Московский государственный технический университет им. Н.Э. Баумана
Кафедра «Системы обработки информации и управления»

Лабораторная работа №3
по дисциплине
«Методы машинного обучения»
на тему
«Обработка признаков»

Выполнила:
студентка группы ИУ5-21М
Базанова А.Г.

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1. Лабораторная №3

Цель лабораторной работы: изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

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

2. Описание данных

- Date - Дата наблюдений
- Location - Название локации, в которой расположена метеорологическая станция
- MinTemp - Минимальная температура в градусах цельсия
- MaxTemp - Максимальная температура в градусах цельсия
- Rainfall - Количество осадков, зафиксированных за день в мм
- Evaporation - Так называемое "pan evaporation" класса A (мм) за 24 часа до 9 утра
- Sunshine - Число солнечных часов за день
- WindGustDir - направление самого сильного порыва ветра за последние 24 часа
- WindGustSpeed - скорость (км / ч) самого сильного порыва ветра за последние 24 часа
- WindDir9am - направление ветра в 9 утра

[1]:
```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
import pandas as pd
import numpy as np
import seaborn as sns
import scipy.stats as stats

import matplotlib.pyplot as plt
```

[2]:
```
data = pd.read_csv('weatherAUS.csv', parse_dates=['Date'])
```

[3]:
```python
total_count = data.shape[0]
num_cols = []
cat_cols = []
for col in data.columns:
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
    elif dt=='object':
        cat_cols.append(col)
```

[4]:
```python
data = data.drop(['Evaporation'], axis = 1)
num_cols.remove('Evaporation')

data['Sunshine'] = data['Sunshine'].fillna(data.median(numeric_only=True))
data['Humidity9am'] = data['Humidity9am'].fillna(data['Humidity9am'].mode())
data = data.fillna(data.mode())
```

[5]:
```python
data[:] = SimpleImputer(missing_values=np.nan, strategy='most_frequent').
↪fit_transform(data)
```

[6]:
```python
data['RainToday'] = data['RainToday'].apply(lambda x: 1 if x == 'Yes' else␣
↪0)
data['RainTomorrow'] = data['RainTomorrow'].apply(lambda x: 1 if x == 'Yes'␣
↪else 0)
cat_cols.remove('RainToday')
cat_cols.remove('RainTomorrow')
```

[7]:
```python
data = data.drop(['RISK_MM'], axis = 1)
```

[87]:
```python
# from sklearn.preprocessing import LabelEncoder

# le = LabelEncoder()
# for col in cat_cols:
#     data[col] = le.fit_transform(data[col])
```

[8]:
```python
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
data['Location'] = le.fit_transform(data['Location'])
```

[9]:
```python
categorical = ['WindDir3pm','WindDir9am', 'WindGustDir']

data = pd.concat([data, pd.get_dummies(data[categorical],␣
↪columns=categorical, drop_first=True)],axis=1)
data.drop(categorical, axis=1, inplace=True)
```

2.1. Нестандартный признак

Преобразуем дату

[10]:
```python
import datetime as dt

data['Date'] = pd.to_datetime(data['Date'])
data['Date'] = data['Date'].map(dt.datetime.toordinal)
```

2.2. Масштабирование данных

[11]:
```python
def arr_to_df(arr_scaled, columns):
    res = pd.DataFrame(arr_scaled, columns=columns)
    return res
```

2.2.1. MinMaxScaler

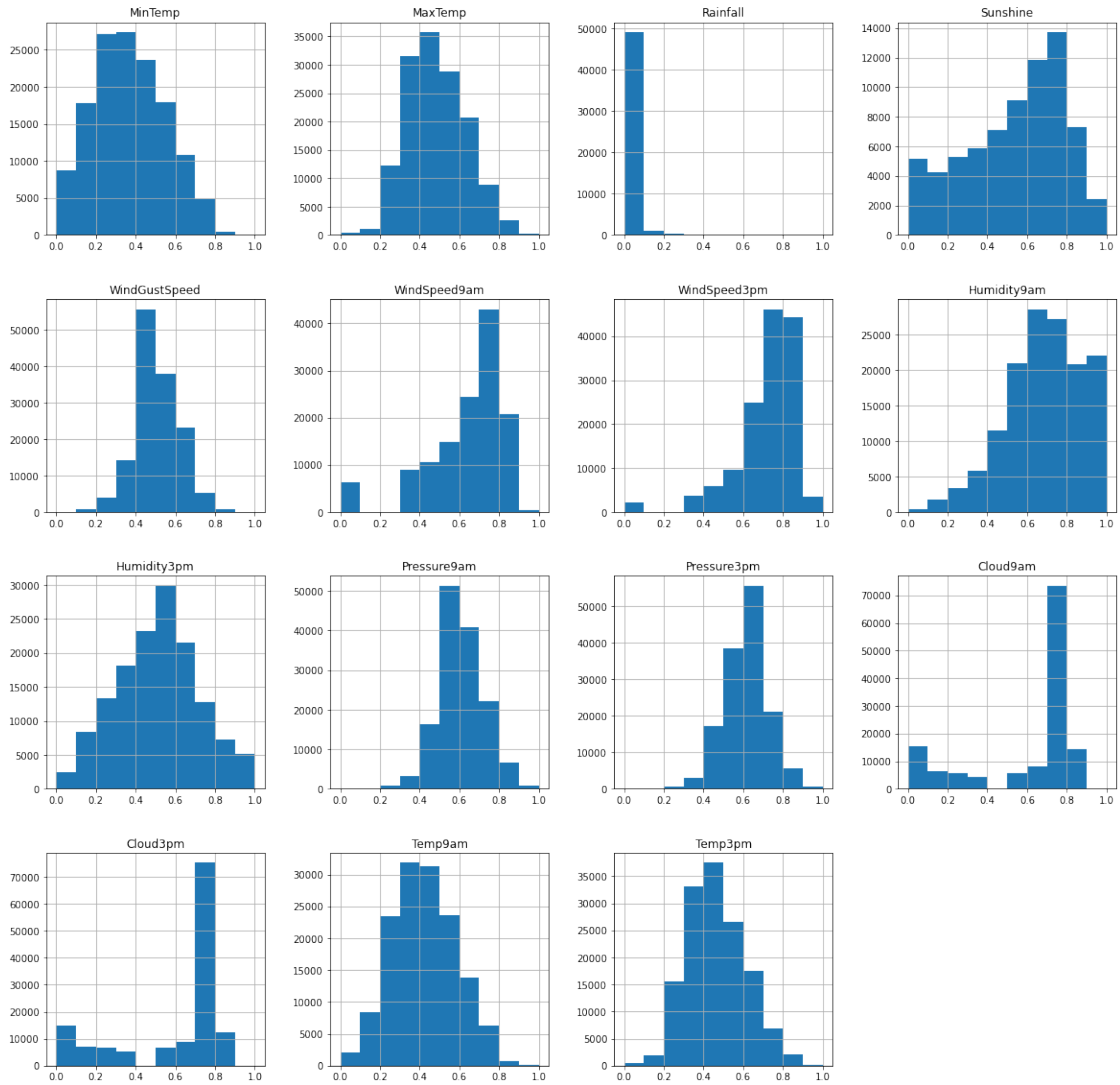
[12]:
```python
from sklearn.preprocessing import MinMaxScaler

min_max_scaler = MinMaxScaler()
data_minmax = arr_to_df( min_max_scaler.fit_transform(data), data.columns )
data_minmax.describe()
```

[12]:
```
                Date       Location        MinTemp        MaxTemp  \
count  142193.000000  142193.000000  142193.000000  142193.000000
mean        0.561300       0.494597       0.487614       0.529669
std         0.261701       0.296615       0.150737       0.134427
min         0.000000       0.000000       0.000000       0.000000
25%         0.329739       0.229167       0.379717       0.429112
50%         0.577185       0.500000       0.483491       0.517958
75%         0.788876       0.750000       0.596698       0.623819
max         1.000000       1.000000       1.000000       1.000000

            Rainfall       Sunshine  WindGustSpeed   WindSpeed9am  \
count  142193.000000  142193.000000  142193.000000  142193.000000
mean        0.006272       0.275058       0.260925       0.107343
std         0.022713       0.323356       0.102294       0.068187
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.193798       0.053846
50%         0.000000       0.013793       0.240310       0.100000
75%         0.001617       0.600000       0.310078       0.146154
max         1.000000       1.000000       1.000000       1.000000

        WindSpeed3pm    Humidity9am  …  WindGustDir_NNW  WindGustDir_NW  \
count  142193.000000  142193.000000  …    142193.000000   142193.000000
mean        0.213026       0.692200  …         0.046142        0.056283
std         0.100627       0.192257  …         0.209792        0.230468
min         0.000000       0.000000  …         0.000000        0.000000
25%         0.149425       0.570000  …         0.000000        0.000000
50%         0.195402       0.700000  …         0.000000        0.000000
75%         0.275862       0.840000  …         0.000000        0.000000
max         1.000000       1.000000  …         1.000000        1.000000
```

```
       WindGustDir_S  WindGustDir_SE  WindGustDir_SSE  WindGustDir_SSW  \
count  142193.000000   142193.000000    142193.000000    142193.000000
mean        0.062936        0.065467         0.063245         0.060552
std         0.242848        0.247350         0.243404         0.238507
min         0.000000        0.000000         0.000000         0.000000
25%         0.000000        0.000000         0.000000         0.000000
50%         0.000000        0.000000         0.000000         0.000000
75%         0.000000        0.000000         0.000000         0.000000
max         1.000000        1.000000         1.000000         1.000000

       WindGustDir_SW  WindGustDir_W  WindGustDir_WNW  WindGustDir_WSW
count   142193.000000  142193.000000    142193.000000    142193.000000
mean         0.061867       0.134395         0.056726         0.062598
std          0.240914       0.341077         0.231319         0.242239
min          0.000000       0.000000         0.000000         0.000000
25%          0.000000       0.000000         0.000000         0.000000
50%          0.000000       0.000000         0.000000         0.000000
75%          0.000000       0.000000         0.000000         0.000000
max          1.000000       1.000000         1.000000         1.000000

[8 rows x 64 columns]
```

[29]:

```
data_minmax[num_cols].hist(figsize=(20,20))
plt.show()
```



[ ]:
```
# draw_kde(['Sunshine', 'WindGustSpeed', 'Pressure9am'], data,␣
↪data_minmax, '      ', '     ')
```

2.2.2. StandardScaler

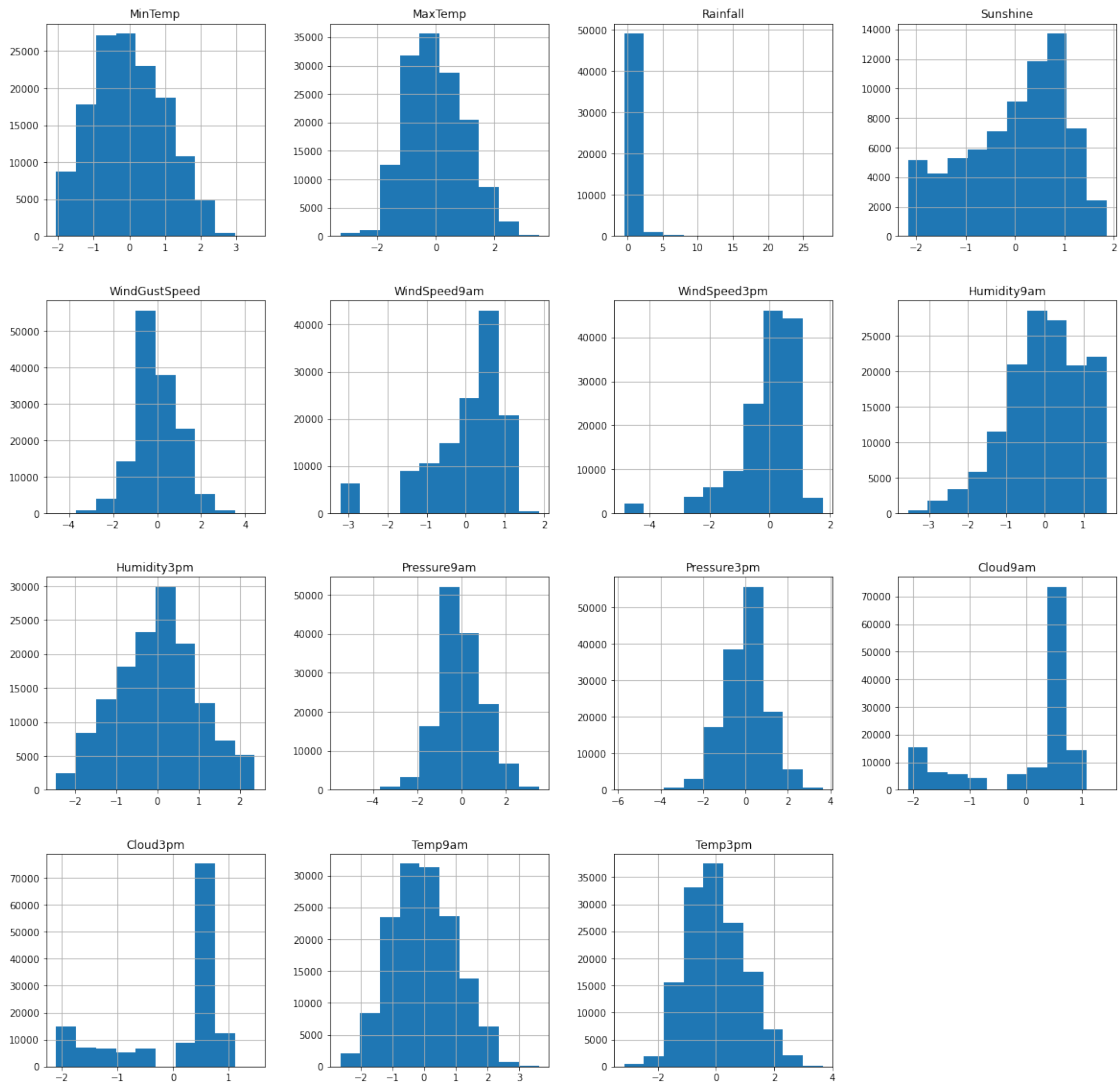
[31]:
```
from sklearn.preprocessing import StandardScaler

cs11 = StandardScaler()
data_stscal = arr_to_df( cs11.fit_transform(data), data.columns )
data_stscal.describe()
```

