МОСКОВСКИЙ ГОСУДАРСТВЕННЫЙ ТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ
им. Н.Э. Баумана

Факультет «Информатика и системы управления»
Кафедра «Систем обработки информации и управления»

ОТЧЕТ

Лабораторная работа №__3__
по дисциплине «Методы машинного обучения»

Тема: «Обработка признаков (часть 2).»

ИСПОЛНИТЕЛЬ: ____Кожуро Б.Е.____
ФИО
группа _____ИУ5-21М_____
____
подпись
"__"_______2024 г.

ПРЕПОДАВАТЕЛЬ: ___Гапанюк Ю.Е.___
ФИО
____
подпись
"__"_________2024 г.

Москва - 2024

Задание

1. Выбрать набор данных (датасет), содержащий категориальные и числовые признаки и пропуски в данных. Для выполнения следующих пунктов можно использовать несколько различных наборов данных (один для обработки пропусков, другой для категориальных признаков и т.д.) Просьба не использовать датасет, на котором данная задача решалась в лекции.
2. Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
    a. масштабирование признаков (не менее чем тремя способами);
    b. обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
    c. обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
    d. отбор признаков:
        i. один метод из группы методов фильтрации (filter methods);
        ii. один метод из группы методов обертывания (wrapper methods);
        iii. один метод из группы методов вложений (embedded methods).
3. Сформировать отчет и разместить его в своем репозитории на github.

Выполнение

Лабораторная работа 3

Кожуро Б.Е.

датасет https://www.kaggle.com/datasets/mikhail1681/walmart-sales

датасет 2 https://www.kaggle.com/datasets/muthuj7/weather-dataset

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import MaxAbsScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
from sklearn.linear_model import Lasso

data = pd.read_csv(r'C:\Users\ksarb\Documents\MMO_2024\Datasets\
weatherHistory.csv', sep=",")
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()

# Первые 5 строк датасета
data.head()
```

```
                  Formatted Date        Summary Precip Type
Temperature (C)  \
0  2006-04-01 00:00:00.000 +0200  Partly Cloudy        rain
9.472222
```

```
1  2006-04-01 01:00:00.000 +0200  Partly Cloudy       rain
9.355556
2  2006-04-01 02:00:00.000 +0200  Mostly Cloudy       rain
9.377778
3  2006-04-01 03:00:00.000 +0200  Partly Cloudy       rain
8.288889
4  2006-04-01 04:00:00.000 +0200  Mostly Cloudy       rain
8.755556

   Apparent Temperature (C)  Humidity  Wind Speed (km/h)  \
0                  7.388889      0.89            14.1197
1                  7.227778      0.86            14.2646
2                  9.377778      0.89             3.9284
3                  5.944444      0.83            14.1036
4                  6.977778      0.83            11.0446

   Wind Bearing (degrees)  Visibility (km)  Loud Cover  Pressure
(millibars)  \
0                   251.0          15.8263         0.0
1015.13
1                   259.0          15.8263         0.0
1015.63
2                   204.0          14.9569         0.0
1015.94
3                   269.0          15.8263         0.0
1016.41
4                   259.0          15.8263         0.0
1016.51

                      Daily Summary
0  Partly cloudy throughout the day.
1  Partly cloudy throughout the day.
2  Partly cloudy throughout the day.
3  Partly cloudy throughout the day.
4  Partly cloudy throughout the day.

data.dtypes

Formatted Date               object
Summary                      object
Precip Type                  object
Temperature (C)             float64
Apparent Temperature (C)    float64
Humidity                    float64
Wind Speed (km/h)           float64
Wind Bearing (degrees)      float64
Visibility (km)             float64
Loud Cover                  float64
Pressure (millibars)        float64
```

```
Daily Summary                    object
dtype: object
```

```
X_ALL = data.drop(['Formatted Date', 'Summary', 'Precip Type', 'Daily
Summary','Loud Cover'], axis=1)

# Функция для восстановления датафрейма
# на основе масштабированных данных
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
    return res
# Разделим выборку на обучающую и тестовую
X_train, X_test, y_train, y_test = train_test_split(X_ALL,
data['Apparent Temperature (C)'],
                                                    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
```

```
((77162, 7), (19291, 7))
```

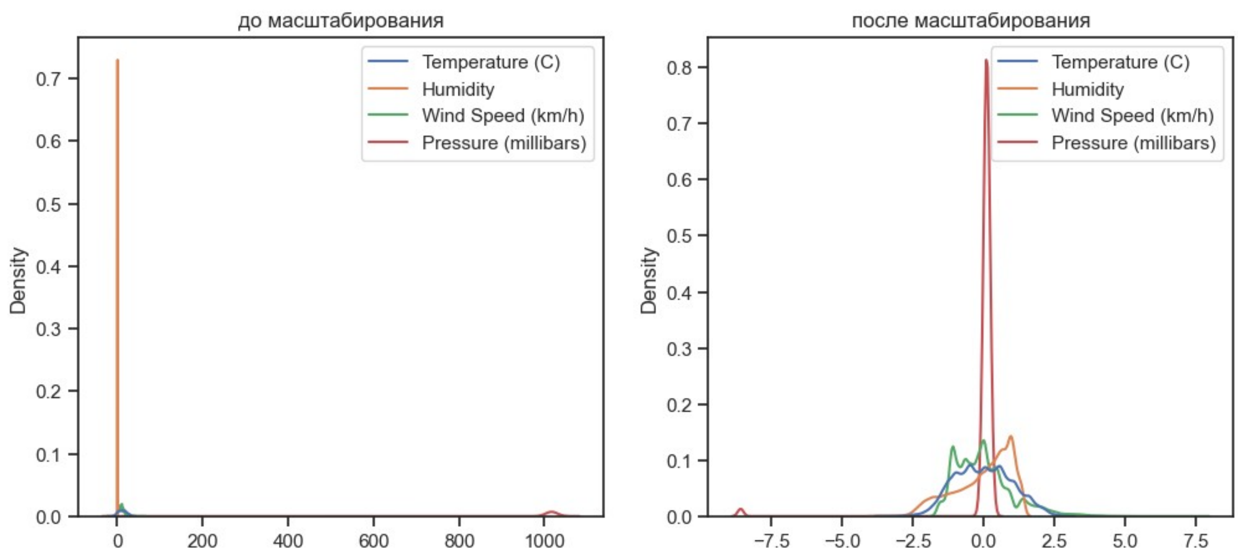
Масштабирование

Standart scaler

```
# 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
```

```
       Temperature (C)  Apparent Temperature (C)  Humidity  Wind Speed
(km/h)  \
0            -0.257599                 -0.324035  0.793470
0.478635
1            -0.269814                 -0.339097  0.639996
0.499594
2            -0.267487                 -0.138102  0.793470           -
0.995473
3            -0.381489                 -0.459071  0.486521
0.476306
4            -0.332631                 -0.362469  0.486521
0.033841
...                ...                       ...       ...
...
96448         1.474532                  1.417400 -1.559811
```

```
0.026855
96449         1.324468                          1.283404 -1.304020         -
0.103556
96450         1.058076                          1.045534 -0.894753         -
0.264241
96451         1.003983                          0.997233 -0.690120         -
0.040680
96452         0.890563                          0.895956 -0.638962         -
0.713693

       Wind Bearing (degrees)  Visibility (km)  Pressure (millibars)
0                    0.591256         1.306976              0.101685
1                    0.665756         1.306976              0.105960
2                    0.153570         1.099586              0.108610
3                    0.758881         1.306976              0.112628
4                    0.665756         1.306976              0.113483
...                       ...              ...                   ...
96448               -1.457488         1.372265              0.095102
96449               -1.559925         1.241686              0.101942
96450               -1.466800         1.372265              0.106216
96451               -1.559925         1.372265              0.108696
96452               -1.382988         1.234005              0.110491

[96453 rows x 7 columns]

# Построение плотности распределения
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    # первый график
    ax1.set_title(label1)
    sns.kdeplot(data=df1[col_list], ax=ax1)
    # второй график
    ax2.set_title(label2)
    sns.kdeplot(data=df2[col_list], ax=ax2)
    plt.show()

draw_kde(['Temperature (C)', 'Humidity', 'Wind Speed (km/h)',
'Pressure (millibars)'], data, data_cs11_scaled, 'до масштабирования',
'после масштабирования')
```



MeanTransform

```
class MeanNormalisation:

    def fit(self, param_df):
        self.means = X_train.mean(axis=0)
        maxs = X_train.max(axis=0)
        mins = X_train.min(axis=0)
        self.ranges = maxs - mins

    def transform(self, param_df):
        param_df_scaled = (param_df - self.means) / self.ranges
        return param_df_scaled

    def fit_transform(self, param_df):
        self.fit(param_df)
        return self.transform(param_df)

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

```
       Temperature (C)  Apparent Temperature (C)      Humidity  \
count     96453.000000              9.645300e+04  96453.000000
mean         -0.000016              3.616382e-07     -0.000143
std           0.154737              1.595089e-01      0.195473
min          -0.546851             -5.751720e-01     -0.735042
25%          -0.117367             -1.274046e-01     -0.135042
50%           0.001074              1.707391e-02      0.044958
75%           0.111866              1.190539e-01      0.154958
max           0.453149              4.248280e-01      0.264958

       Wind Speed (km/h)  Wind Bearing (degrees)  Visibility (km)  \
```

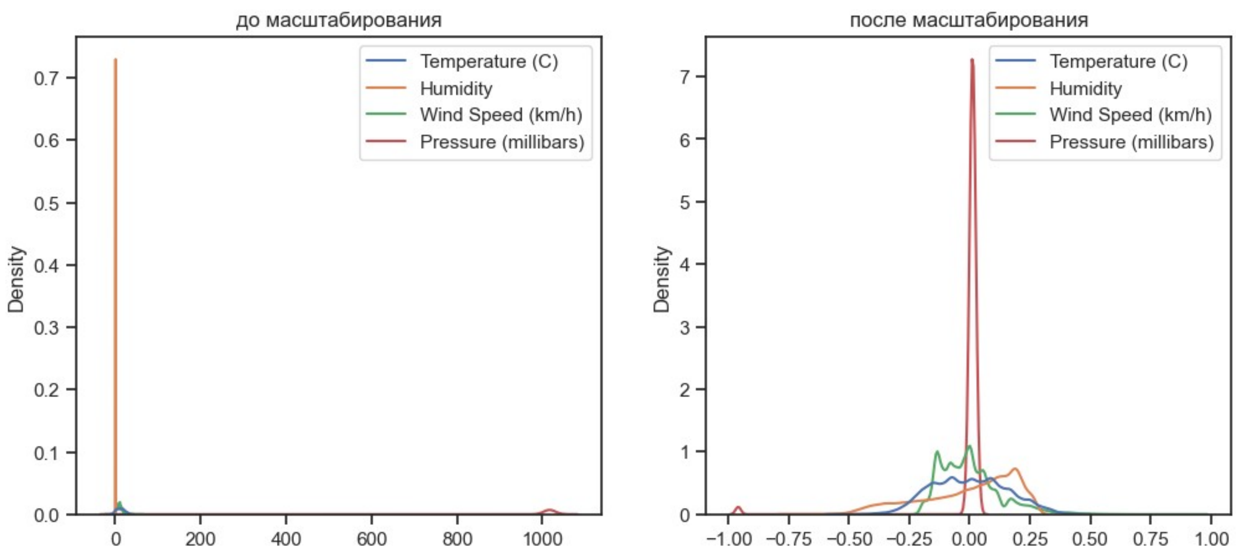
```
count       96453.000000                96453.000000     96453.000000
mean           -0.000398                    0.000252        -0.000138
std             0.123608                    0.299118         0.260380
min            -0.193682                   -0.522058        -0.642829
25%            -0.089480                   -0.198938        -0.124829
50%            -0.015502                   -0.020665        -0.018829
75%             0.059052                    0.285742         0.277171
max             0.947941                    0.477942         0.357171

       Pressure (millibars)
count          96453.000000
mean              -0.000104
std                0.111785
min               -0.958872
25%                0.008176
50%                0.012524
75%                0.016959
max                0.041128
```

