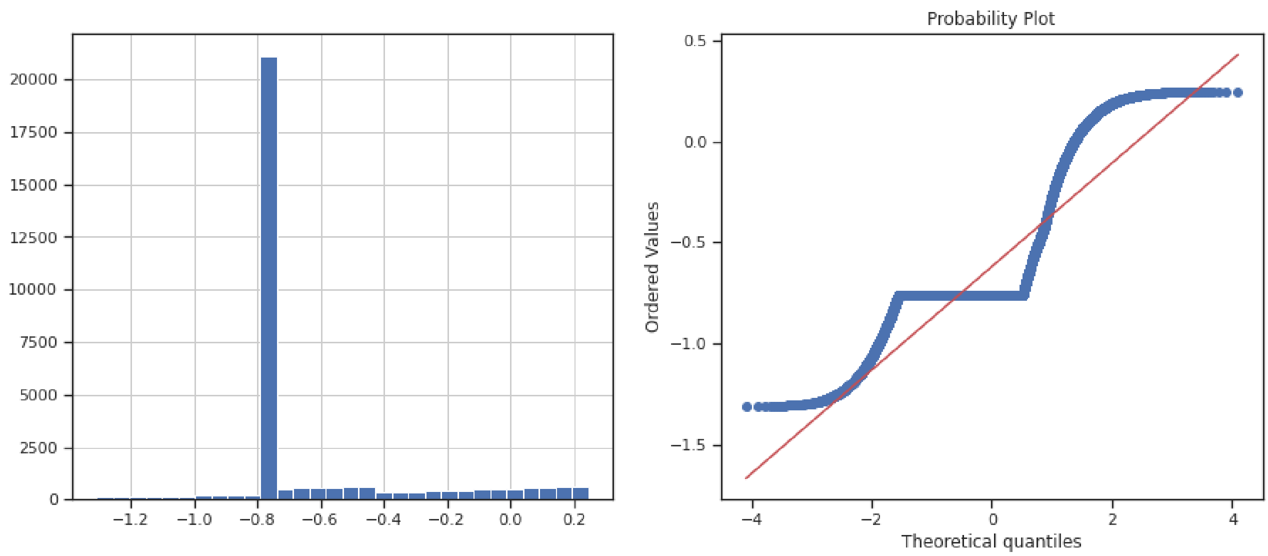
In [ ]:

```
diagnostic_plots(data, 'Gamma')
```



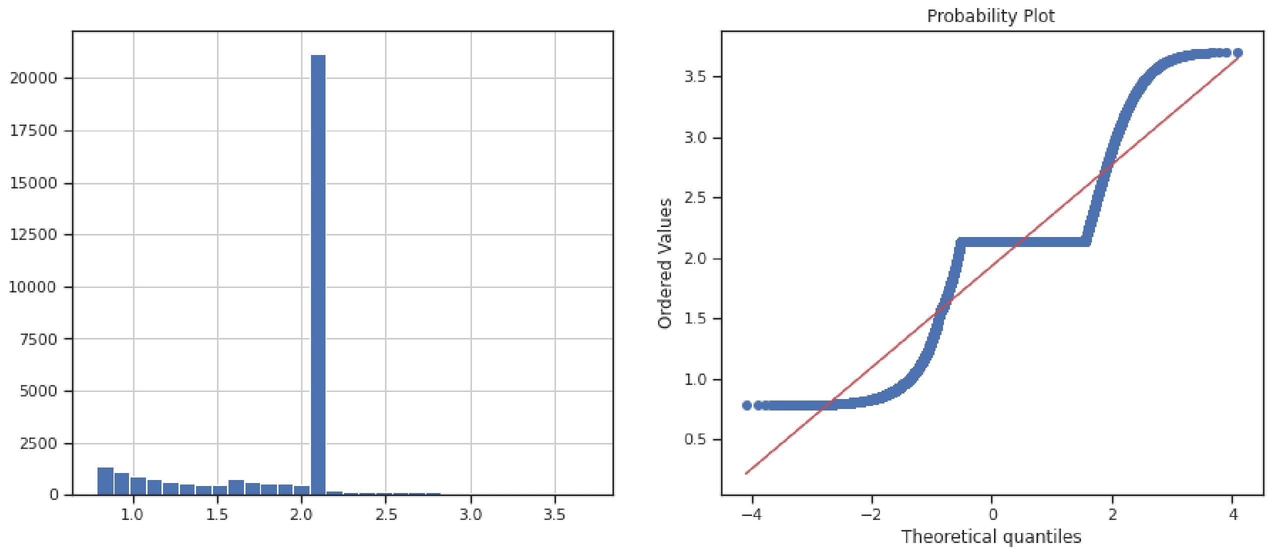
In [ ]:

```
data['Gamma_log'] = np.log(data['Gamma'])
diagnostic_plots(data, 'Gamma_log')
```



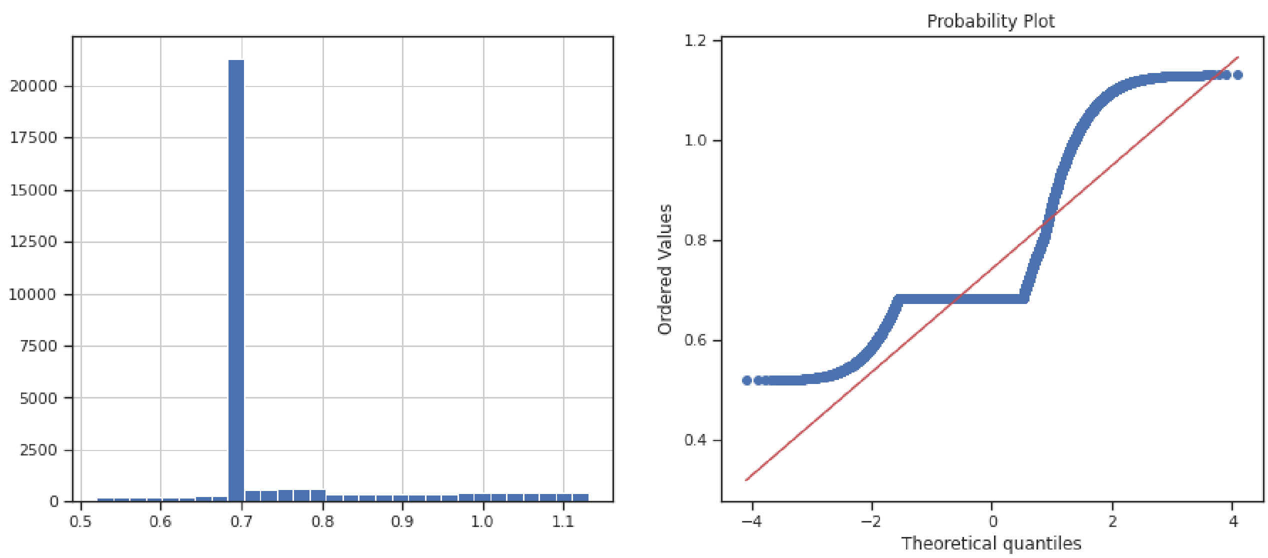
In [ ]:

```
data['Gamma_reciprocal'] = 1 / (data['Gamma'])
diagnostic_plots(data, 'Gamma_reciprocal')
```



In [ ]:

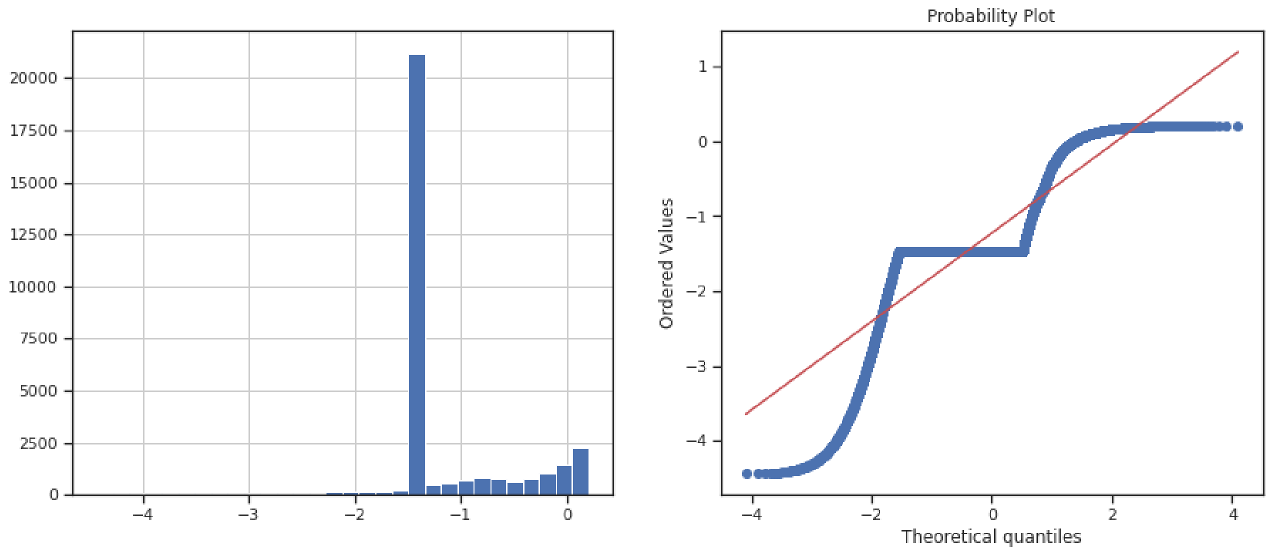
```
data['Gamma_sqr'] = data['Gamma']**(1/2)
diagnostic_plots(data, 'Gamma_sqr')
```



In [ ]:

```
data['Gamma_boxcox'], param = stats.boxcox(data['Gamma'])
print('Оптимальное значение λ = {}'.format(param))
diagnostic_plots(data, 'Gamma_boxcox')
```

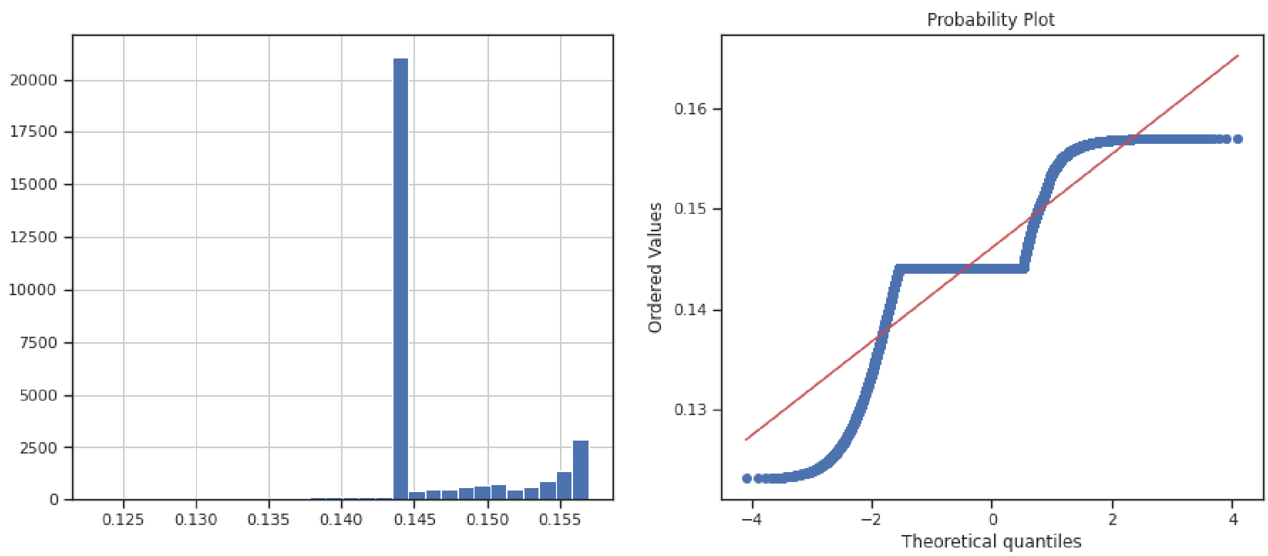
```
Оптимальное значение λ = -1.597211394590668
```



In [ ]:

```
# Необходимо преобразовать данные к действительному типу
data['Gamma'] = data['Gamma'].astype('float')
data['Gamma_yeojohnson'], param = stats.yeojohnson(data['Gamma'])
print('Оптимальное значение λ = {}'.format(param))
diagnostic_plots(data, 'Gamma_yeojohnson')
```

Оптимальное значение λ = -6.335929584796748



Масштабирование признаков

На основе Z-оценки

In [ ]:

```
from sklearn.datasets import load_boston
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.preprocessing import MaxAbsScaler
```

In [ ]:

```
cols_to_scale = [ 'Delta', 'Lunationnumber', 'Sarosnumber', 'Gamma', 'Sunazimuth
```

```
data_to_scale = data_loaded[cols_to_scale]
data_to_scale = data_to_scale.dropna()
data_to_scale.describe()
```

Out[ ]:

	Delta	Lunationnumber	Sarosnumber	Gamma	Sunazimuth	UNIXTime
count	11898.000000	11898.000000	11898.000000	11898.000000	11898.000000	1.189800e+04
mean	12142.172802	44567.074971	87.483190	0.742000	180.264330	1.475260e+09
std	13583.402888	19443.399140	48.380284	0.280094	110.745408	1.721177e+06
min	-6.000000	1.000000	-13.000000	0.270100	0.000000	1.472724e+09
25%	970.250000	50038.250000	47.000000	0.518025	89.000000	1.473790e+09
50%	5636.500000	53012.500000	87.000000	0.684550	180.000000	1.474776e+09
75%	20943.500000	55986.750000	128.000000	0.981975	272.000000	1.477099e+09
max	46438.000000	58961.000000	190.000000	1.279400	360.000000	1.477994e+09

In [ ]:

```
X_ALL = data_to_scale.drop('Sarosnumber', axis=1)
X_ALL
```

Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
0	46438.0	49456.0	0.2701	344.0	1475229326
1	46426.0	49457.0	0.2702	21.0	1475229023
2	46415.0	49458.0	0.2703	151.0	1475228726
3	46403.0	49459.0	0.2704	74.0	1475228421
4	46393.0	49460.0	0.2705	281.0	1475228124
...	...	...	...	...	...
11893	4414.0	12355.0	0.6485	179.0	1476646820
11894	4417.0	12360.0	0.6486	146.0	1476646521
11895	4420.0	12366.0	0.6487	137.0	1476646222
11896	4424.0	12372.0	0.6488	166.0	1476645923
11897	4428.0	12378.0	0.6489	16.0	1476645622

11898 rows × 5 columns

In [ ]:

```
# Функция восстановления датафрейма на основе масштабированных данных
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res
```

In [ ]:

```
# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL, data_to_scale['Delta'
                                                    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[ ]: ((9518, 5), (2380, 5))

In [ ]:

```
# 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[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
0	2.524939	0.251455	-1.684859	1.478549	-0.017953
1	2.524056	0.251506	-1.684502	-1.438173	-0.018129
2	2.523246	0.251557	-1.684145	-0.264260	-0.018301
3	2.522363	0.251609	-1.683788	-0.959577	-0.018478
4	2.521626	0.251660	-1.683431	0.909653	-0.018651
...	...	...	...	...	...
11893	-0.568966	-1.656780	-0.333829	-0.011417	0.805643
11894	-0.568745	-1.656523	-0.333472	-0.309410	0.805469
11895	-0.568525	-1.656214	-0.333115	-0.390681	0.805295
11896	-0.568230	-1.655905	-0.332758	-0.128808	0.805122
11897	-0.567936	-1.655597	-0.332401	-1.483323	0.804947

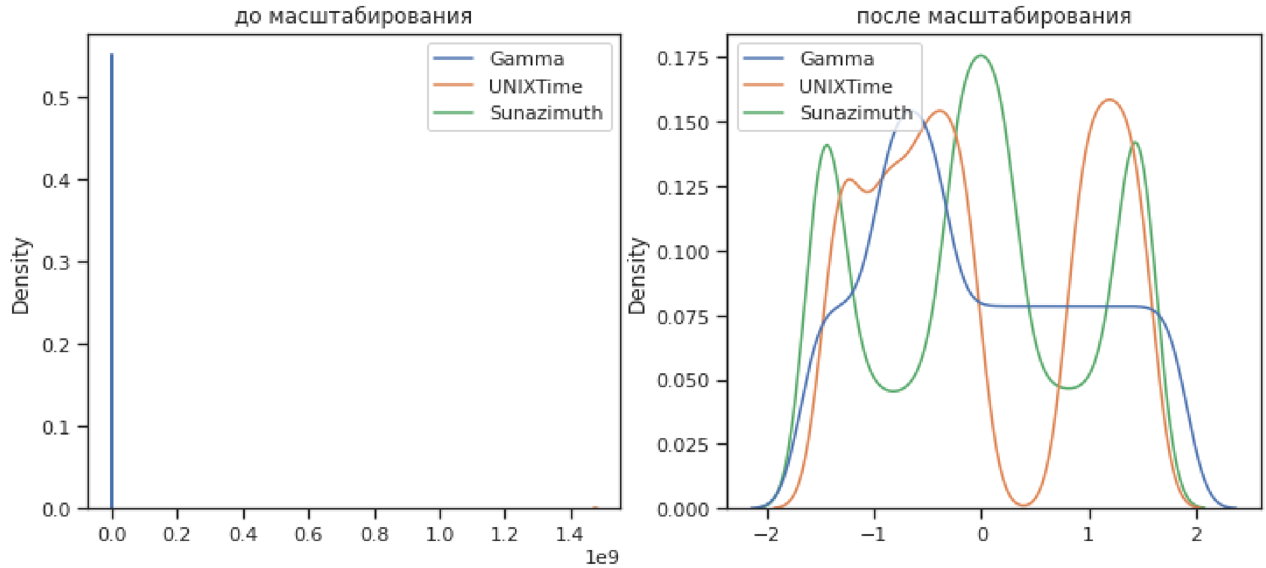
11898 rows × 5 columns

In [ ]:

```
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 [ ]:

```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_to_scale, data_cs11_scaled, '
```



In [ ]:

```
# Обучаем StandardScaler на обучающей выборке
# и масштабируем обучающую и тестовую выборки
cs12 = StandardScaler()
cs12.fit(X_train)
data_cs12_scaled_train_temp = cs12.transform(X_train)
data_cs12_scaled_test_temp = cs12.transform(X_test)
# формируем DataFrame на основе массива
data_cs12_scaled_train = arr_to_df(data_cs12_scaled_train_temp)
data_cs12_scaled_test = arr_to_df(data_cs12_scaled_test_temp)
```

In [ ]:

```
data_cs12_scaled_train.describe()
```

Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	9.518000e+03	9.518000e+03	9.518000e+03	9.518000e+03	9.518000e+03
mean	6.270812e-17	1.524370e-16	2.076273e-18	-5.431554e-17	-1.940655e-15
std	1.000053e+00	1.000053e+00	1.000053e+00	1.000053e+00	1.000053e+00
min	-8.910189e-01	-2.283891e+00	-1.692118e+00	-1.630871e+00	-1.470371e+00
25%	-8.192373e-01	2.833294e-01	-8.001160e-01	-8.172697e-01	-8.565046e-01
50%	-4.855315e-01	4.361728e-01	-2.038979e-01	5.371963e-03	-2.820099e-01
75%	6.424649e-01	5.894395e-01	8.575454e-01	8.280137e-01	1.066264e+00
max	2.541490e+00	7.411670e-01	1.917737e+00	1.623535e+00	1.583937e+00

In [ ]:

```
data_cs12_scaled_test.describe()
```

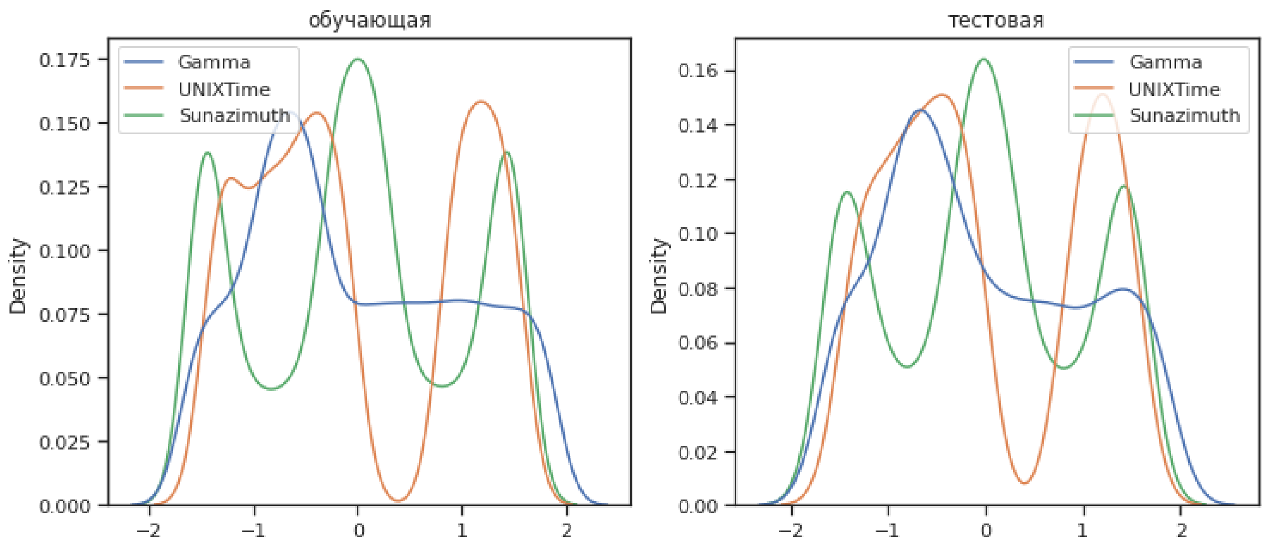
Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	2380.000000	2380.000000	2380.000000	2380.000000	2380.000000
mean	0.034038	0.013290	-0.021623	-0.006391	-0.002078
std	1.018901	0.987776	1.008701	1.005675	0.987785

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
min	-0.891019	-2.283327	-1.690688	-1.630871	-1.470195
25%	-0.817223	0.283432	-0.827030	-0.853430	-0.836857
50%	-0.419792	0.433684	-0.229471	-0.012708	-0.278011
75%	0.697433	0.585771	0.838411	0.837054	1.060439
max	2.538164	0.740911	1.916306	1.623535	1.584109

In [ ]:

```
# распределения для обучающей и тестовой выборки немного отличаются
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_cs12_scaled_train, data_cs12_
```



Масштабирование "Mean Normalisation"

In [ ]:

```
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 [ ]:

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

Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	11898.000000	11898.000000	11898.000000	11898.000000	11898.000000
mean	0.001984	0.000879	-0.001198	-0.000393	-0.000136
std	0.292468	0.329773	0.277513	0.307626	0.326611
min	-0.259582	-0.754991	-0.468750	-0.501127	-0.481409
25%	-0.238562	0.093674	-0.223109	-0.253905	-0.279130
50%	-0.138092	0.144119	-0.058118	-0.001127	-0.092104
75%	0.191488	0.194564	0.236566	0.254428	0.348818
max	0.740418	0.245009	0.531250	0.498873	0.518648

In [ ]:

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

In [ ]:

```
data_cs22_scaled_train.describe()
```

Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	9.518000e+03	9.518000e+03	9.518000e+03	9.518000e+03	9.518000e+03
mean	1.947964e-17	4.507729e-17	2.165915e-16	-2.150634e-18	-6.369071e-16
std	2.913474e-01	3.305895e-01	2.770340e-01	3.072918e-01	3.274236e-01
min	-2.595824e-01	-7.549908e-01	-4.687496e-01	-5.011271e-01	-4.814087e-01
25%	-2.386701e-01	9.366079e-02	-2.216477e-01	-2.511271e-01	-2.804251e-01
50%	-1.414509e-01	1.441866e-01	-5.648368e-02	1.650674e-03	-9.233187e-02
75%	1.871707e-01	1.948523e-01	2.375567e-01	2.544285e-01	3.491017e-01
max	7.404176e-01	2.450092e-01	5.312504e-01	4.988729e-01	5.185913e-01

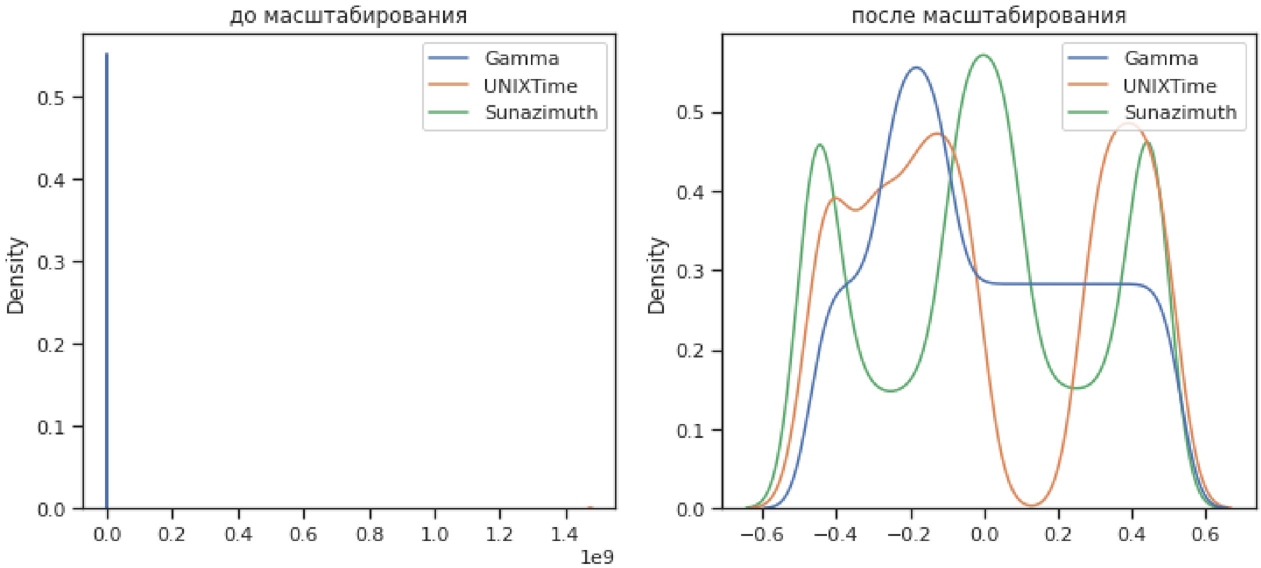
In [ ]:

```
data_cs22_scaled_test.describe()
```

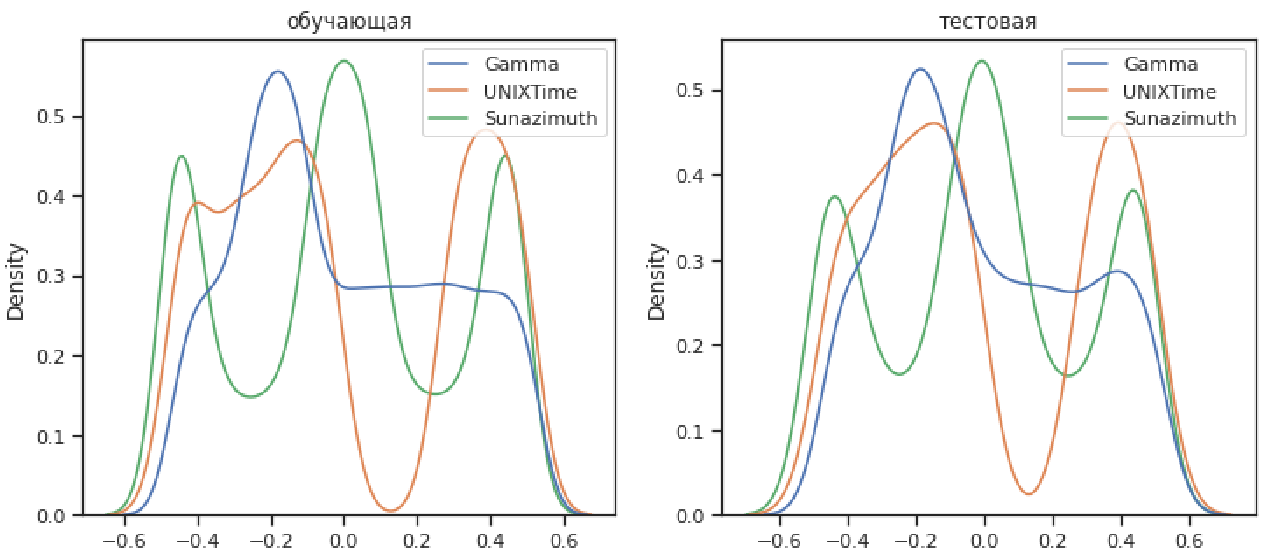
Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	2380.000000	2380.000000	2380.000000	2380.000000	2380.000000
mean	0.009916	0.004393	-0.005990	-0.001964	-0.000680
std	0.296839	0.326531	0.279430	0.309019	0.323407
min	-0.259582	-0.754804	-0.468353	-0.501127	-0.481351
25%	-0.238083	0.093695	-0.229103	-0.262238	-0.273992
50%	-0.122299	0.143364	-0.063568	-0.003905	-0.091022
75%	0.203185	0.193640	0.232256	0.257206	0.347195
max	0.739449	0.244924	0.530854	0.498873	0.518648

In [ ]:
```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_to_scale, data_cs21_scaled, '
```



In [ ]:
```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_cs22_scaled_train, data_cs22_
```



Min-Max Масштабирование

In [ ]:
```
# 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[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	11898.000000	11898.000000	11898.000000	11898.000000	11898.000000
mean	0.261566	0.755870	0.467551	0.500734	0.481246

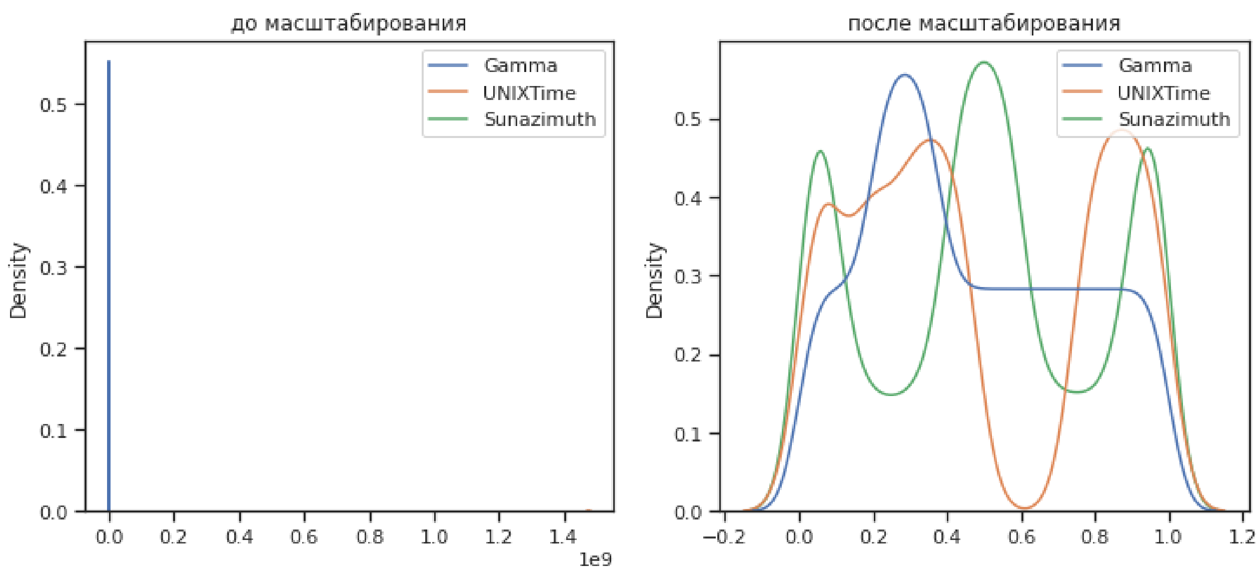
	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
std	0.292468	0.329773	0.277513	0.307626	0.326592
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.021020	0.848664	0.245641	0.247222	0.202267
50%	0.121490	0.899110	0.410631	0.500000	0.389283
75%	0.451070	0.949555	0.705316	0.755556	0.830180
max	1.000000	1.000000	1.000000	1.000000	1.000000

In [ ]:

```
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)
```

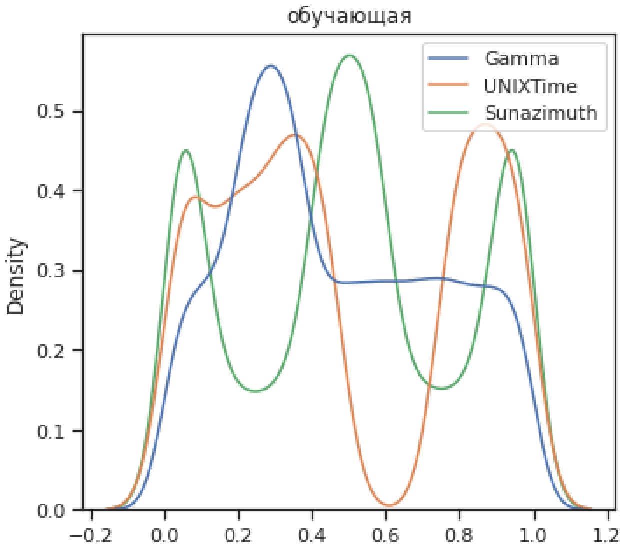
In [ ]:

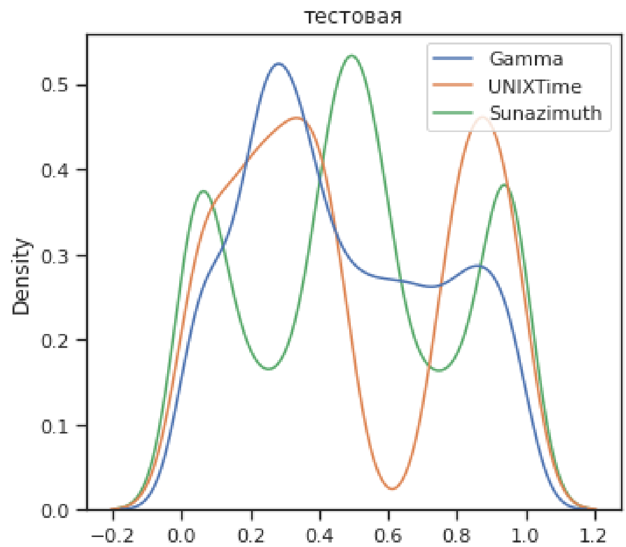
```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_to_scale, data_cs31_scaled, '
```



In [ ]:

```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_cs32_scaled_train, data_cs32_
```





Масштабирование по медиане

In [ ]:

```
cs41 = RobustScaler()
data_cs41_scaled_temp = cs41.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs41_scaled = arr_to_df(data_cs41_scaled_temp)
data_cs41_scaled.describe()
```

Out[ ]:

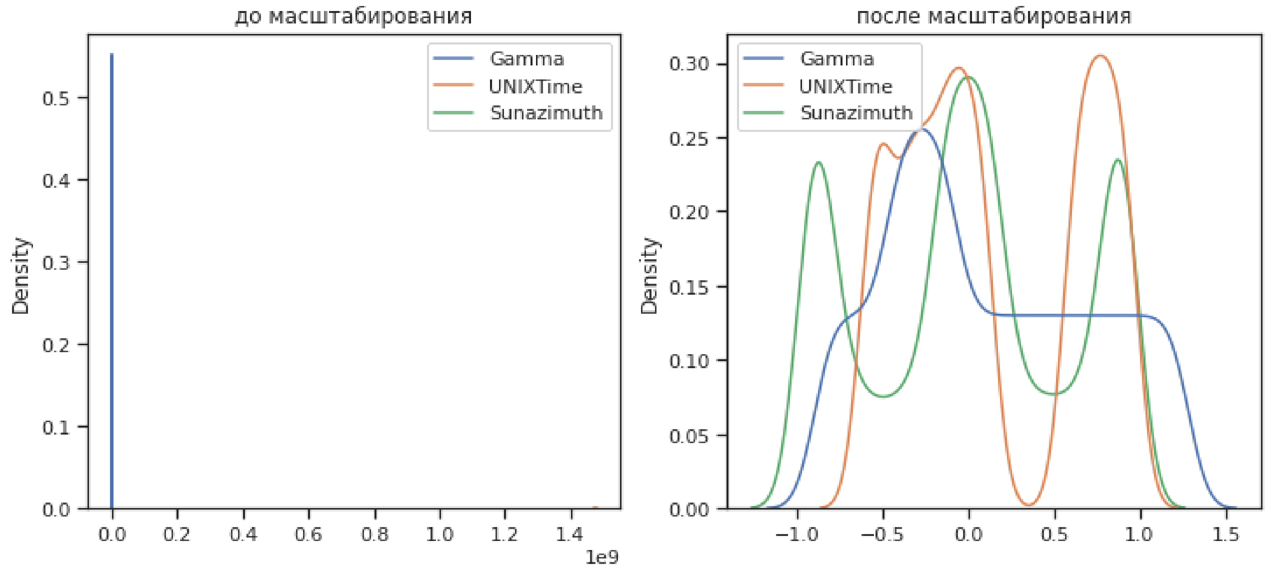
	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	11898.000000	11898.000000	11898.000000	11898.000000	11898.000000
mean	0.325719	-1.419757	0.123827	0.001444	0.146457
std	0.680080	3.268622	0.603717	0.605166	0.520124
min	-0.282503	-8.911742	-0.893307	-0.983607	-0.619964
25%	-0.233625	-0.500000	-0.358929	-0.497268	-0.297838
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.766375	0.500000	0.641071	0.502732	0.702162
max	2.042807	1.000000	1.282142	0.983607	0.972615

In [ ]:

```
cs42 = RobustScaler()
cs42.fit(X_train)
data_cs42_scaled_train_temp = cs42.transform(X_train)
data_cs42_scaled_test_temp = cs42.transform(X_test)
# формируем DataFrame на основе массива
data_cs42_scaled_train = arr_to_df(data_cs42_scaled_train_temp)
data_cs42_scaled_test = arr_to_df(data_cs42_scaled_test_temp)
```

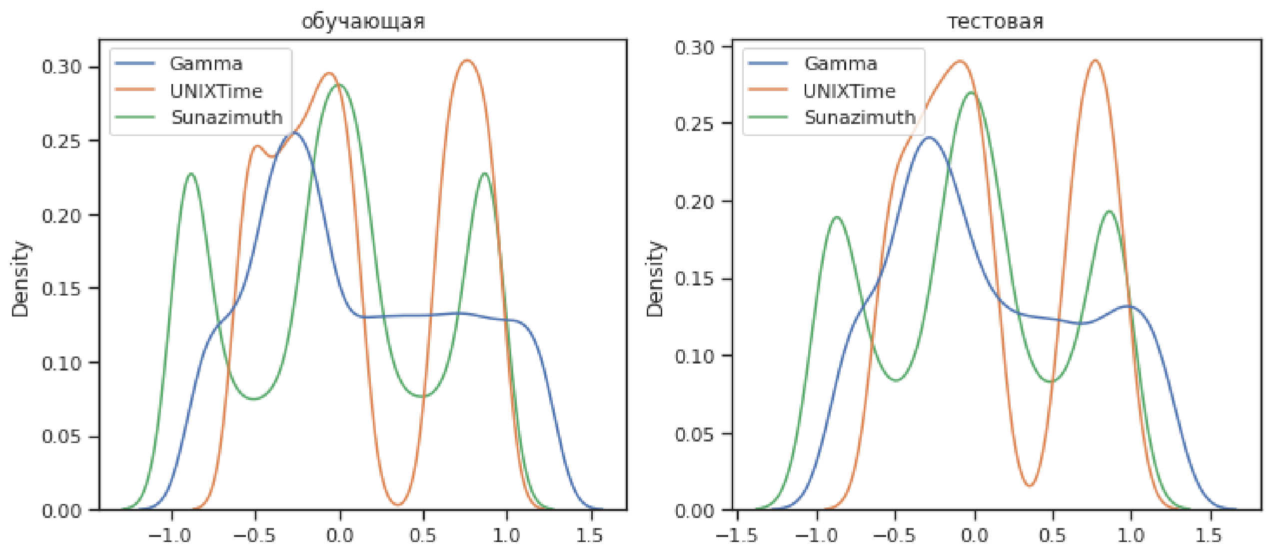
In [ ]:

```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_to_scale, data_cs41_scaled, '
```



In [ ]:

```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_cs42_scaled_train, data_cs42_
```



Масштабирование по максимальному значению

In [ ]:

```
cs51 = MaxAbsScaler()
data_cs51_scaled_temp = cs51.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs51_scaled = arr_to_df(data_cs51_scaled_temp)
data_cs51_scaled.describe()
```

Out[ ]:

	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
count	11898.000000	11898.000000	11898.000000	11898.000000	11898.000000
mean	0.261471	0.755874	0.579959	0.500734	0.998150
std	0.292506	0.329767	0.218926	0.307626	0.001165
min	-0.000129	0.000017	0.211115	0.000000	0.996434
25%	0.020893	0.848667	0.404897	0.247222	0.997156
50%	0.121377	0.899111	0.535055	0.500000	0.997822

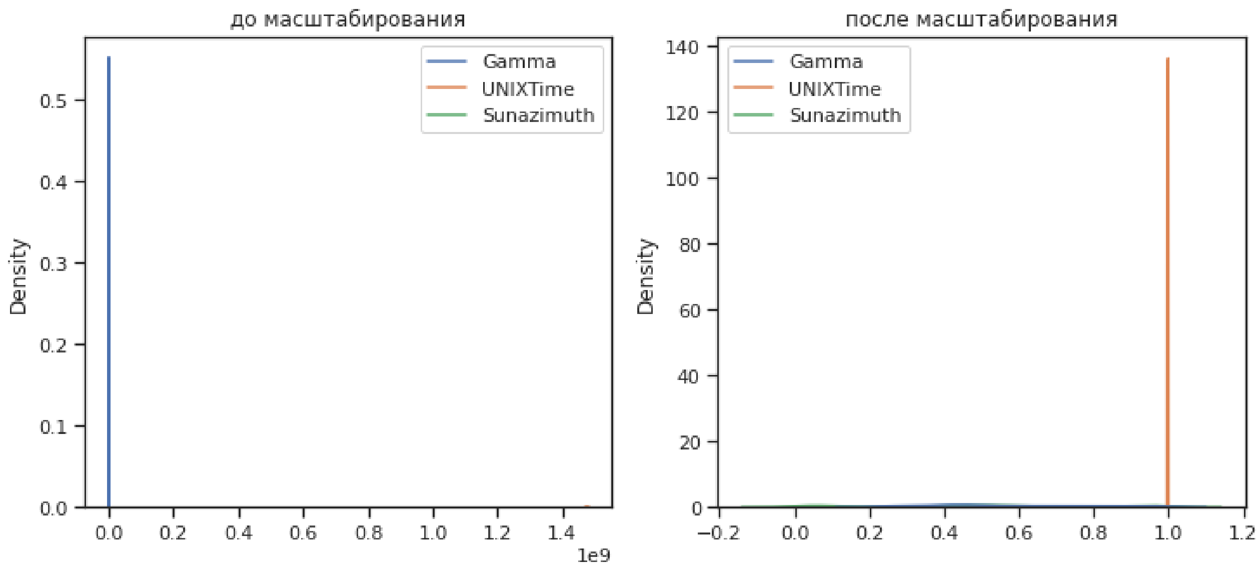
	Delta	Lunationnumber	Gamma	Sunazimuth	UNIXTime
75%	0.450999	0.949556	0.767528	0.755556	0.999394
max	1.000000	1.000000	1.000000	1.000000	1.000000

In [ ]:

```
cs52_mas = MaxAbsScaler()
cs52_mean = StandardScaler(with_mean=True, with_std=False)

cs52_mas.fit(X_train)
cs52_mean.fit(X_train)

data_cs52_scaled_train_temp = cs52_mas.transform(cs52_mean.transform(X_train))
data_cs52_scaled_test_temp = cs52_mas.transform(cs52_mean.transform(X_test))
# формируем DataFrame на основе массива
data_cs52_scaled_train = arr_to_df(data_cs52_scaled_train_temp)
data_cs52_scaled_test = arr_to_df(data_cs52_scaled_test_temp)
```

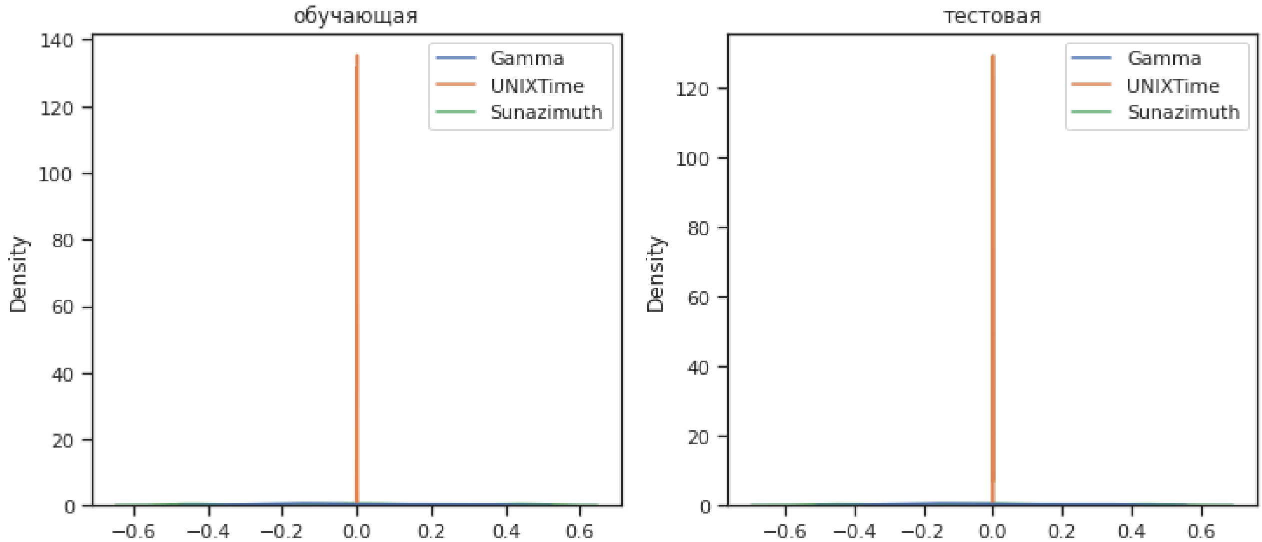
In [ ]:

```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_to_scale, data_cs51_scaled, '
```



In [ ]:

```
draw_kde(['Gamma', 'UNIXTime', 'Sunazimuth'], data_cs52_scaled_train, data_cs52_
```



Обучение моделей с различными вариантами масштабирования признаков

In [ ]:

```
class MetricLogger:

    def __init__(self):
        self.df = pd.DataFrame(
            {'metric': pd.Series([], dtype='str'),
            'alg': pd.Series([], dtype='str'),
            'value': pd.Series([], dtype='float')})

    def add(self, metric, alg, value):
        """
        Добавление значения
        """
        # Удаление значения если оно уже было ранее добавлено
        self.df.drop(self.df[(self.df['metric']==metric)&(self.df['alg']==alg)].
        # Добавление нового значения
        temp = [{'metric':metric, 'alg':alg, 'value':value}]
        self.df = self.df.append(temp, ignore_index=True)

    def get_data_for_metric(self, metric, ascending=True):
        """
        Формирование данных с фильтром по метрике
        """
        temp_data = self.df[self.df['metric']==metric]
        temp_data_2 = temp_data.sort_values(by='value', ascending=ascending)
        return temp_data_2['alg'].values, temp_data_2['value'].values

    def plot(self, str_header, metric, ascending=True, figsize=(5, 5)):
        """
        Вывод графика
        """
        array_labels, array_metric = self.get_data_for_metric(metric, ascending)
        fig, ax1 = plt.subplots(figsize=figsize)
        pos = np.arange(len(array_metric))
        rects = ax1.barh(pos, array_metric,
                         align='center',
                         height=0.5,
```

```
                         tick_label=array_labels)
        ax1.set_title(str_header)
        for a,b in zip(pos, array_metric):
            plt.text(0.5, a-0.05, str(round(b,3)), color='white')
        plt.show()
```

In [ ]:

```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error
```

In [ ]:

```
clas_models_dict = {'LinR': LinearRegression(),
                    'SVR': SVR(),
                    'KNN_5':KNeighborsRegressor(n_neighbors=5),
                    'Tree':DecisionTreeRegressor(random_state=1),
                    'GB': GradientBoostingRegressor(random_state=1),
                    'RF':RandomForestRegressor(n_estimators=50, random_state=1)}
```

In [ ]:

```
X_data_dict = {'Original': (X_train_df, X_test_df),
               'StandardScaler': (data_cs12_scaled_train, data_cs12_scaled_test)
               'MeanNormalisation': (data_cs22_scaled_train, data_cs22_scaled_te
               'MinMaxScaler': (data_cs32_scaled_train, data_cs32_scaled_test),
               'RobustScaler': (data_cs42_scaled_train, data_cs42_scaled_test),
               'MaxAbsScaler': (data_cs52_scaled_train, data_cs52_scaled_test)}
```

In [ ]:

```
def test_models(clas_models_dict, X_data_dict, y_train, y_test):

    logger = MetricLogger()

    for model_name, model in clas_models_dict.items():

        for data_name, data_tuple in X_data_dict.items():

            X_train, X_test = data_tuple

            model.fit(X_train, y_train)
            y_pred = model.predict(X_test)
            mse = mean_squared_error(y_test, y_pred)
            logger.add(model_name, data_name, mse)

    return logger
```

In [ ]:

```
%%time
logger = test_models(clas_models_dict, X_data_dict, y_train, y_test)
```

```
CPU times: user 1min 5s, sys: 376 ms, total: 1min 6s
Wall time: 1min 5s
```

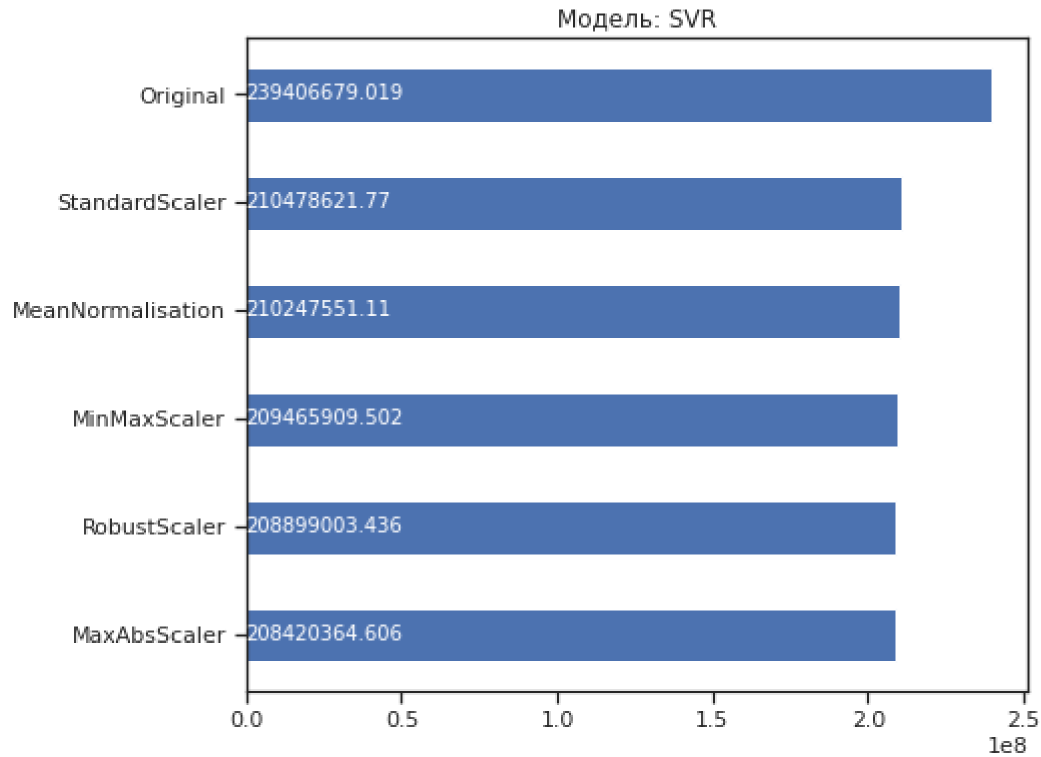
In [ ]:

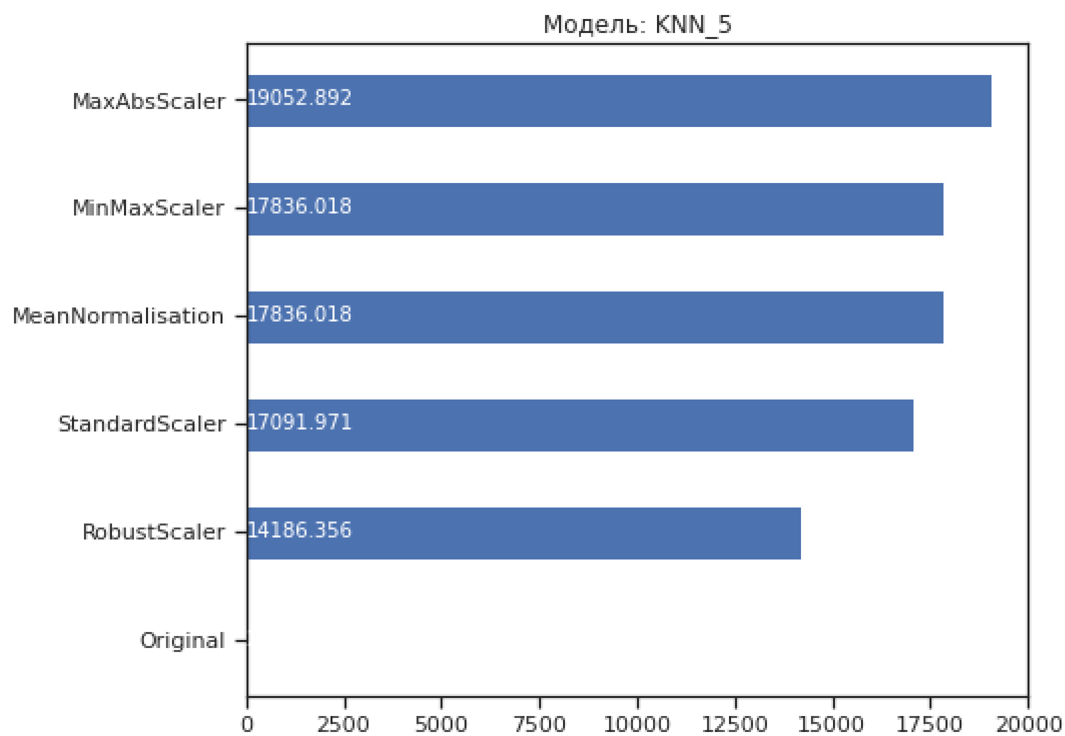
```
# Построим графики метрик качества модели
for model in clas_models_dict:
```

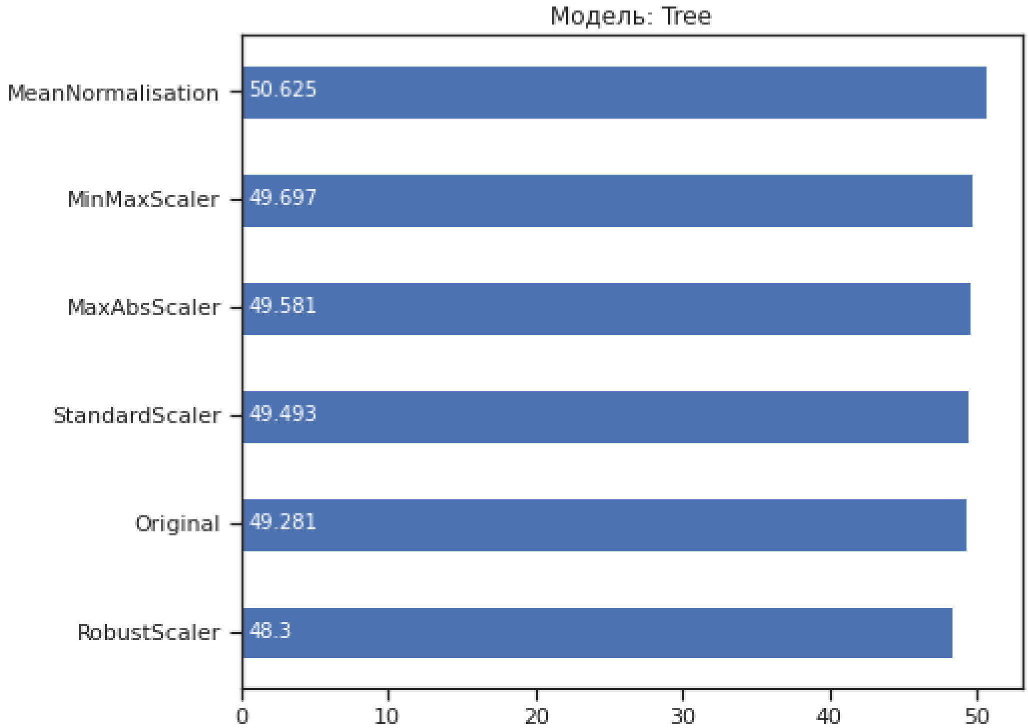
```
    logger.plot('Модель: ' + model, model, figsize=(7, 6))
```

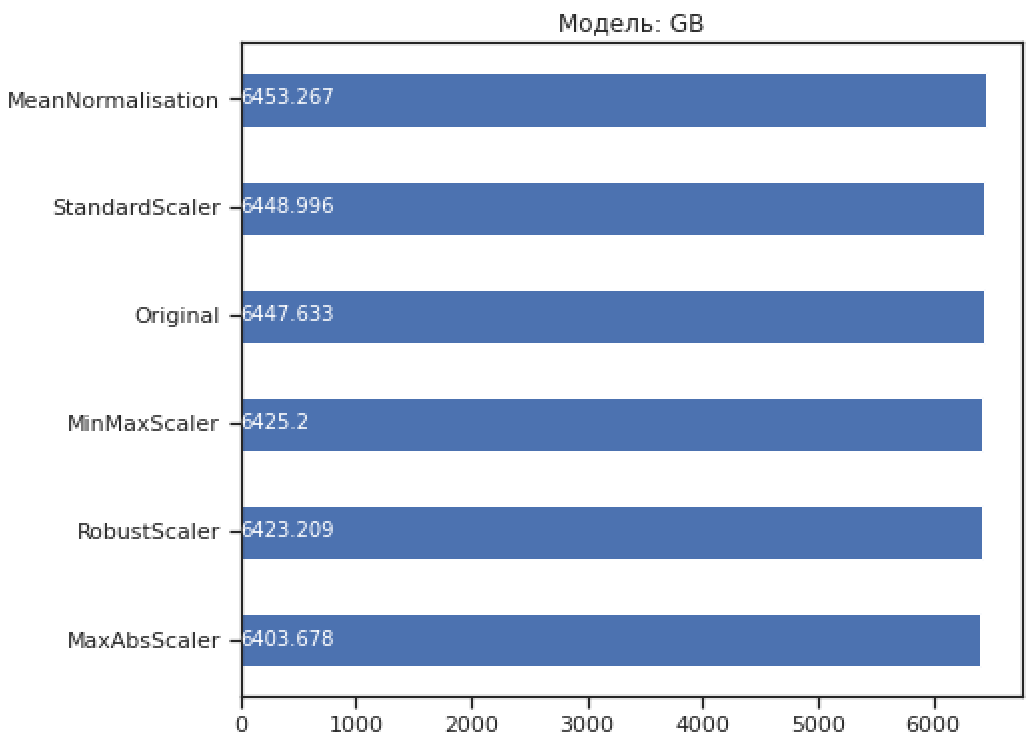
```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
/usr/local/lib/python3.7/dist-packages/IPython/core/formatters.py in __call__(se
lf, obj)
    332                 pass
    333             else:
--> 334                 return printer(obj)
    335             # Finally look for special method names
    336             method = get_real_method(obj, self.print_method)