[31]:
```
                Date      Location       MinTemp       MaxTemp      Rainfall  ␣
↪\
```

```
count   1.421930e+05  1.421930e+05  1.386310e+05  1.420740e+05  5.051200e+04
mean   -4.568480e-14 -2.375395e-14 -1.336574e-15  2.392474e-15 -2.656044e-15
std     1.000004e+00  1.000004e+00  1.000004e+00  1.000004e+00  1.000010e+00
min    -2.144822e+00 -1.667479e+00 -2.053193e+00 -3.268740e+00 -4.914842e-01
25%    -8.848332e-01 -8.948690e-01 -7.487198e-01 -7.401830e-01 -4.686239e-01
50%     6.070062e-02  1.821567e-02 -5.520230e-02 -9.038626e-02 -3.467024e-01
75%     8.696092e-01  8.610630e-01  7.373891e-01  7.006706e-01  3.430218e-02
max     1.676349e+00  1.703910e+00  3.527971e+00  3.511748e+00  2.777144e+01

           Sunshine  WindGustSpeed  WindSpeed9am  WindSpeed3pm   Humidity9am
 \
count   7.206900e+04   1.421930e+05  1.290370e+05  1.400850e+05  1.421920e+05
mean    4.377702e-15  -3.502465e-14 -9.523038e-15 -2.349945e-14  6.442510e-15
std     1.000007e+00   1.000004e+00  1.000004e+00  1.000004e+00  1.000004e+00
min    -2.168449e+00  -4.573230e+00 -3.210179e+00 -4.840631e+00 -3.548564e+00
25%    -7.170551e-01  -6.062049e-01 -3.813041e-01 -2.485033e-01 -6.356637e-01
50%     2.040219e-01  -8.375331e-02  1.958465e-01  3.442135e-01  4.054519e-02
75%     7.901618e-01   5.882498e-01  6.864940e-01  6.404108e-01  7.687702e-01
max     1.850796e+00   4.435776e+00  1.864534e+00  1.758688e+00  1.601027e+00

        …  WindGustDir_NNW  WindGustDir_NW  WindGustDir_S  WindGustDir_SE  \
count   …     1.421930e+05    1.421930e+05   1.421930e+05    1.421930e+05
mean    …    -4.877081e-14   -4.700070e-15   3.792482e-14    6.031890e-15
std     …     1.000004e+00    1.000004e+00   1.000004e+00    1.000004e+00
min     …    -2.199399e-01   -2.442116e-01  -2.591573e-01   -2.646764e-01
25%     …    -2.199399e-01   -2.442116e-01  -2.591573e-01   -2.646764e-01
50%     …    -2.199399e-01   -2.442116e-01  -2.591573e-01   -2.646764e-01
75%     …    -2.199399e-01   -2.442116e-01  -2.591573e-01   -2.646764e-01
max     …     4.546698e+00    4.094809e+00   3.858661e+00    3.778199e+00

       WindGustDir_SSE  WindGustDir_SSW  WindGustDir_SW  WindGustDir_W  \
count     1.421930e+05     1.421930e+05    1.421930e+05   1.421930e+05
mean      3.959005e-14     6.386993e-15    3.722020e-14  -1.571981e-13
std       1.000004e+00     1.000004e+00    1.000004e+00   1.000004e+00
min      -2.598365e-01    -2.538785e-01   -2.568005e-01  -3.940318e-01
25%      -2.598365e-01    -2.538785e-01   -2.568005e-01  -3.940318e-01
50%      -2.598365e-01    -2.538785e-01   -2.568005e-01  -3.940318e-01
75%      -2.598365e-01    -2.538785e-01   -2.568005e-01  -3.940318e-01
max       3.848574e+00     3.938892e+00    3.894073e+00   2.537866e+00

       WindGustDir_WNW  WindGustDir_WSW
count     1.421930e+05     1.421930e+05
mean     -1.142116e-14     3.108642e-14
std       1.000004e+00     1.000004e+00
min      -2.452285e-01    -2.584148e-01
25%      -2.452285e-01    -2.584148e-01
50%      -2.452285e-01    -2.584148e-01
75%      -2.452285e-01    -2.584148e-01
max       4.077829e+00     3.869748e+00
```

```
[8 rows x 65 columns]
```

[32]:
```
data_stscal[num_cols].hist(figsize=(20,20))
plt.show()
```



2.2.3. MeanNormalisation

[30]:
```
class MeanNormalisation:

    def fit(self, param_df):
        self.means = param_df.mean(axis=0)
        maxs = param_df.max(axis=0)
```

```
        mins = param_df.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)
```

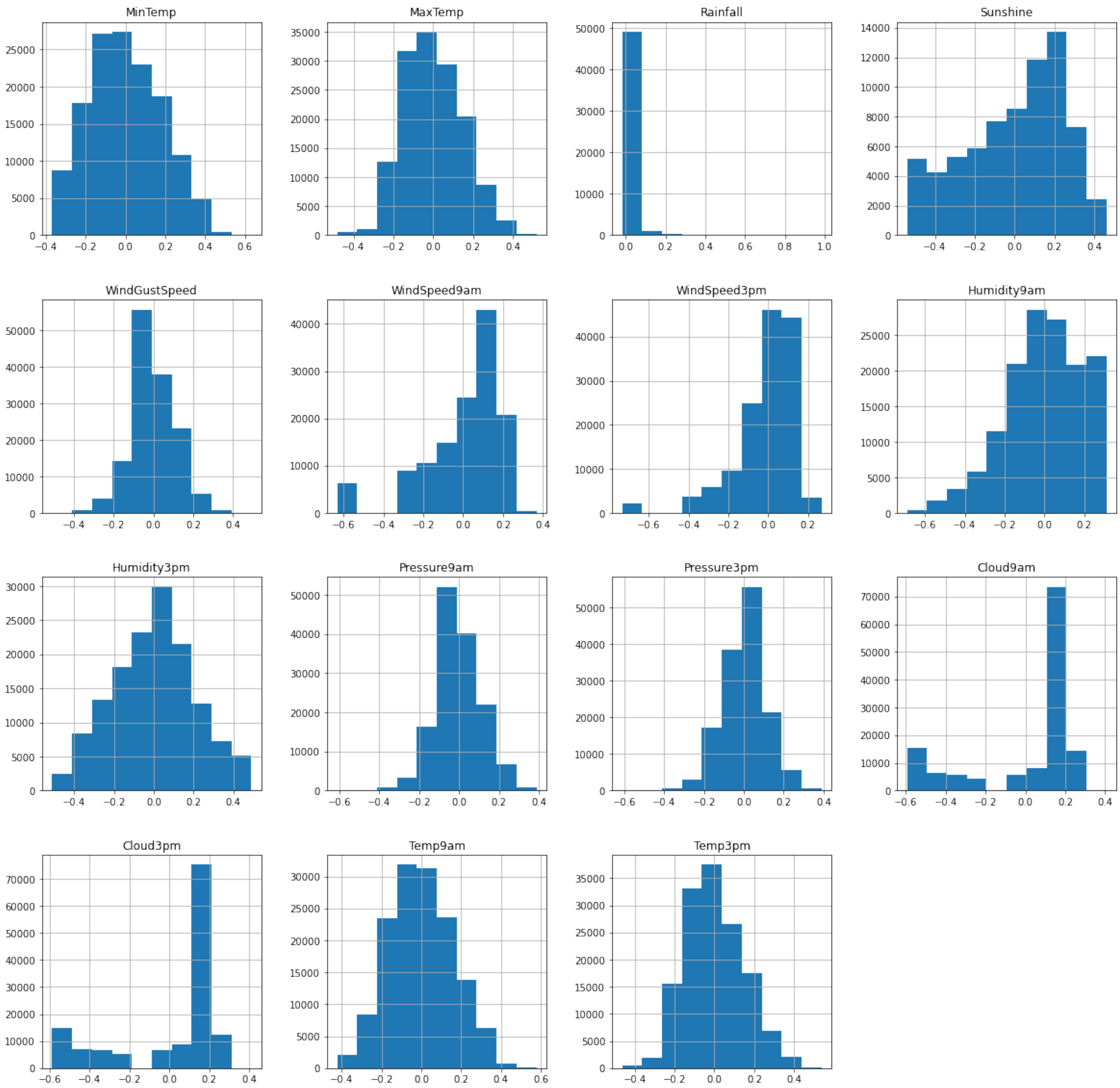
[33]:
```
sc21 = MeanNormalisation()
data_meann = sc21.fit_transform(data)
data_meann.describe()
```

[33]:
```
               Date      Location       MinTemp       MaxTemp      Rainfall  ␣
↪\
count  1.421930e+05  1.421930e+05  1.386310e+05  1.420740e+05  5.051200e+04
mean  -1.208120e-14  1.560273e-15  2.332991e-15 -1.451398e-17 -2.861866e-15
std    2.617008e-01  2.966147e-01  1.791747e-01  1.474825e-01  3.538240e-02
min   -5.612997e-01 -4.945970e-01 -3.678790e-01 -4.820803e-01 -1.738972e-02
25%   -2.315607e-01 -2.654303e-01 -1.341512e-01 -1.091637e-01 -1.658087e-02
50%    1.588535e-02  5.403014e-03 -9.890822e-03 -1.333035e-02 -1.226704e-02
75%    2.275766e-01  2.554030e-01  1.321210e-01  1.033363e-01  1.213681e-03
max    4.387003e-01  5.054030e-01  6.321210e-01  5.179197e-01  9.826103e-01

           Sunshine  WindGustSpeed  WindSpeed9am  WindSpeed3pm   Humidity9am␣
↪ \
count  7.206900e+04   1.421930e+05  1.290370e+05  1.400850e+05  1.421920e+05
mean   3.269599e-15   3.085900e-13  2.661581e-14 -7.969160e-15  5.170696e-16
std    2.488047e-01   1.110004e-01  1.970563e-01  1.515313e-01  1.941909e-01
min   -5.395165e-01  -5.076287e-01 -6.325833e-01 -7.335047e-01 -6.890962e-01
25%   -1.784054e-01  -6.728876e-02 -7.513807e-02 -3.765590e-02 -1.234397e-01
50%    5.076125e-02  -9.296620e-03  3.859262e-02  5.215895e-02  7.873477e-03
75%    1.965946e-01   6.529575e-02  1.352774e-01  9.704196e-02  1.492876e-01
max    4.604835e-01   4.923713e-01  3.674167e-01  2.664953e-01  3.109038e-01

       …  WindGustDir_NNW  WindGustDir_NW  WindGustDir_S  WindGustDir_SE  \
count  …     1.421930e+05    1.421930e+05   1.421930e+05    1.421930e+05
mean   …     1.194564e-14   -4.687252e-15   1.109732e-14   -2.955912e-15
std    …     2.097922e-01    2.304676e-01   2.428479e-01    2.473496e-01
min    …    -4.614151e-02   -5.628266e-02  -6.293559e-02   -6.546736e-02
25%    …    -4.614151e-02   -5.628266e-02  -6.293559e-02   -6.546736e-02
50%    …    -4.614151e-02   -5.628266e-02  -6.293559e-02   -6.546736e-02
75%    …    -4.614151e-02   -5.628266e-02  -6.293559e-02   -6.546736e-02
max    …     9.538585e-01    9.437173e-01   9.370644e-01    9.345326e-01

       WindGustDir_SSE  WindGustDir_SSW  WindGustDir_SW  WindGustDir_W  \
count     1.421930e+05     1.421930e+05    1.421930e+05   1.421930e+05
mean     -6.655636e-16    -6.216279e-15   -8.795634e-15  -1.982616e-14
```

```
std       2.434040e-01    2.385066e-01    2.409140e-01   3.410772e-01
min      -6.324503e-02   -6.055150e-02   -6.186662e-02  -1.343948e-01
25%      -6.324503e-02   -6.055150e-02   -6.186662e-02  -1.343948e-01
50%      -6.324503e-02   -6.055150e-02   -6.186662e-02  -1.343948e-01
75%      -6.324503e-02   -6.055150e-02   -6.186662e-02  -1.343948e-01
max       9.367550e-01    9.394485e-01    9.381334e-01   8.656052e-01

       WindGustDir_WNW  WindGustDir_WSW
count     1.421930e+05     1.421930e+05
mean     -2.724218e-15    -9.036343e-15
std       2.313186e-01     2.422394e-01
min      -5.672572e-02    -6.259802e-02
25%      -5.672572e-02    -6.259802e-02
50%      -5.672572e-02    -6.259802e-02
75%      -5.672572e-02    -6.259802e-02
max       9.432743e-01     9.374020e-01

[8 rows x 65 columns]
```

[35]:

```
data_meann[num_cols].hist(figsize=(20,20))
plt.show()
```



[13]:
```
data = data_minmax
```

2.3. Обработка выбросов для числовых признаков

[86]:
```
def diagnostic_plots_out(df, variable, title):
    fig, ax = plt.subplots(figsize=(10,7))
    #
    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)
    #
    plt.subplot(2, 2, 3)
```

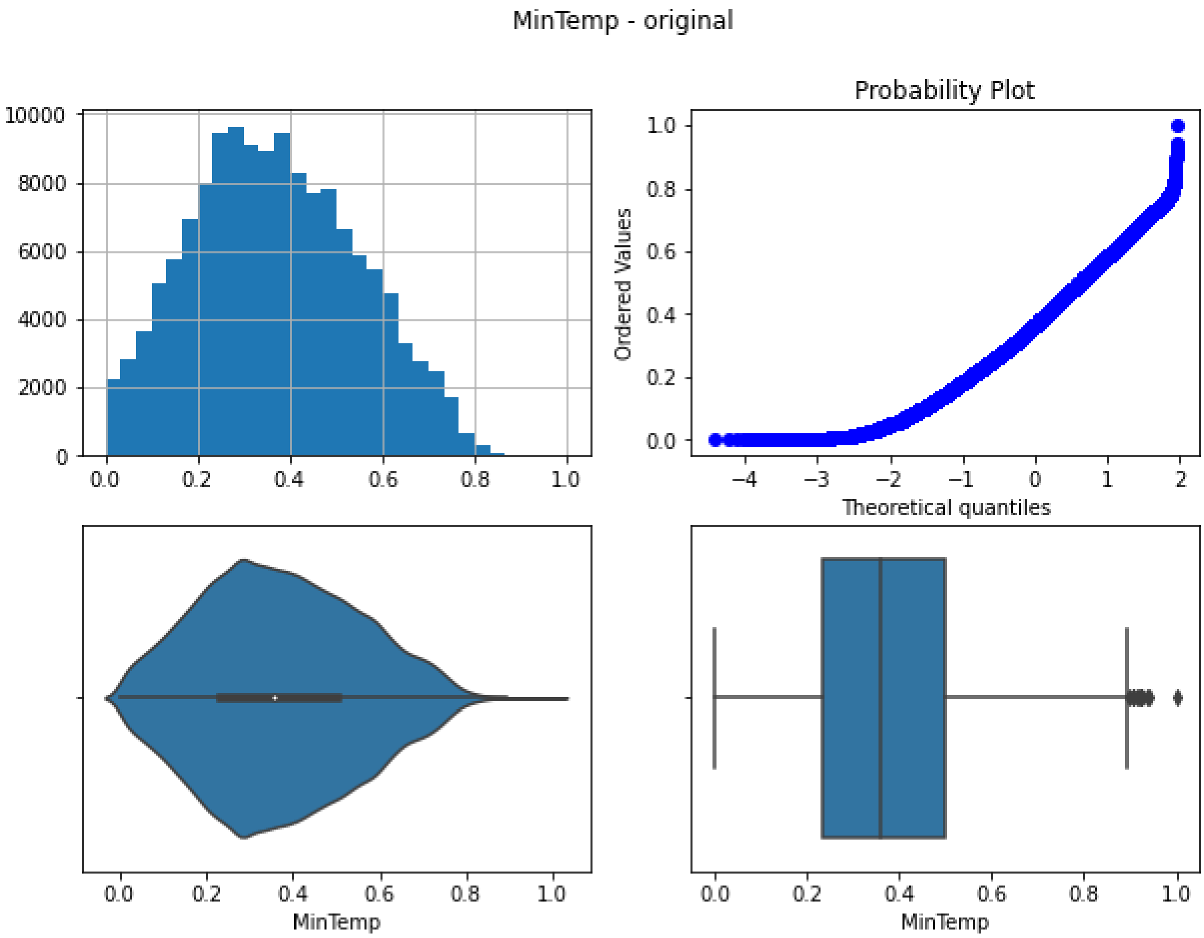
```
    sns.violinplot(x=df[variable])
    #
    plt.subplot(2, 2, 4)
    sns.boxplot(x=df[variable])
    fig.suptitle(title)
    plt.show()
```

