осковский 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 (часть 2)»

Выполнил: Ван Пэй

Группа：ИУ5-22М

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Цель лабораторной работы:

изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

Задание:

Выбрать набор данных (датасет), содержащий категориальные и числовые признаки и пропуски в данных.

Для выполнения следующих пунктов можно использовать несколько различных наборов данных

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).

```
import numpy as np
import pandas as pd
```

```
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import xgboost as xgb
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
import scipy.stats as stats
from sklearn.svm import SVR
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.metrics import mean_squared_error
from IPython.display import Image
from sklearn.datasets import load_iris
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.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature_selection import mutual_info_classif, mutual_info_regressic
from sklearn.feature_selection import SelectKBest, SelectPercentile

%matplotlib inline
sns.set(style="ticks")
```

```
train_data = pd.read_csv('C:/Users/王沛/Desktop/winequality-red.csv',index_col=0
train_y = train_data['quality']
train_data.drop(['quality'],axis=1,inplace=True)

data = train_data
features = data.columns
sns.set_style('whitegrid')
```

:
```
data.head()
```
:

fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	a
7.4	0.70	0.00	1.9	0.076	11	34	0.9978	3.51	0.56	
7.8	0.88	0.00	2.6	0.098	25	67	0.9968	3.20	0.68	
7.8	0.76	0.04	2.3	0.092	15	54	0.9970	3.26	0.65	
11.2	0.28	0.56	1.9	0.075	17	60	0.9980	3.16	0.58	
7.4	0.70	0.00	1.9	0.076	11	34	0.9978	3.51	0.56	

```
data.describe()
```

	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	1
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	
mean	0.527821	0.270976	2.538806	0.087467	15.875547	46.468418	
std	0.179060	0.194801	1.409928	0.047065	10.460434	32.895920	
min	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	
25%	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	
50%	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	
75%	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	
max	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	

Масштабирование

```
def arr_to_df(arr_scaled):
    res = pd.DataFrame(arr_scaled, columns=data.columns)
    return res
```

Масштабирование данных на основе Z-оценки

$x' = x - \mu(x)\sigma(x)$

```
cs11 = StandardScaler()
data_cs11_scaled_temp = cs11.fit_transform(data)
data_cs11_scaled =  arr_to_df(data_cs11_scaled_temp)
data_cs11_scaled
```

	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
0	0.961877	-1.391472	-0.453218	-0.243707	-0.466240	-0.379145	0.558274	1.2886
1	1.967442	-1.391472	0.043416	0.223875	0.872555	0.624333	0.028261	-0.7199
2	1.297065	-1.186070	-0.169427	0.096353	-0.083727	0.229023	0.134264	-0.3311
3	-1.384443	1.484154	-0.453218	-0.264960	0.107529	0.411474	0.664277	-0.9791
4	0.961877	-1.391472	-0.453218	-0.243707	-0.466240	-0.379145	0.558274	1.2886
...	...	...	...	...	...	...	...	
1594	0.403229	-0.980669	-0.382271	0.053845	1.541953	-0.075061	-0.978765	0.8998
1595	0.123905	-0.877968	-0.240375	-0.541259	2.211351	0.137798	-0.862162	1.3534
1596	-0.099554	-0.723916	-0.169427	-0.243707	1.255068	-0.196694	-0.533554	0.7055
1597	0.654620	-0.775267	-0.382271	-0.264960	1.541953	-0.075061	-0.676657	1.6774
1598	-1.216849	1.021999	0.752894	-0.434990	0.203158	-0.135878	-0.666057	0.5111