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

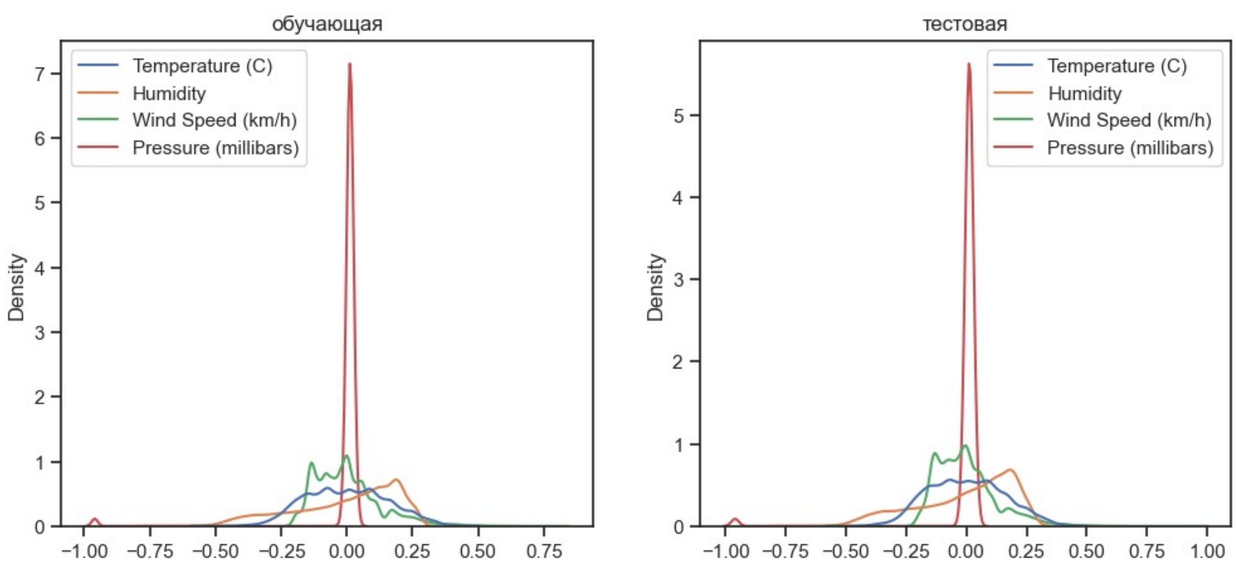
```
       Temperature (C)  Apparent Temperature (C)      Humidity  \
count     7.716200e+04              7.716200e+04  7.716200e+04
mean      2.441391e-17             -1.853201e-18  1.253501e-16
std       1.546322e-01              1.594559e-01  1.954000e-01
min      -5.468511e-01             -5.751720e-01 -7.350417e-01
25%      -1.170068e-01             -1.273217e-01 -1.350417e-01
50%       1.344410e-03              1.732244e-02  4.495827e-02
75%       1.118655e-01              1.190539e-01  1.549583e-01
max       4.531489e-01              4.248280e-01  2.649583e-01

       Wind Speed (km/h)  Wind Bearing (degrees)  Visibility (km)  \
count       7.716200e+04            7.716200e+04     7.716200e+04
mean        2.414917e-17            3.006560e-17    -1.604113e-16
std         1.237208e-01            2.992257e-01     2.607270e-01
min        -1.936823e-01           -5.220576e-01    -6.428290e-01
25%        -8.890397e-02           -1.989379e-01    -1.248290e-01
50%        -1.435014e-02           -2.066488e-02    -1.882896e-02
75%         5.905227e-02            2.857418e-01     2.791710e-01
max         8.063177e-01            4.779424e-01     3.571710e-01

       Pressure (millibars)
count          7.716200e+04
mean           5.836433e-17
std            1.112816e-01
min           -9.588722e-01
```

```
25%              8.166548e-03
50%              1.250532e-02
75%              1.694921e-02
max              4.112780e-02
```

```
draw_kde(['Temperature (C)', 'Humidity', 'Wind Speed (km/h)',
'Pressure (millibars)'], data, data_cs21_scaled, 'до масштабирования',
'после масштабирования')
```




```
draw_kde(['Temperature (C)', 'Humidity', 'Wind Speed (km/h)',
'Pressure (millibars)'], data_cs22_scaled_train,
data_cs22_scaled_test, 'обучающая', 'тестовая')
```



MinMax

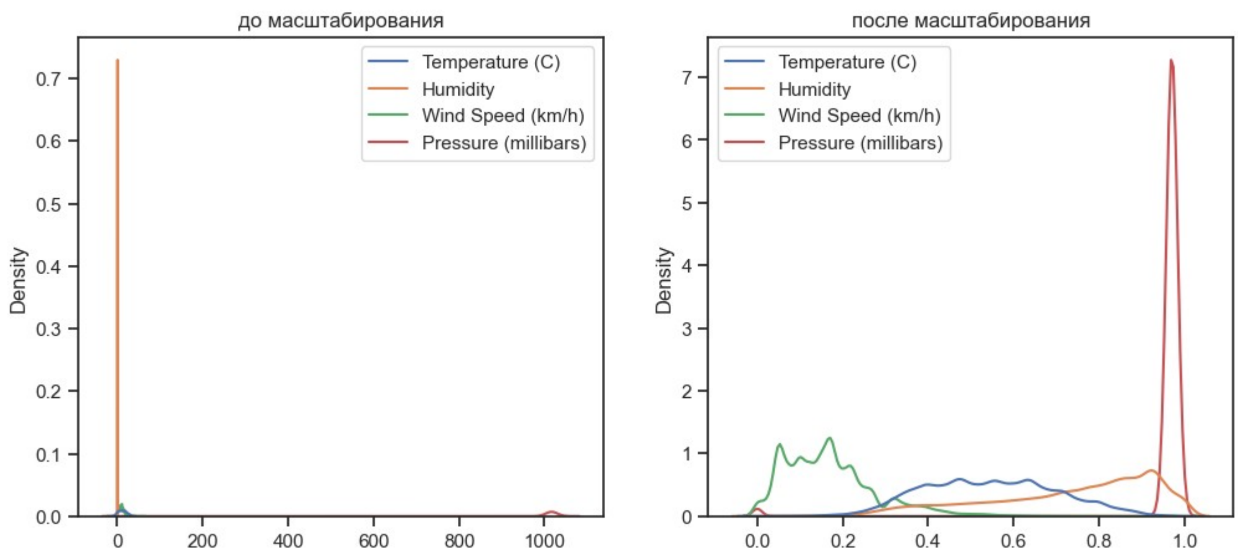
```
# Обучаем StandardScaler на всей выборке и масштабируем
cs31 = MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()
```

	Temperature (C)	Apparent Temperature (C)	Humidity
count	96453.000000	96453.000000	96453.000000
mean	0.546835	0.575172	0.734899
std	0.154737	0.159509	0.195473
min	0.000000	0.000000	0.000000
25%	0.429484	0.447767	0.600000
50%	0.547925	0.592246	0.780000
75%	0.658717	0.694226	0.890000
max	1.000000	1.000000	1.000000

	Wind Speed (km/h)	Wind Bearing (degrees)	Visibility (km)
count	96453.000000	96453.000000	96453.000000
mean	0.169306	0.522310	0.642691
std	0.108274	0.299118	0.260380
min	0.000000	0.000000	0.000000
25%	0.091276	0.323120	0.518000
50%	0.156077	0.501393	0.624000
75%	0.221382	0.807799	0.920000
max	1.000000	1.000000	1.000000

	Pressure (millibars)
count	96453.000000
mean	0.958768
std	0.111785
min	0.000000
25%	0.967048
50%	0.971397
75%	0.975831
max	1.000000

```
draw_kde(['Temperature (C)', 'Humidity', 'Wind Speed (km/h)',
'Pressure (millibars)'], data, data_cs31_scaled, 'до масштабирования',
'после масштабирования')
```

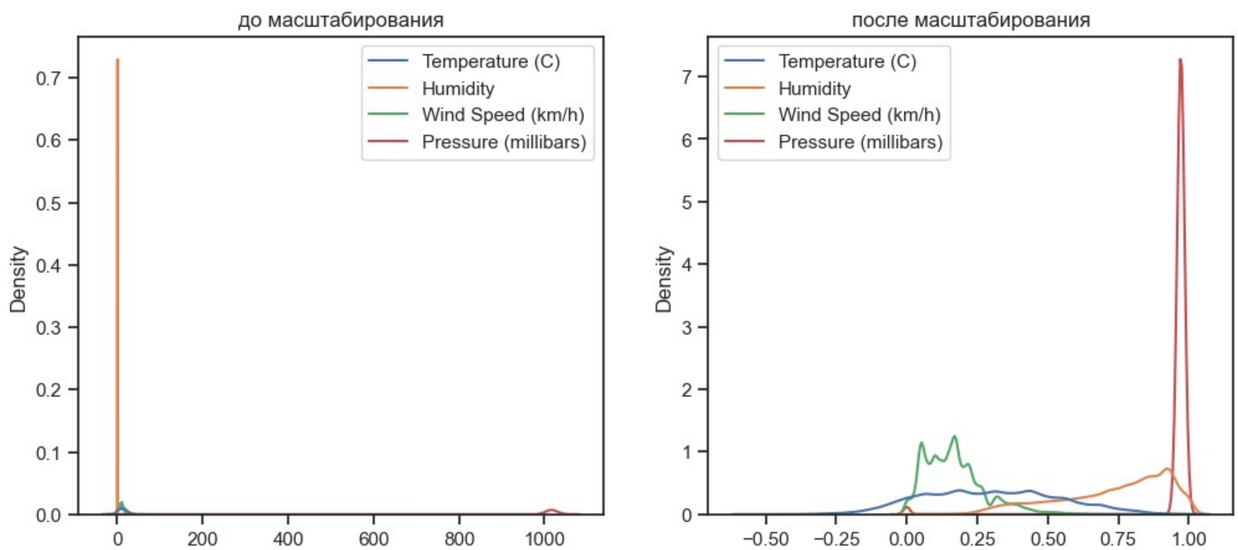


по Max

```
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()
```

```
       Temperature (C)  Apparent Temperature (C)      Humidity  \
count     96453.000000              96453.000000  96453.000000
mean          0.299023                  0.275897      0.734899
std           0.239354                  0.271877      0.195473
min          -0.546847                 -0.704462      0.000000
25%           0.117500                  0.058740      0.600000
50%           0.300710                  0.304999      0.780000
75%           0.472087                  0.478820      0.890000
max           1.000000                  1.000000      1.000000

       Wind Speed (km/h)  Wind Bearing (degrees)  Visibility (km)  \
count       96453.000000            96453.000000     96453.000000
mean            0.169306                0.522310         0.642691
std             0.108274                0.299118         0.260380
min             0.000000                0.000000         0.000000
25%             0.091276                0.323120         0.518000
50%             0.156077                0.501393         0.624000
75%             0.221382                0.807799         0.920000
max             1.000000                1.000000         1.000000

       Pressure (millibars)
count          96453.000000
mean               0.958768
std                0.111785
min                0.000000
```