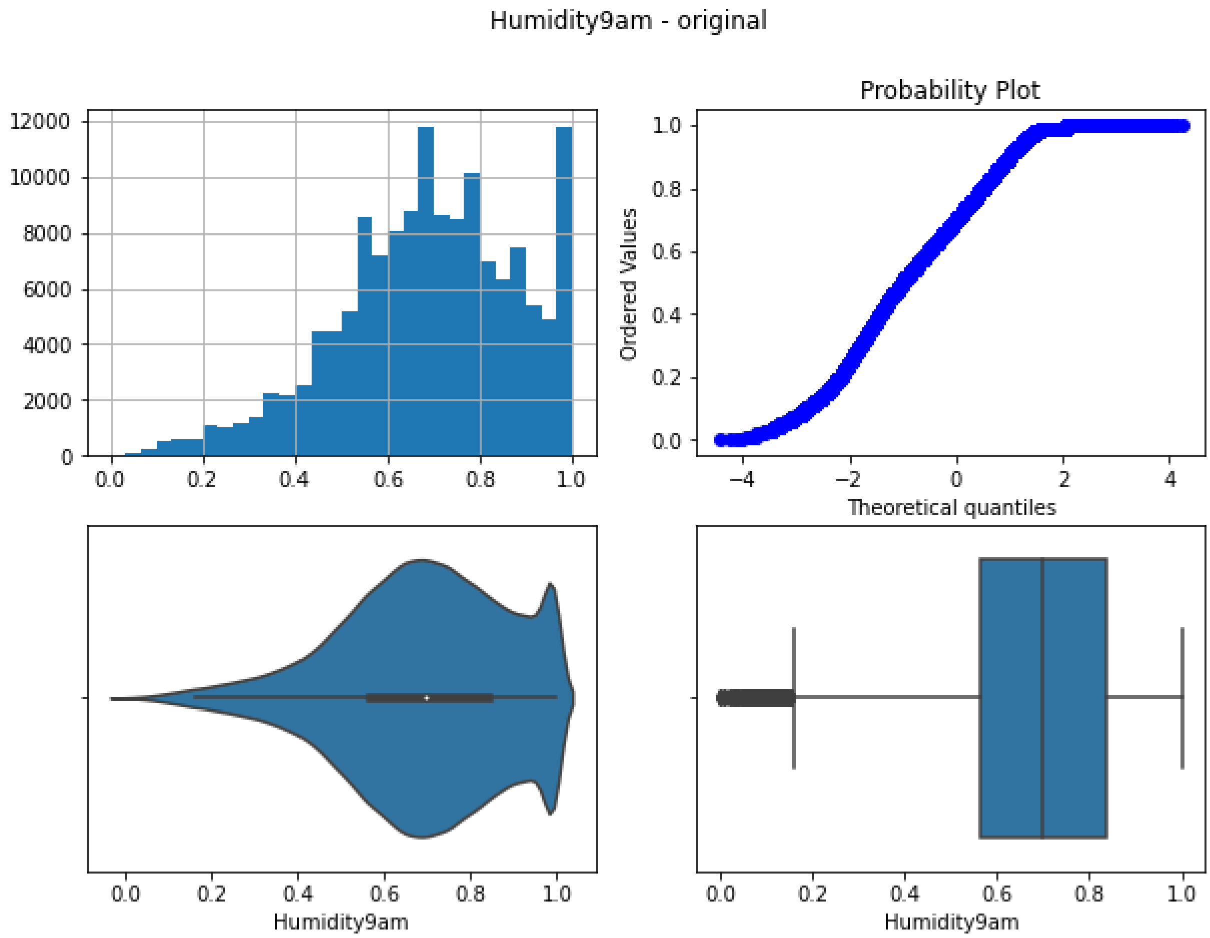
[62]:
```
#
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3
```

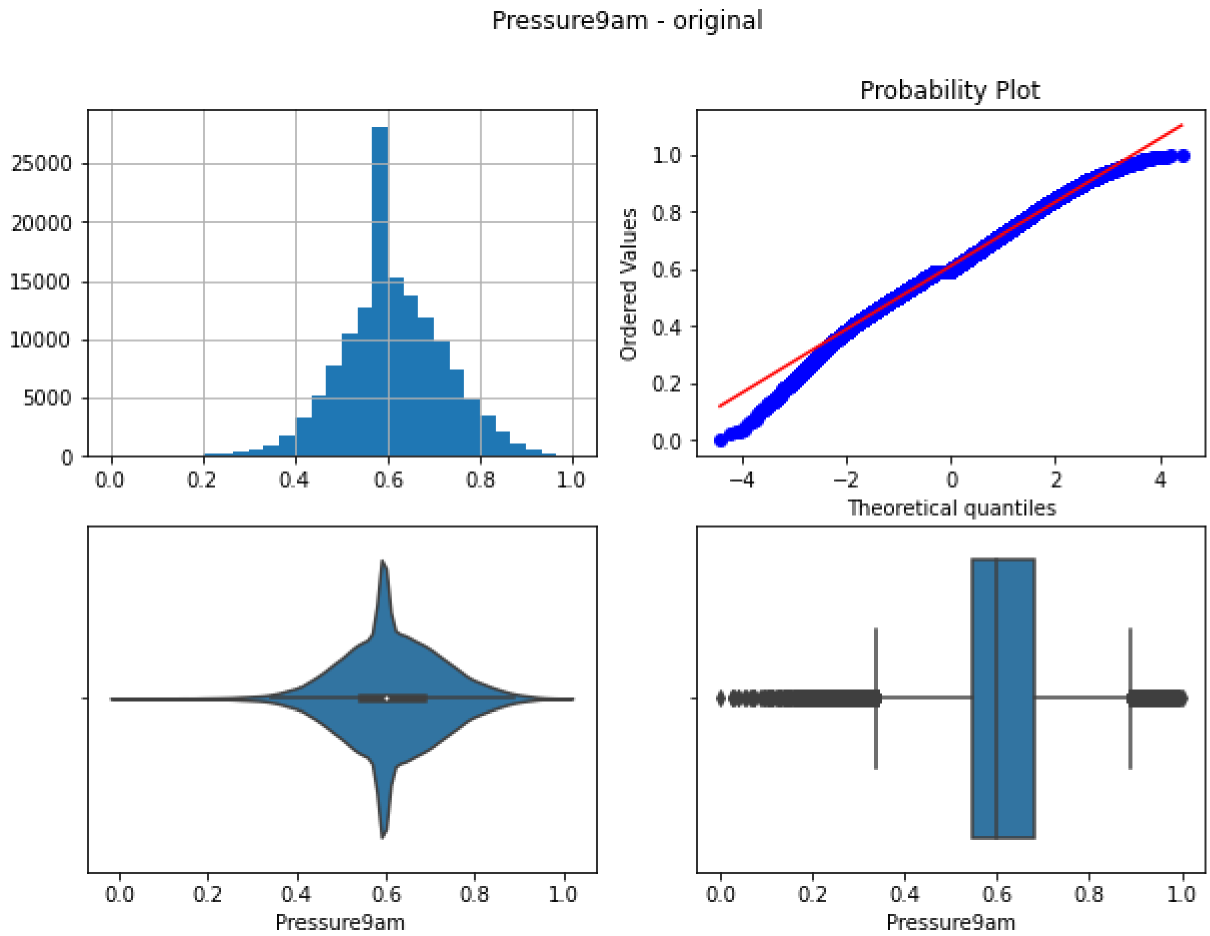
[63]:
```
#
def get_outlier_boundaries(df, col, outlier_boundary_type:␣
 ↪OutlierBoundaryType):
    if outlier_boundary_type == OutlierBoundaryType.SIGMA:
        K1 = 3
        lower_boundary = df[col].mean() - (K1 * df[col].std())
        upper_boundary = df[col].mean() + (K1 * df[col].std())

    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
```

[60]:
```
col_list = ['MinTemp', 'Humidity9am', 'Pressure9am']
```

[90]:
```
for col in col_list:
    diagnostic_plots_out(data, col, col + ' - original')
```