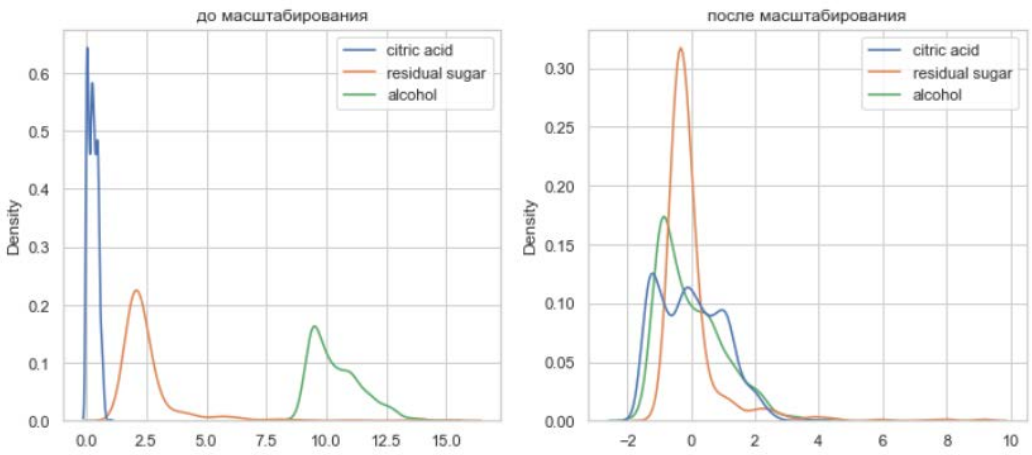
1599 rows × 10 columns

```
data_cs11_scaled.describe()
```

	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	tot
count	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e+03	1.599(
mean	1.699704e-16	4.335355e-16	-1.905223e-16	4.838739e-16	1.309667e-16	-8.324
std	1.000313e+00	1.000313e+00	1.000313e+00	1.000313e+00	1.000313e+00	1.000
min	-2.278280e+00	-1.391472e+00	-1.162696e+00	-1.603945e+00	-1.422522e+00	-1.230
25%	-7.699311e-01	-9.293181e-01	-4.532184e-01	-3.712290e-01	-8.487529e-01	-7.440
50%	-4.368911e-02	-5.636026e-02	-2.403750e-01	-1.799455e-01	-1.793553e-01	-2.575
75%	6.266881e-01	7.652471e-01	4.341614e-02	5.384542e-02	4.900424e-01	4.722
max	5.877976e+00	3.743574e+00	9.195681e+00	1.112703e+01	5.367083e+00	7.375(

```
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    ax1.set_title(label1)
    sns.kdeplot(data=df1[col_list], ax=ax1)
    ax2.set_title(label2)
    sns.kdeplot(data=df2[col_list], ax=ax2)
    plt.show()
```

```
draw_kde(['citric acid', 'residual sugar', 'alcohol'], data, data_cs11_scaled, '
```



Масштабирование "Mean Normalisation"

$x' = x - \mu(x) \max(x) - \min(x)$

```
class MeanNormalisation:

    def fit(self, param_df):
        self.means = train_data.mean(axis=0)
        maxs = data.max(axis=0)
        mins = data.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(data)
data_cs21_scaled.describe()
```

:

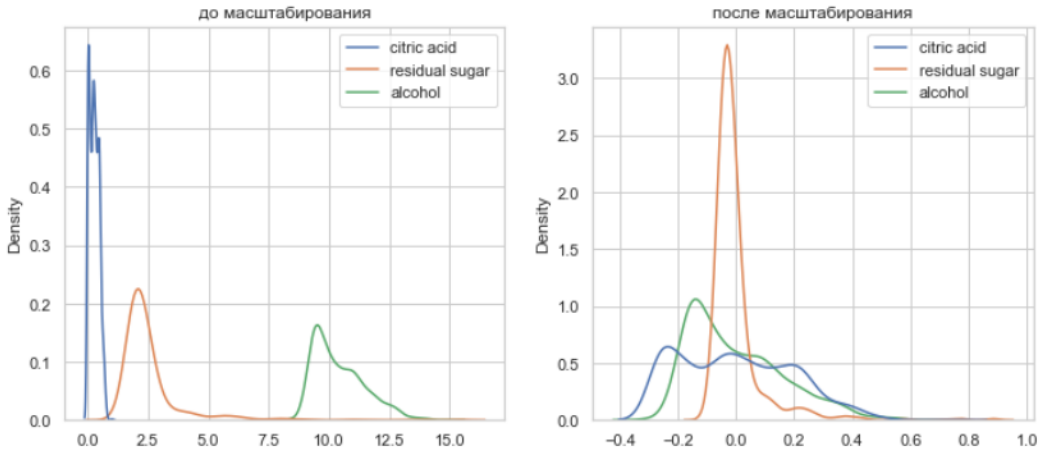
	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total su dio
count	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e
mean	-2.036277e-16	1.144609e-15	-1.260284e-16	4.019177e-16	-7.763403e-18	1.086399e
std	1.226436e-01	1.948011e-01	9.657042e-02	7.857313e-02	1.473301e-01	1.162400e
min	-2.793291e-01	-2.709756e-01	-1.122470e-01	-1.259875e-01	-2.095147e-01	-1.4299
25%	-9.439761e-02	-1.809756e-01	-4.375380e-02	-2.915950e-02	-1.250077e-01	-8.6460
50%	-5.356516e-03	-1.097561e-02	-2.320586e-02	-1.413446e-02	-2.641616e-02	-2.9923
75%	7.683527e-02	1.490244e-01	4.191404e-03	4.229480e-03	7.217539e-02	5.488192e
max	7.206709e-01	7.290244e-01	8.877530e-01	8.740125e-01	7.904853e-01	8.570021e

:
```
cs22 = MeanNormalisation()
cs22.fit(train_data)
data_cs22_scaled_train = cs22.transform(train_data)
```

:
```
data_cs22_scaled_train.describe()
```

	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total su diox
count	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e+03	1.599000e
mean	-2.036277e-16	1.144609e-15	-1.260284e-16	4.019177e-16	-7.763403e-18	1.086399e
std	1.226436e-01	1.948011e-01	9.657042e-02	7.857313e-02	1.473301e-01	1.162400e
min	-2.793291e-01	-2.709756e-01	-1.122470e-01	-1.259875e-01	-2.095147e-01	-1.42997
25%	-9.439761e-02	-1.809756e-01	-4.375380e-02	-2.915950e-02	-1.250077e-01	-8.64608
50%	-5.356516e-03	-1.097561e-02	-2.320586e-02	-1.413446e-02	-2.641616e-02	-2.99237
75%	7.683527e-02	1.490244e-01	4.191404e-03	4.229480e-03	7.217539e-02	5.488192e
max	7.206709e-01	7.290244e-01	8.877530e-01	8.740125e-01	7.904853e-01	8.570021e

```
draw_kde(['citric acid', 'residual sugar', 'alcohol'], data, data_cs21_scaled, '
```



MinMax-масштабирование

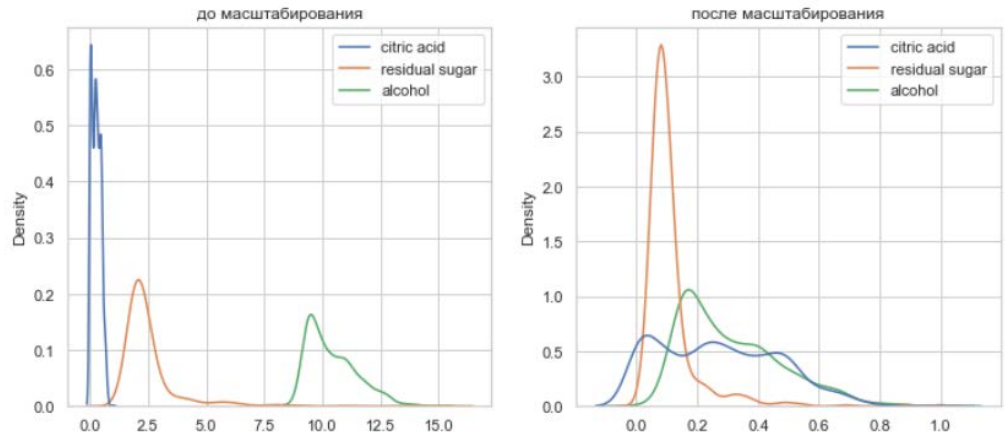
$x' = x - \min(x) \max(x) - \min(x)$

```
cs31 = MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(data)
# формируем DataFrame на основе массива
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()
```