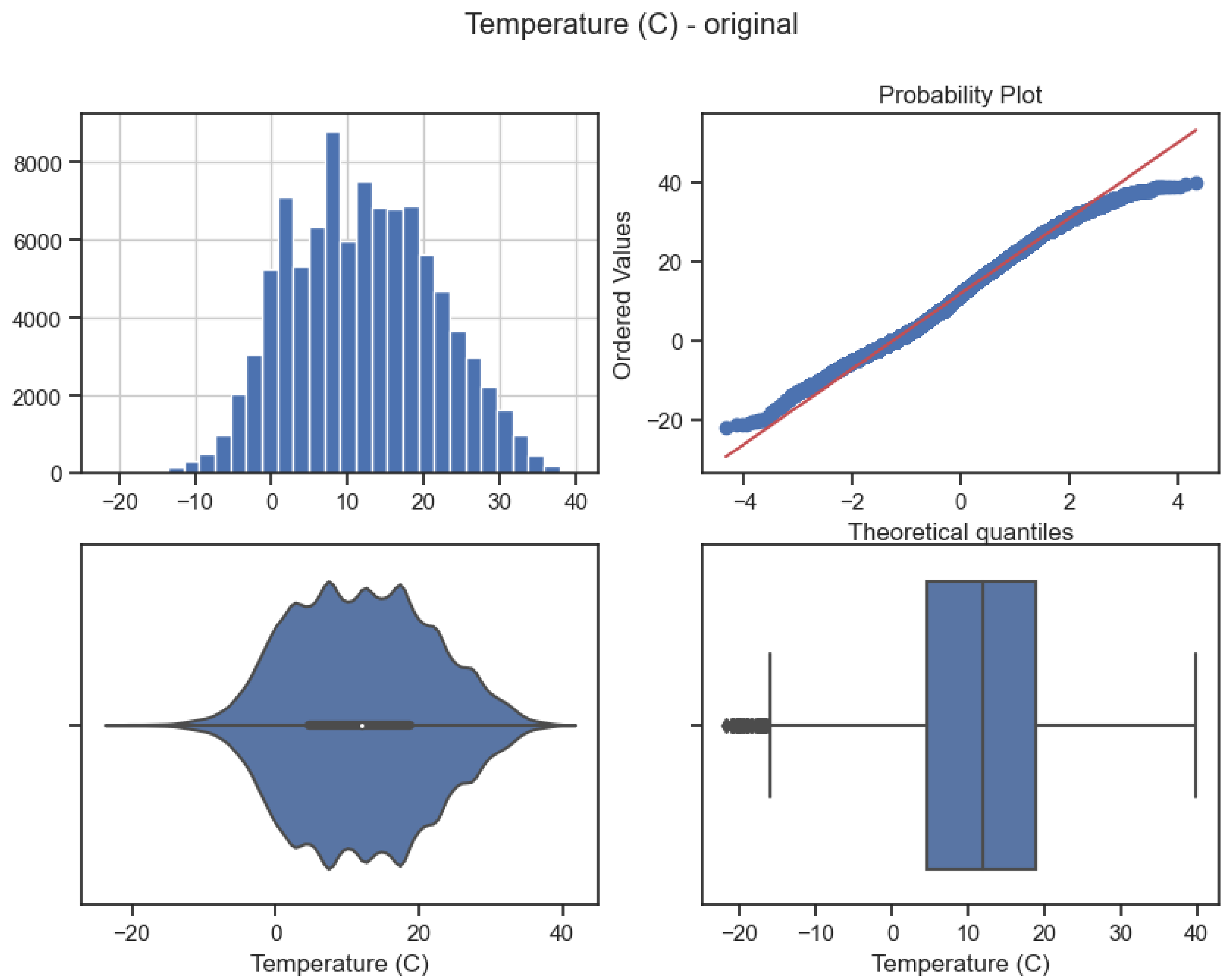
```
25%                     0.967048
50%                     0.971397
75%                     0.975831
max                     1.000000

draw_kde(['Temperature (C)', 'Humidity', 'Wind Speed (km/h)',
'Pressure (millibars)'], data, data_cs51_scaled, 'до масштабирования',
'после масштабирования')
```



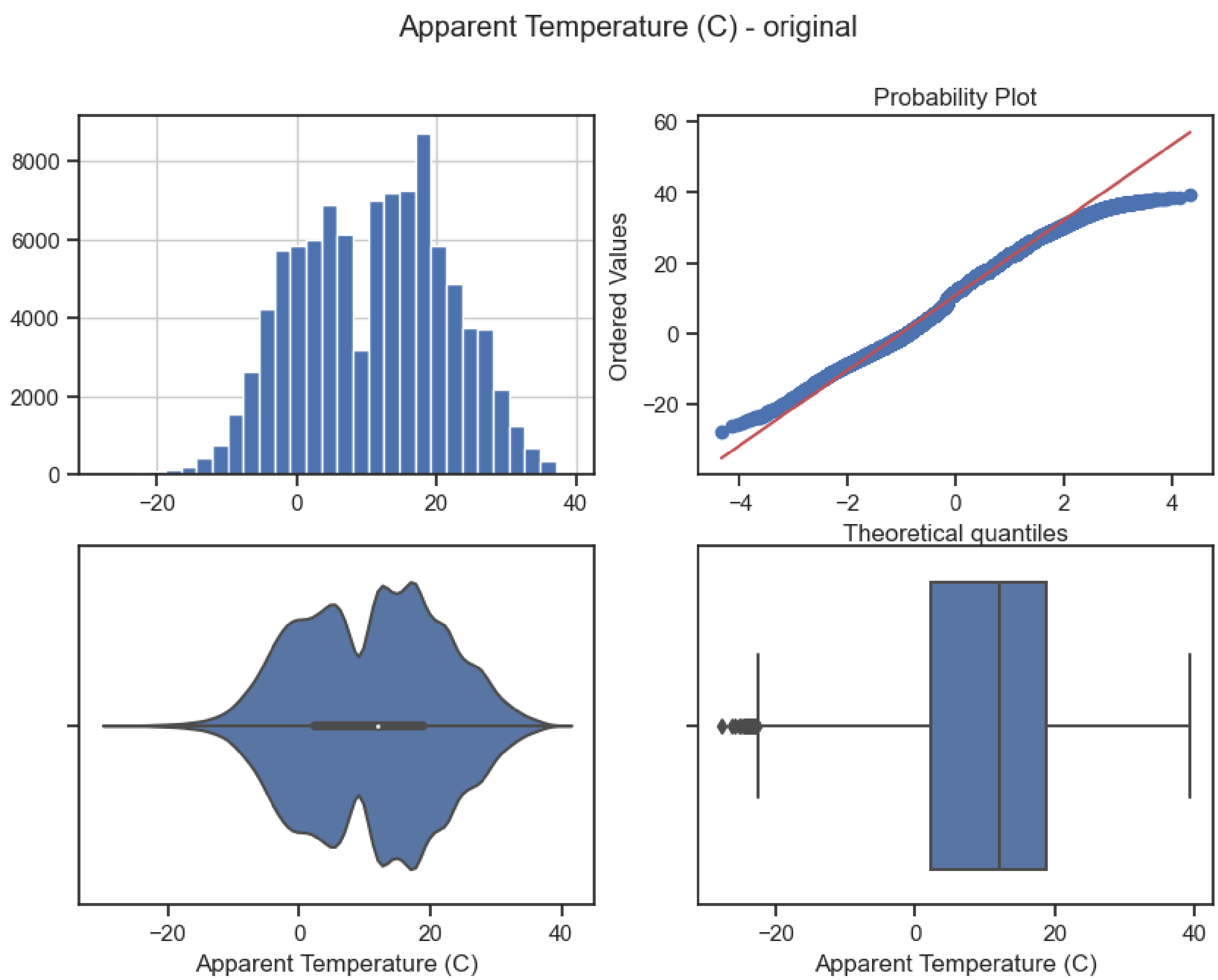
Отработка выбросов

```
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()

for col in data:
    if data.dtypes[col]=='float64':
        diagnostic_plots(data, col, col+' - original')
```