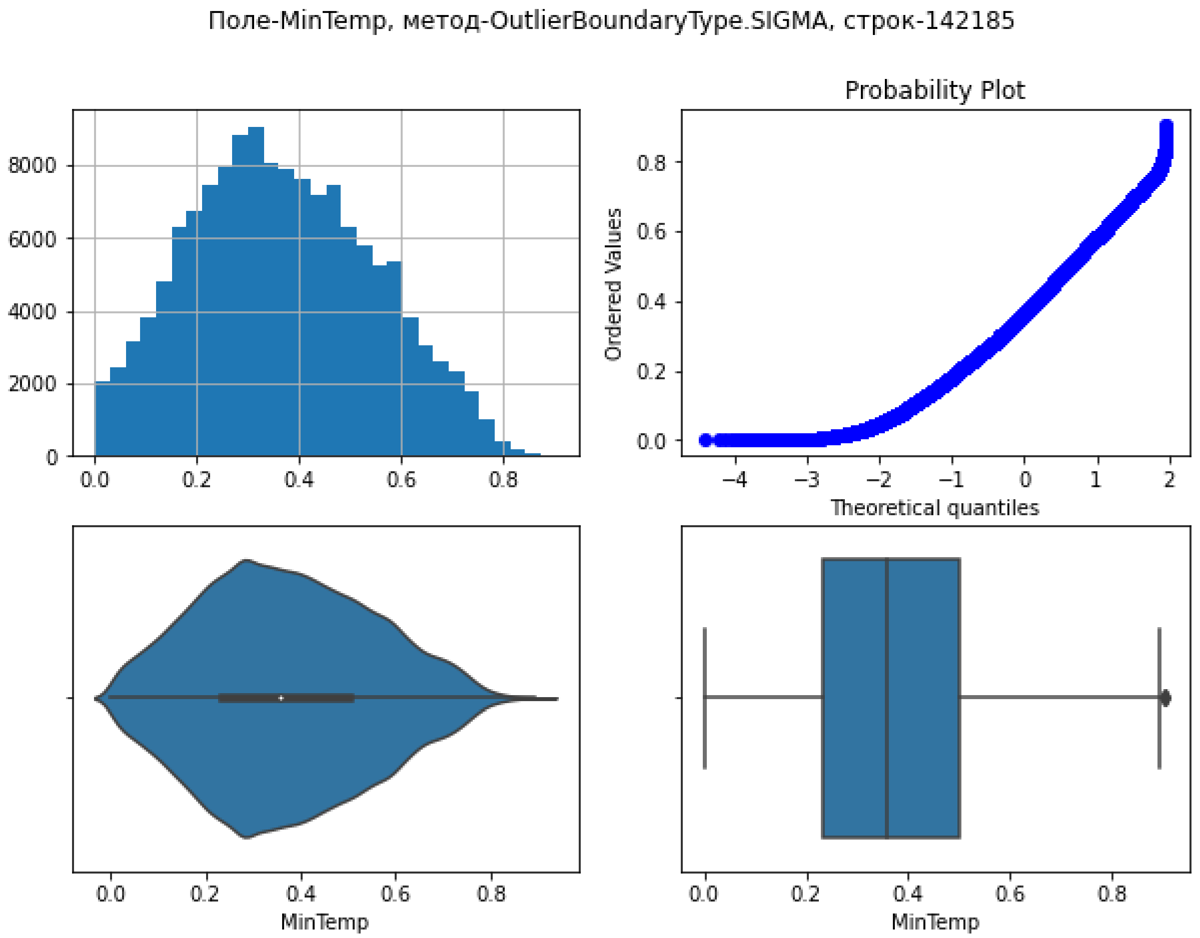

MinTemp - original
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp

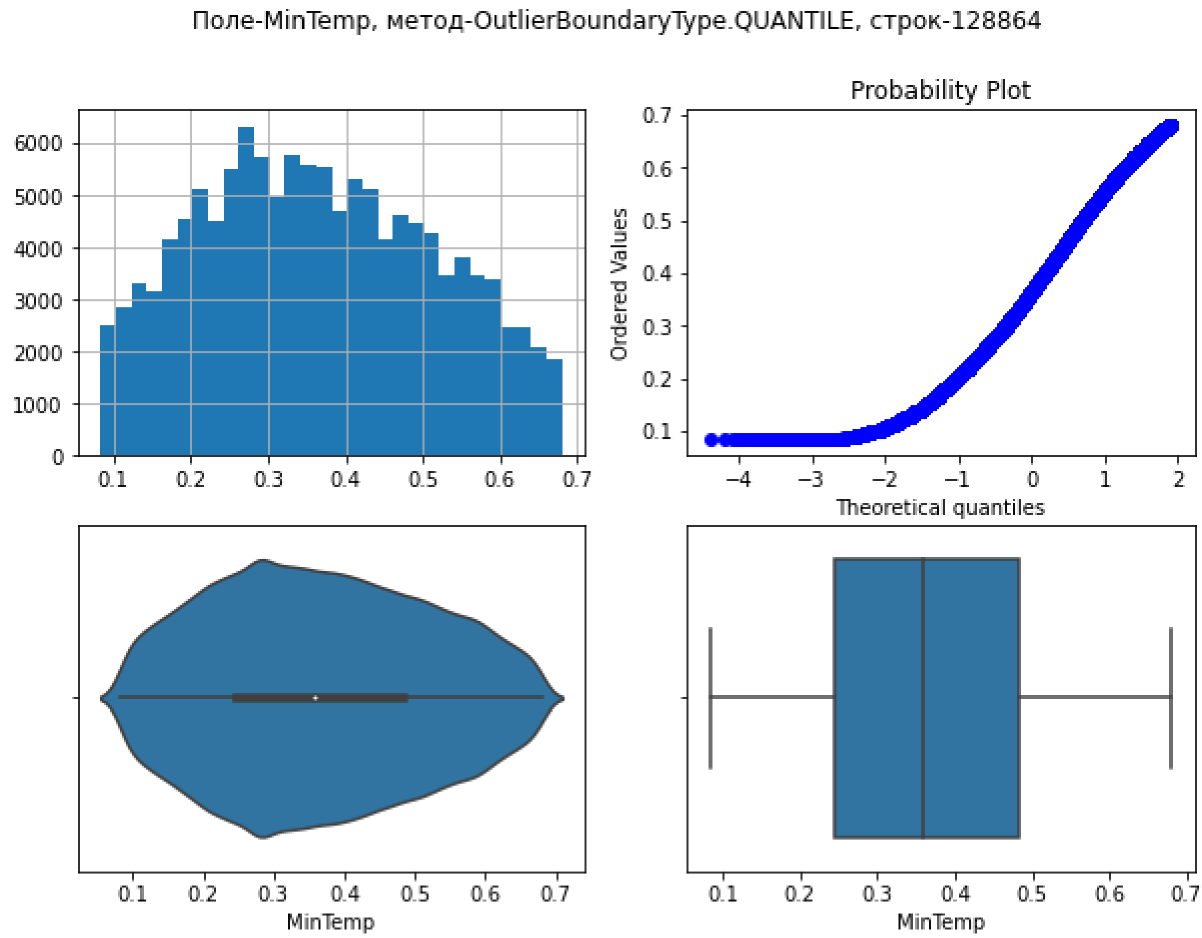

Humidity9am - original
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am

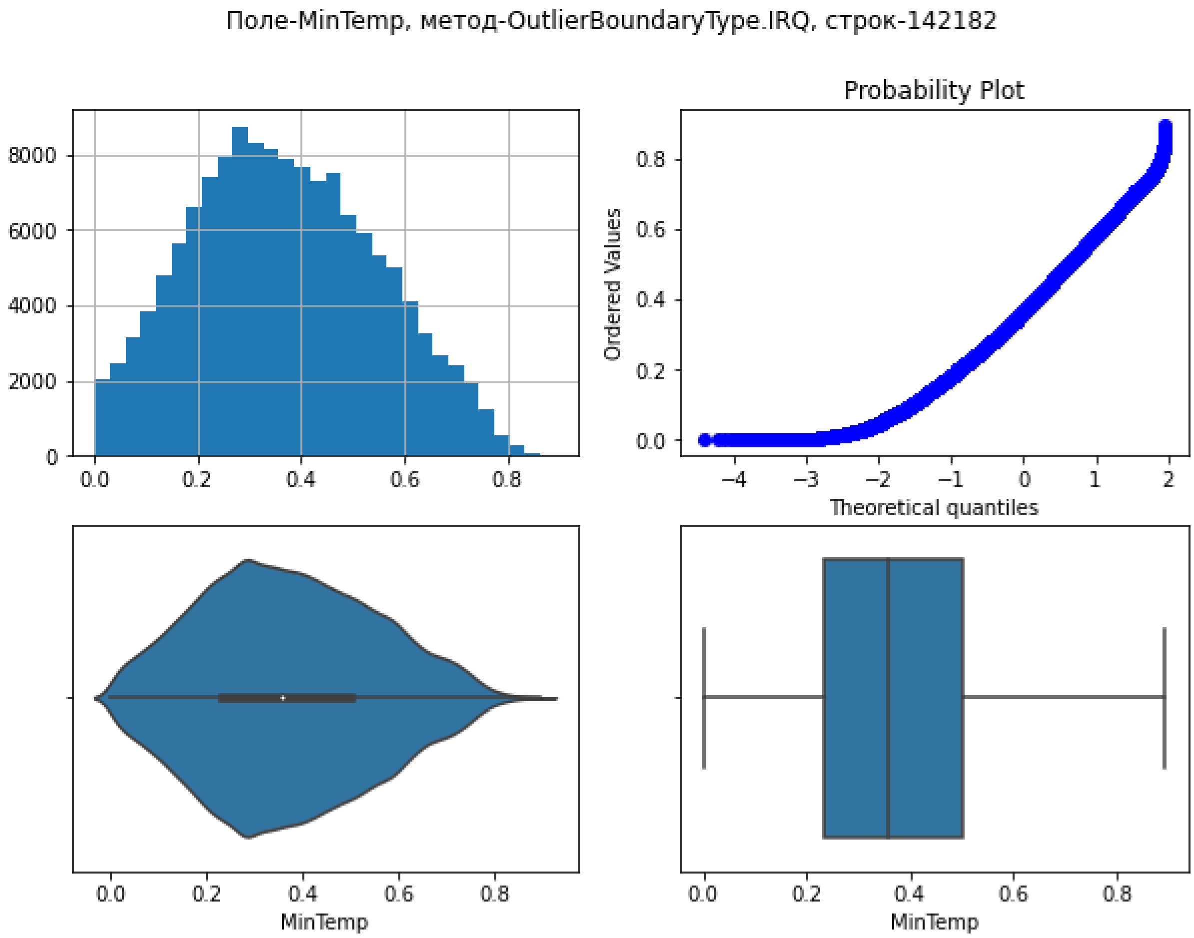


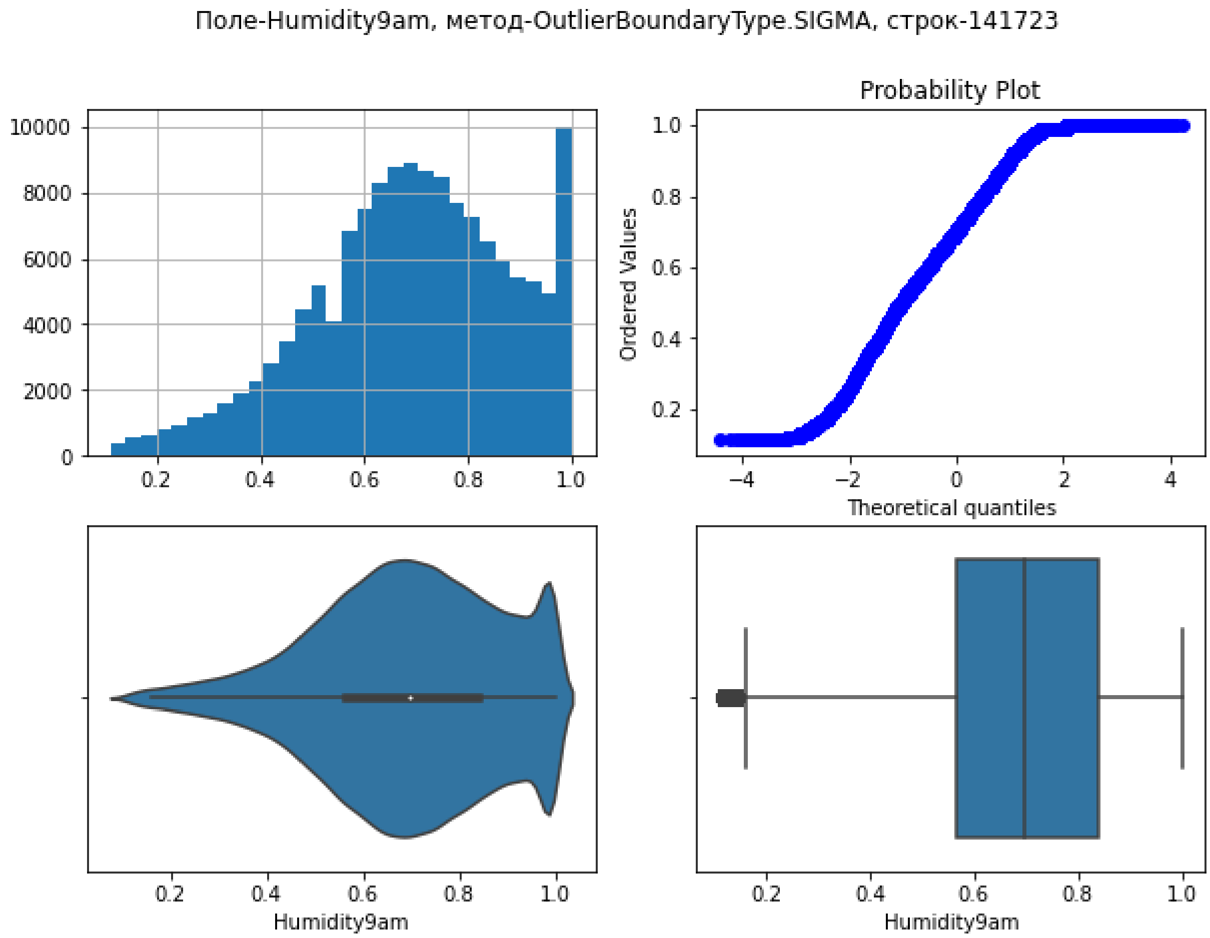
2.3.1. Удаление выбросов

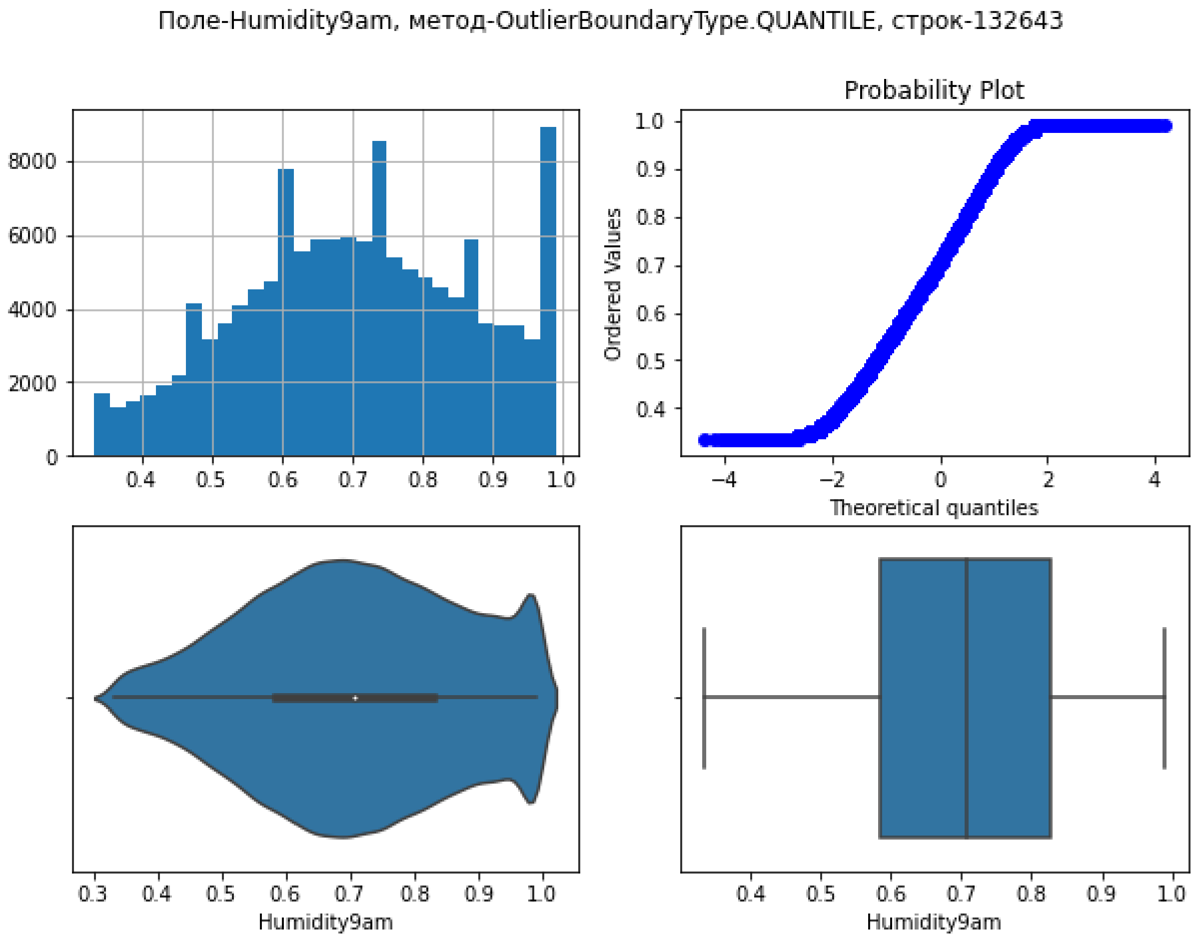
[55]:
```
for col in col_list:
    for obt in OutlierBoundaryType:
        #
        lower_boundary, upper_boundary = get_outlier_boundaries(data, col,␣
 ↪obt)
        #
        outliers_temp = np.where(data[col] > upper_boundary, True,
                                 np.where(data[col] < lower_boundary, True,␣
 ↪False))
        #
        data_trimmed = data.loc[~(outliers_temp), ]
        title = '  -{},    -{},    -{}'.format(col, obt, data_trimmed.
 ↪shape[0])
        diagnostic_plots_out(data_trimmed, col, title)
```


Поле-MinTemp, метод-OutlierBoundaryType.SIGMA, строк-142185
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp

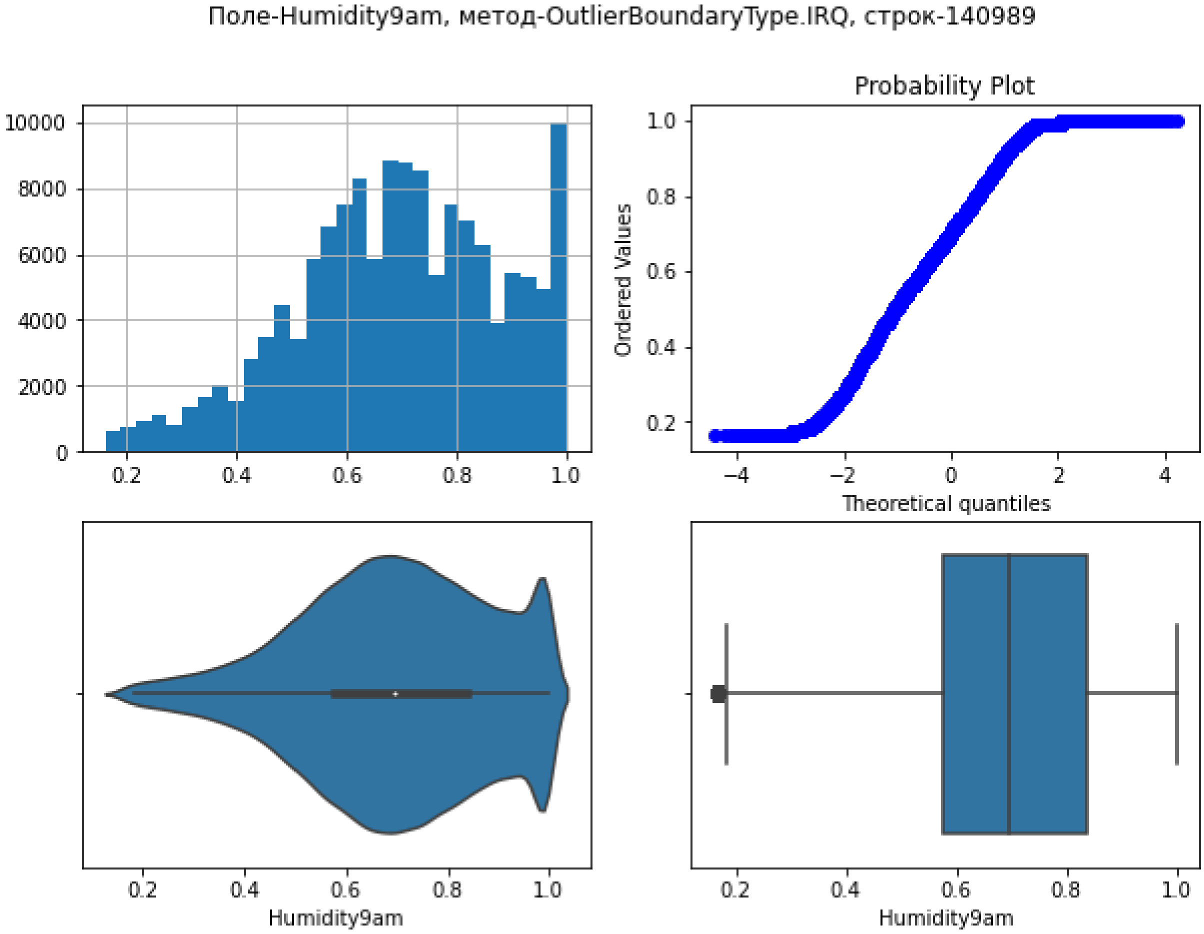

Поле-MinTemp, метод-OutlierBoundaryType.QUANTILE, строк-128864
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp

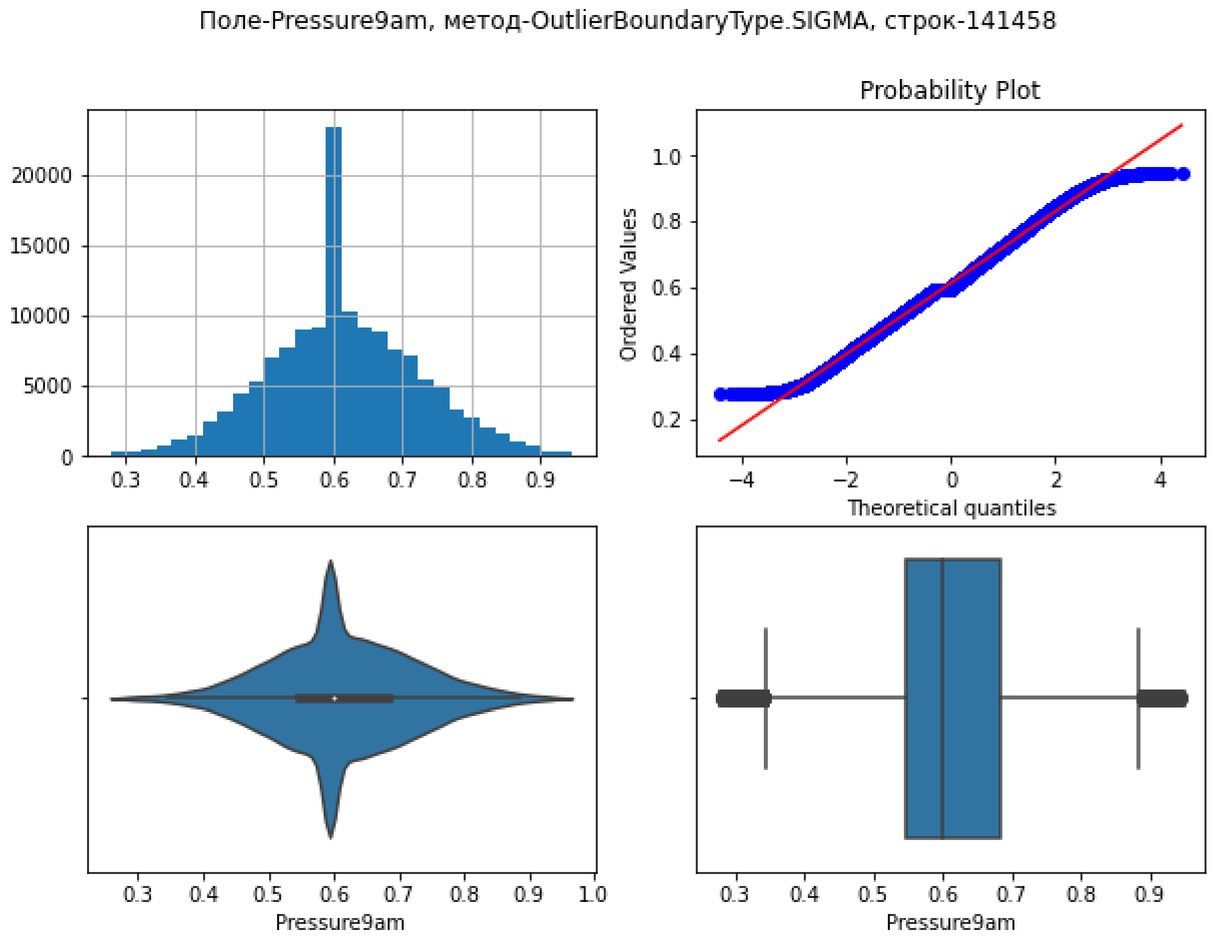

Поле-MinTemp, метод-OutlierBoundaryType.IRQ, строк-142182
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp


Поле-Humidity9am, метод-OutlierBoundaryType.SIGMA, строк-141723
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am

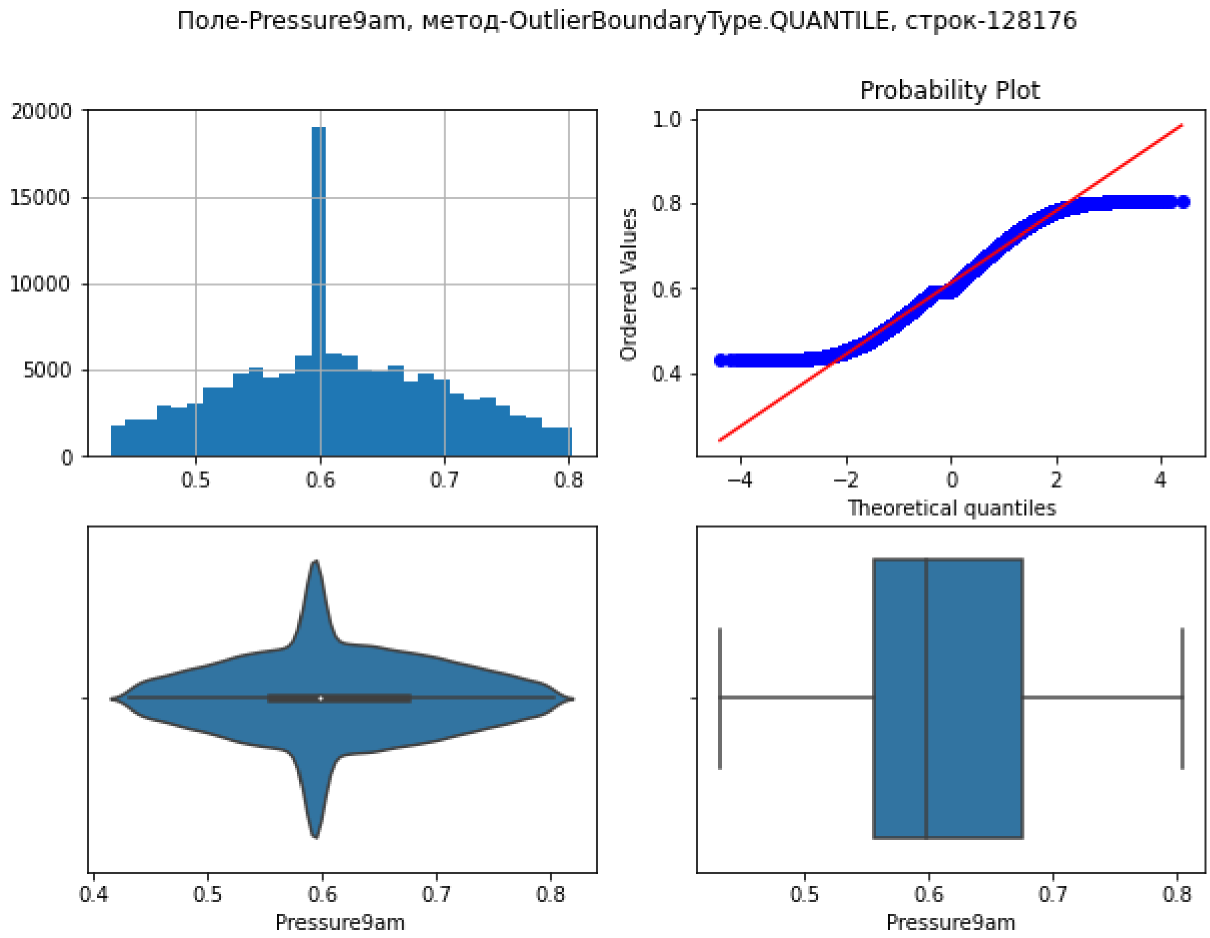


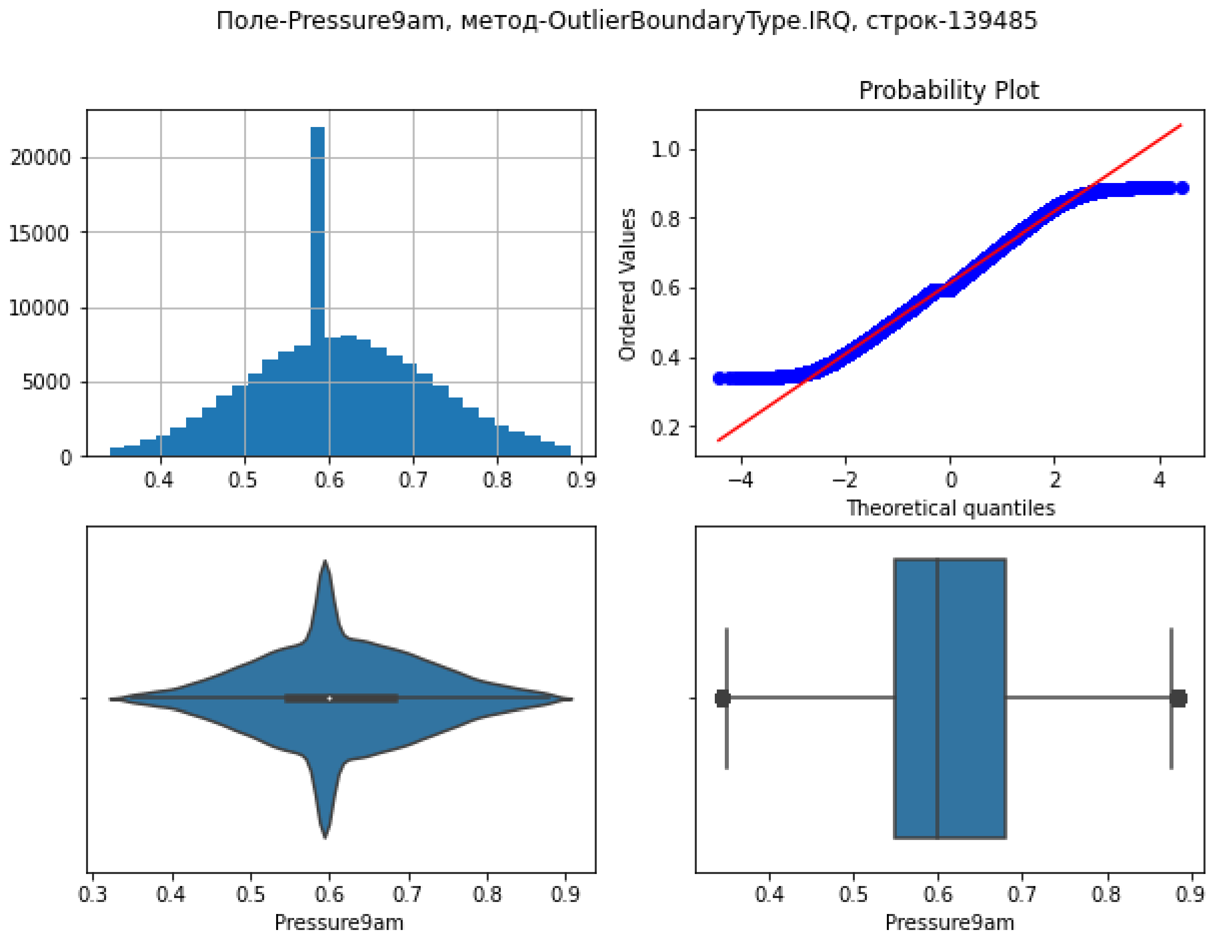
Поле-Humidity9am, метод-OutlierBoundaryType.QUANTILE, строк-132643
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am


Поле-Humidity9am, метод-OutlierBoundaryType.IRQ, строк-140989
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am
0
2000
4000
6000
8000
10000
0.2
0.4
0.6
0.8
1.0
−4
−2
0
2
4



Поле-Pressure9am, метод-OutlierBoundaryType.SIGMA, строк-141458
Probability Plot
Ordered Values
Theoretical quantiles
Pressure9am
Pressure9am

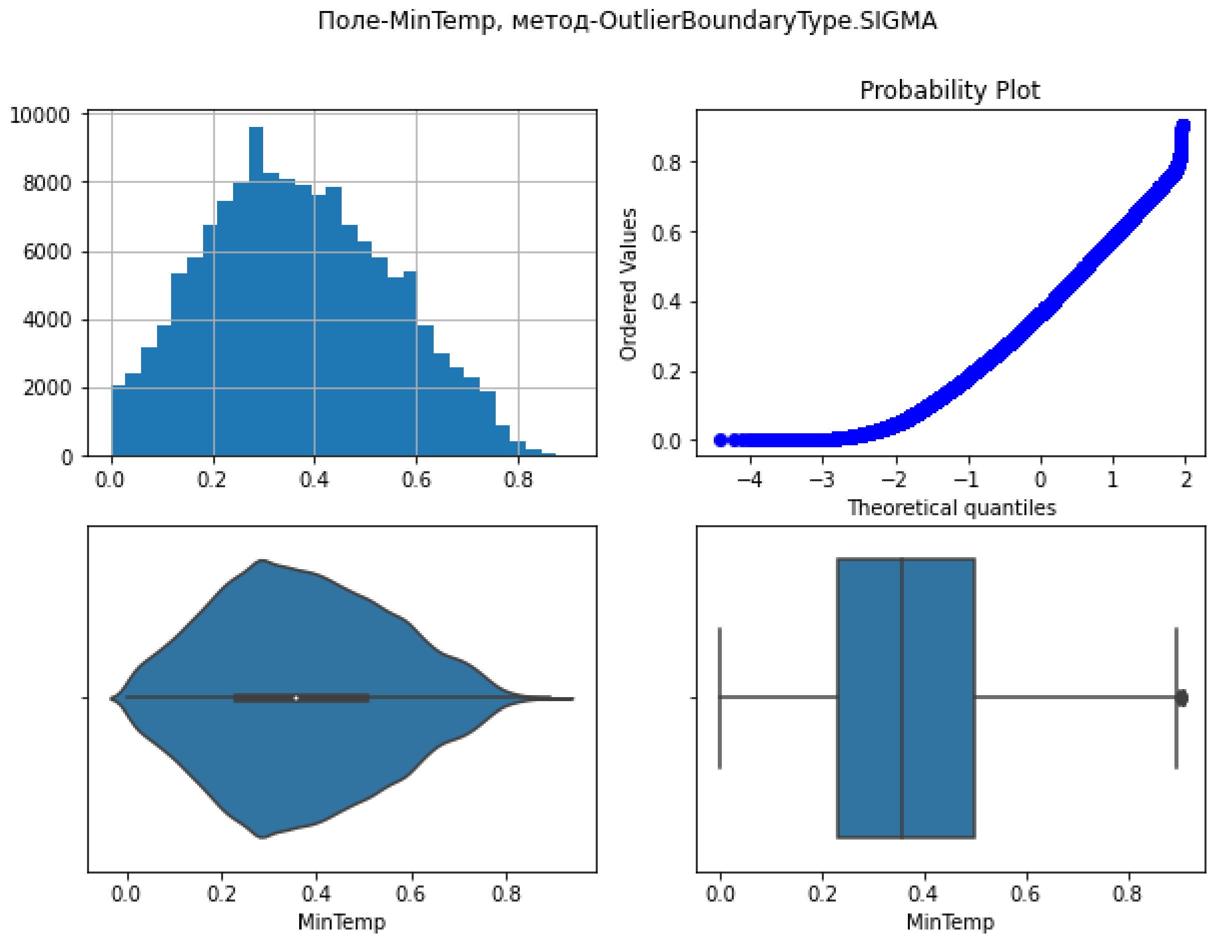

Поле-Pressure9am, метод-OutlierBoundaryType.QUANTILE, строк-128176
Probability Plot
Ordered Values
Theoretical quantiles
Pressure9am
Pressure9am