	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	1
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	
mean	0.279329	0.270976	0.112247	0.125988	0.209515	0.142998	
std	0.122644	0.194801	0.096570	0.078573	0.147330	0.116240	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.184932	0.090000	0.068493	0.096828	0.084507	0.056537	
50%	0.273973	0.260000	0.089041	0.111853	0.183099	0.113074	
75%	0.356164	0.420000	0.116438	0.130217	0.281690	0.197880	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

```
cs32 = MinMaxScaler()
cs32.fit(train_data)
data_cs32_scaled_train_temp = cs32.transform(train_data)
# формируем DataFrame на основе массива
data_cs32_scaled_train = arr_to_df(data_cs32_scaled_train_temp)
```

```
draw_kde(['citric acid', 'residual sugar', 'alcohol'], data, data_cs31_scaled, '
```

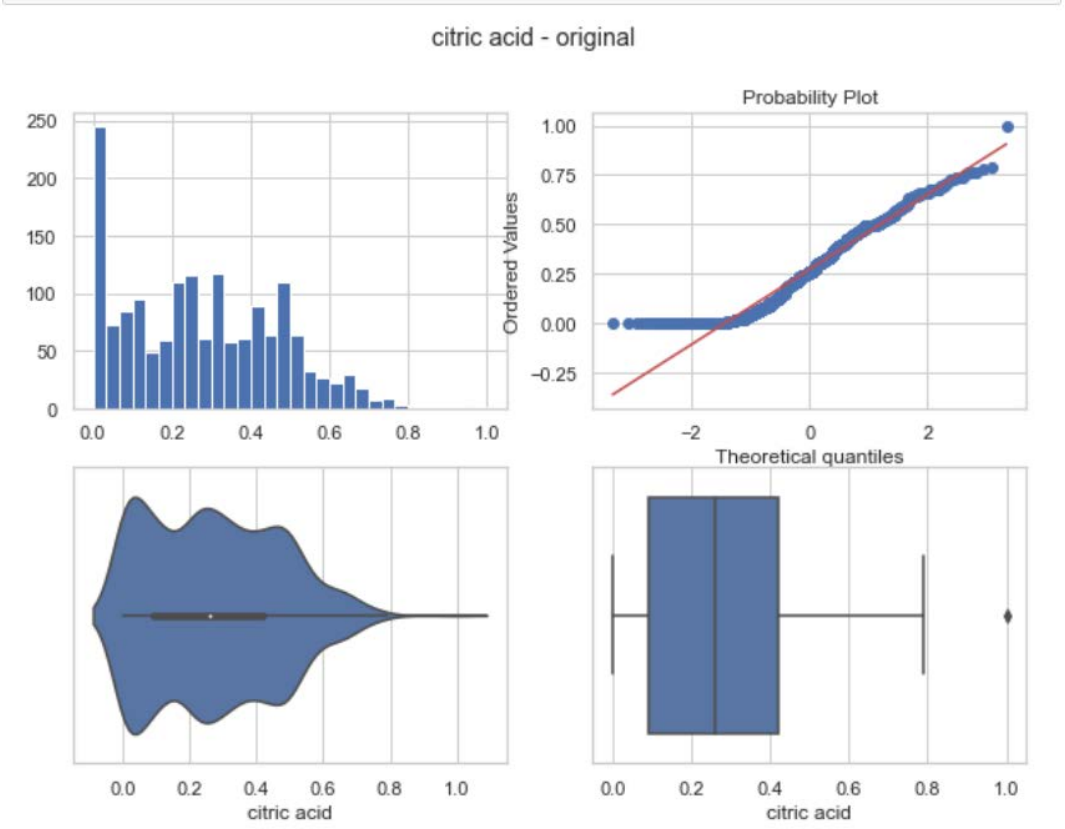


Обработка выбросов

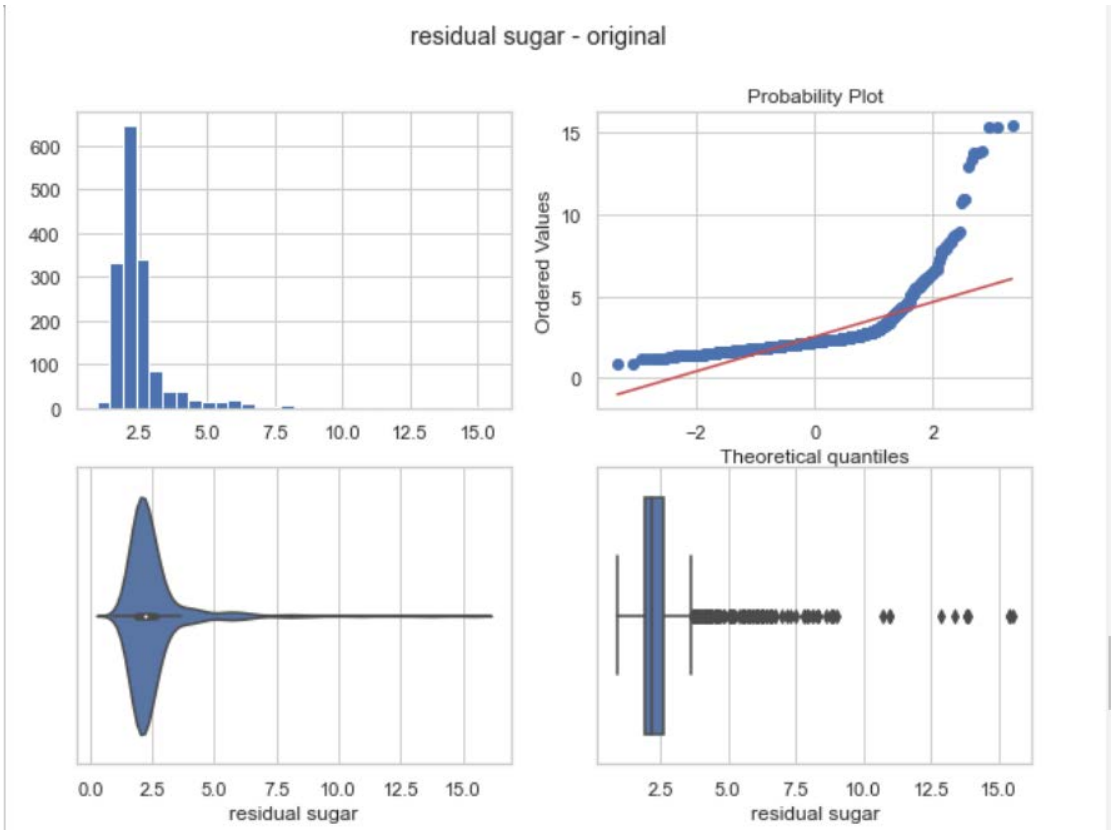
```
x_col_list = ['citric acid', 'residual sugar', 'alcohol']
```

```
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()
```