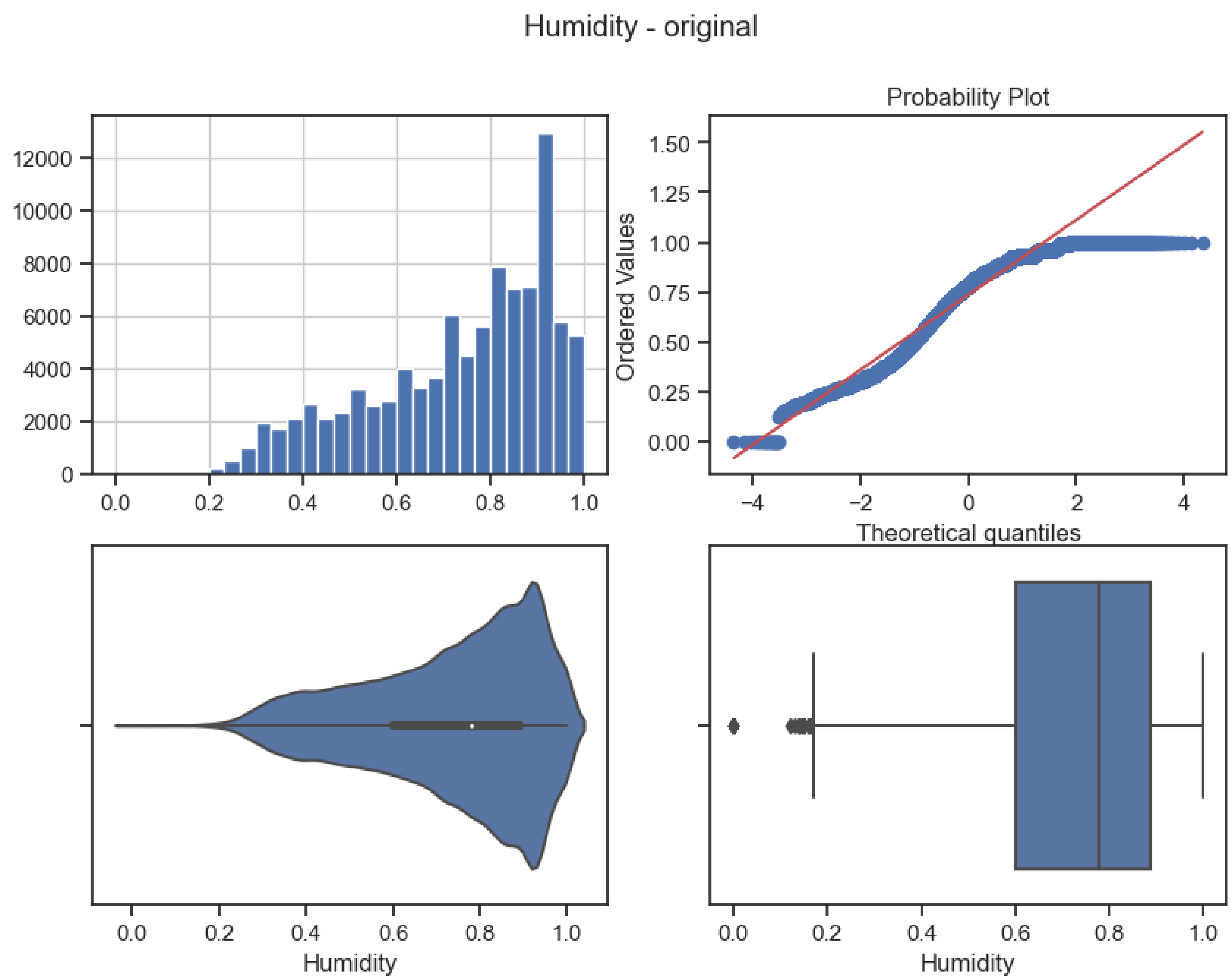
```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



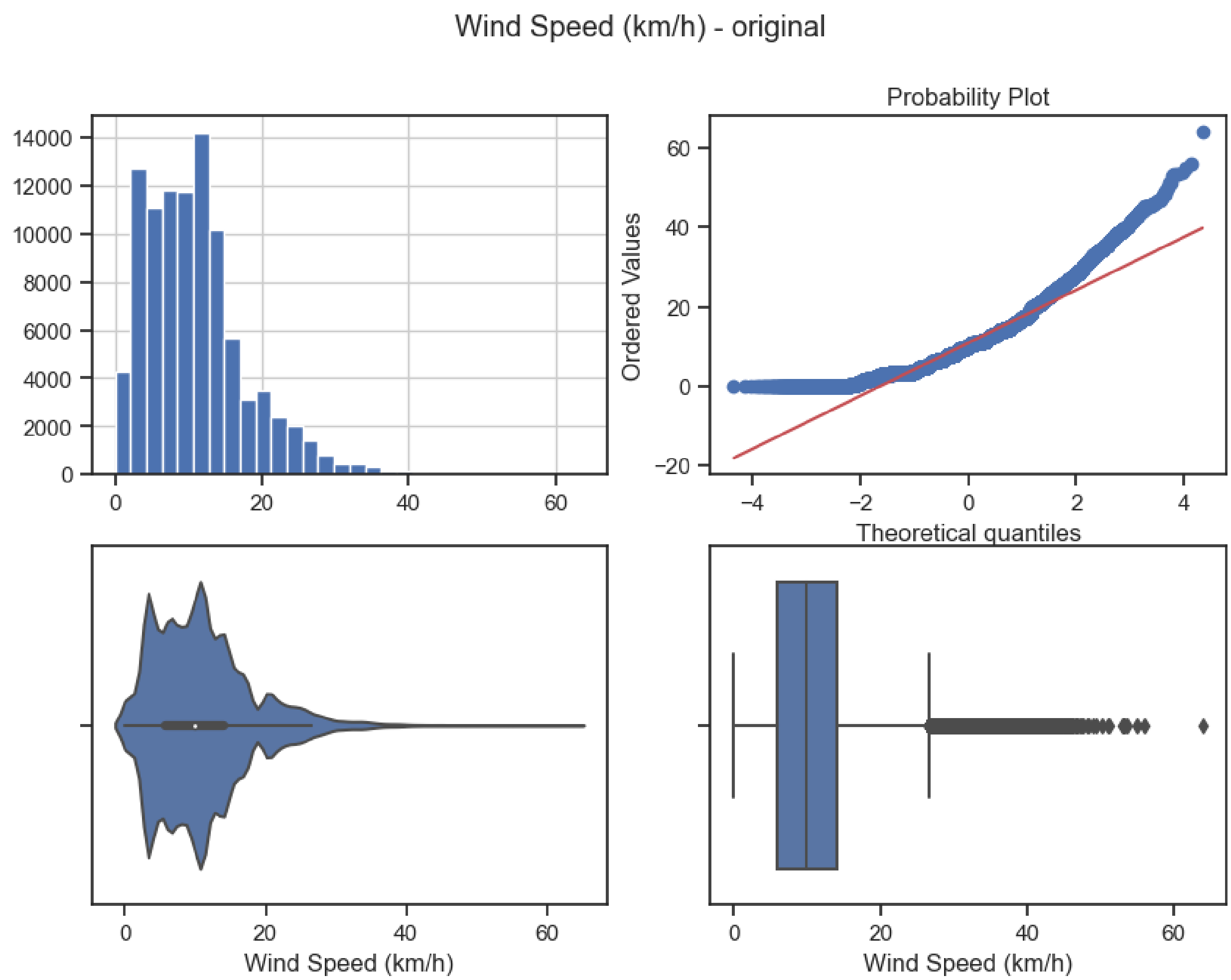

```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



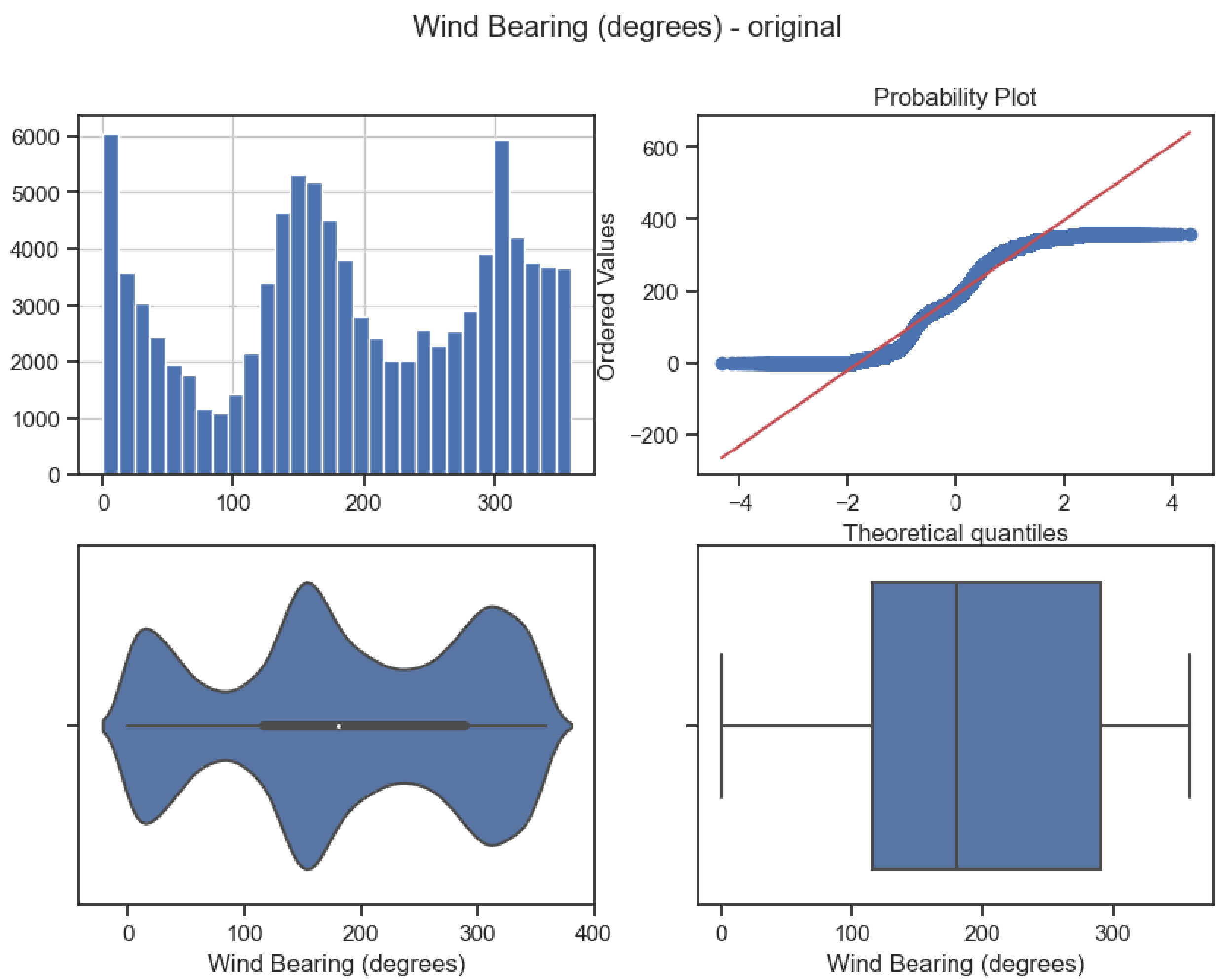

```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



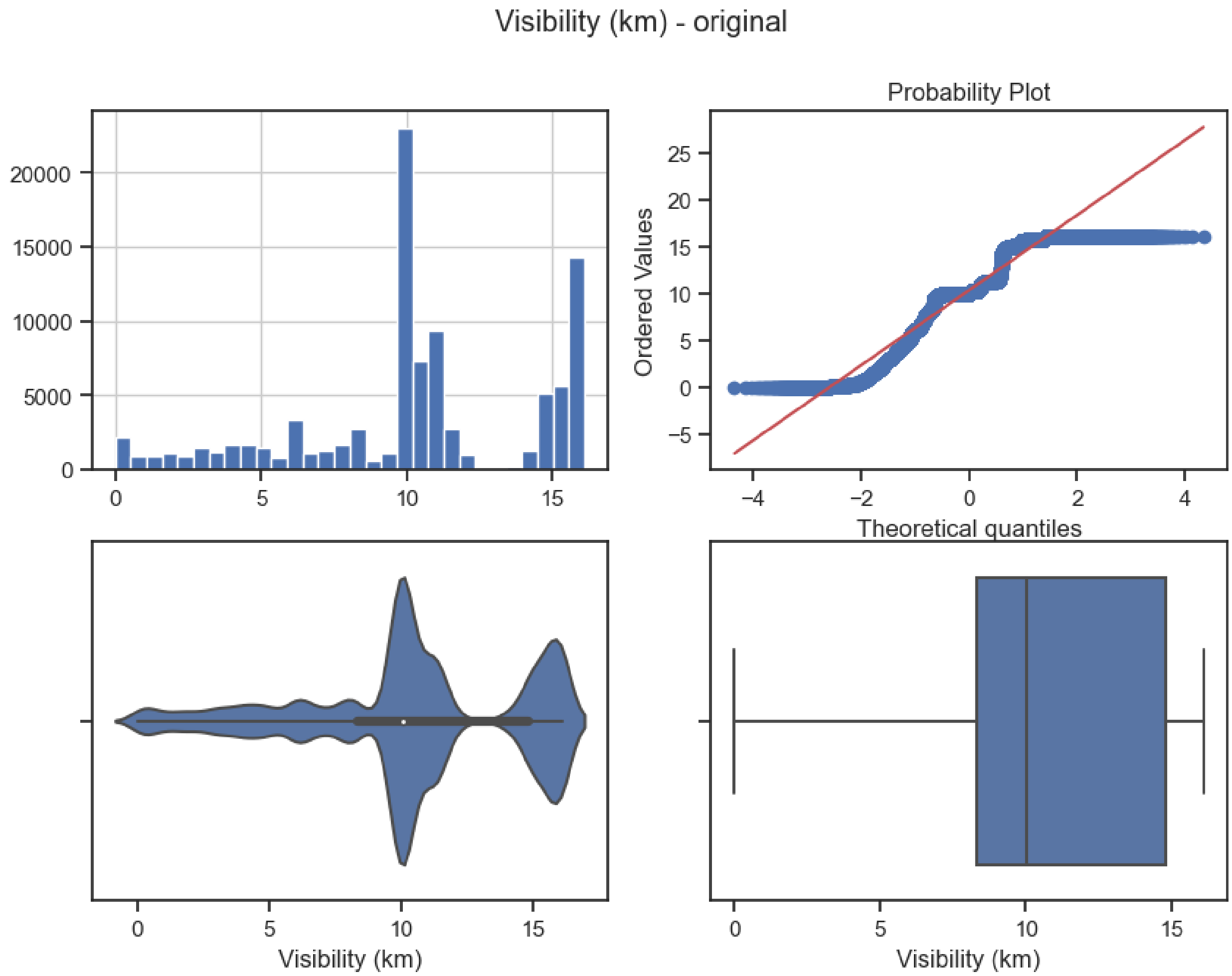