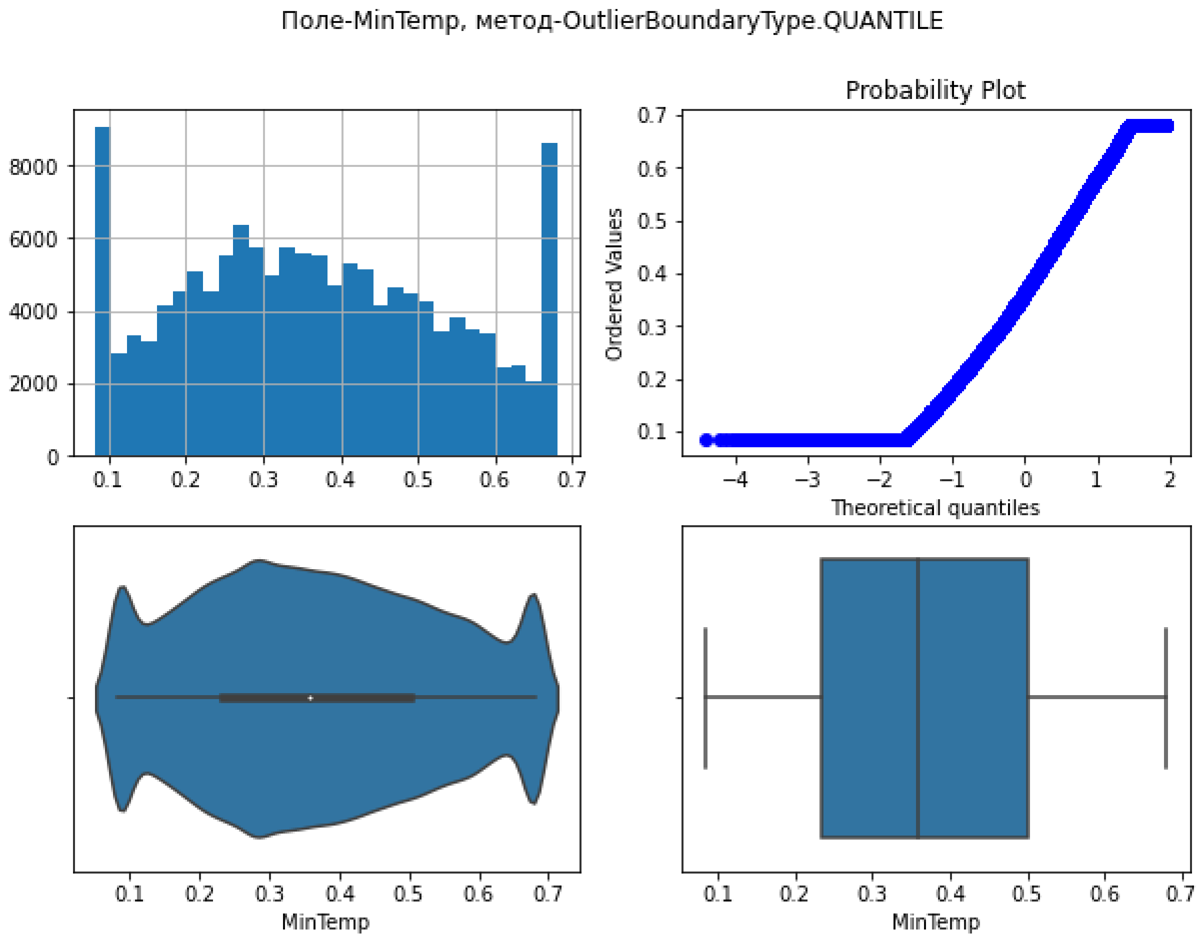


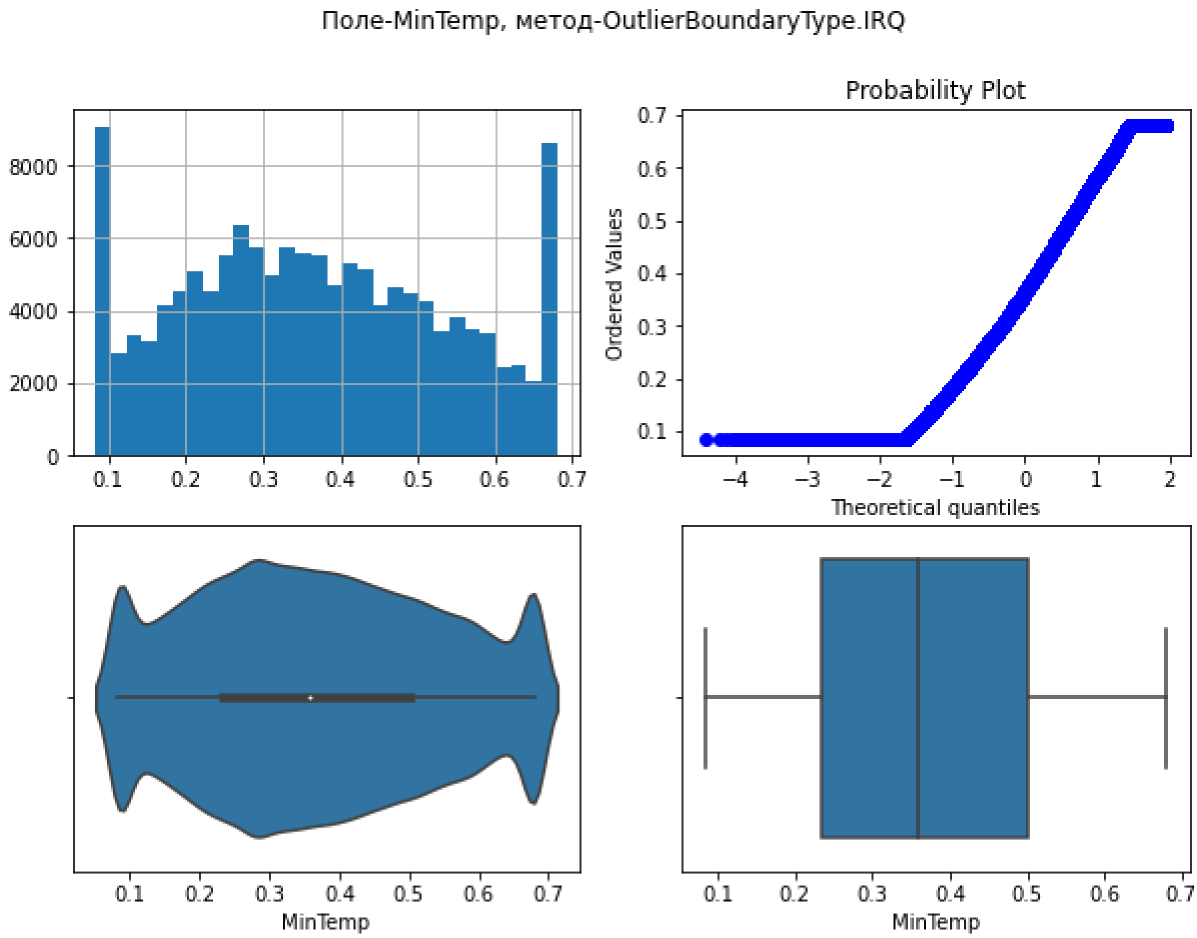
MinTemp - IRQ Humidity9am - IRQ Pressure9am

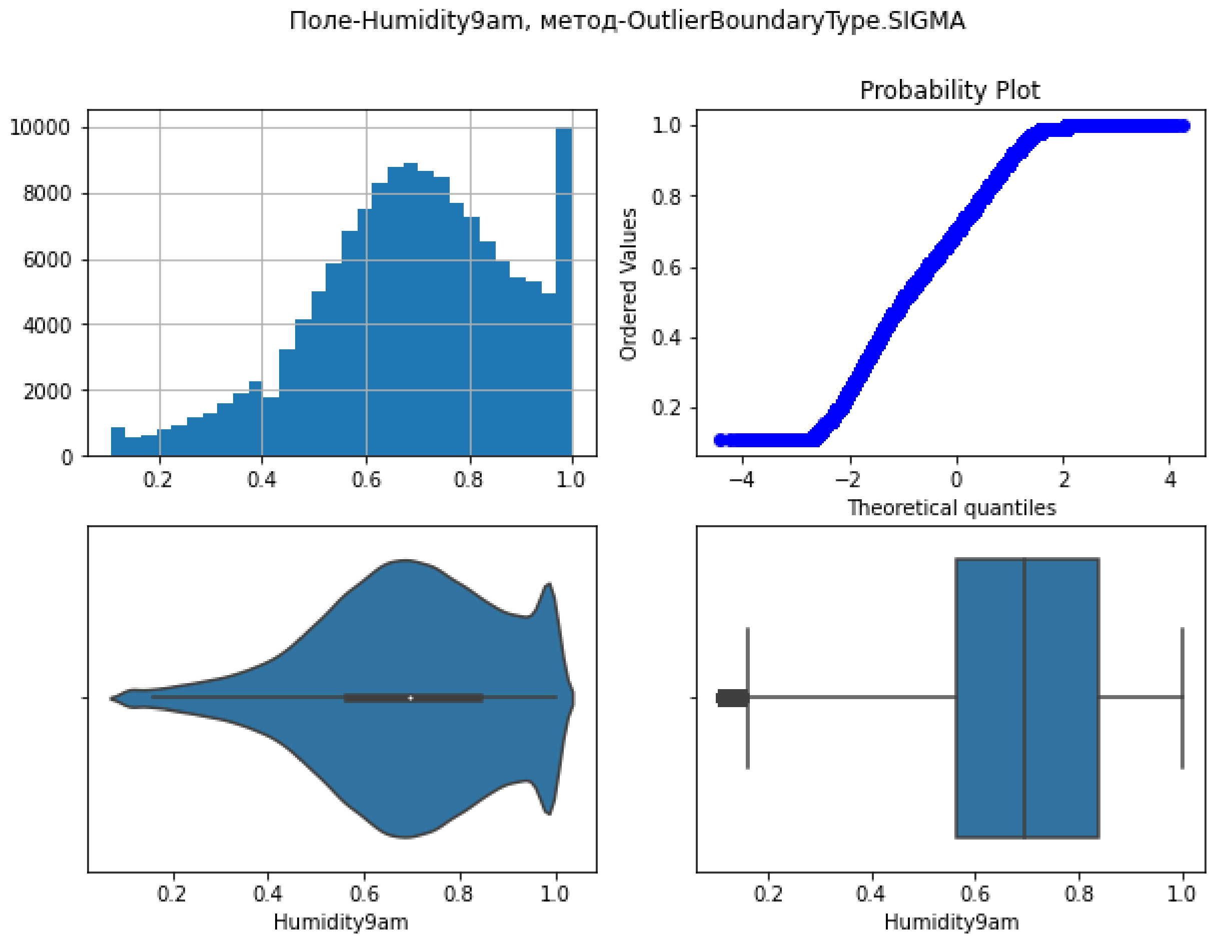
2.3.2. Замена выбросов

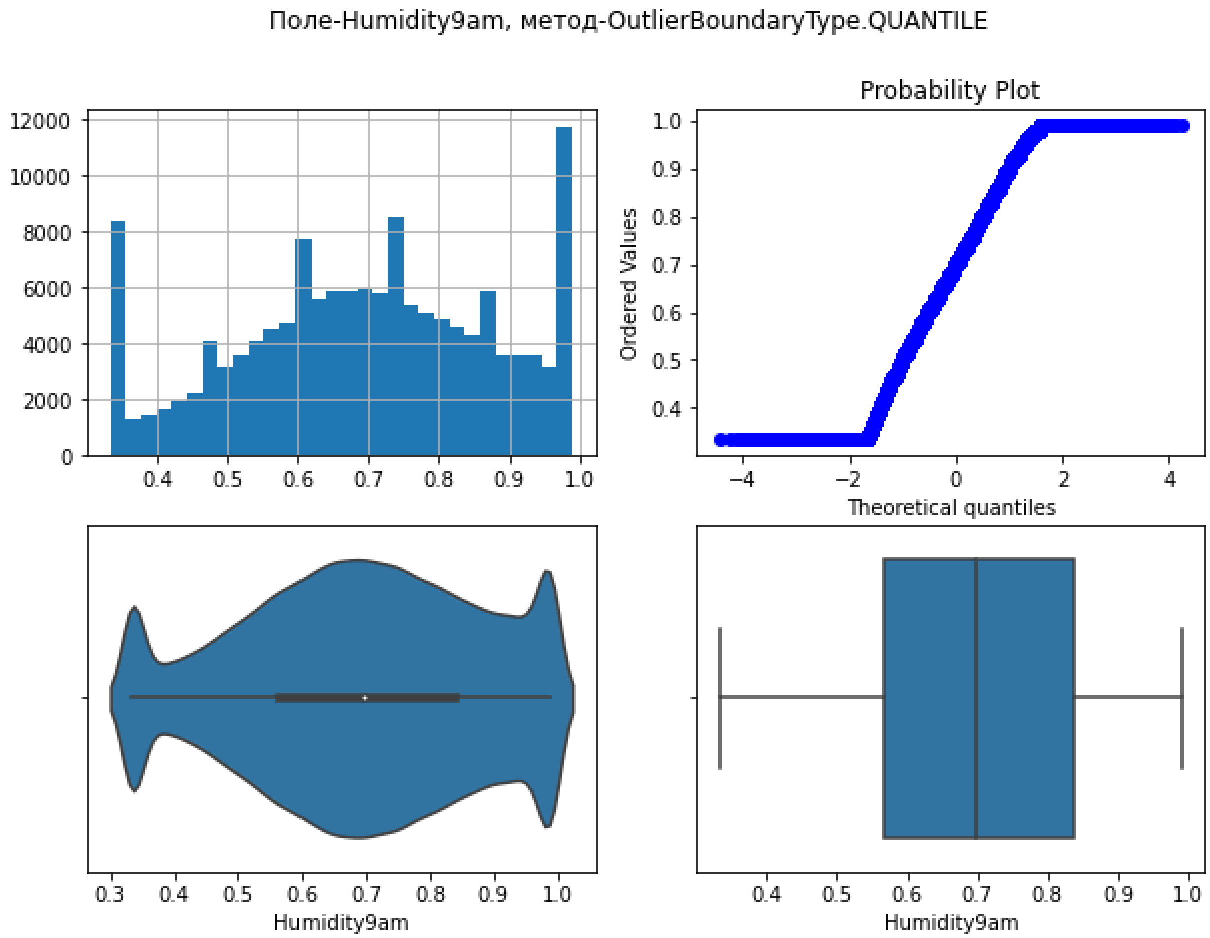
[63]:
```
for col in col_list:
    for obt in OutlierBoundaryType:
        #
        lower_boundary, upper_boundary = get_outlier_boundaries(data, col,␣
↪obt)
        #
        data[col] = np.where(data[col] > upper_boundary, upper_boundary,
                             np.where(data[col] < lower_boundary,␣
↪lower_boundary, data[col]))
        title = '  -{},    -{}'.format(col, obt)
        diagnostic_plots_out(data, col, title)
```


Поле-MinTemp, метод-OutlierBoundaryType.SIGMA
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp

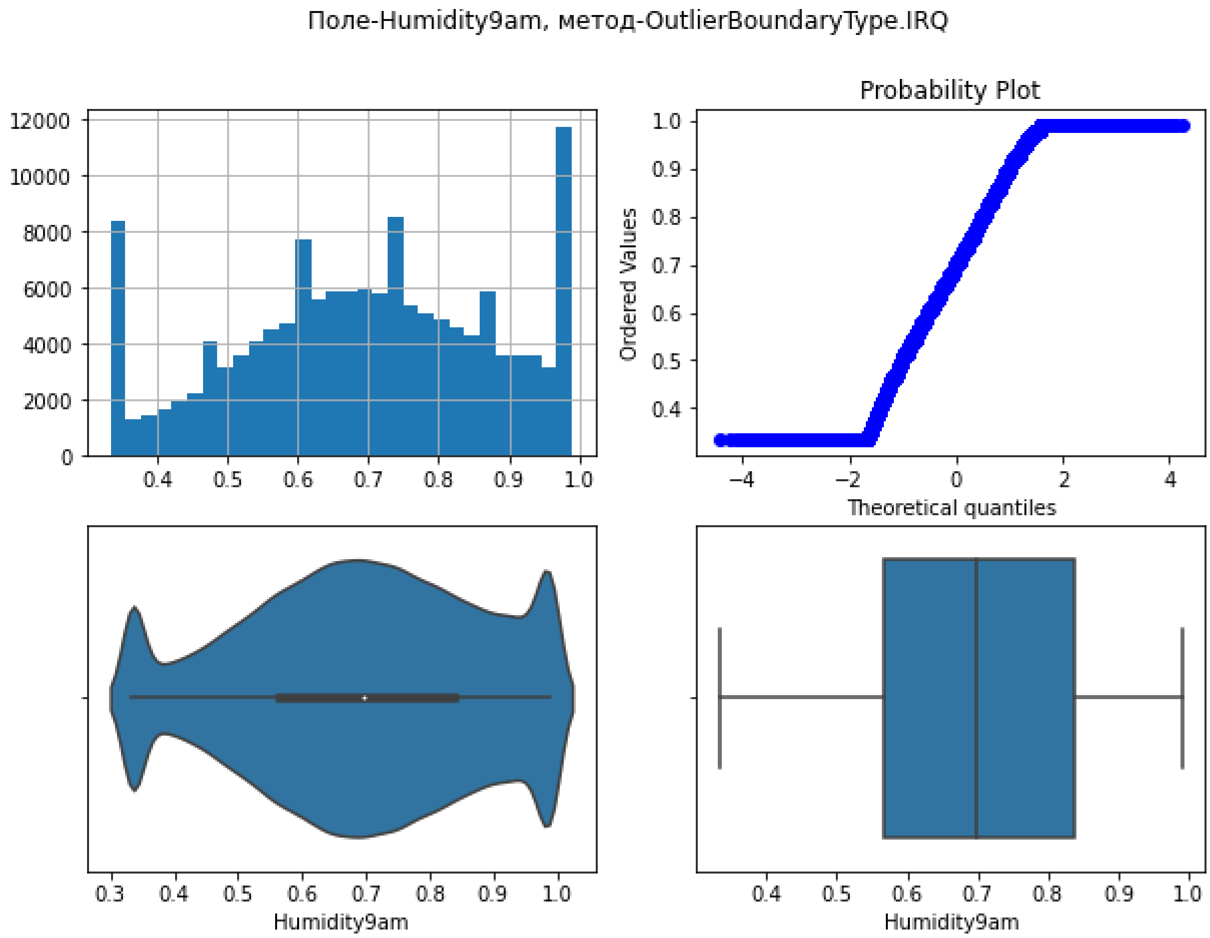

Поле-MinTemp, метод-OutlierBoundaryType.QUANTILE
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp

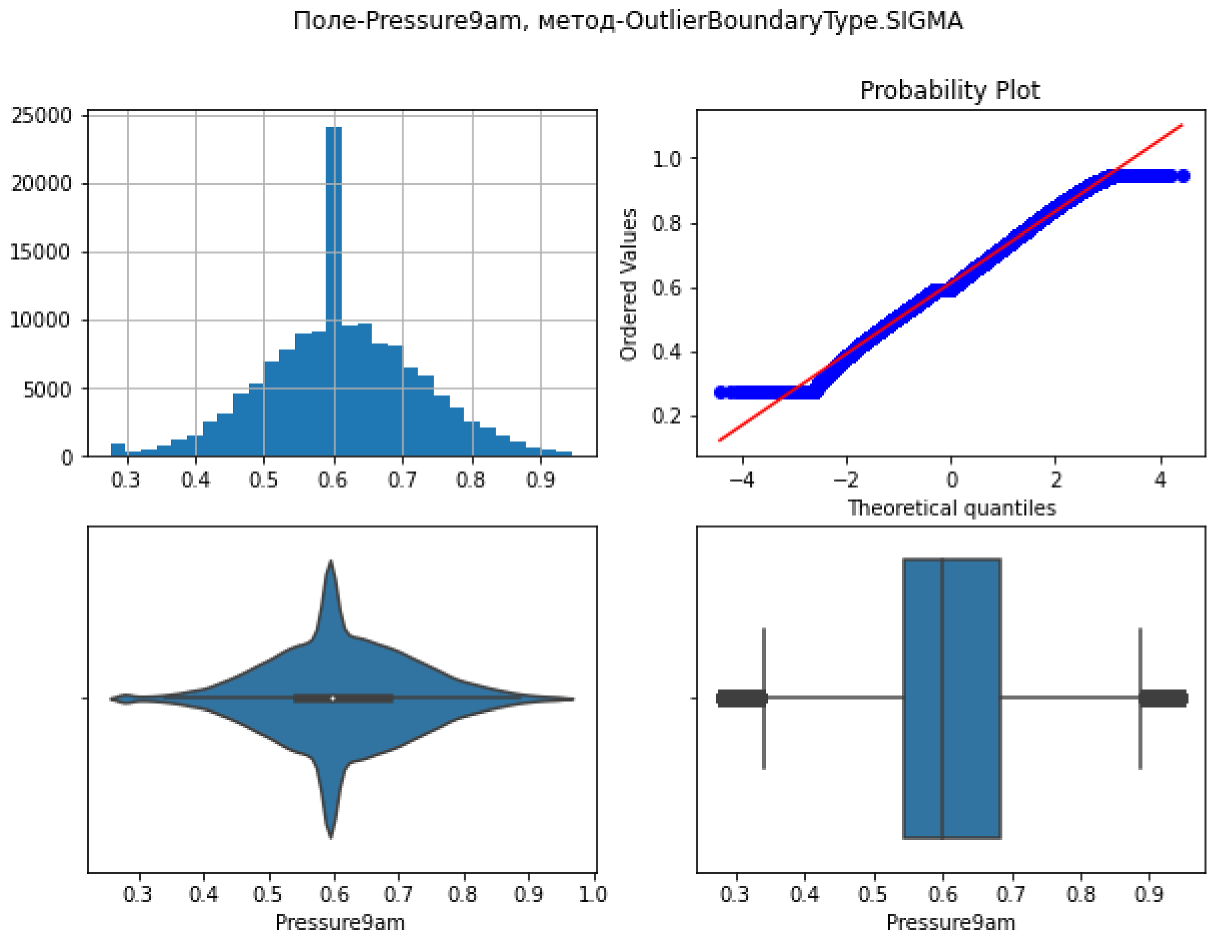

Поле-MinTemp, метод-OutlierBoundaryType.IRQ
Probability Plot
Ordered Values
Theoretical quantiles
MinTemp
MinTemp

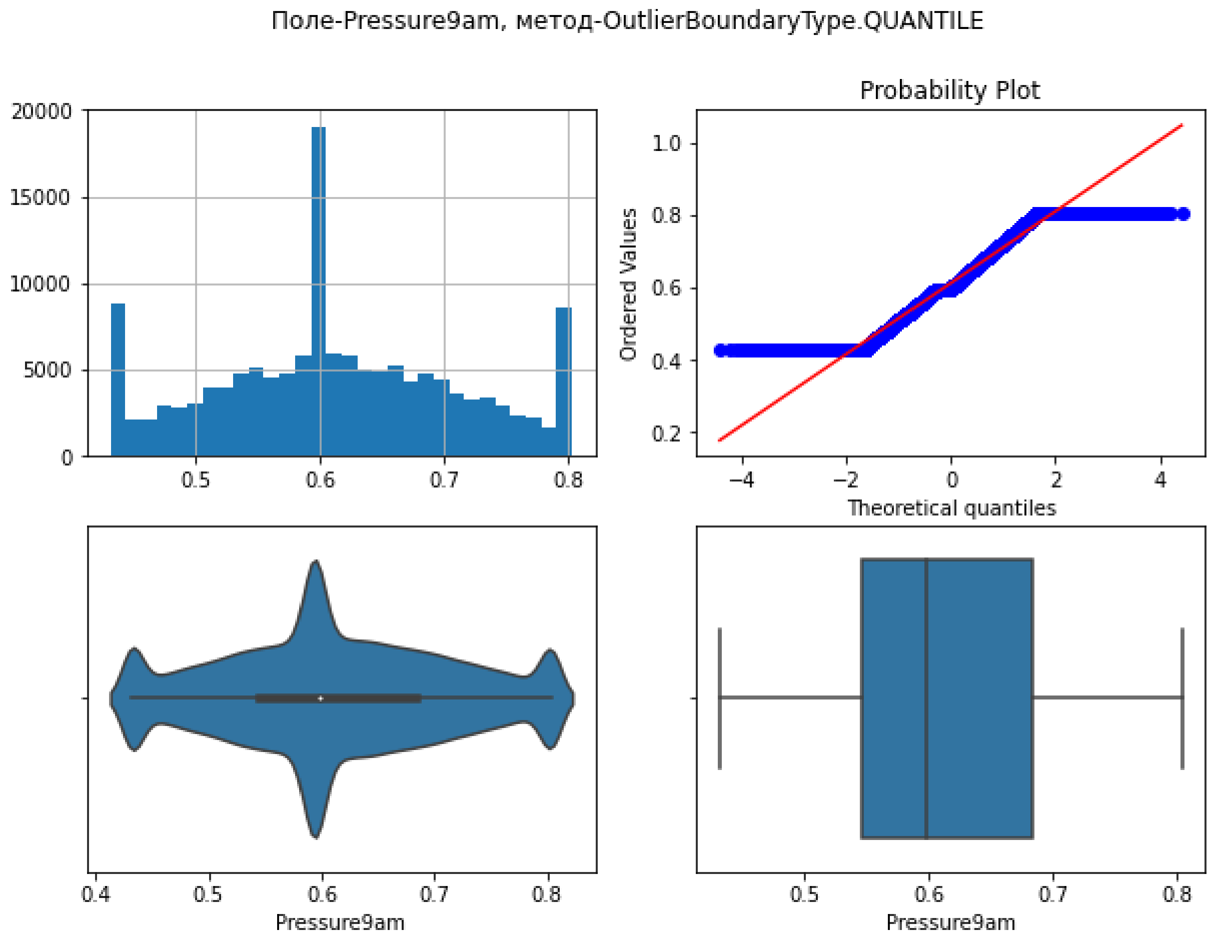

Поле-Humidity9am, метод-OutlierBoundaryType.SIGMA
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am

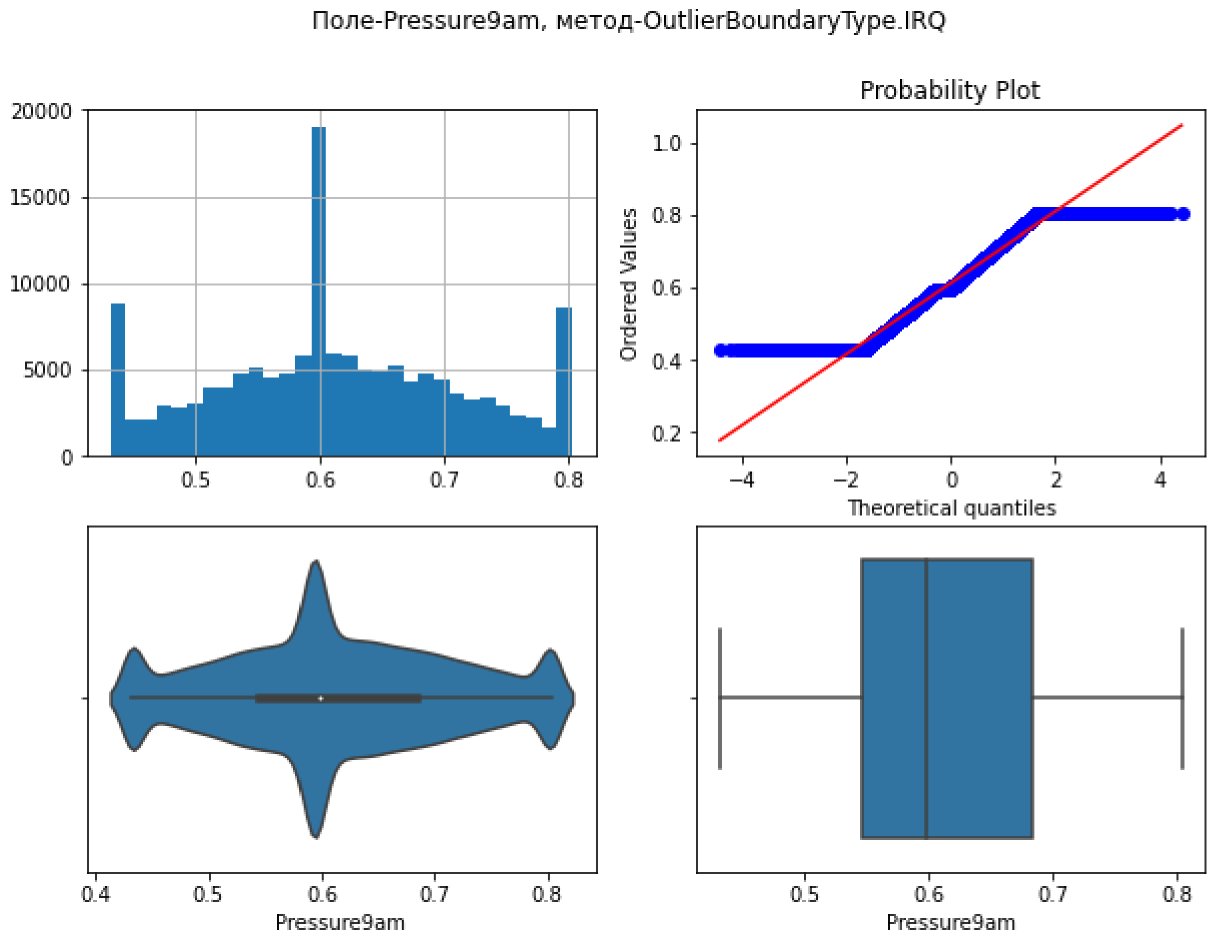


Поле-Humidity9am, метод-OutlierBoundaryType.QUANTILE
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am


Поле-Humidity9am, метод-OutlierBoundaryType.IRQ
Probability Plot
Ordered Values
Theoretical quantiles
Humidity9am
Humidity9am


Поле-Pressure9am, метод-OutlierBoundaryType.SIGMA
Probability Plot
Ordered Values
Theoretical quantiles
Pressure9am
Pressure9am


Поле-Pressure9am, метод-OutlierBoundaryType.QUANTILE
Probability Plot
Ordered Values
Theoretical quantiles
Pressure9am
Pressure9am



[59]:
```
# DataFrame
# data_train = data.drop(['RISK_MM'], axis = 1)

y = data['RainTomorrow']
data_x = data.drop(['RainTomorrow'], axis = 1)

#
X_train, X_test, y_train, y_test = train_test_split(data_x, y,
                                                    test_size=0.2,
                                                    random_state=1)
#                DataFrame
X_train_df = pd.DataFrame(X_train, columns=data.columns)
X_test_df = pd.DataFrame(X_test, columns=data.columns)

X_train_df.shape, X_test_df.shape
```

[59]: ((113754, 22), (28439, 22))

[69]:
```
#
for obt in OutlierBoundaryType:
    df1 = X_train_df.copy()
    count = 0
```

```
    for col in col_list:
        lower_boundary, upper_boundary = get_outlier_boundaries(df1, col,␣
↪obt)
        temp = np.where(df1[col] > upper_boundary, True,
                        np.where(df1[col] < lower_boundary, True,␣
↪False))
        if count==0:
            outliers = temp
        else:
            outliers = outliers + temp
        count += 1

    data_train_trimmed = df1.loc[~(outliers), ]
```

[72]:
```
#
for obt in OutlierBoundaryType:

    df2 = X_train_df.copy()

    for col in col_list:
        lower_boundary, upper_boundary = get_outlier_boundaries(df2, col,␣
↪obt)
        df2[col] = np.where(df2[col] > upper_boundary, upper_boundary,
                            np.where(df2[col] < lower_boundary,␣
↪lower_boundary, df2[col]))

    data_train_updated = df2
```

[77]:
```
X_train_df.shape
```

[77]: (113754, 22)

[75]:
```
data_train_trimmed.shape
```

[75]: (110595, 22)

[74]:
```
data_train_updated.shape
```

[74]: (113754, 22)

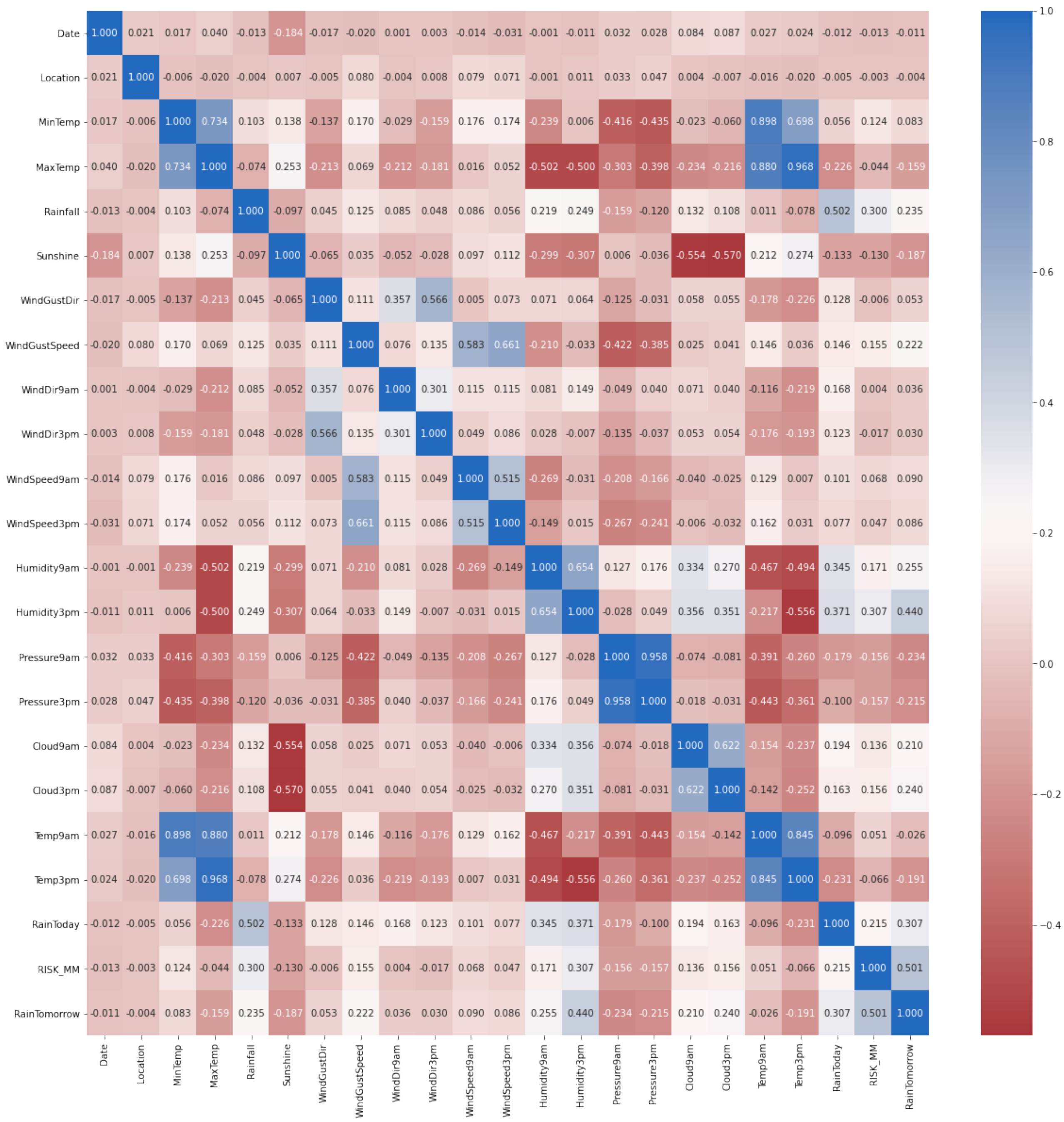
2.4. Отбор признаков

[14]:
```
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import mutual_info_classif,␣
↪mutual_info_regression
from sklearn.feature_selection import SelectKBest, SelectPercentile
```