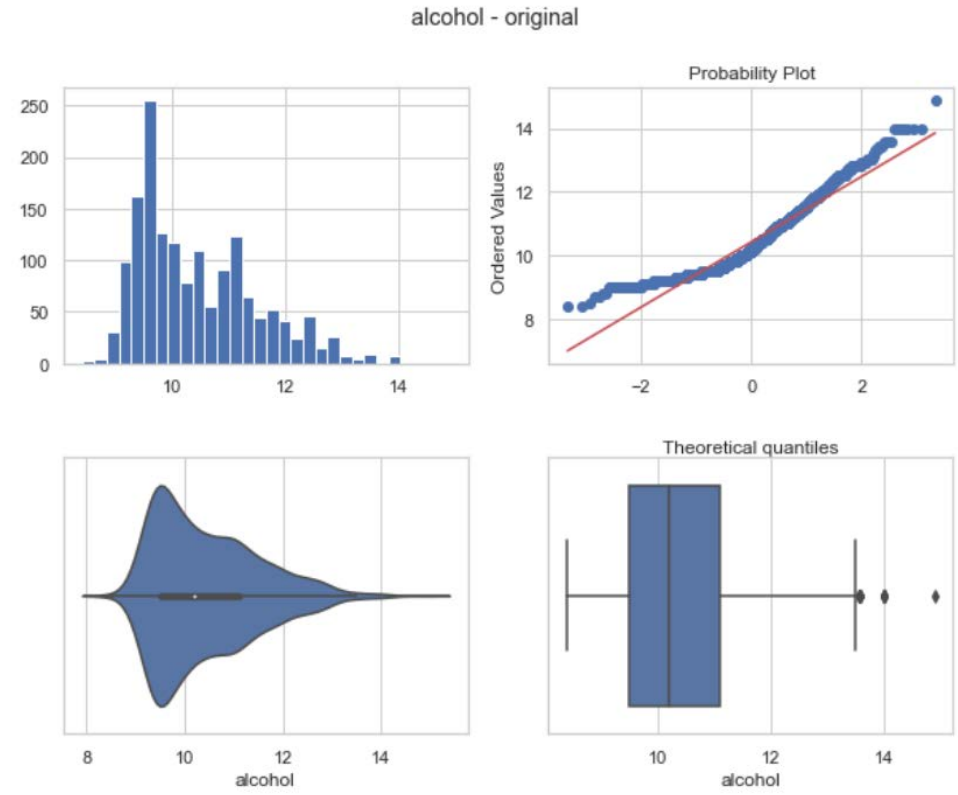
```
diagnostic_plots(data, 'citric acid', 'citric acid - original')
```




```
]: diagnostic_plots(data, 'residual sugar', 'residual sugar - original')
```




```
diagnostic_plots(data, 'alcohol', 'alcohol - original')
```

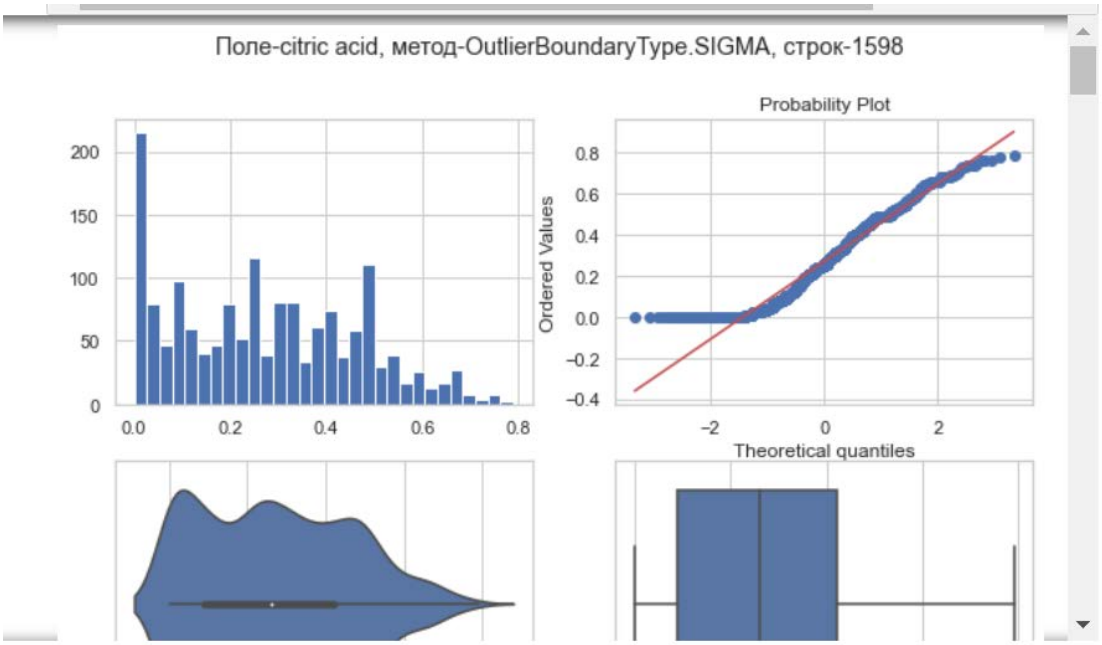


```
# Тип вычисления верхней и нижней границы вы
from enum import Enum
class OutlierBoundaryType(Enum):
    SIGMA = 1
    QUANTILE = 2
    IRQ = 3
```

```
]: 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
```