/usr/local/lib/python3.7/dist-packages/IPython/core/pylabtools.py in <lambda>(fi
g)
    239 
    240     if 'png' in formats:
--> 241         png_formatter.for_type(Figure, lambda fig: print_figure(fig, 'pn
g', **kwargs))
    242     if 'retina' in formats or 'png2x' in formats:
    243         png_formatter.for_type(Figure, lambda fig: retina_figure(fig, **
kwargs))

/usr/local/lib/python3.7/dist-packages/IPython/core/pylabtools.py in print_figur
e(fig, fmt, bbox_inches, **kwargs)
    123 
    124     bytes_io = BytesIO()
--> 125     fig.canvas.print_figure(bytes_io, **kw)
    126     data = bytes_io.getvalue()
    127     if fmt == 'svg':

/usr/local/lib/python3.7/dist-packages/matplotlib/backend_bases.py in print_figu
re(self, filename, dpi, facecolor, edgecolor, orientation, format, bbox_inches,
 **kwargs)
   2124                     orientation=orientation,
   2125                     bbox_inches_restore=_bbox_inches_restore,
-> 2126                     **kwargs)
   2127             finally:
   2128                 if bbox_inches and restore_bbox:

/usr/local/lib/python3.7/dist-packages/matplotlib/backends/backend_agg.py in pri
nt_png(self, filename_or_obj, metadata, pil_kwargs, *args, **kwargs)
    512         }
    513 
--> 514         FigureCanvasAgg.draw(self)
    515         if pil_kwargs is not None:
    516             from PIL import Image

/usr/local/lib/python3.7/dist-packages/matplotlib/backends/backend_agg.py in dra
w(self)
    386         Draw the figure using the renderer.
    387         """
--> 388         self.renderer = self.get_renderer(cleared=True)
    389         # Acquire a lock on the shared font cache.
    390         with RendererAgg.lock, \

/usr/local/lib/python3.7/dist-packages/matplotlib/backends/backend_agg.py in get
_renderer(self, cleared)
    402                          and getattr(self, "_lastKey", None) == key)
    403         if not reuse_renderer:
--> 404             self.renderer = RendererAgg(w, h, self.figure.dpi)
    405             self._lastKey = key
    406         elif cleared:

/usr/local/lib/python3.7/dist-packages/matplotlib/backends/backend_agg.py in __i
```

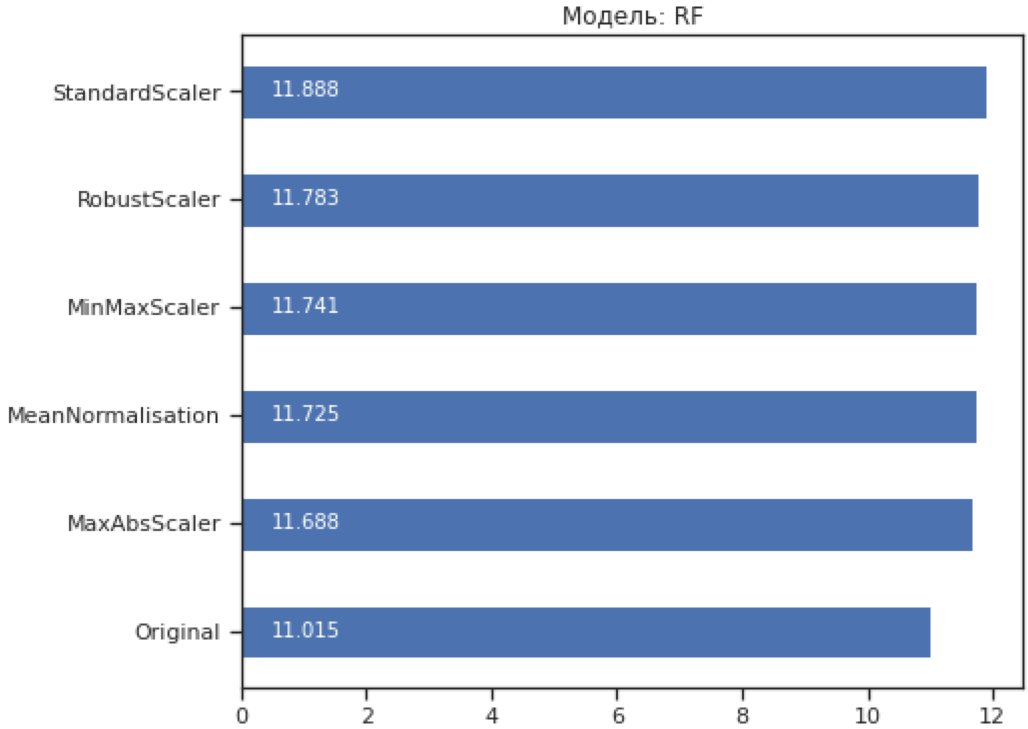
```
nit__(self, width, height, dpi)
     90         self.width = width
     91         self.height = height
---> 92         self._renderer = _RendererAgg(int(width), int(height), dpi)
     93         self._filter_renderers = []
     94

ValueError: Image size of -376441515x389 pixels is too large. It must be less th
an 2^16 in each direction.
<Figure size 504x432 with 1 Axes>
```






Модель: Tree
MeanNormalisation
MinMaxScaler
MaxAbsScaler
StandardScaler
Original
RobustScaler
50.625
49.697
49.581
49.493
49.281
48.3
0
10
20
30
40
50


Модель: GB
MeanNormalisation
StandardScaler
Original
MinMaxScaler
RobustScaler
MaxAbsScaler
6453.267
6448.996
6447.633
6425.2
6423.209
6403.678
0
1000
2000
3000
4000
5000
6000



Обработка выбросов

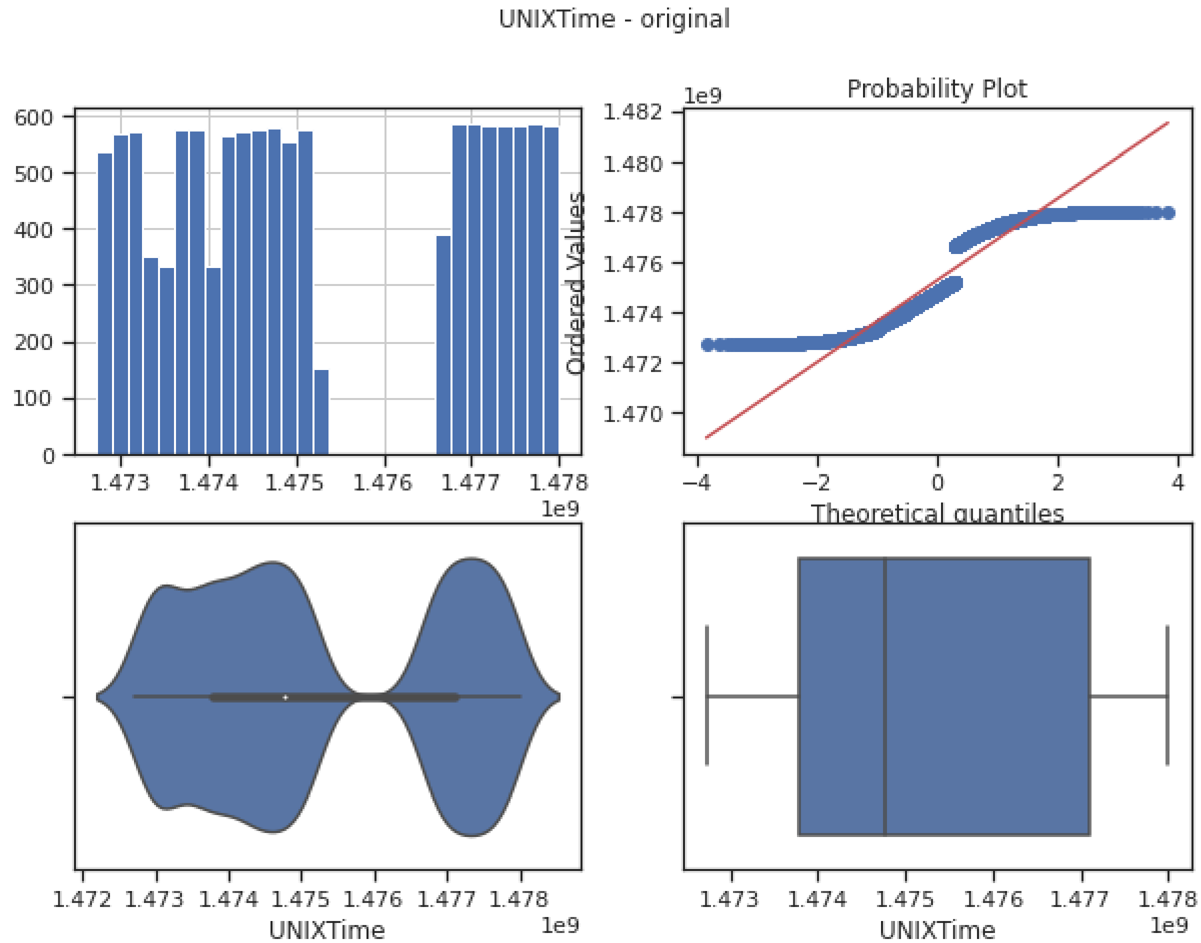
In [ ]:
```
x_col_list = ['UNIXTime', 'Sunazimuth', 'Gamma']
```

In [ ]:
```
data_to_scale.shape
```

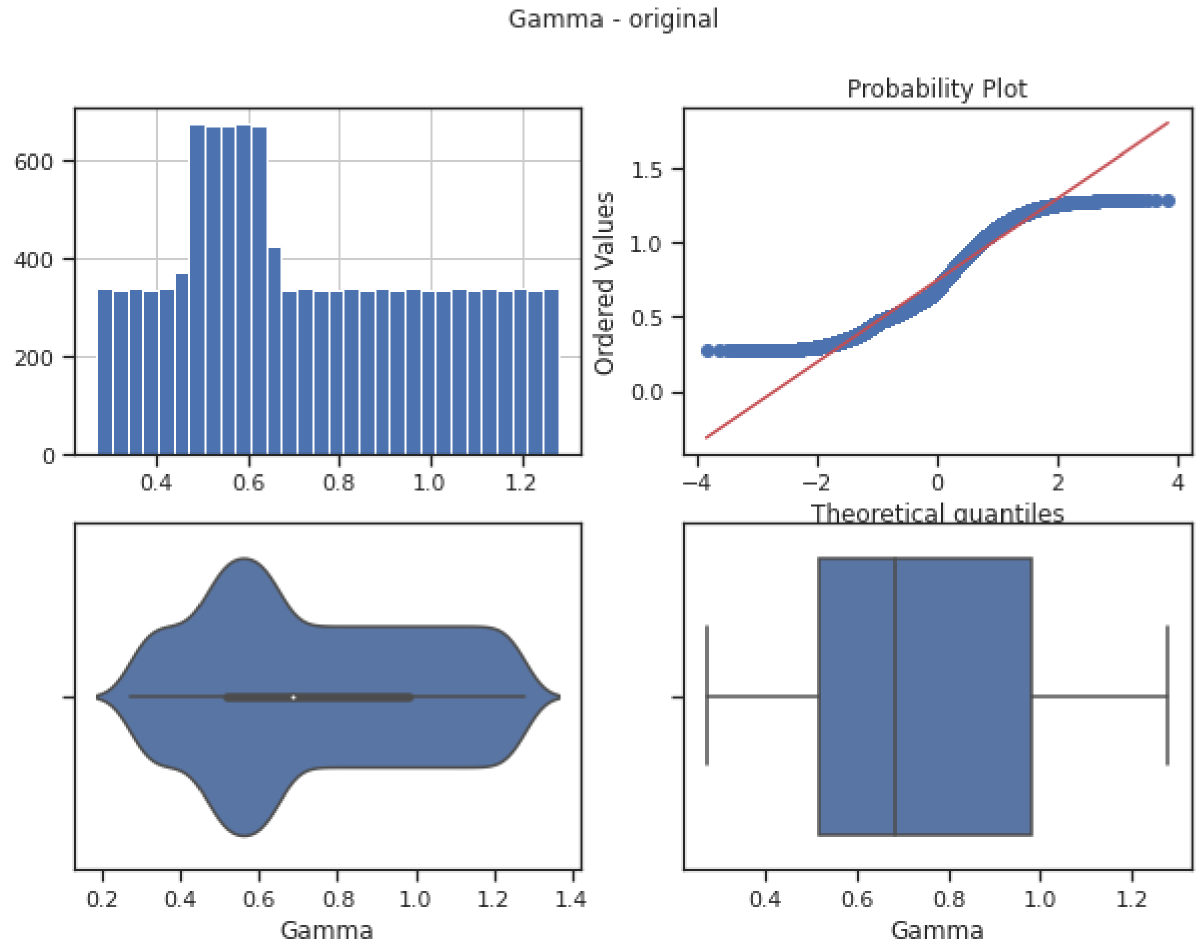
Out[ ]: (11898, 6)

In [ ]:
```
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 [ ]:
```
diagnostic_plots(data_to_scale, 'UNIXTime', 'UNIXTime - original')
```

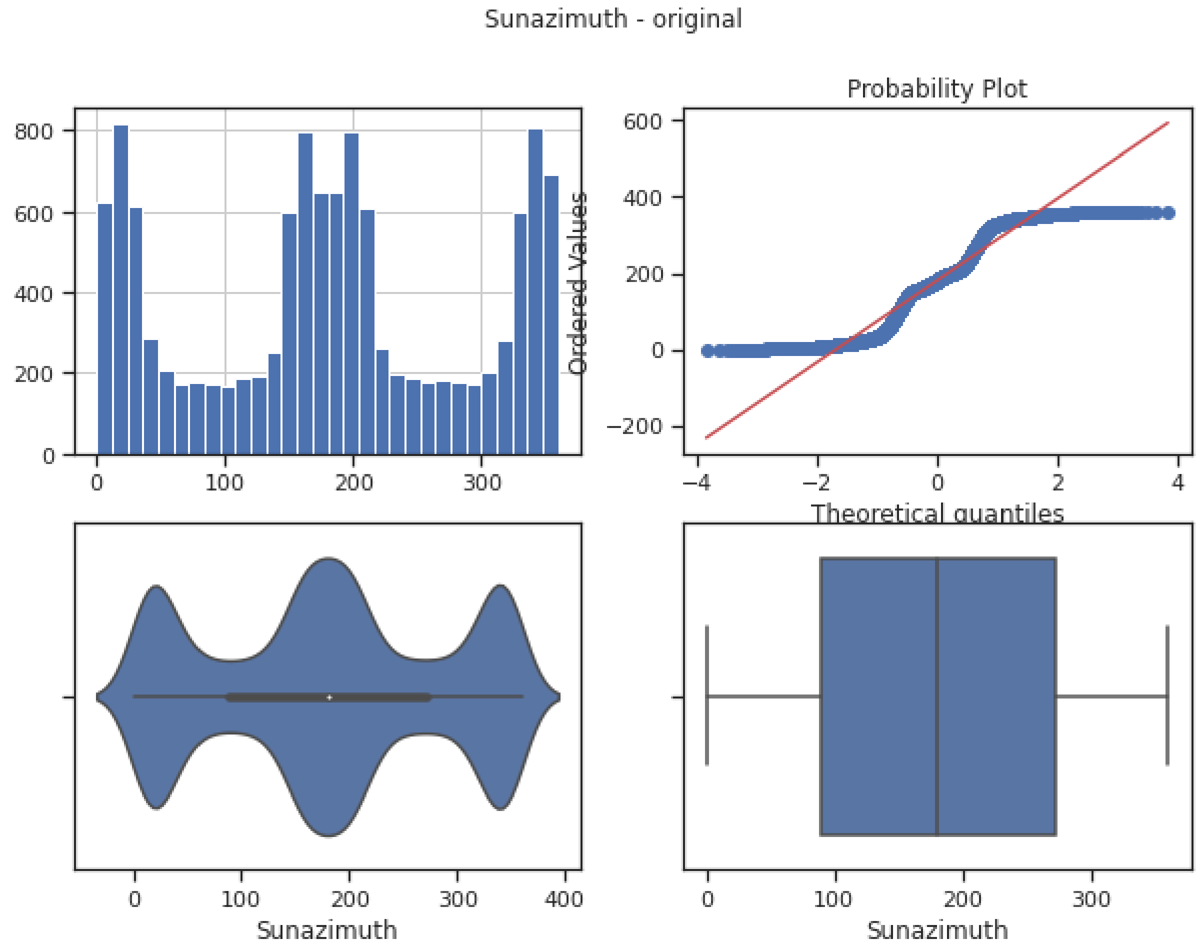


In [ ]:
```
diagnostic_plots(data_to_scale, 'Gamma', 'Gamma - original')
```



In [ ]:

```
diagnostic_plots(data_to_scale, 'Sunazimuth', 'Sunazimuth - original')
```



Обнаружение выбросов

In [ ]:

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

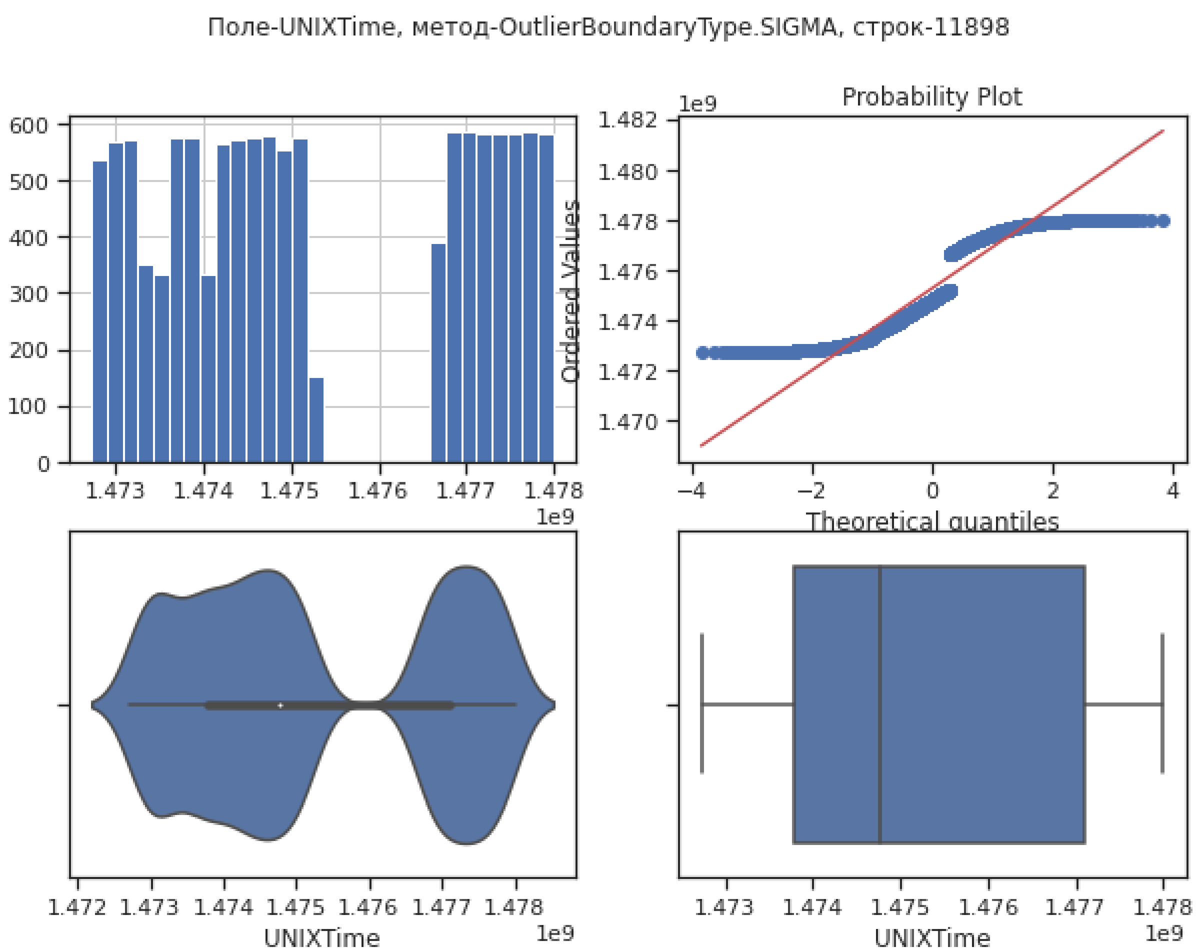
In [ ]:

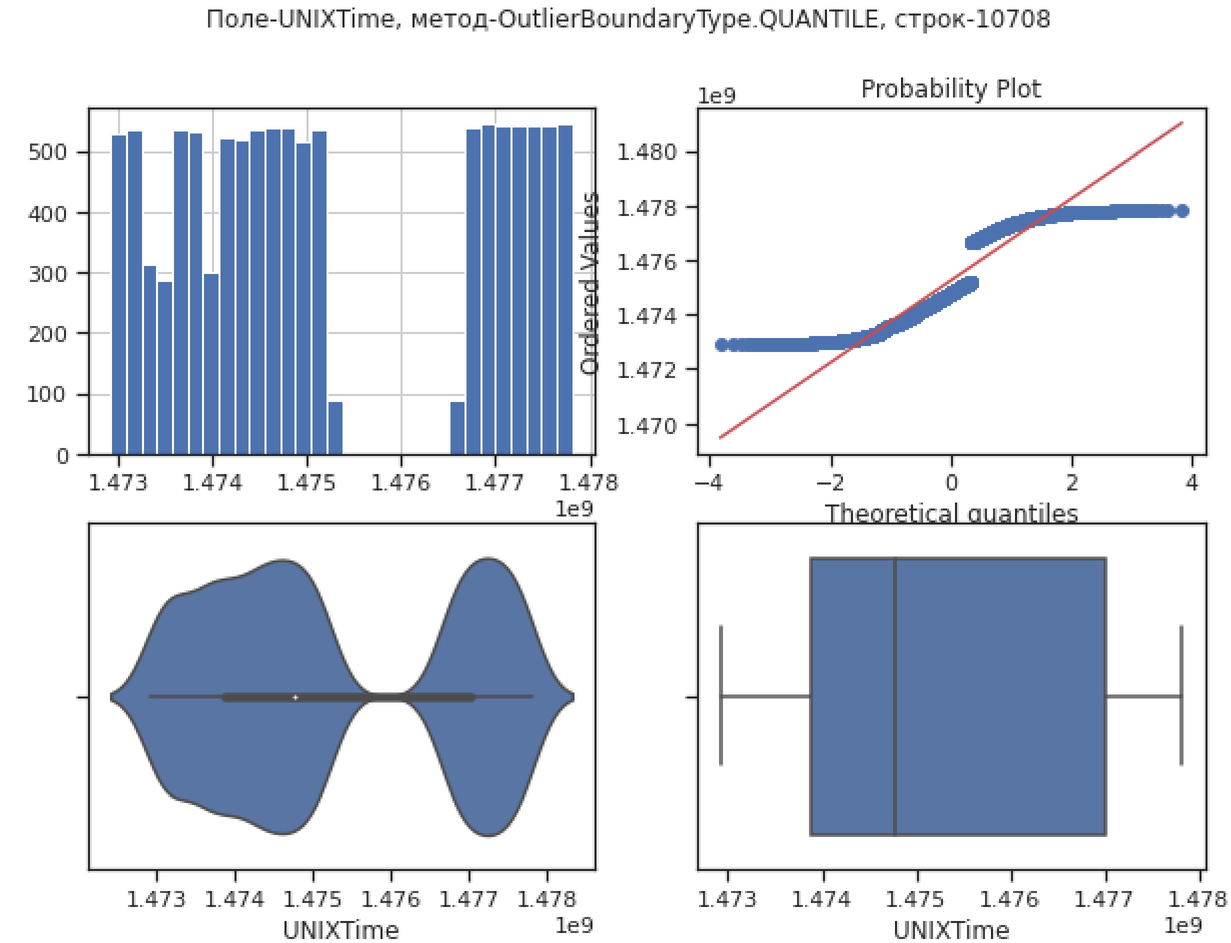
```
# Функция вычисления верхней и нижней границы выбросов
def get_outlier_boundaries(df, col, outlier_boundary_type: OutlierBoundaryType):
    if outlier_boundary_type == OutlierBoundaryType.SIGMA:
        K1 = 3
        lower_boundary = df[col].mean() - (K1 * df[col].std())
        upper_boundary = df[col].mean() + (K1 * df[col].std())

    elif outlier_boundary_type == OutlierBoundaryType.QUANTILE:
        lower_boundary = df[col].quantile(0.05)
        upper_boundary = df[col].quantile(0.95)

    elif outlier_boundary_type == OutlierBoundaryType.IRQ:
        K2 = 1.5
        IQR = df[col].quantile(0.75) - df[col].quantile(0.25)
        lower_boundary = df[col].quantile(0.25) - (K2 * IQR)
        upper_boundary = df[col].quantile(0.75) + (K2 * IQR)

    else:
        raise NameError('Unknown Outlier Boundary Type')
```

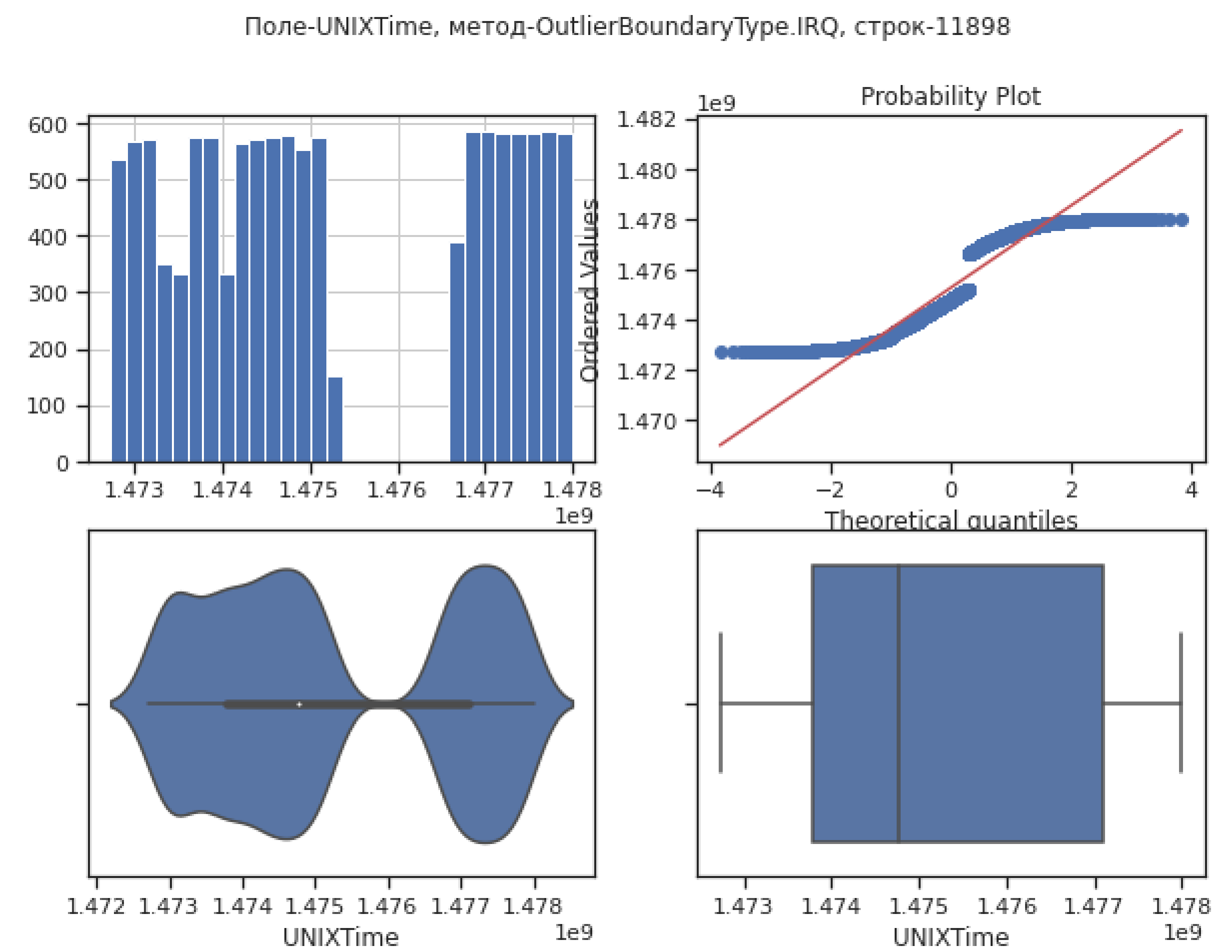
```
    return lower_boundary, upper_boundary
```

In [ ]:

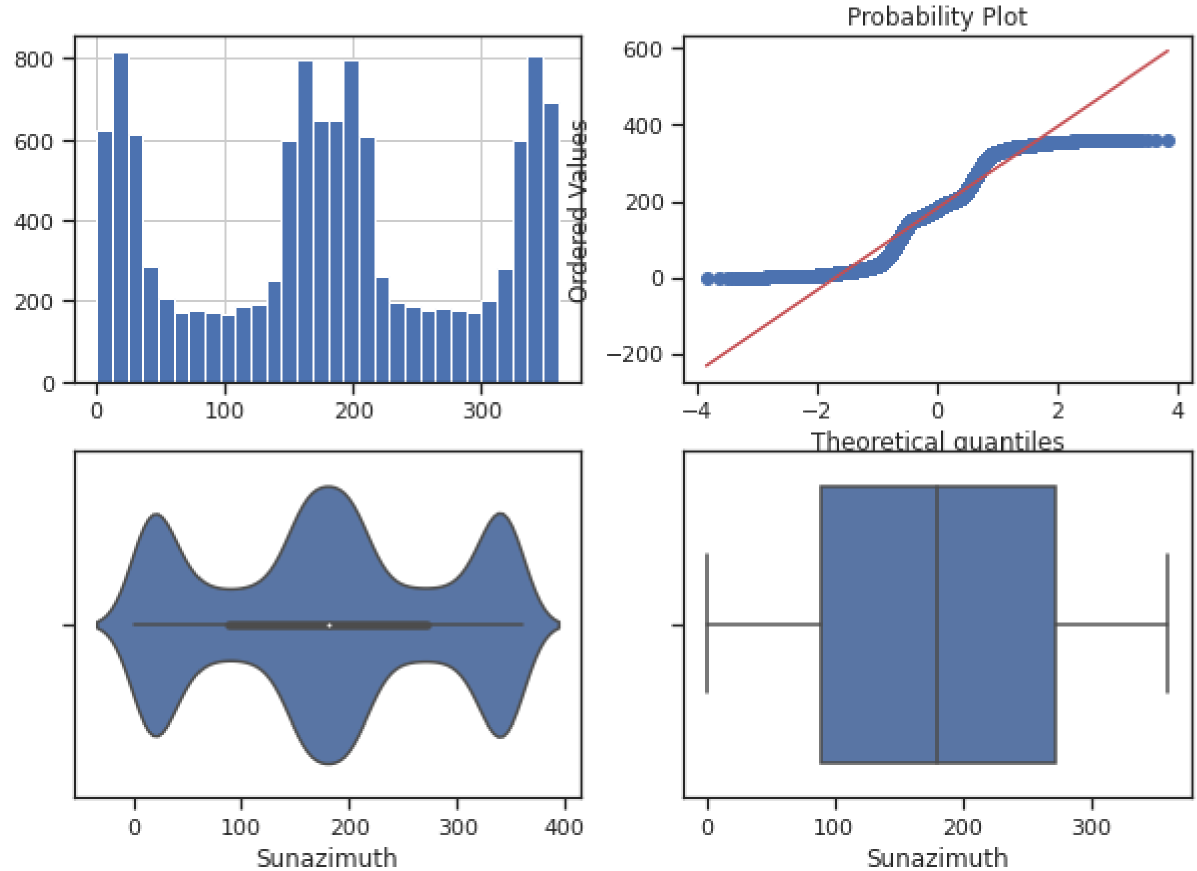
```
for col in x_col_list:
    for obt in OutlierBoundaryType:
        # Вычисление верхней и нижней границы
        lower_boundary, upper_boundary = get_outlier_boundaries(data_to_scale, c
        # Флаги для удаления выбросов
        outliers_temp = np.where(data_to_scale[col] > upper_boundary, True,
                                 np.where(data_to_scale[col] < lower_boundary, T
        # Удаление данных на основе флага
        data_trimmed = data_to_scale.loc[~(outliers_temp), ]
        title = 'Поле-{}, метод-{}, строк-{}'.format(col, obt, data_trimmed.shape[
        diagnostic_plots(data_trimmed, col, title)
```



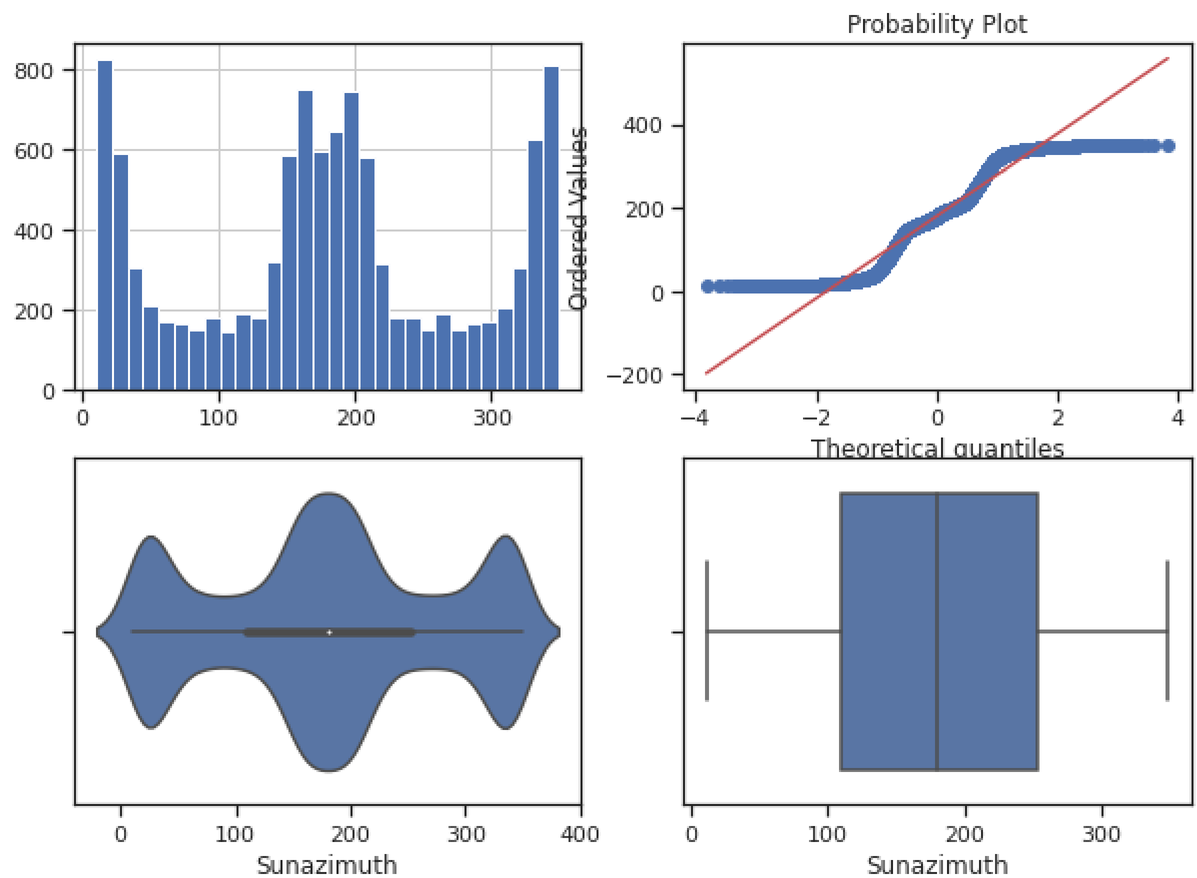

Поле-UNIXTime, метод-OutlierBoundaryType.QUANTILE, строк-10708
Probability Plot
Ordered Values
Theoretical quantiles
UNIXTime
UNIXTime
1e9

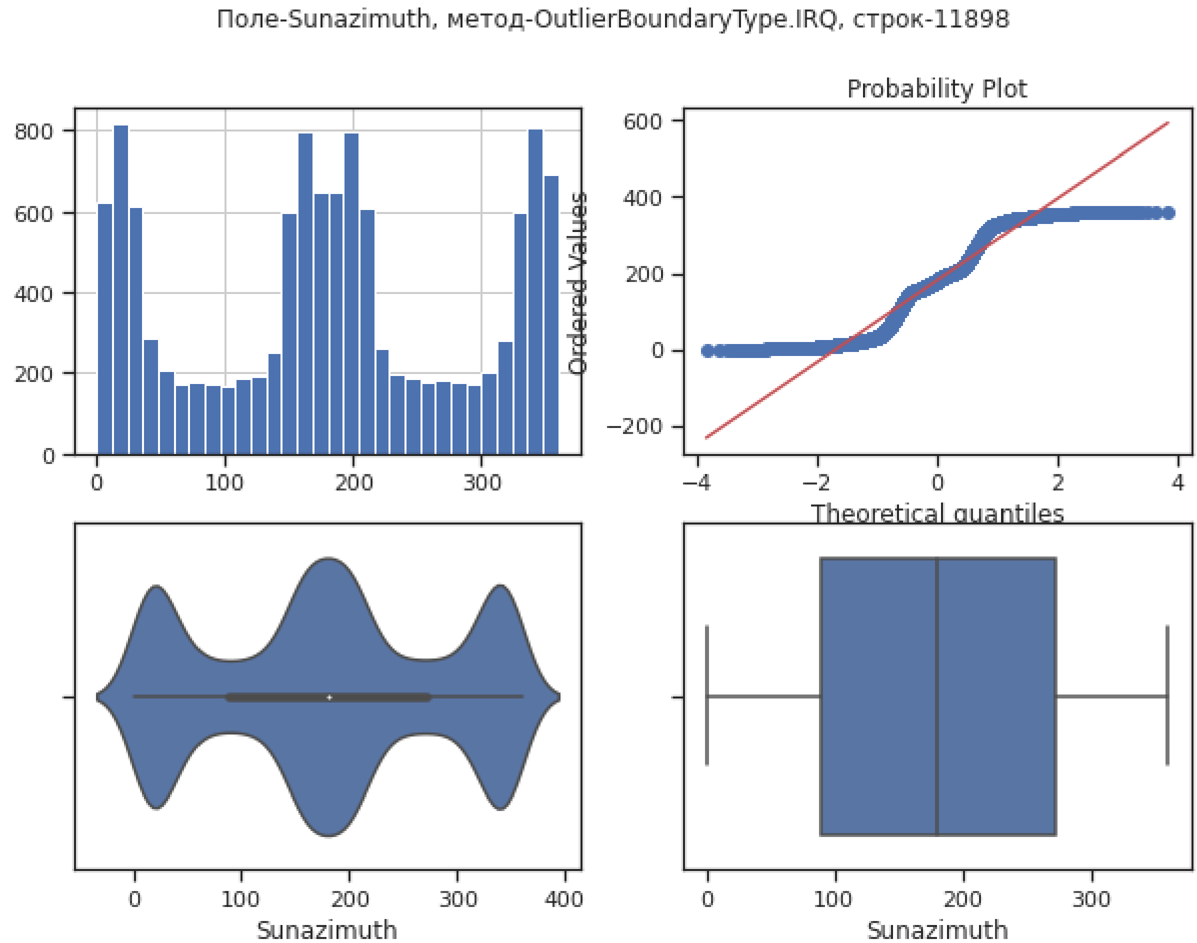

Поле-UNIXTime, метод-OutlierBoundaryType.IRQ, строк-11898
Probability Plot
Ordered Values
Theoretical quantiles
UNIXTime
UNIXTime
1e9