2.4.1. filter method

[92]:
```
import sys
import numpy
numpy.set_printoptions(threshold=sys.maxsize)

corrmat = data.corr()
plt.figure(figsize=(20,20))
sns.heatmap(corrmat, annot=True, fmt='.3f', cmap="vlag_r")
```

[92]: <matplotlib.axes._subplots.AxesSubplot at 0x7f84e29edd90>



Выделим группы сильно коррелирующих признаков (придётся оставить только по одному признаку из группы)

[97]:
```
def corr_groups(cr):
    grouped_feature_list = []
    correlated_groups = []

    for feature in cr['f1'].unique():
        if feature not in grouped_feature_list:
            #
            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
```

[98]:
```
corr_groups(make_corr_df(data))
```

[98]:
```
[['Temp3pm', 'Temp9am', 'MaxTemp'],
 ['Pressure3pm', 'Pressure9am'],
 ['Temp9am', 'MinTemp']]
```

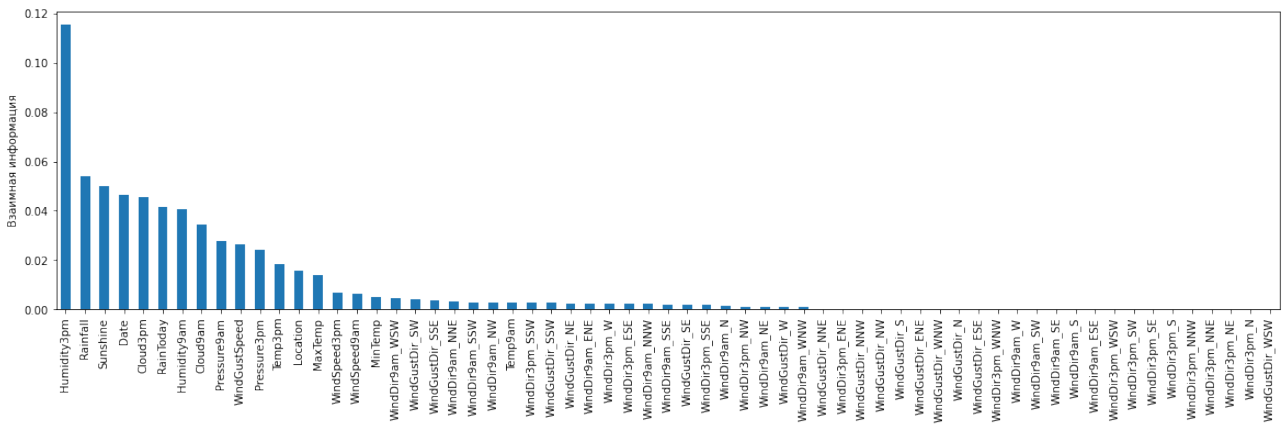
[15]:
```
data_y = data['RainTomorrow']
data_X = data.drop(['RainTomorrow'], axis = 1)
```

[ ]:
```
data = data.drop(['MaxTemp'], axis = 1)
data = data.drop(['Temp9am'], axis = 1)
data = data.drop(['Pressure3pm'], axis = 1)
```

Рассмотрим метод, основанный на статистических характеристиках

[139]:
```
mi = mutual_info_regression(data_X, data_y)
mi = pd.Series(mi)
mi.index = data_X.columns
mi.sort_values(ascending=False).plot.bar(figsize=(20,5))
plt.ylabel('             ')
```

[139]:
```
Text(0, 0.5, '             ')
```



[27]:
```
sel_mi = SelectKBest(mutual_info_regression, k=15).fit(data_X, data_y)
```

[28]:
```
data_filter = data_X[ data_X.columns[ sel_mi.get_support() ] ]
data_filter
```

[28]:
```
            Date  Location   MaxTemp  Rainfall  Sunshine  WindGustSpeed  \
0       0.112372  0.041667  0.523629  0.001617       0.0       0.294574
1       0.112656  0.041667  0.565217  0.000000       0.0       0.294574
2       0.112940  0.041667  0.576560  0.000000       0.0       0.310078
3       0.113224  0.041667  0.620038  0.000000       0.0       0.139535
4       0.113507  0.041667  0.701323  0.002695       0.0       0.271318
…            …         …         …         …         …            …
142188  0.998581  0.854167  0.502836  0.000000       0.0       0.193798
142189  0.998865  0.854167  0.533081  0.000000       0.0       0.193798
142190  0.999149  0.854167  0.568998  0.000000       0.0       0.124031
142191  0.999432  0.854167  0.599244  0.000000       0.0       0.240310
142192  0.999716  0.854167  0.601134  0.000000       0.0       0.170543

        WindSpeed9am  Humidity9am  Humidity3pm  Pressure9am  Pressure3pm  \
0           0.153846         0.71         0.22     0.449587       0.4800
1           0.030769         0.44         0.25     0.497521       0.4912
2           0.146154         0.38         0.30     0.447934       0.5056
3           0.084615         0.45         0.16     0.613223       0.5712
4           0.053846         0.82         0.33     0.500826       0.4624
…                  …            …            …            …            …
142188      0.115385         0.59         0.27     0.730579       0.7056
142189      0.100000         0.51         0.24     0.728926       0.6912
142190      0.100000         0.56         0.21     0.710744       0.6720
142191      0.069231         0.53         0.24     0.669421       0.6352
142192      0.100000         0.51         0.24     0.642975       0.6304

        Cloud9am  Cloud3pm   Temp3pm  RainToday
0       0.888889  0.777778  0.522073        0.0
1       0.777778  0.777778  0.570058        0.0
2       0.777778  0.222222  0.548944        0.0
3       0.777778  0.777778  0.612284        0.0
4       0.777778  0.888889  0.673704        0.0
…              …         …         …          …
142188  0.777778  0.777778  0.504798        0.0
142189  0.777778  0.777778  0.533589        0.0
142190  0.777778  0.777778  0.573896        0.0
142191  0.777778  0.777778  0.604607        0.0
142192  0.333333  0.222222  0.602687        0.0

[142193 rows x 15 columns]
```

[29]:
```
data = data_filter
```

2.4.2. wrapper methods

[20]:
```
f = ['Location','Sunshine','Humidity3pm', 'Rainfall','Pressure3pm']
```

[21]:
```
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=3)
```

[22]:
```
efs1 = EFS(knn,
           min_features=2,
           max_features=4,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs1 = efs1.fit(data_X[f], data_y)

print('Best accuracy score: %.2f' % efs1.best_score_)
print('Best subset (indices):', efs1.best_idx_)
print('Best subset (corresponding names):', efs1.best_feature_names_)
```

```
Features: 25/25

Best accuracy score: 0.80
Best subset (indices): (1, 2, 3, 4)
Best subset (corresponding names): ('Sunshine', 'Humidity3pm', 'Rainfall',
'Pressure3pm')
```

[23]:
```
efs2 = EFS(knn,
           min_features=1,
           max_features=2,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs2 = efs2.fit(data_X[f], data_y)

print('Best accuracy score: %.2f' % efs2.best_score_)
print('Best subset (indices):', efs2.best_idx_)
print('Best subset (corresponding names):', efs2.best_feature_names_)
```

```
Features: 15/15

Best accuracy score: 0.79
Best subset (indices): (2, 3)
Best subset (corresponding names): ('Humidity3pm', 'Rainfall')
```

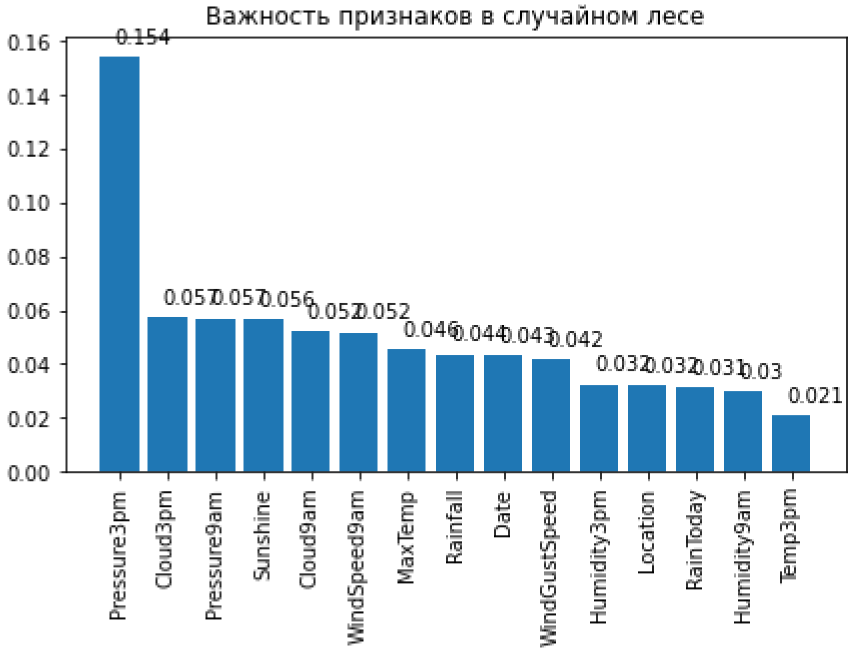
2.4.3. embedded methods

[30]:
```
from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, title, figsize=(7,4)):
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.
 ↪feature_importances_))
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
    labels = [x for x,_ in sorted_list]
    data = [x for _,x in sorted_list]
    fig, ax = plt.subplots(figsize=figsize)
    ax.set_title(title)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    for a,b in zip(ind, data):
        plt.text(a-0.1, b+0.005, str(round(b,3)))
    plt.show()
    return labels, data
```

[31]:
```
from sklearn.ensemble import RandomForestClassifier

rfc1 = RandomForestClassifier()
rfc1.fit(data_X, data_y)

rfc1.feature_importances_, sum(rfc1.feature_importances_)
```

[31]:
```
(array([0.04320436, 0.03220221, 0.04571939, 0.04367239, 0.05638106,
        0.04165753, 0.05174298, 0.02984923, 0.03235927, 0.05697392,
        0.15417893, 0.0520393 , 0.05720983, 0.02097681, 0.03143727,
        0.04214319, 0.0477941 , 0.02290208, 0.002475  , 0.00250836,
        0.00371666, 0.00307322, 0.00302294, 0.00354523, 0.00363331,
        0.00304484, 0.00357458, 0.00278262, 0.00266085, 0.00264402,
        0.0033277 , 0.00355065, 0.0028926 , 0.00253051, 0.0021238 ,
        0.00514911, 0.00294493, 0.00365726, 0.00345479, 0.0035056 ,
        0.00272323, 0.00254388, 0.00255291, 0.00282769, 0.00293154,
        0.00328644, 0.00303503, 0.00287954, 0.0022409 , 0.0021827 ,
        0.0035386 , 0.00274261, 0.00281811, 0.00306787, 0.00340139,
        0.00313234, 0.00275369, 0.00273714, 0.00287839, 0.00296505,
        0.00436388, 0.00325074, 0.00288393]),
 1.0)
```

[32]:
```
_,_=draw_feature_importances(rfc1, data, '                      ')
```



[36]:
```
filter_index = data_X.columns[ SelectFromModel(rfc1, threshold='0.1*mean').
↪fit(data_X, data_y).get_support() ]
```

[38]:
```
data_filter = data_X[filter_index]
data_filter
```

[38]:
```
            Date  Location   MinTemp   MaxTemp  Rainfall  Sunshine  \
0       0.112372  0.041667  0.516509  0.523629  0.001617       0.0
1       0.112656  0.041667  0.375000  0.565217  0.000000       0.0
2       0.112940  0.041667  0.504717  0.576560  0.000000       0.0
3       0.113224  0.041667  0.417453  0.620038  0.000000       0.0
4       0.113507  0.041667  0.613208  0.701323  0.002695       0.0
…            …         …         …         …         …
142188  0.998581  0.854167  0.283019  0.502836  0.000000       0.0
142189  0.998865  0.854167  0.266509  0.533081  0.000000       0.0
142190  0.999149  0.854167  0.285377  0.568998  0.000000       0.0
142191  0.999432  0.854167  0.327830  0.599244  0.000000       0.0
142192  0.999716  0.854167  0.384434  0.601134  0.000000       0.0

        WindGustSpeed  WindSpeed9am  WindSpeed3pm  Humidity9am  …  \
0            0.294574      0.153846      0.275862         0.71  …
1            0.294574      0.030769      0.252874         0.44  …
2            0.310078      0.146154      0.298851         0.38  …
3            0.139535      0.084615      0.103448         0.45  …
4            0.271318      0.053846      0.229885         0.82  …
…                 …             …             …          …  …
142188       0.193798      0.115385      0.149425         0.59  …
142189       0.193798      0.100000      0.126437         0.51  …
142190       0.124031      0.100000      0.103448         0.56  …
```

```
142191       0.240310      0.069231      0.103448           0.53  …
142192       0.170543      0.100000      0.080460           0.51  …

        WindGustDir_NNW  WindGustDir_NW  WindGustDir_S  WindGustDir_SE  \
0                   0.0             0.0            0.0             0.0
1                   0.0             0.0            0.0             0.0
2                   0.0             0.0            0.0             0.0
3                   0.0             0.0            0.0             0.0
4                   0.0             0.0            0.0             0.0
…                     …               …              …               …
142188              0.0             0.0            0.0             0.0
142189              0.0             0.0            0.0             0.0
142190              1.0             0.0            0.0             0.0
142191              0.0             0.0            0.0             0.0
142192              0.0             0.0            0.0             1.0

        WindGustDir_SSE  WindGustDir_SSW  WindGustDir_SW  WindGustDir_W  \
0                   0.0              0.0             0.0            1.0
1                   0.0              0.0             0.0            0.0
2                   0.0              0.0             0.0            0.0
3                   0.0              0.0             0.0            0.0
4                   0.0              0.0             0.0            1.0
…                     …                …               …              …
142188              0.0              0.0             0.0            0.0
142189              0.0              0.0             0.0            0.0
142190              0.0              0.0             0.0            0.0
142191              0.0              0.0             0.0            0.0
142192              0.0              0.0             0.0            0.0

        WindGustDir_WNW  WindGustDir_WSW
0                   0.0              0.0
1                   1.0              0.0
2                   0.0              1.0
3                   0.0              0.0
4                   0.0              0.0
…                     …                …
142188              0.0              0.0
142189              0.0              0.0
142190              0.0              0.0
142191              0.0              0.0
142192              0.0              0.0

[142193 rows x 63 columns]
```