```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



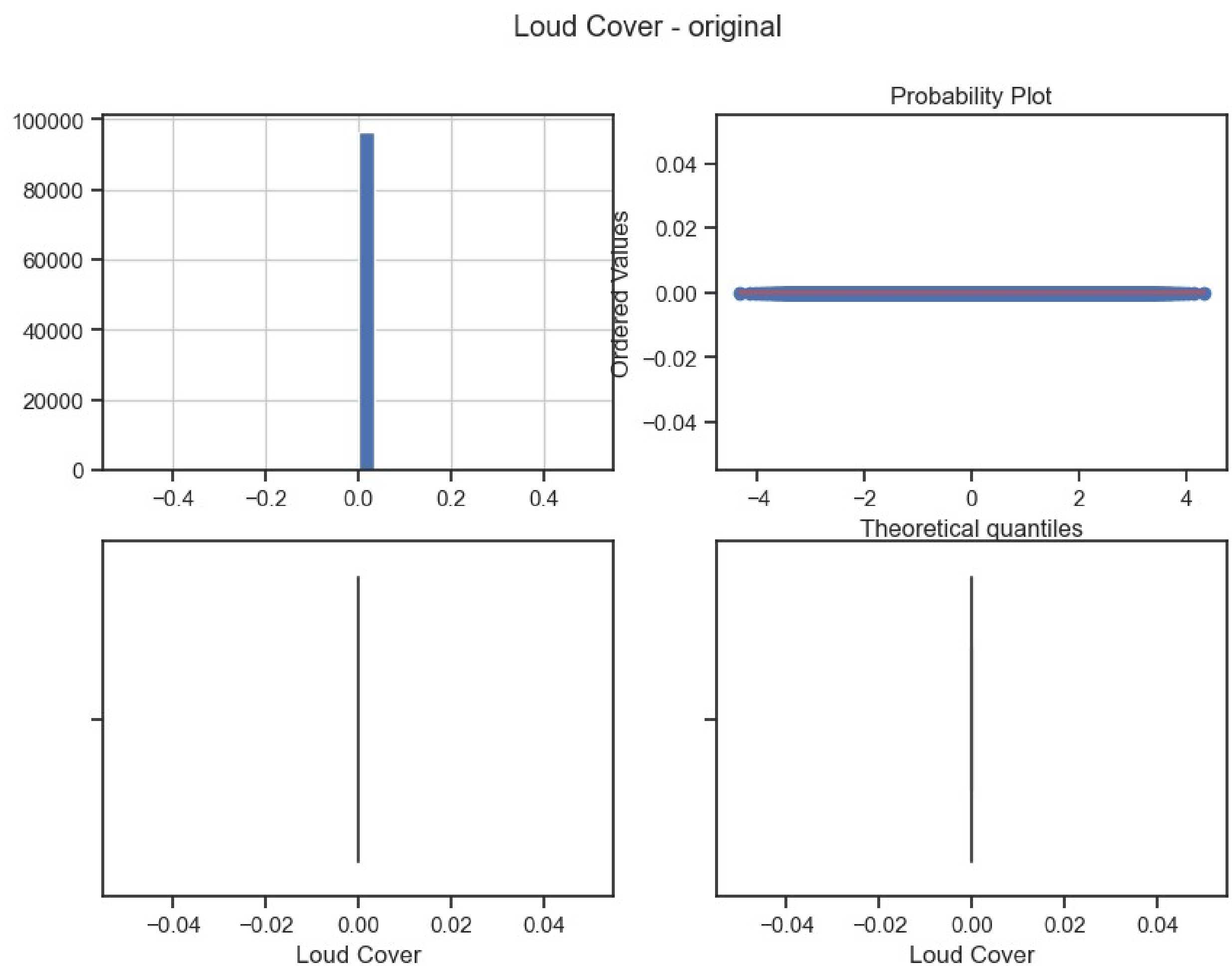

```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



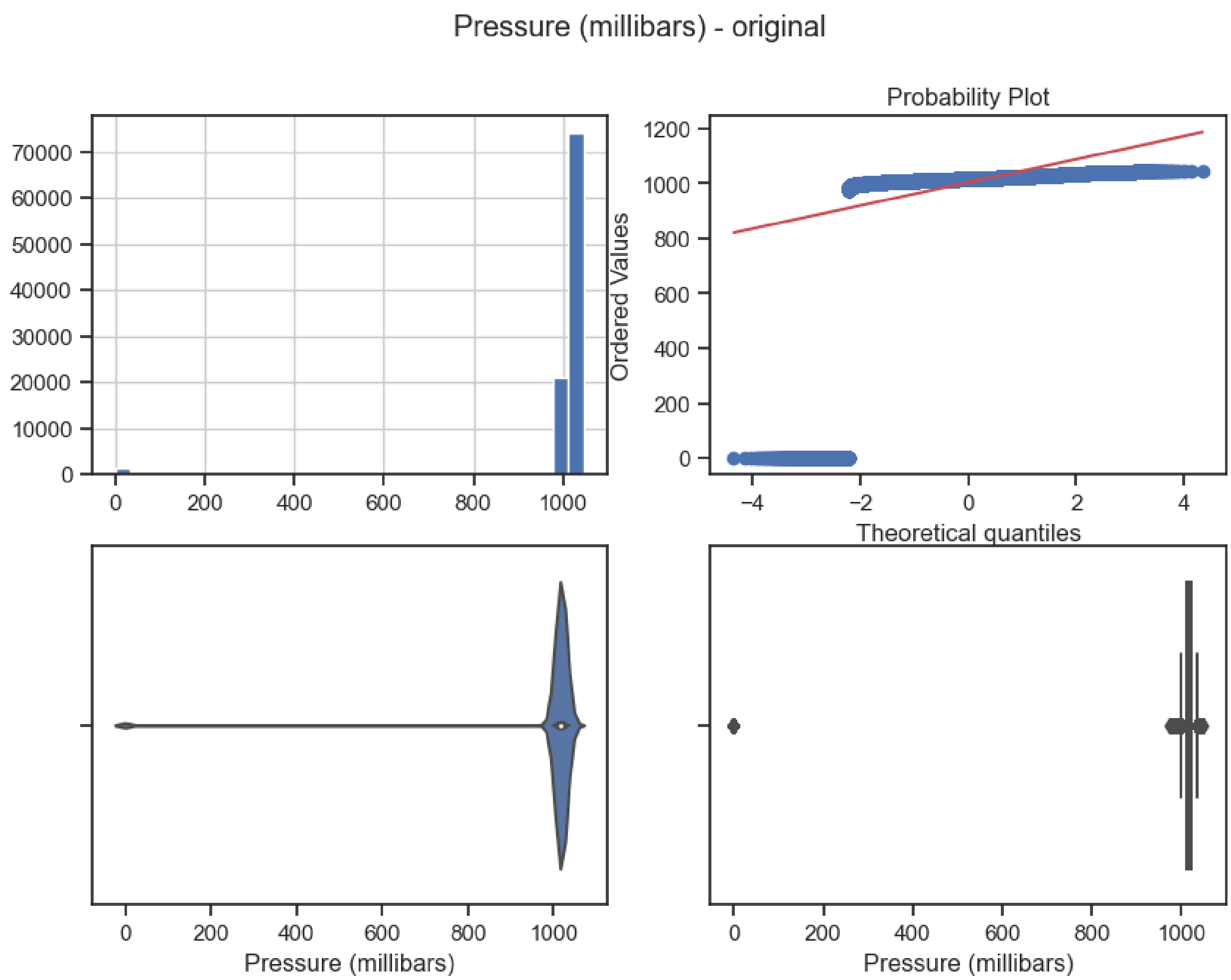

```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```




```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```