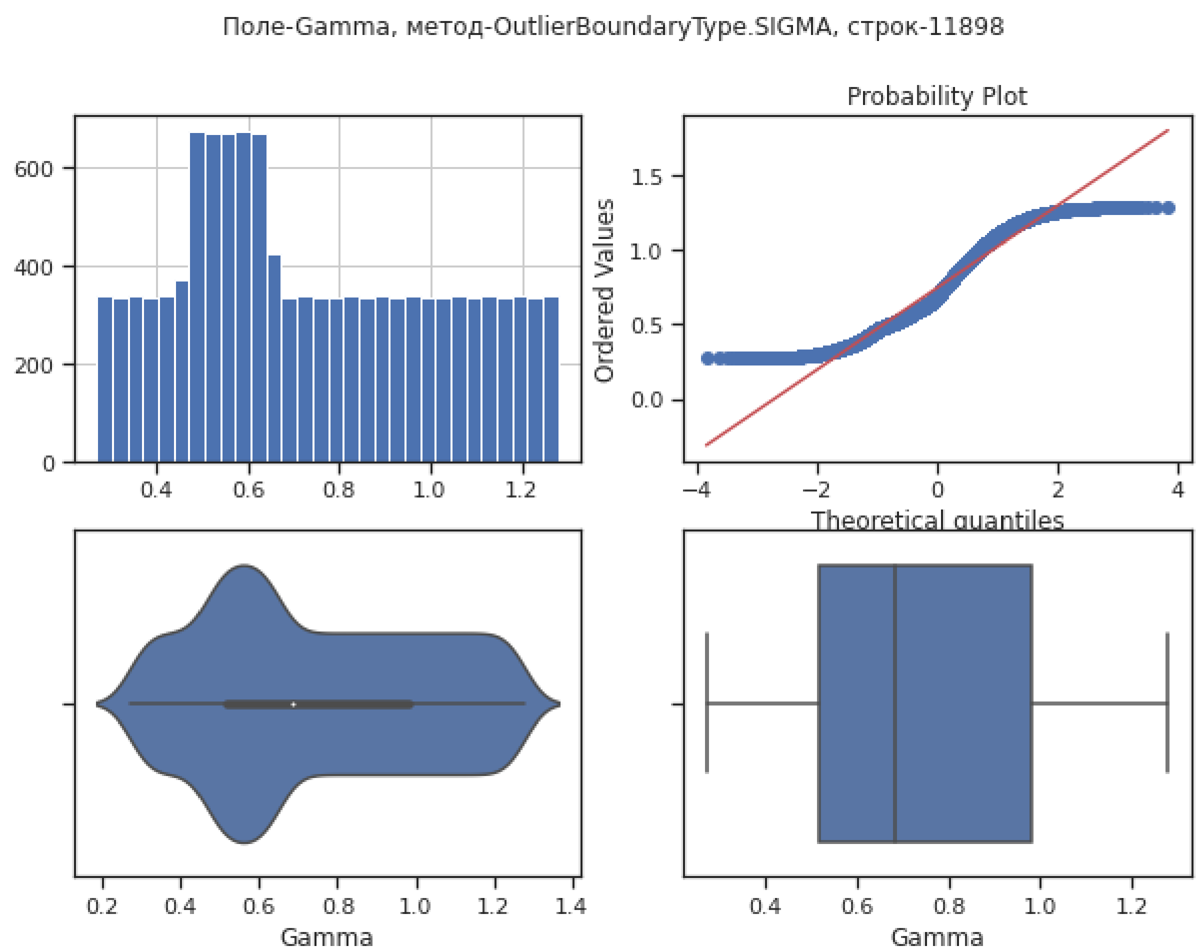
Поле-Sunazimuth, метод-OutlierBoundaryType.SIGMA, строк-11898

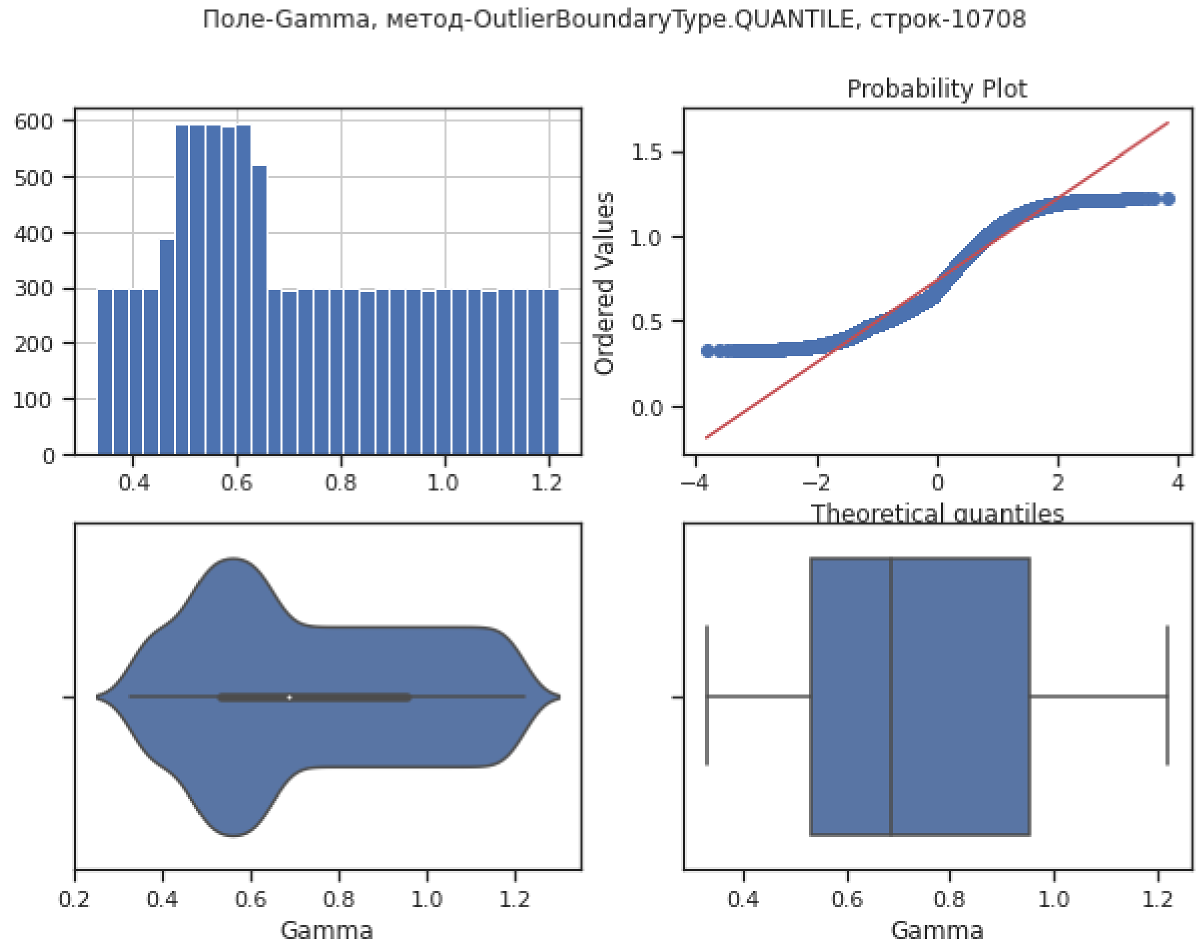


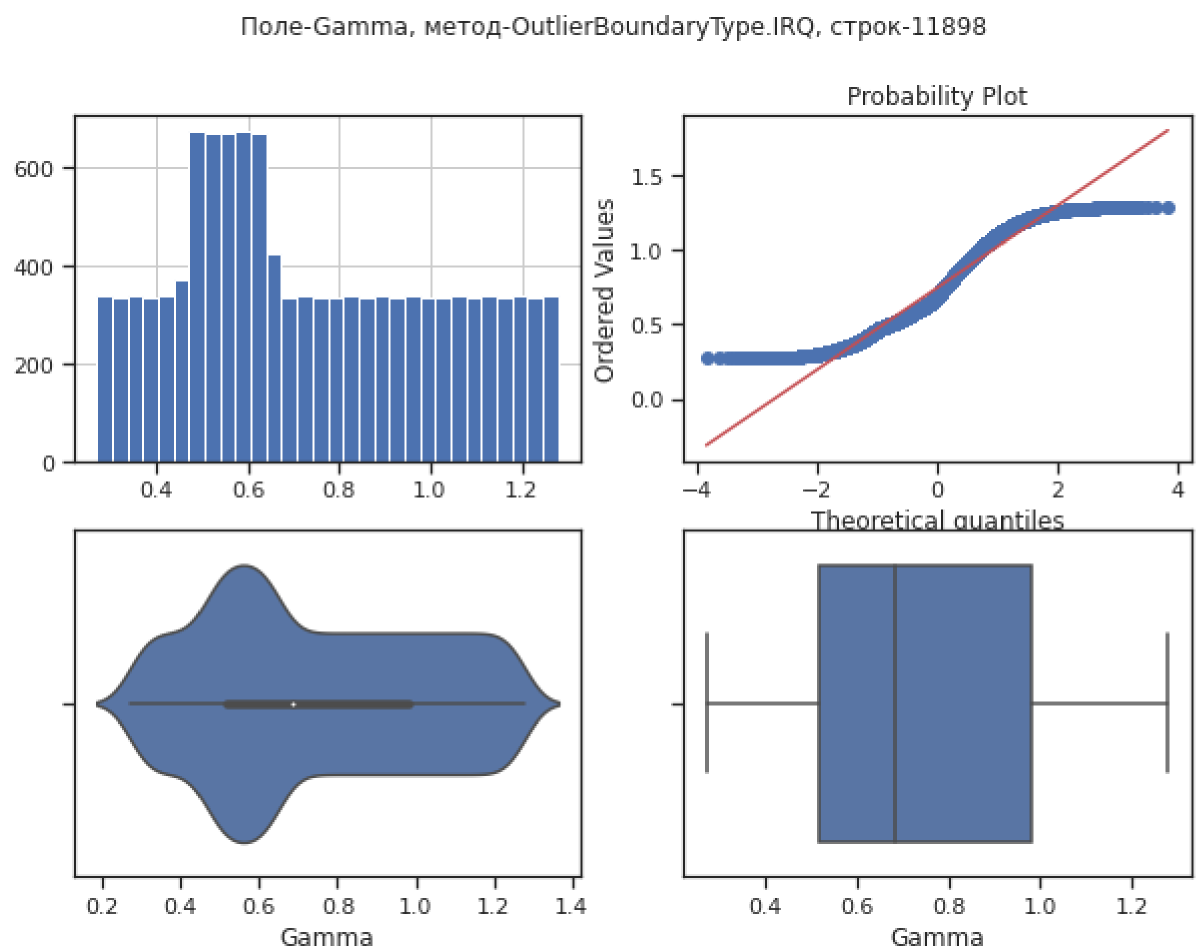
Поле-Sunazimuth, метод-OutlierBoundaryType.QUANTILE, строк-10755




Поле-Sunazimuth, метод-OutlierBoundaryType.IRQ, строк-11898
Probability Plot
Ordered Values
Theoretical quantiles
Sunazimuth
Sunazimuth

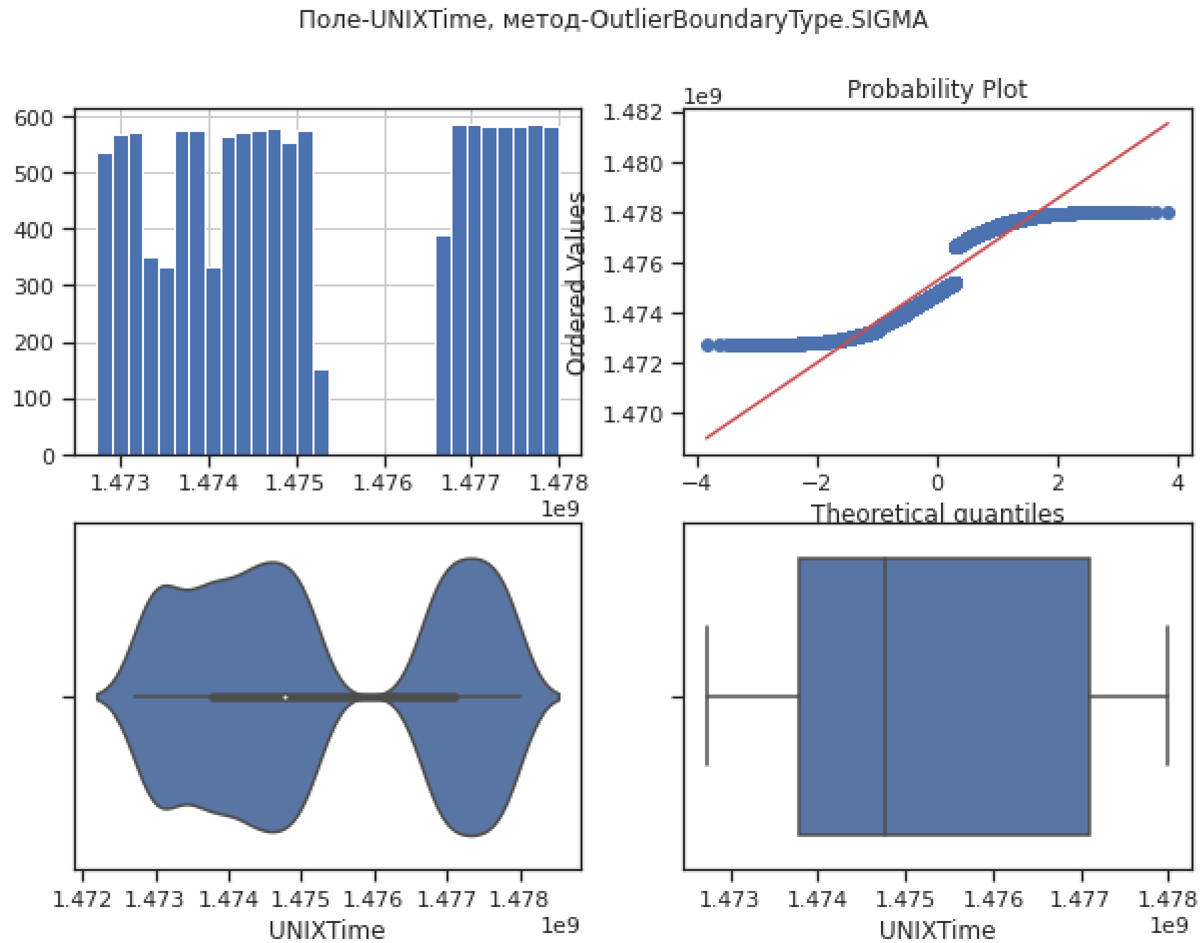

Поле-Gamma, метод-OutlierBoundaryType.SIGMA, строк-11898
Probability Plot
Ordered Values
Theoretical quantiles
Gamma
Gamma

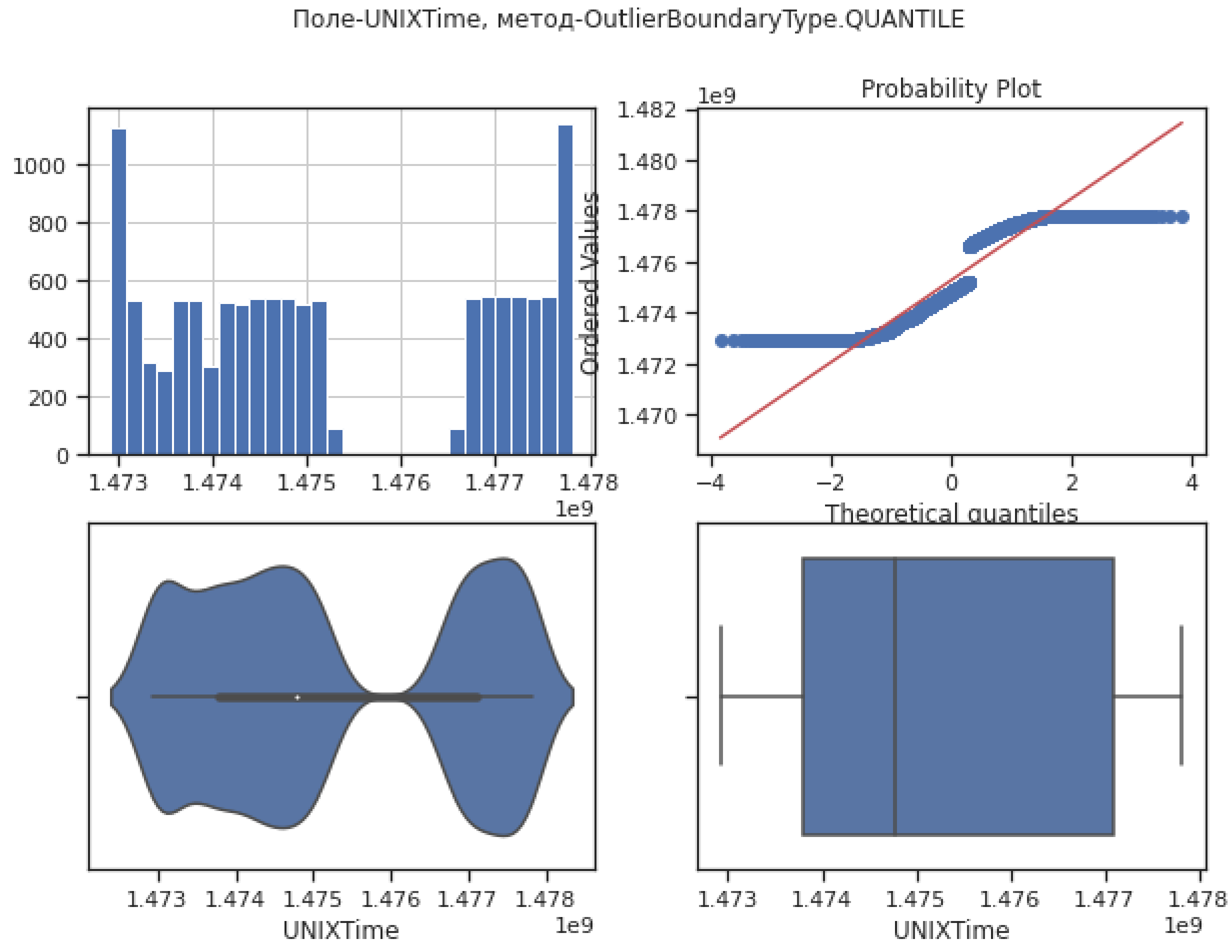

Поле-Gamma, метод-OutlierBoundaryType.QUANTILE, строк-10708
Probability Plot
Ordered Values
Theoretical quantiles
Gamma
Gamma