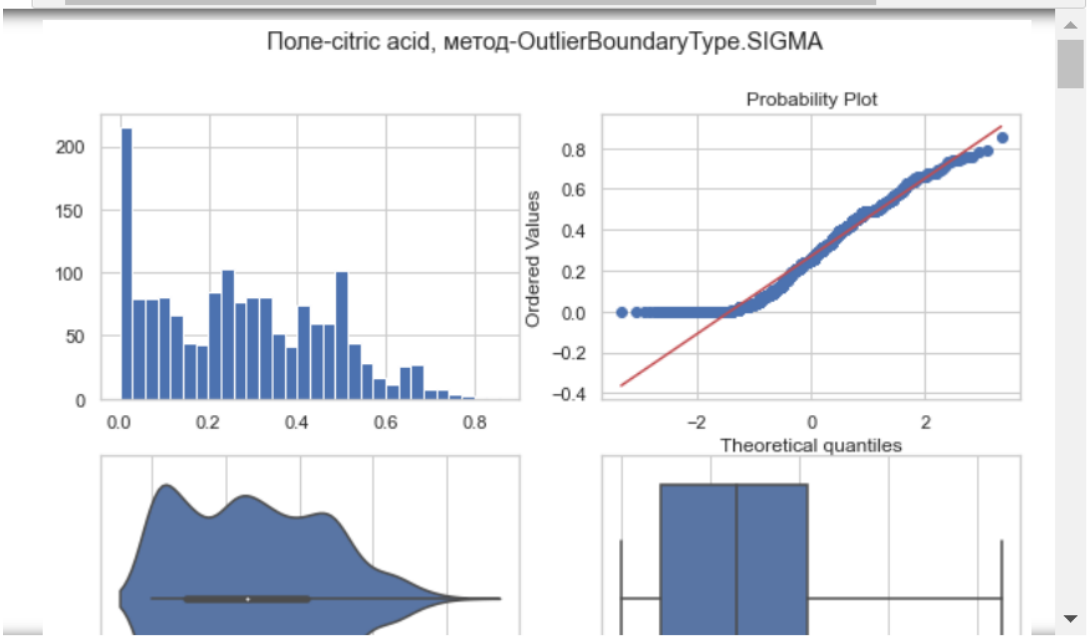
Удаление выбросов

```
: for col in x_col_list:
    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, Fals
        # Удаление данных на основе флага
        data_trimmed = data.loc[~(outliers_temp), ]
        title = 'Поле-{}, метод-{}, строк-{}'.format(col, obt, dat
        diagnostic_plots(data_trimmed, col, title)
```



Замена выбросов

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



Feature selection

Методы фильтрации (filter methods)

```
lst_arr_1211 = [[1, 2, 1, 21], [1, 2, 2, 22], [1, 2, 3, 23], [1, 2, 4, 24],
                [1, 2, 5, 25], [1, 2, 6, 26], [1, 2, 7, 27], [1, 1, 8, 28]]
arr_1211 = np.array(lst_arr_1211)
data_1211 = pd.DataFrame(arr_1211, columns=['f1', 'f2', 'f3', 'f4'])
data_1211
```