```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```

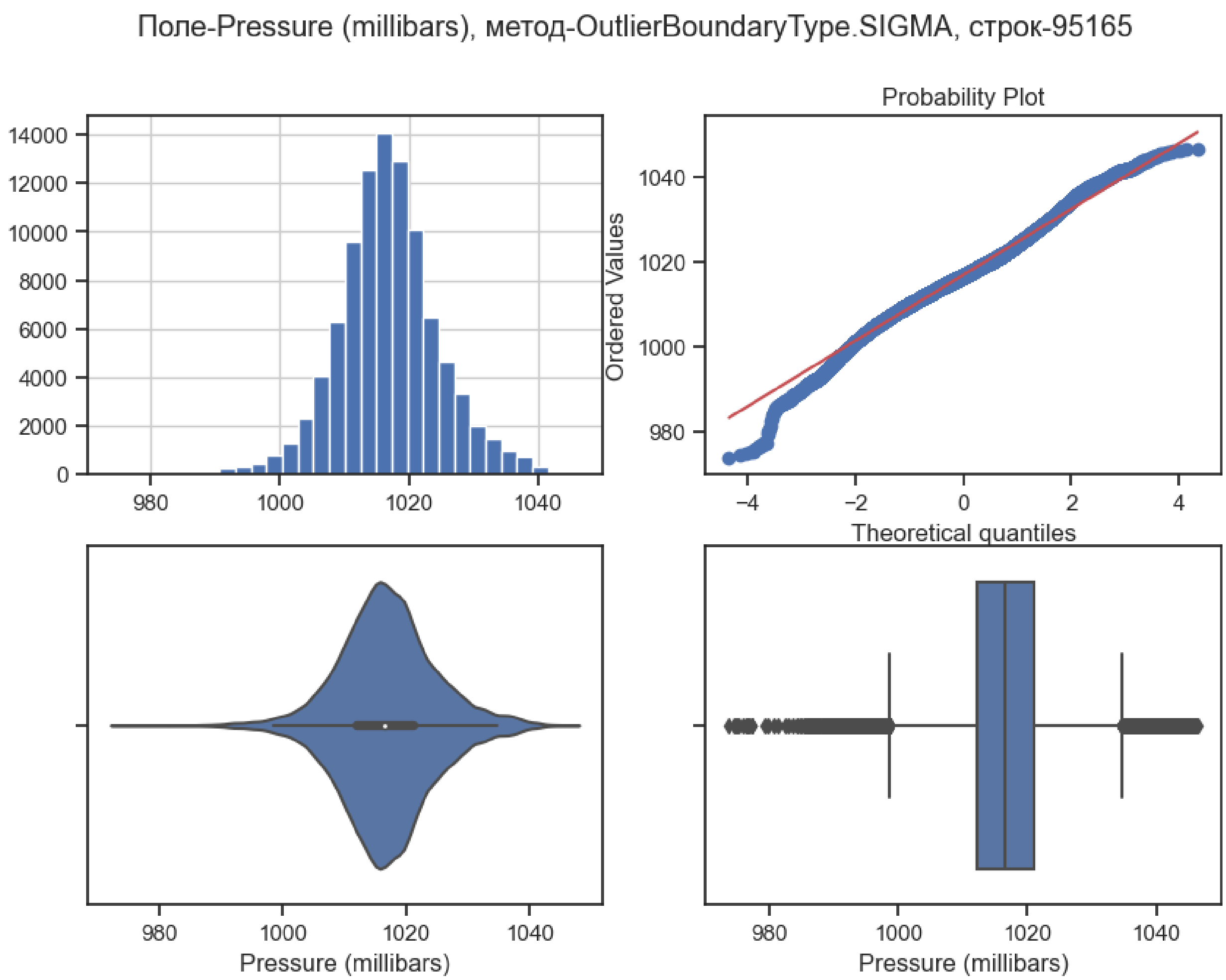


Видим, что ярко выражены квантили в pressure - вероятно, были неисправны приборы. Удалим их.

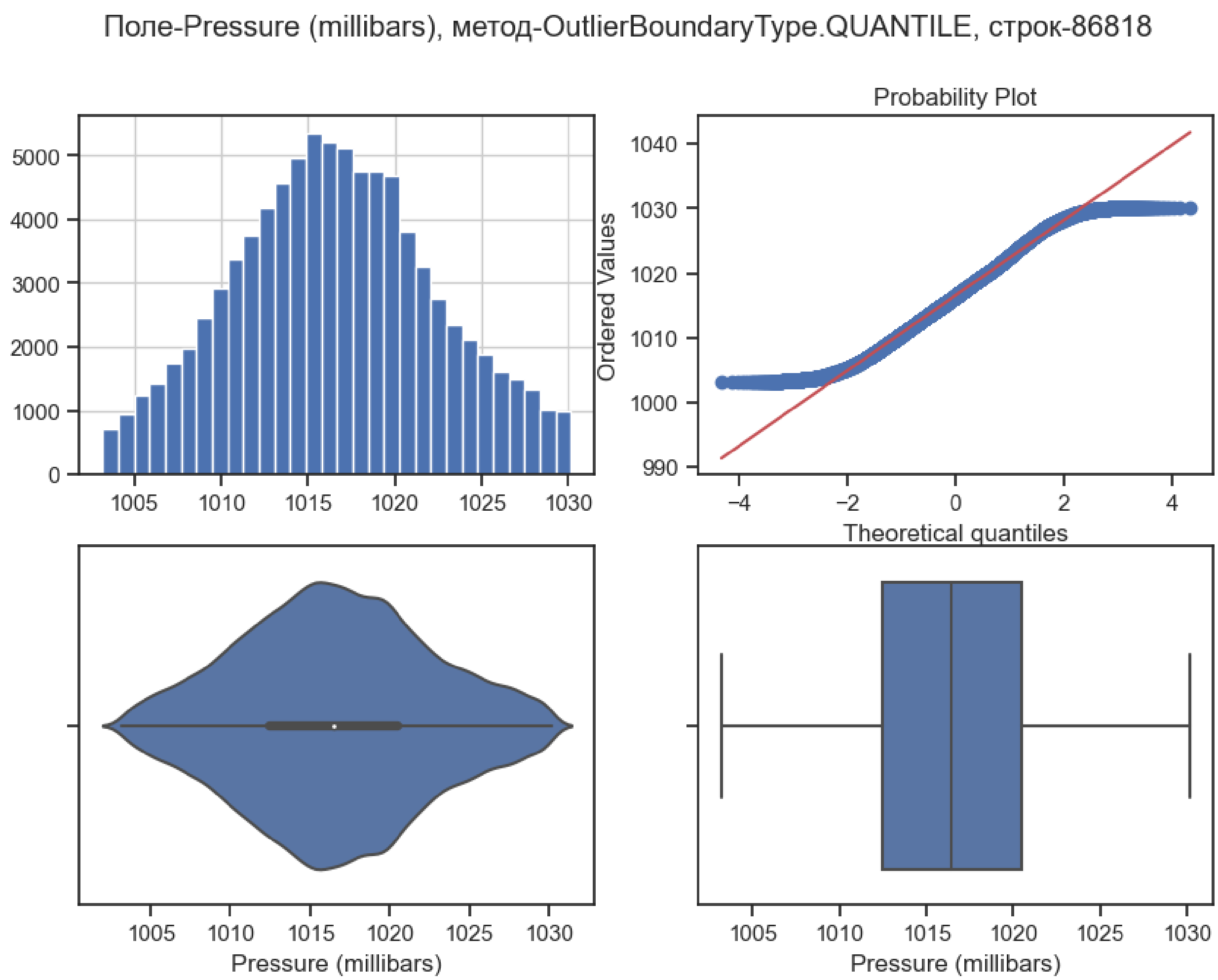
```
# Тип вычисления верхней и нижней границы выбросов
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3
# Функция вычисления верхней и нижней границы выбросов
def get_outlier_boundaries(df, col, outlier_boundary_type:
OutlierBoundaryType):
    if outlier_boundary_type == 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

col = 'Pressure (millibars)'
if data.dtypes[col]=='float64':
     for obt in OutlierBoundaryType:
        # Вычисление верхней и нижней границы
        lower_boundary, upper_boundary = get_outlier_boundaries(data, 
col, obt)
        # Флаги для удаления выбросов
        outliers_temp = np.where(data[col] > upper_boundary, True, 
                             np.where(data[col] < lower_boundary, 
True, False))
        # Удаление данных на основе флага
        data_trimmed = data.loc[~(outliers_temp), ]
        title = 'Поле-{}, метод-{}, строк-{}'.format(col, obt, 
data_trimmed.shape[0])
        diagnostic_plots(data_trimmed, col, title)
```

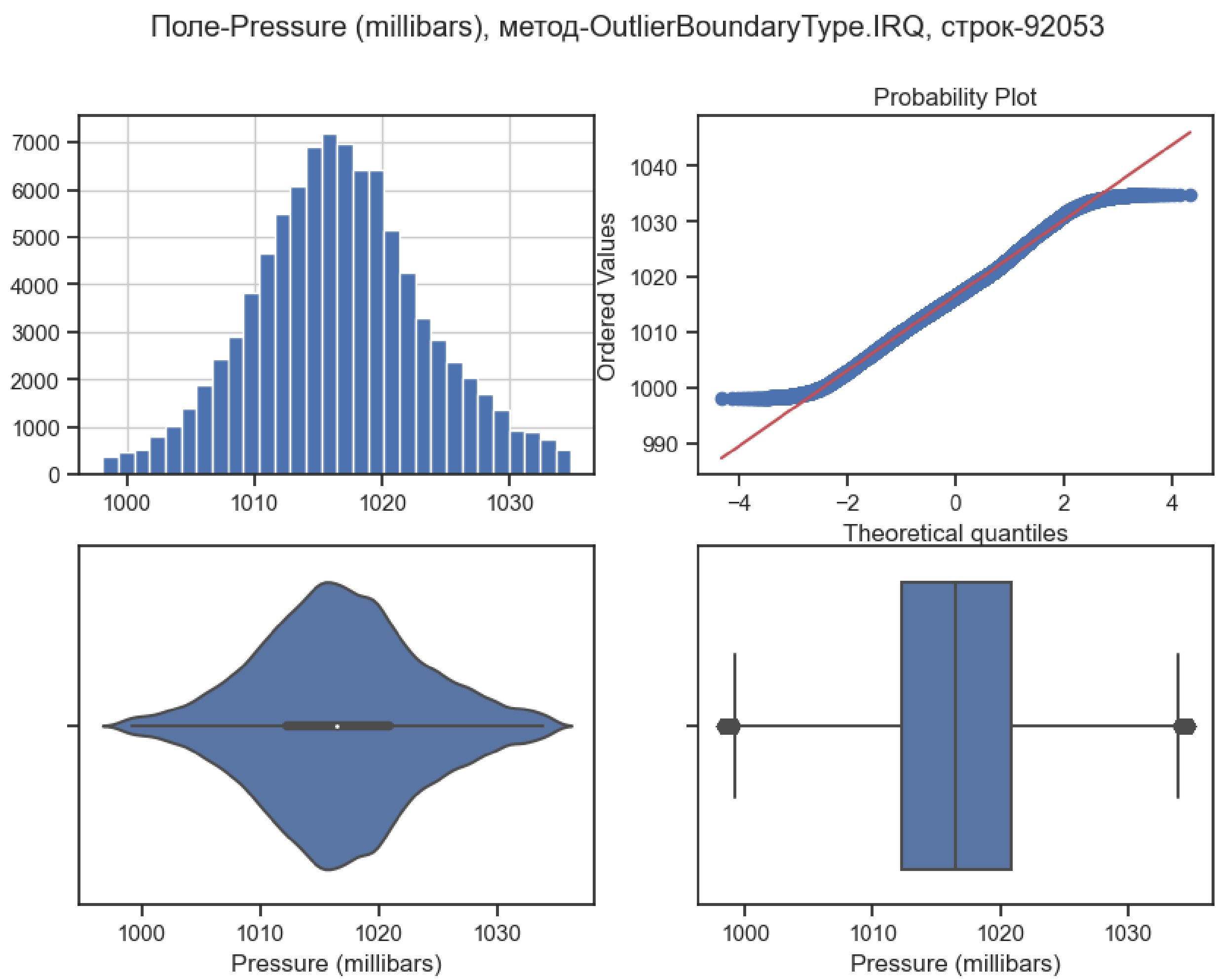
```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4: 
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is 
deprecated since 3.6 and will be removed two minor releases later; 
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```