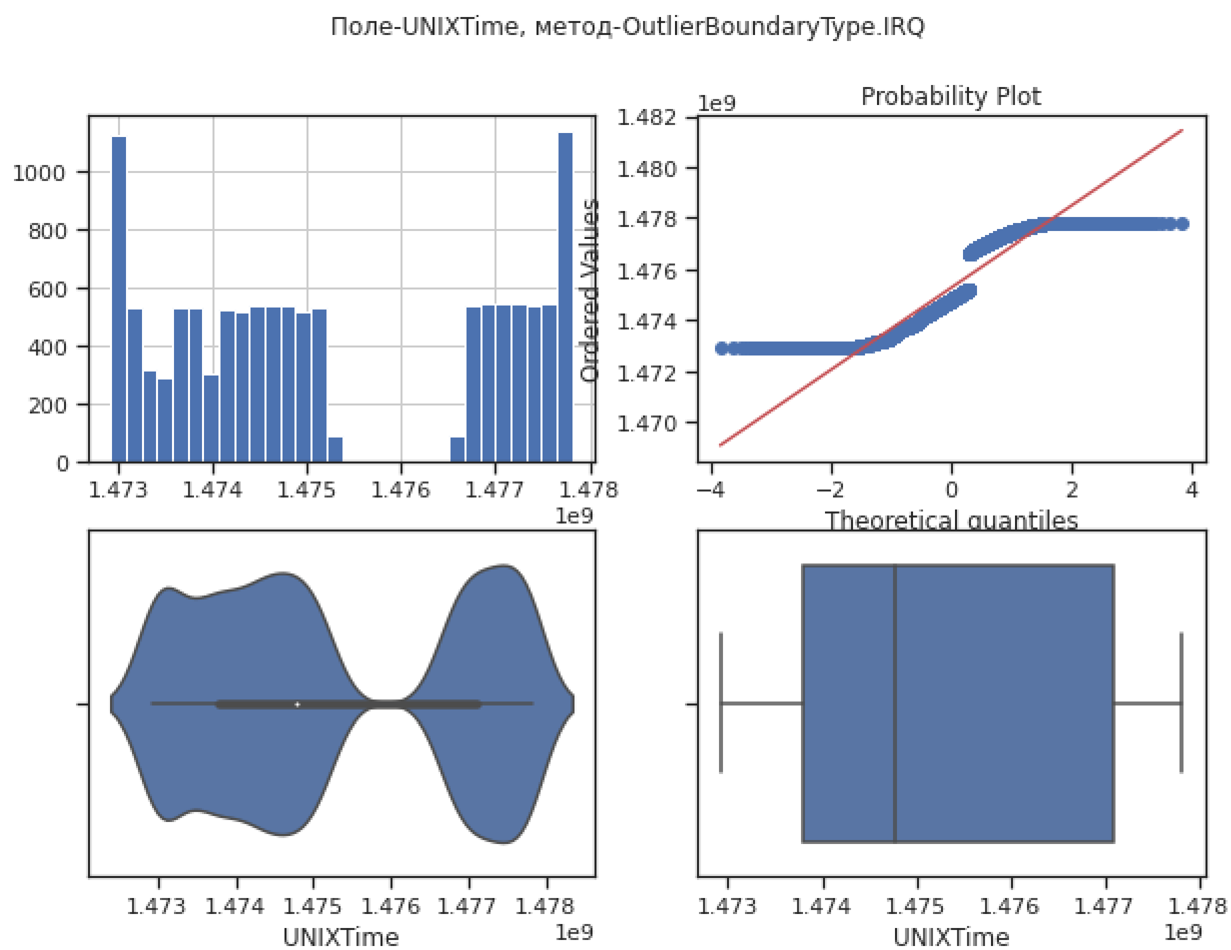

Поле-Gamma, метод-OutlierBoundaryType.IRQ, строк-11898
Probability Plot
Ordered Values
Theoretical quantiles
Gamma
Gamma

Замена выбросов

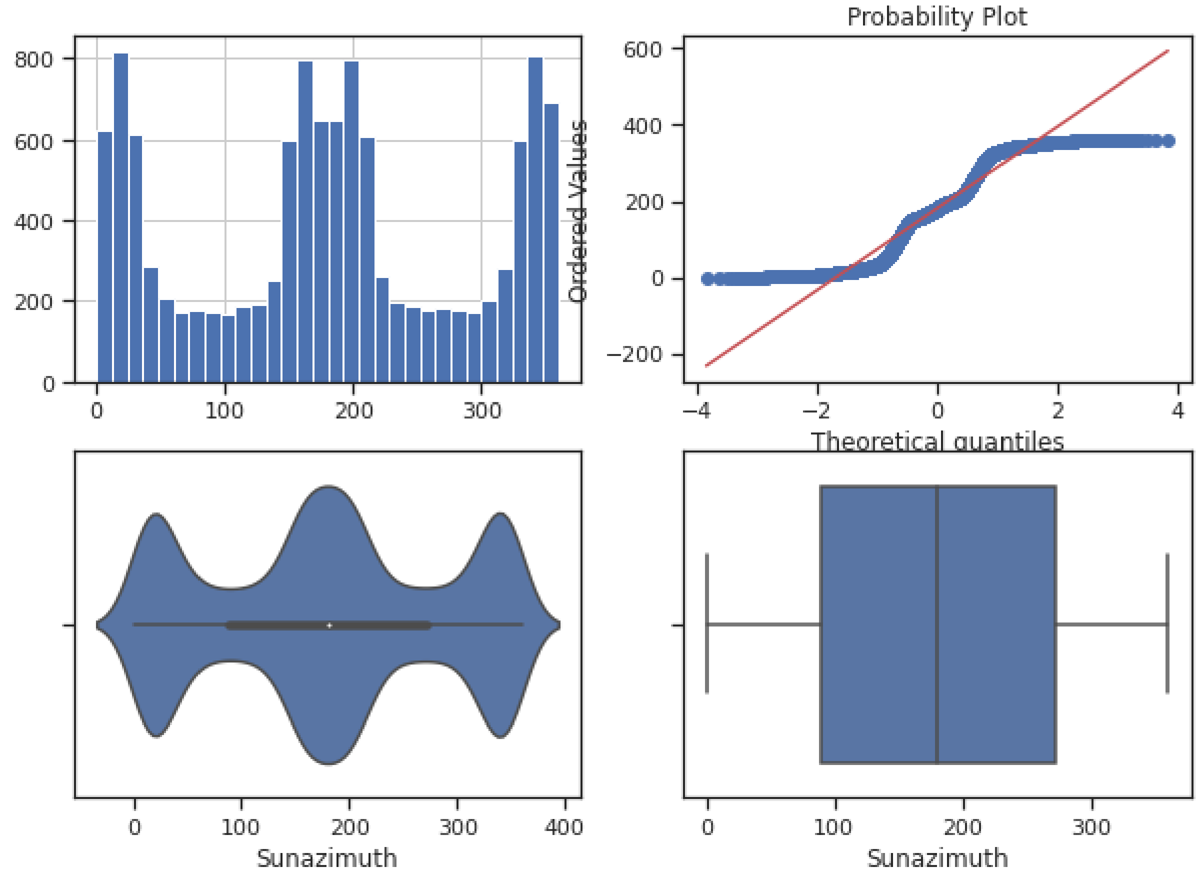
In [ ]:
```
for col in x_col_list:
    for obt in OutlierBoundaryType:
        # Вычисление верхней и нижней границы
        lower_boundary, upper_boundary = get_outlier_boundaries(data_to_scale, c
        # Изменение данных
        data_to_scale[col] = np.where(data_to_scale[col] > upper_boundary, upper
                                      np.where(data_to_scale[col] < lower_boundary, l
        title = 'Поле-{}, метод-{}'.format(col, obt)
        diagnostic_plots(data_to_scale, col, title)
```



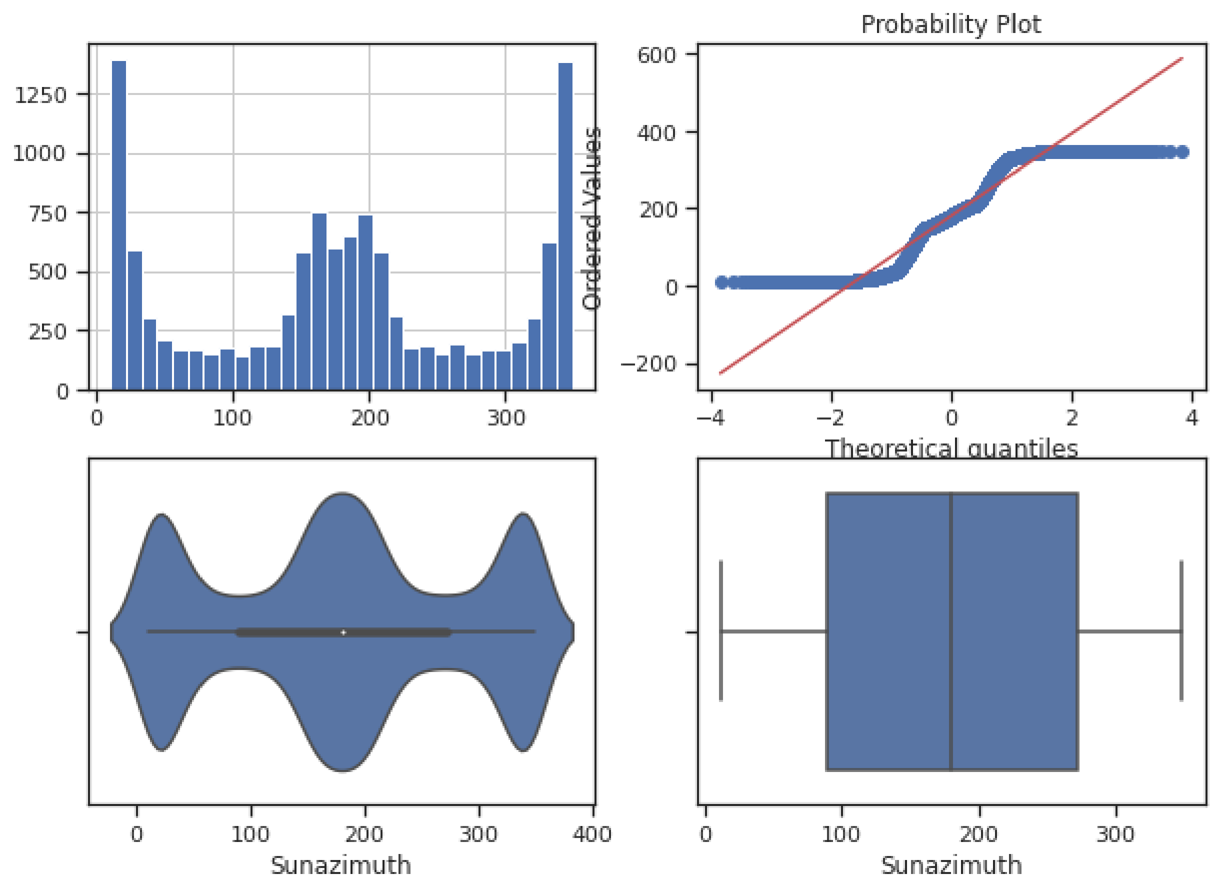

Поле-UNIXTime, метод-OutlierBoundaryType.QUANTILE
Probability Plot
Ordered Values
Theoretical quantiles
UNIXTime
UNIXTime


Поле-UNIXTime, метод-OutlierBoundaryType.IRQ
Probability Plot
Ordered Values
Theoretical quantiles
UNIXTime
UNIXTime

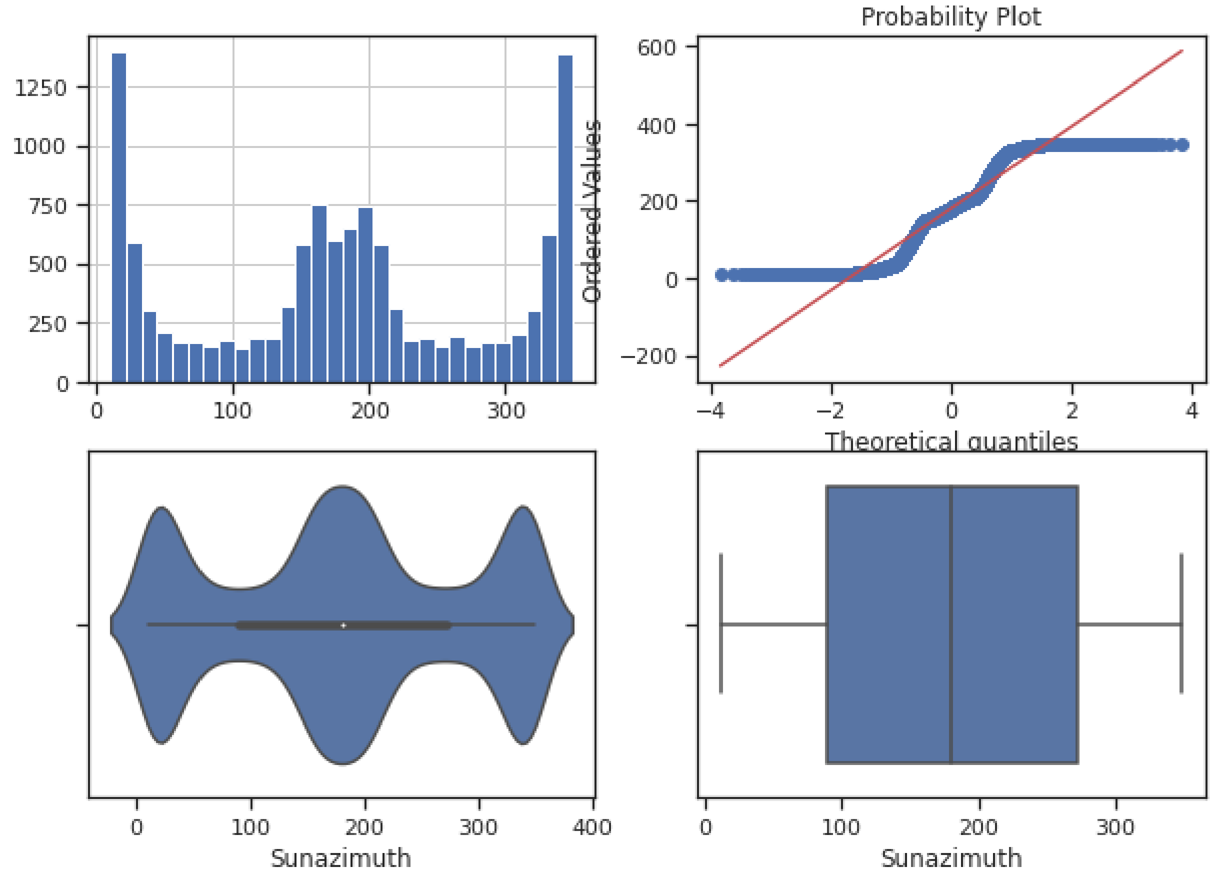
Поле-Sunazimuth, метод-OutlierBoundaryType.SIGMA



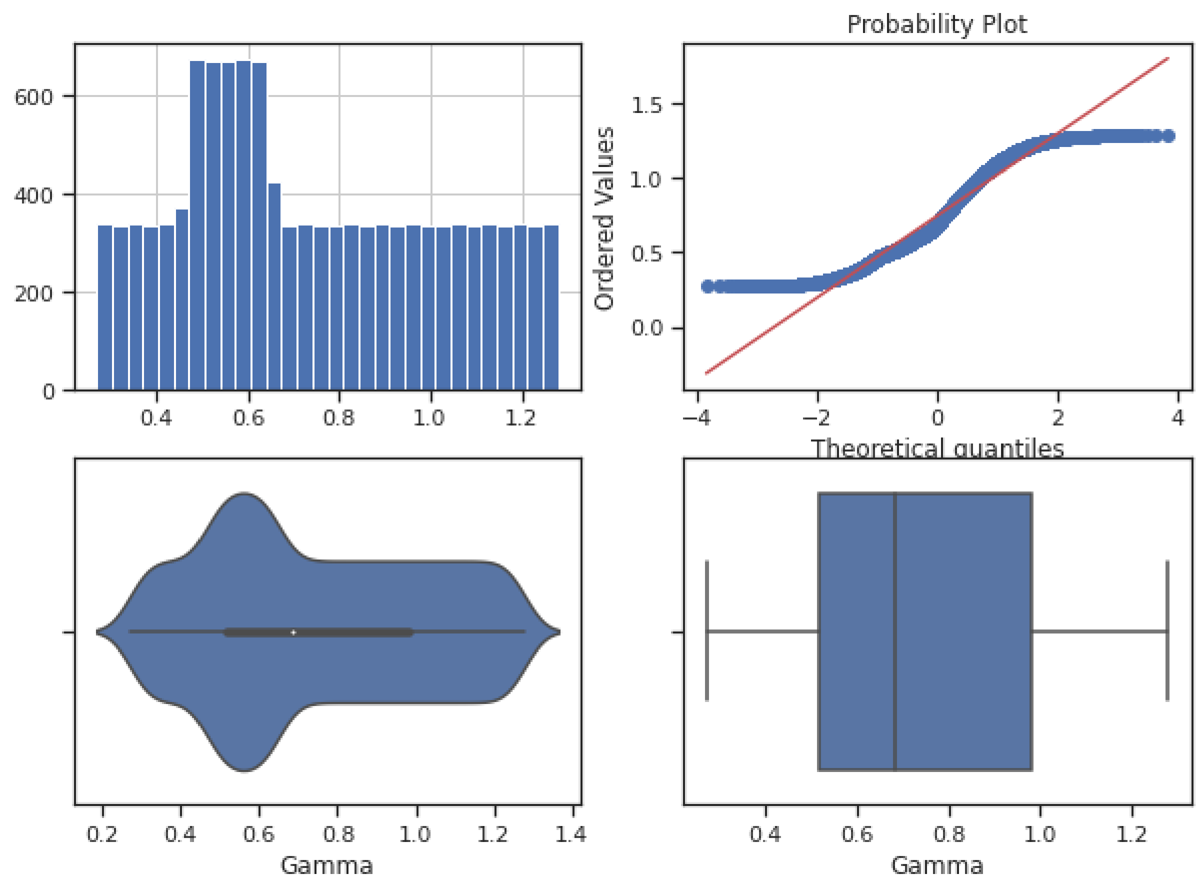
Поле-Sunazimuth, метод-OutlierBoundaryType.QUANTILE



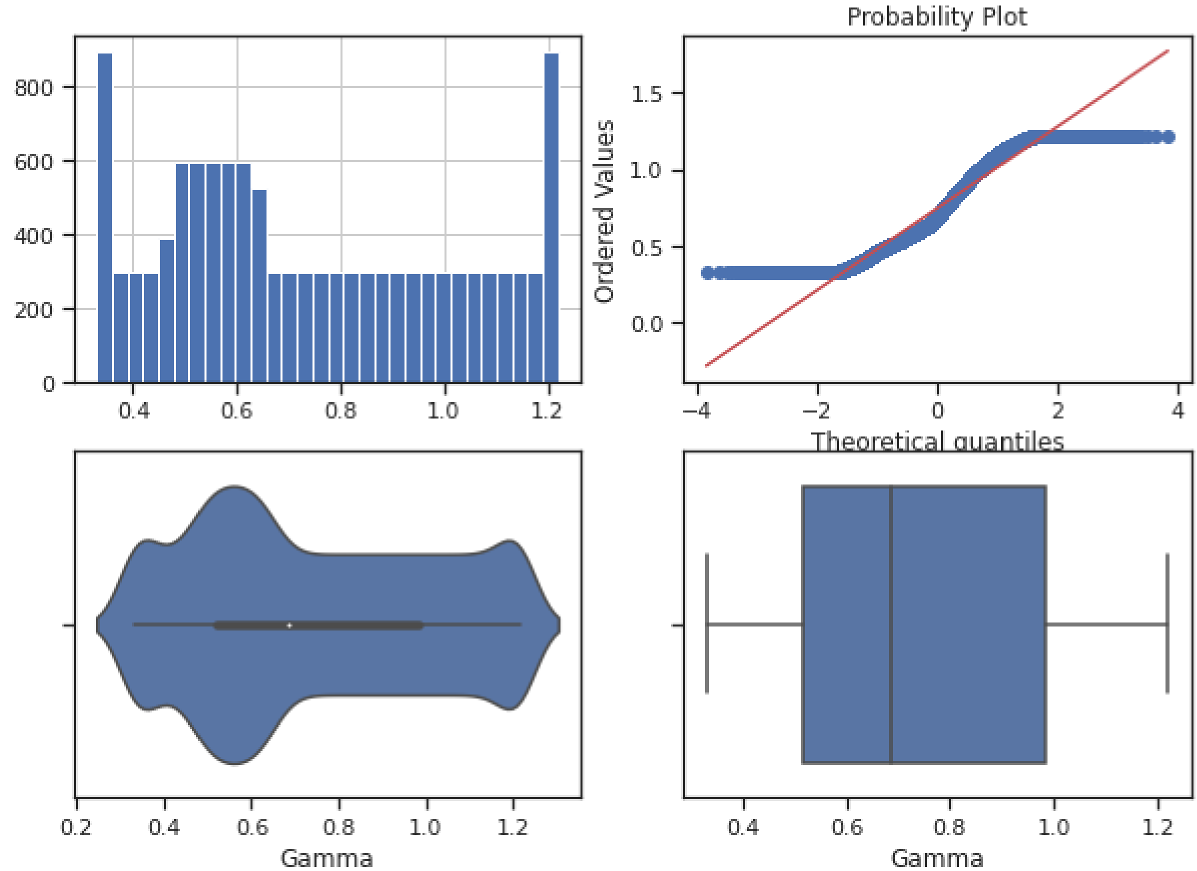
Поле-Sunazimuth, метод-OutlierBoundaryType.IRQ



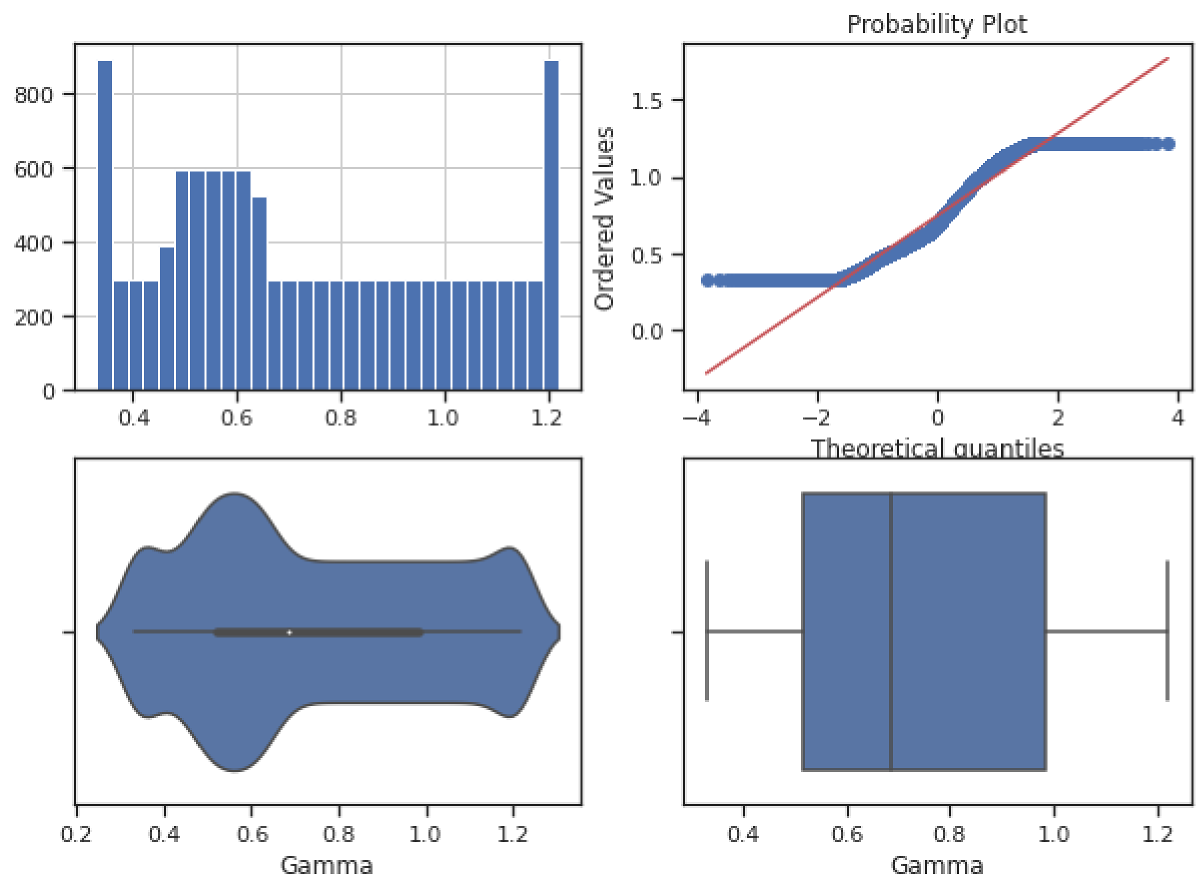
Поле-Gamma, метод-OutlierBoundaryType.SIGMA



Поле-Gamma, метод-OutlierBoundaryType.QUANTILE



Поле-Gamma, метод-OutlierBoundaryType.IRQ



Типы признаков:

1. Бинарный - Gender
2. Вещественный
3. Категориальный
4. Порядковый
5. Set-valued --> (Heard about school form?) - признак являющийся подмножеством какого-либо множества (например, список просмотренных пользователем фильмов - подмножество всех фильмов). В данном случае - признак 'Откуда узнал о Школе21' - подмножество всех возможных способов рекламы

Отбор признаков

Метод фильтрации

Метод, основынный на корреляции

In [ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.datasets import load_boston
import scipy.stats as stats
from sklearn.svm import SVR
from sklearn.svm import LinearSVC
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import Lasso
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import mutual_info_classif, mutual_info_regressio
from sklearn.feature_selection import SelectKBest, SelectPercentile
from IPython.display import Image
%matplotlib inline
sns.set(style="ticks")
```

In [ ]:
```
cols_to_fs = ['Catalog Number','Delta','Lunationnumber','Sarosnumber',
              'Gamma','Eclipsemagnitude','Sunaltitude','Sunazimuth',  'PathWidth
              'UNIXTime', 'WindDirection(Degrees)']
fs_data = data_loaded[cols_to_fs].copy()
fs_data.shape
```

Out[ ]: (32686, 11)

In [ ]:
```
fs_data_features = list(zip(
[i for i in fs_data.columns],
zip(
    #типы колонок
    [str(i) for i in fs_data.dtypes],
    #проверка, есть ли пропущенные значения
    [i for i in fs_data.isnull().sum()]
)))
fs_data_features
```

Out[ ]:
```
[('Catalog Number', ('float64', 20788)),
 ('Delta', ('float64', 20788)),
 ('Lunationnumber', ('float64', 20788)),
 ('Sarosnumber', ('float64', 20788)),
 ('Gamma', ('float64', 20788)),
 ('Eclipsemagnitude', ('float64', 20788)),
 ('Sunaltitude', ('float64', 20788)),
 ('Sunazimuth', ('float64', 20788)),
 ('PathWidth (km)', ('float64', 20835)),
 ('UNIXTime', ('int64', 0)),
 ('WindDirection(Degrees)', ('float64', 0))]
```

In [ ]:
```
fs_data.tail()
```

Out[ ]:

	Catalog Number	Delta	Lunationnumber	Sarosnumber	Gamma	Eclipsemagnitude	Sunaltitude	S
32681	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
32682	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
32683	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
32684	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
32685	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [ ]:
```
fs_data = fs_data.dropna()
fs_data.shape
```

Out[ ]: (11851, 11)

In [ ]:
```
g_cat_enc_le = le.fit_transform(fs_data['UNIXTime'])
g_cat_enc_le
```

Out[ ]: array([7416, 7415, 7414, ..., 7419, 7418, 7417])

In [ ]:
```
fs_data['Gender'] = g_cat_enc_le
fs_data['Gender']
```

Out[ ]:
```
0        7416
1        7415
2        7414
```

```
3        7413
4        7412
         ...
11890    7421
11891    7420
11894    7419
11896    7418
11897    7417
Name: Gender, Length: 11851, dtype: int64
```

In [ ]:

```
fs_data
```

Out[ ]:

	Catalog Number	Delta	Lunationnumber	Sarosnumber	Gamma	Eclipsemagnitude	Sunaltitude
0	1.0	46438.0	49456.0	5.0	0.2701	1.0733	74.0
1	2.0	46426.0	49457.0	10.0	0.2702	0.9382	76.0
2	3.0	46415.0	49458.0	15.0	0.2703	1.0284	60.0
3	4.0	46403.0	49459.0	20.0	0.2704	0.9806	25.0
4	5.0	46393.0	49460.0	-13.0	0.2705	0.1611	0.0
...	...	...	...	...	...	...	...
11890	11891.0	4403.0	12337.0	172.0	0.6482	0.9916	74.0
11891	11892.0	4406.0	12343.0	177.0	0.6483	0.9696	57.0
11894	11895.0	4417.0	12360.0	154.0	0.6486	1.0566	33.0
11896	11897.0	4424.0	12372.0	164.0	0.6488	1.0222	82.0
11897	11898.0	4428.0	12378.0	169.0	0.6489	1.0049	77.0

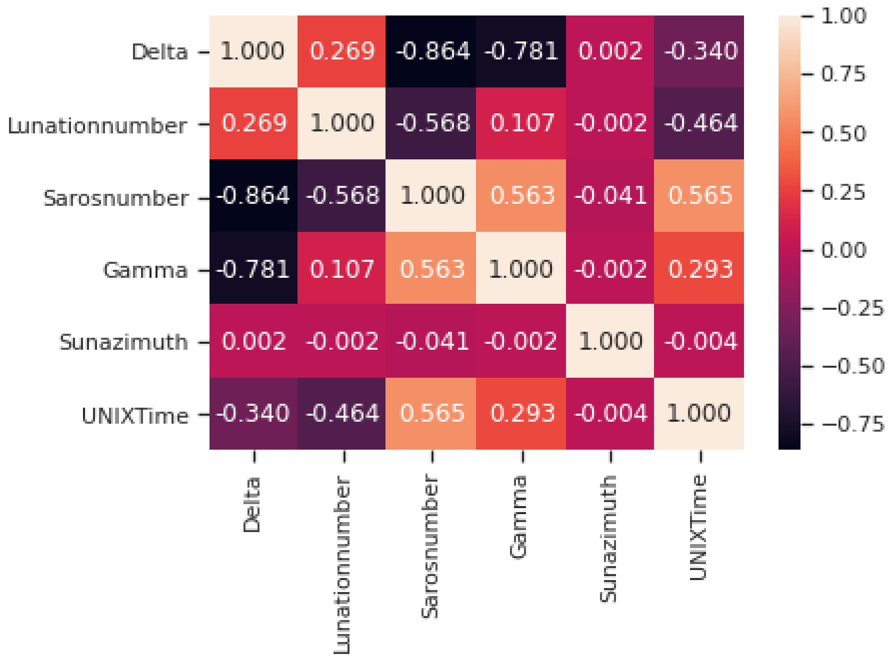
11851 rows × 12 columns

In [ ]:

```
heatmap_cols = [ 'Delta', 'Lunationnumber', 'Sarosnumber', 'Gamma', 'Sunazimuth'
sns.heatmap(fs_data[heatmap_cols].corr(), annot=True, fmt='.3f')
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f06a1d04e10>
```



In [ ]:

```
# Формирование DataFrame с сильными корреляциями
def make_corr_df(df):
    cr = df.corr() # !!!вот здесь был недочет - data.corr -> df.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 [ ]:

```
make_corr_df(fs_data)
```

Out[ ]:

	f1	f2	corr
0	Gender	UNIXTime	0.979178
1	UNIXTime	Gender	0.979178
2	Catalog Number	Sarosnumber	0.965395
3	Sarosnumber	Catalog Number	0.965395
4	PathWidth (km)	Catalog Number	0.959233
5	Catalog Number	PathWidth (km)	0.959233
6	PathWidth (km)	Sarosnumber	0.926418
7	Sarosnumber	PathWidth (km)	0.926418
8	Delta	Catalog Number	0.898682
9	Catalog Number	Delta	0.898682
10	Delta	PathWidth (km)	0.884973
11	PathWidth (km)	Delta	0.884973
12	Sarosnumber	Delta	0.864006

	f1	f2	corr
13	Delta	Sarosnumber	0.864006
14	Gamma	Delta	0.780531
15	Delta	Gamma	0.780531
16	Eclipsemagnitude	Sunaltitude	0.693032
17	Sunaltitude	Eclipsemagnitude	0.693032
18	Gamma	PathWidth (km)	0.595749
19	PathWidth (km)	Gamma	0.595749
20	Gamma	Catalog Number	0.587237
21	Catalog Number	Gamma	0.587237
22	Catalog Number	Lunationnumber	0.583969
23	Lunationnumber	Catalog Number	0.583969
24	UNIXTime	Catalog Number	0.580642
25	Catalog Number	UNIXTime	0.580642
26	Lunationnumber	Sarosnumber	0.568098
27	Sarosnumber	Lunationnumber	0.568098
28	UNIXTime	Sarosnumber	0.564735
29	Sarosnumber	UNIXTime	0.564735
30	Sarosnumber	Gamma	0.562509
31	Gamma	Sarosnumber	0.562509
32	PathWidth (km)	UNIXTime	0.561324
33	UNIXTime	PathWidth (km)	0.561324
34	PathWidth (km)	Lunationnumber	0.544136
35	Lunationnumber	PathWidth (km)	0.544136
36	UNIXTime	Lunationnumber	0.464001
37	Lunationnumber	UNIXTime	0.464001
38	Catalog Number	Gender	0.404952
39	Gender	Catalog Number	0.404952
40	Sarosnumber	Gender	0.395567
41	Gender	Sarosnumber	0.395567
42	PathWidth (km)	Gender	0.394400
43	Gender	PathWidth (km)	0.394400
44	Gender	Lunationnumber	0.363722
45	Lunationnumber	Gender	0.363722
46	Delta	UNIXTime	0.340023
47	UNIXTime	Delta	0.340023

In [ ]:

```
# 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 [ ]:

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

Out[ ]:

```
[['UNIXTime',
  'Catalog Number',
  'Sarosnumber',
  'PathWidth (km)',
  'Lunationnumber',
  'Gender'],
 ['Catalog Number',
  'PathWidth (km)',
  'Sarosnumber',
  'Gamma',
  'UNIXTime',
  'Delta'],
 ['Sunaltitude', 'Eclipsemagnitude']]
```

Метод, основанный на статистических характеристиках

In [ ]:

```
from sklearn.feature_selection import mutual_info_classif, mutual_info_regressio
from sklearn.feature_selection import SelectKBest, SelectPercentile
```

In [ ]:

```
x = fs_data.drop('UNIXTime', axis=1)
x
```

Out[ ]:

	Catalog Number	Delta	Lunationnumber	Sarosnumber	Gamma	Eclipsemagnitude	Sunaltitude
0	1.0	46438.0	49456.0	5.0	0.2701	1.0733	74.0
1	2.0	46426.0	49457.0	10.0	0.2702	0.9382	76.0
2	3.0	46415.0	49458.0	15.0	0.2703	1.0284	60.0
3	4.0	46403.0	49459.0	20.0	0.2704	0.9806	25.0
4	5.0	46393.0	49460.0	-13.0	0.2705	0.1611	0.0
...	...	...	...	...	...	...	...
11890	11891.0	4403.0	12337.0	172.0	0.6482	0.9916	74.0
11891	11892.0	4406.0	12343.0	177.0	0.6483	0.9696	57.0

	Catalog Number	Delta	Lunationnumber	Sarosnumber	Gamma	Eclipsemagnitude	Sunaltitude
11894	11895.0	4417.0	12360.0	154.0	0.6486	1.0566	33.0
11896	11897.0	4424.0	12372.0	164.0	0.6488	1.0222	82.0
11897	11898.0	4428.0	12378.0	169.0	0.6489	1.0049	77.0

11851 rows × 11 columns

In [ ]:

```
y = fs_data['UNIXTime']
y
```

Out[ ]:

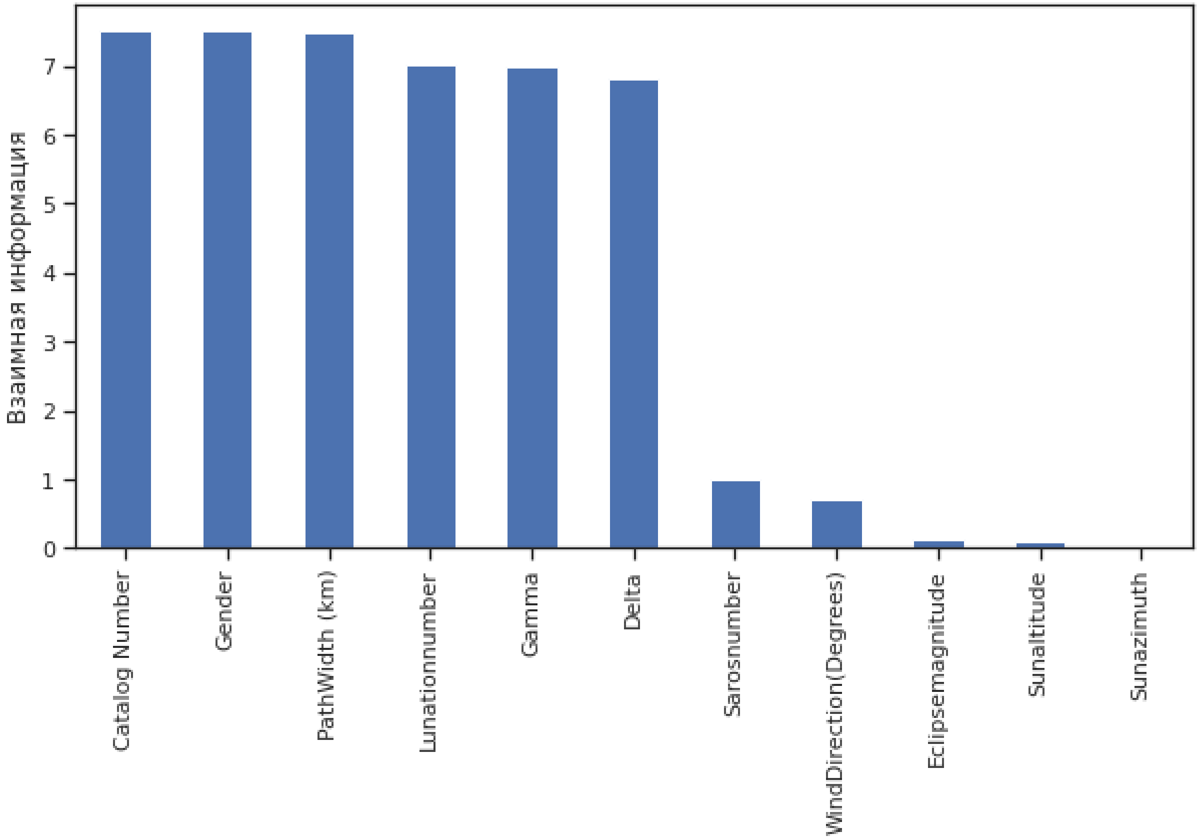
```
0        1475229326
1        1475229023
2        1475228726
3        1475228421
4        1475228124
            ...
11890    1476647720
11891    1476647419
11894    1476646521
11896    1476645923
11897    1476645622
Name: UNIXTime, Length: 11851, dtype: int64
```

In [ ]:

```
mi = mutual_info_regression(x, y)
mi = pd.Series(mi)
mi.index = x.columns
mi.sort_values(ascending=False).plot.bar(figsize=(10,5))
plt.ylabel('Взаимная информация')
```

Out[ ]:

```
Text(0, 0.5, 'Взаимная информация')
```



In [ ]:

```
sel_mi = SelectKBest(mutual_info_regression, k=5).fit(x, y)

list(zip(x.columns, sel_mi.get_support()))
```

Out[ ]:

```
[('Catalog Number', True),
 ('Delta', False),
 ('Lunationnumber', True),
 ('Sarosnumber', False),
 ('Gamma', True),
 ('Eclipsemagnitude', False),
 ('Sunaltitude', False),
 ('Sunazimuth', False),
 ('PathWidth (km)', True),
 ('WindDirection(Degrees)', False),
 ('Gender', True)]
```

New Section