```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```

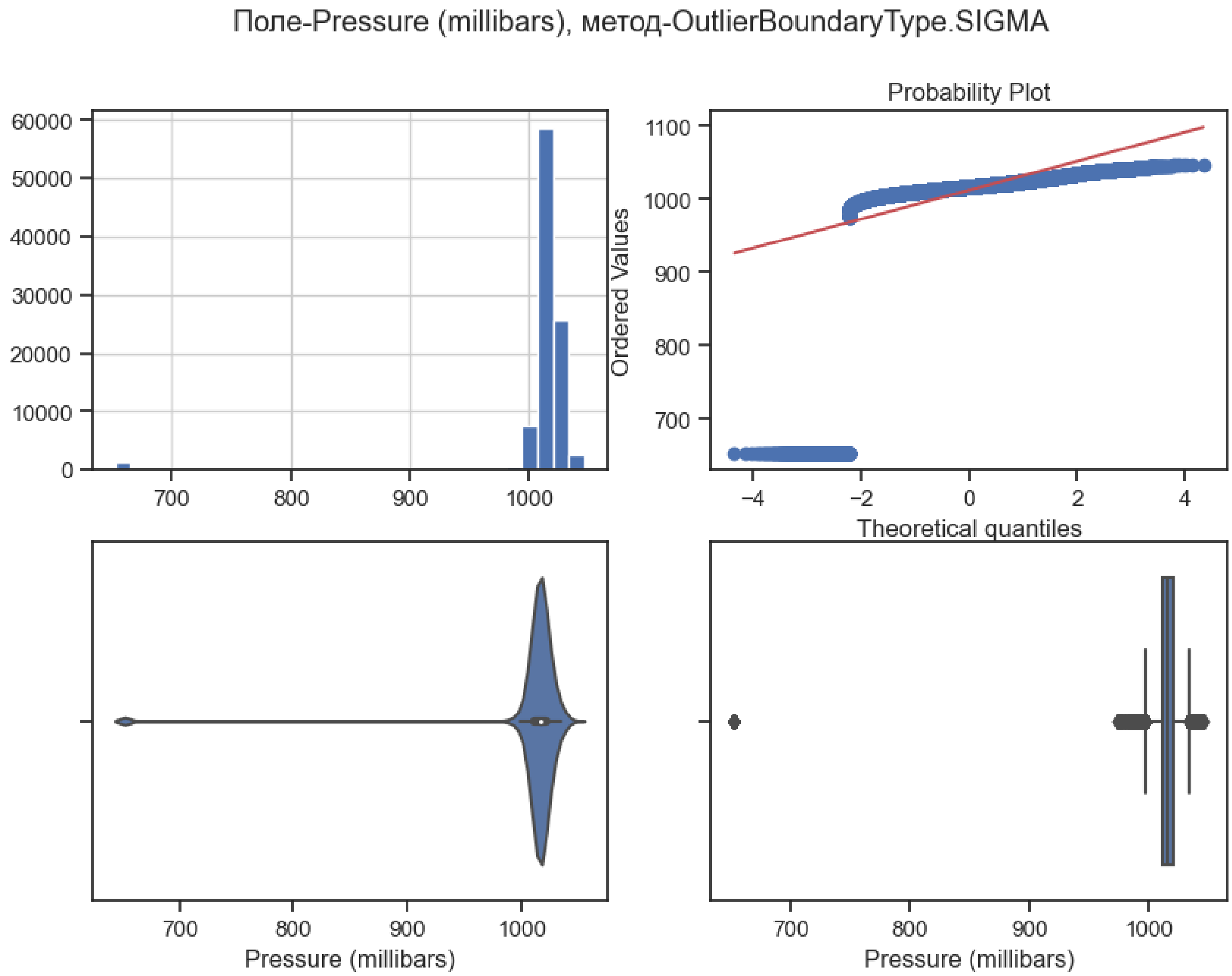



```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



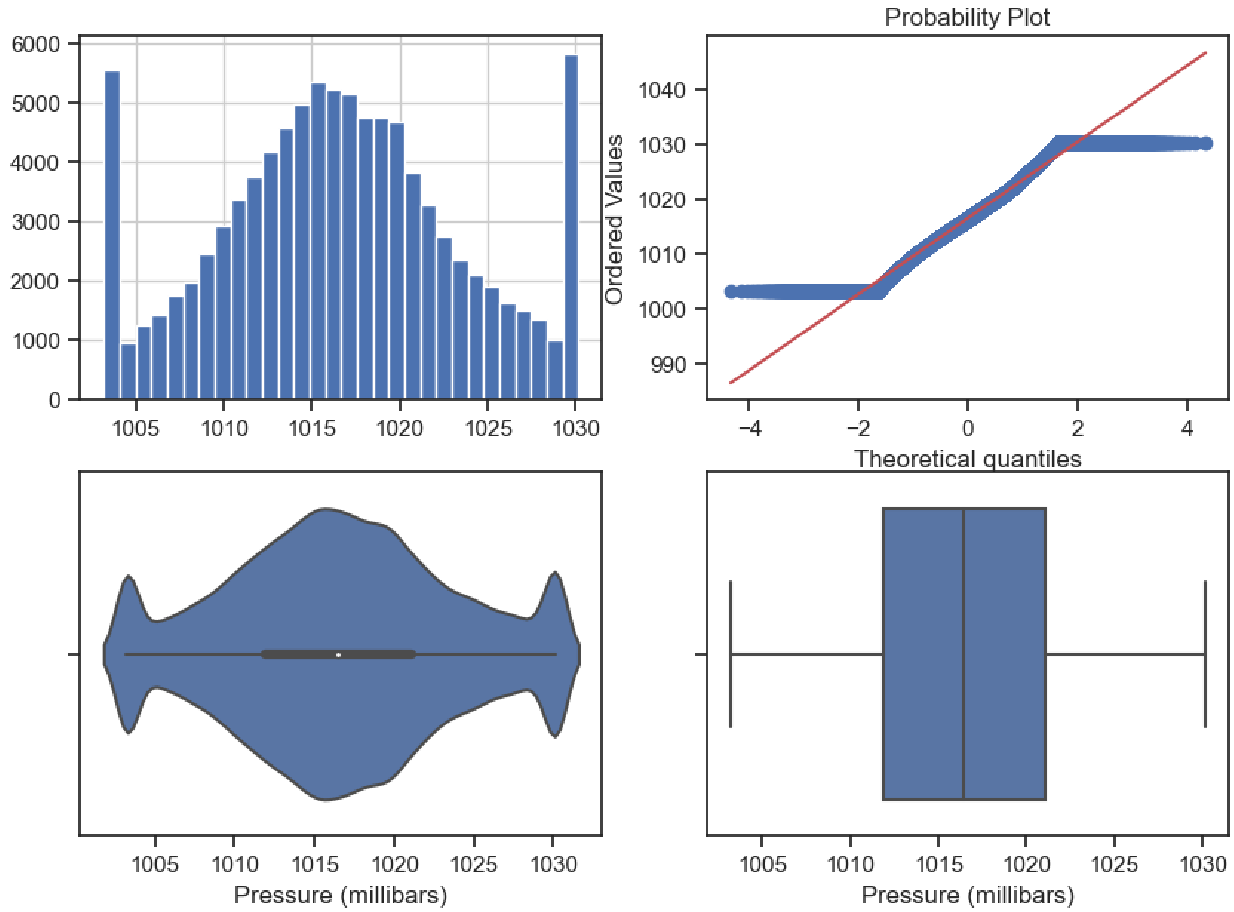

```
for obt in OutlierBoundaryType:
    data_copy = data.copy()
    # Вычисление верхней и нижней границы
    lower_boundary, upper_boundary = get_outlier_boundaries(data_copy, col, obt)
    # Изменение данных
    data_copy[col] = np.where(data_copy[col] > upper_boundary, upper_boundary,
           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

```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```

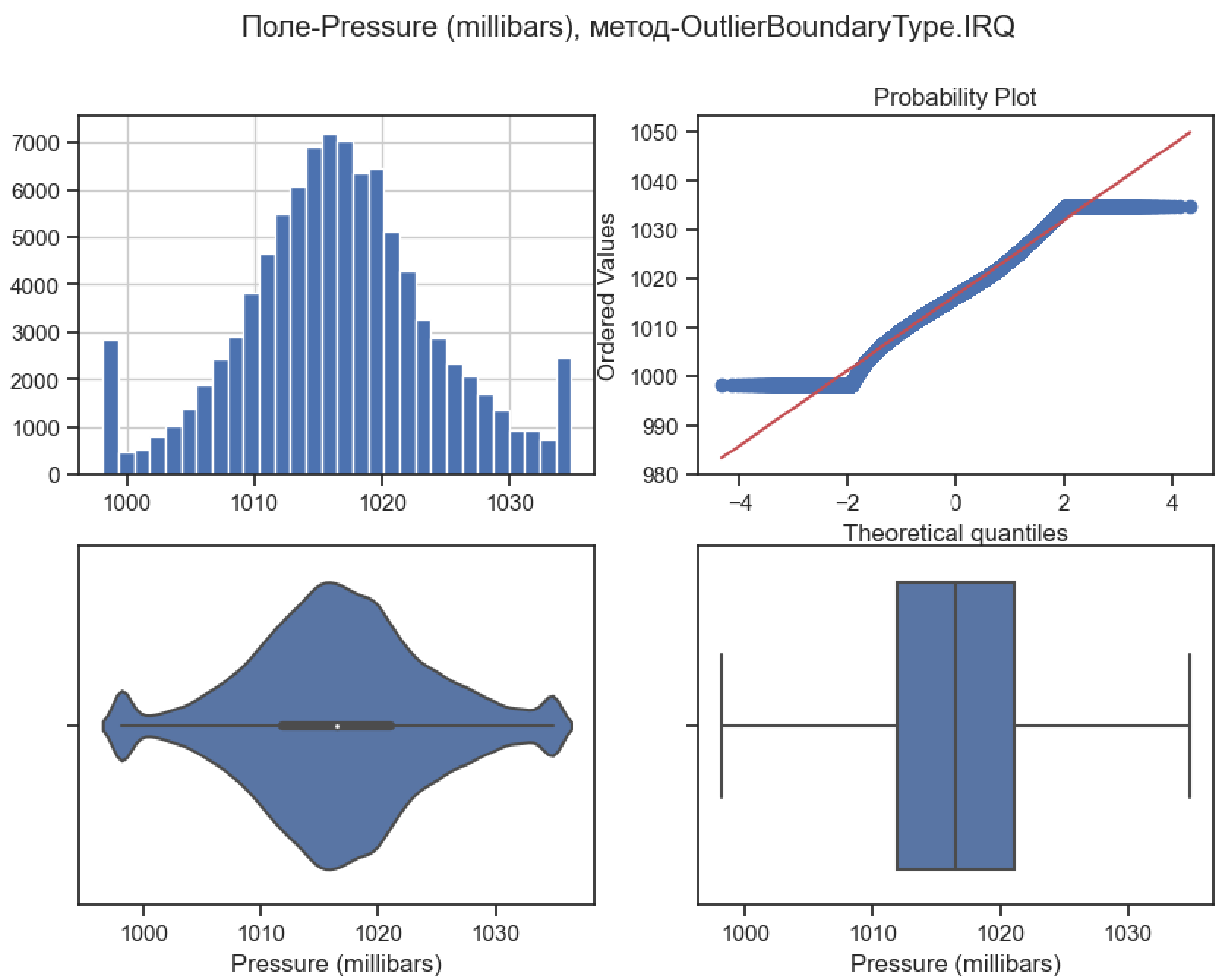



```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```

Поле-Pressure (millibars), метод-OutlierBoundaryType.QUANTILE




```
C:\Users\ksarb\AppData\Local\Temp\ipykernel_14512\223523601.py:4:
MatplotlibDeprecationWarning: Auto-removal of overlapping axes is
deprecated since 3.6 and will be removed two minor releases later;
explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



Отработка признака - извлечём месяц.

```
data_copy = data.copy()

data_copy['f'] = pd.to_datetime(data_copy['Formatted Date'])

data['month'] = data_copy['f'].apply(lambda x: x.month)

data.head()
```

```
                  Formatted Date        Summary Precip Type
Temperature (C)  \
0  2006-04-01 00:00:00.000 +0200  Partly Cloudy        rain
9.472222
1  2006-04-01 01:00:00.000 +0200  Partly Cloudy        rain
9.355556
2  2006-04-01 02:00:00.000 +0200  Mostly Cloudy        rain
9.377778
3  2006-04-01 03:00:00.000 +0200  Partly Cloudy        rain
8.288889
```

```
4  2006-04-01 04:00:00.000 +0200  Mostly Cloudy        rain
8.755556

   Apparent Temperature (C)  Humidity  Wind Speed (km/h)  \
0                  7.388889      0.89            14.1197
1                  7.227778      0.86            14.2646
2                  9.377778      0.89             3.9284
3                  5.944444      0.83            14.1036
4                  6.977778      0.83            11.0446

   Wind Bearing (degrees)  Visibility (km)  Loud Cover  Pressure
(millibars)  \
0                   251.0          15.8263         0.0
1015.13
1                   259.0          15.8263         0.0
1015.63
2                   204.0          14.9569         0.0
1015.94
3                   269.0          15.8263         0.0
1016.41
4                   259.0          15.8263         0.0
1016.51

                      Daily Summary  month
0  Partly cloudy throughout the day.      4
1  Partly cloudy throughout the day.      4
2  Partly cloudy throughout the day.      4
3  Partly cloudy throughout the day.      4
4  Partly cloudy throughout the day.      4
```

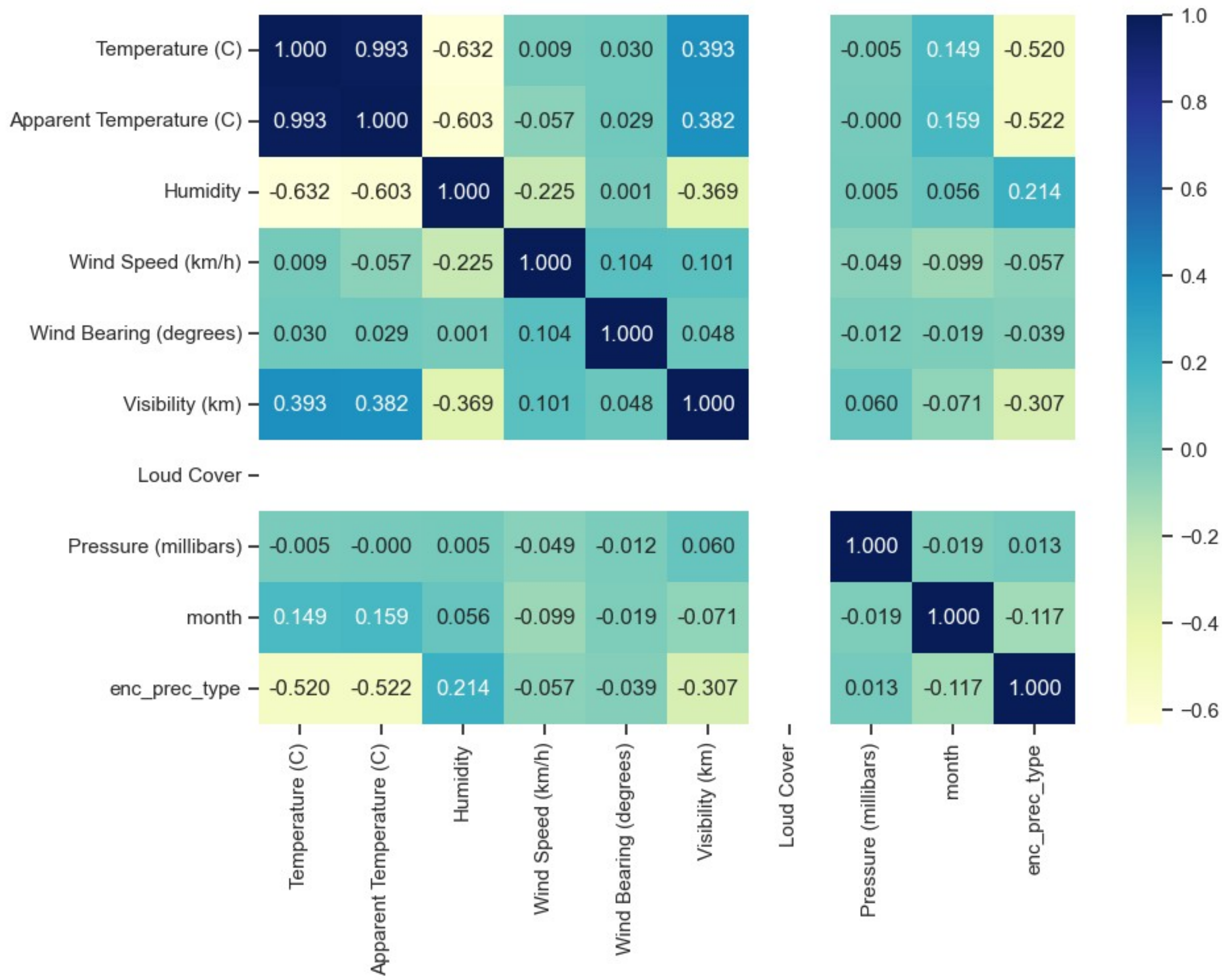
Отбор признаков

preparation

```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

cat_enc_le = le.fit_transform(data['Precip Type'])

data['enc_prec_type']=le.transform(data['Precip Type'])

data.head()
```

```
                  Formatted Date        Summary Precip Type
Temperature (C)  \
0  2006-04-01 00:00:00.000 +0200  Partly Cloudy        rain
9.472222
1  2006-04-01 01:00:00.000 +0200  Partly Cloudy        rain
9.355556
2  2006-04-01 02:00:00.000 +0200  Mostly Cloudy        rain
```

```
9.377778
3  2006-04-01 03:00:00.000 +0200  Partly Cloudy        rain
8.288889
4  2006-04-01 04:00:00.000 +0200  Mostly Cloudy        rain
8.755556

   Apparent Temperature (C)  Humidity  Wind Speed (km/h)  \
0                  7.388889      0.89            14.1197
1                  7.227778      0.86            14.2646
2                  9.377778      0.89             3.9284
3                  5.944444      0.83            14.1036
4                  6.977778      0.83            11.0446

   Wind Bearing (degrees)  Visibility (km)  Loud Cover  Pressure
(millibars)  \
0                   251.0          15.8263         0.0
1015.13
1                   259.0          15.8263         0.0
1015.63
2                   204.0          14.9569         0.0
1015.94
3                   269.0          15.8263         0.0
1016.41
4                   259.0          15.8263         0.0
1016.51

                       Daily Summary  month  enc_prec_type
0  Partly cloudy throughout the day.      4              0
1  Partly cloudy throughout the day.      4              0
2  Partly cloudy throughout the day.      4              0
3  Partly cloudy throughout the day.      4              0
4  Partly cloudy throughout the day.      4              0

data_numeric = data.drop(columns=['Formatted Date','Summary','Precip
Type', 'Daily Summary'])
fig, ax = plt.subplots(figsize=(10,7))
sns.heatmap(data_numeric.corr(), cmap='YlGnBu', annot=True, fmt='.3f')
plt.show()
```



Считаем целевым Apparent temperature - нужно вычислить, как себя чувствует человек при некой температуре.

Filter

```
# Формирование DataFrame с сильными корреляциями
def make_corr_df(df):
    cr = df.corr()
    cr = cr.abs().unstack()
    cr = cr.sort_values(ascending=False)
    cr = cr[cr >= 0.5]
    cr = cr[cr < 1]
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']
    return cr

make_corr_df(data_numeric)
```

	f1	f2	corr
0	Apparent Temperature (C)	Temperature (C)	0.992629

```
1           Temperature (C)  Apparent Temperature (C)  0.992629
2                  Humidity           Temperature (C)  0.632255
3           Temperature (C)                  Humidity  0.632255
4  Apparent Temperature (C)                  Humidity  0.602571
5                  Humidity  Apparent Temperature (C)  0.602571
6             enc_prec_type  Apparent Temperature (C)  0.521781
7  Apparent Temperature (C)             enc_prec_type  0.521781
8             enc_prec_type           Temperature (C)  0.520381
9           Temperature (C)             enc_prec_type  0.520381
```

```
# 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

corr_groups(make_corr_df(data_numeric))
```

```
[['Temperature (C)', 'Humidity', 'enc_prec_type', 'Apparent
Temperature (C)']]
```

Wrapper

```
from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
data_X = data_numeric.drop(columns=['Apparent Temperature (C)'])
data_Y = data_numeric['Apparent Temperature (C)']
knn = KNeighborsRegressor(n_neighbors=3)

efs1 = EFS(knn,
           min_features=2,
           max_features=4,
           scoring='r2',
           print_progress=True,
           cv=5)

efs1 = efs1.fit(data_X, 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: 246/246
```

```
Best accuracy score: 1.00
Best subset (indices): (0, 1, 2)
Best subset (corresponding names): ('Temperature (C)', 'Humidity',
'Wind Speed (km/h)')
```

Методы вложений (embedded methods)

```
# Используем L1-регуляризацию
e_ls1 = Lasso(random_state=1)
e_ls1.fit(data_X, data_Y)
# Коэффициенты регрессии
list(zip(list(data_X.columns.values), e_ls1.coef_))
```

```
[('Temperature (C)', 1.101087753312272),
 ('Humidity', 0.0),
 ('Wind Speed (km/h)', -0.08087790939102855),
 ('Wind Bearing (degrees)', 0.0004107880410152464),
 ('Visibility (km)', 0.0),
 ('Loud Cover', 0.0),
 ('Pressure (millibars)', 0.00016554852457849832),
 ('month', 0.0),
 ('enc_prec_type', -0.0)]
```

```
sel_e_ls1 = SelectFromModel(e_ls1)
sel_e_ls1.fit(data_X, data_Y)
list(zip(list(data_X.columns.values), sel_e_ls1.get_support()))
```

```
[('Temperature (C)', True),
 ('Humidity', False),
 ('Wind Speed (km/h)', True),
 ('Wind Bearing (degrees)', True),
 ('Visibility (km)', False),
 ('Loud Cover', False),
 ('Pressure (millibars)', True),
 ('month', False),
 ('enc_prec_type', False)]
```

Вывод:

Датасет необходимо подготавливать перед проведением любой работы по машинному обучению.

Масштабирование данных позволяет привести все параметры к одному диапазону, при этом не меняя формы распределения. Часть методов центрирует распределение, часть сохраняет смещение на отрезке.

Для некоторых зависимостей может быть полезно удалить или заменить выбросы. В рассматриваемом погодном датасете были выбросы по неисправности оборудования. Для них эффективнее удалить значения, или заменять краем распределения – но не интервалом, поскольку дистанция между выбросом и центром распределения слишком велика.

Нестандартный признак обработан как дата – год мало влияет на ощущение температуры, номер дня тоже – а вот сезонная, или помесячная смена может иметь корреляцию.

Отбор признаков позволил отбросить малозначимые признаки, оставив только сильно влияющие на целевой – ощущаемую температуру. Ими, ожидаемо, стали исходная температура, ветер и влажность.