	f1	f2	f3	f4
0	1	2	1	21
1	1	2	2	22
2	1	2	3	23
3	1	2	4	24
4	1	2	5	25
5	1	2	6	26
6	1	2	7	27
7	1	1	8	28

```
selector_1211 = VarianceThreshold(threshold=0.15)
selector_1211.fit(data_1211)
# Значения дисперсий для каждого признака
selector_1211.variances_
```

```
array([0.       , 0.109375, 5.25    , 5.25    ])
```

```
selector_1211.transform(data_1211)
```

```
array([[ 1, 21],
       [ 2, 22],
       [ 3, 23],
       [ 4, 24],
       [ 5, 25],
       [ 6, 26],
       [ 7, 27],
       [ 8, 28]])
```

```
lst_arr_1212 = [[21, 1, 2, 21, 1, 3, 21],
                [22, 2, 2, 22, 2, 3, 22],
                [23, 3, 2, 23, 3, 3, 23],
                [24, 4, 2, 24, 4, 3, 24]]
arr_1212 = np.array(lst_arr_1212)
data_1212 = pd.DataFrame(arr_1212, columns=['f1', 'f2', 'f3', 'f4', 'f5', 'f6',
data_1212
```

	f1	f2	f3	f4	f5	f6	f7
0	21	1	2	21	1	3	21
1	22	2	2	22	2	3	22
2	23	3	2	23	3	3	23
3	24	4	2	24	4	3	24

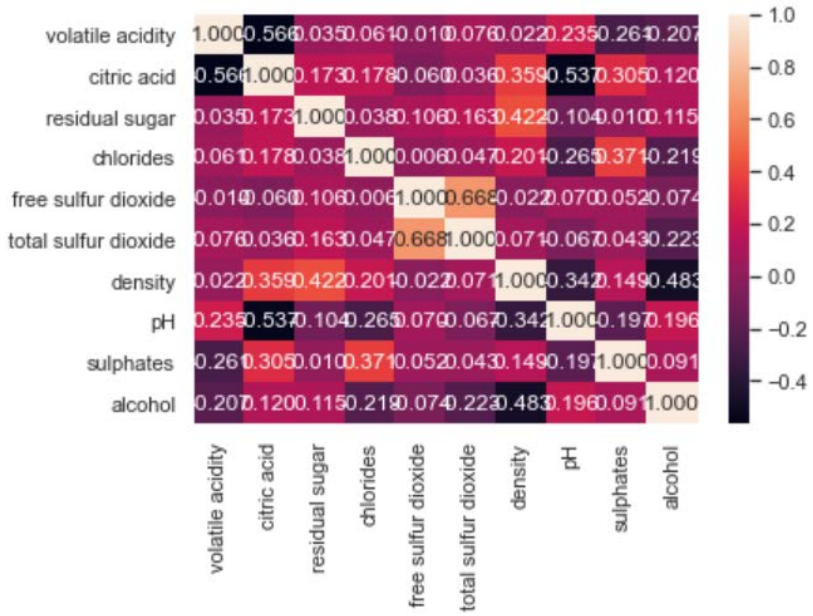
```
def get_duplicates(X):
    """
    Поиск дубликатов в колонках
    X - DataFrame
    """

    pairs = {}
    dups = []

    # Перебор всех колонок (внешний)
    for i in range(X.shape[1]):

        # текущая колонка
        feat_outer = X.columns[i]

        # если текущая колонка не является дубл
        if feat_outer not in dups:

            # создаем запись в словаре, колонка яв
            pairs[feat_outer] = []

            # Перебор оставшихся колонок (внутрен
            for feat_inner in X.columns[i + 1:]:

                # Если колонки идентичны
                if X[feat_outer].equals(X[feat_inner]):

                    # добавление в словарь и список д
                    pairs[feat_outer].append(feat_inner)
                    dups.append(feat_inner)

    return pairs
```

```
get_duplicates(data_1212)
```

```
{'f1': ['f4', 'f7'], 'f2': ['f5'], 'f3': [], 'f6': []}
```

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

```
<AxesSubplot:>
```




```
# Формирование DataFrame с сильными корреляциями
def make_corr_df(df):
    cr = data.corr()
    cr = cr.abs().unstack()
    cr = cr.sort_values(ascending=False)
    cr = cr[cr >= 0.8]
    cr = cr[cr < 1]
    cr = pd.DataFrame(cr).reset_index()
    cr.columns = ['f1', 'f2', 'corr']
    return cr
```

```
make_corr_df(data)
```

	f1	f2	corr

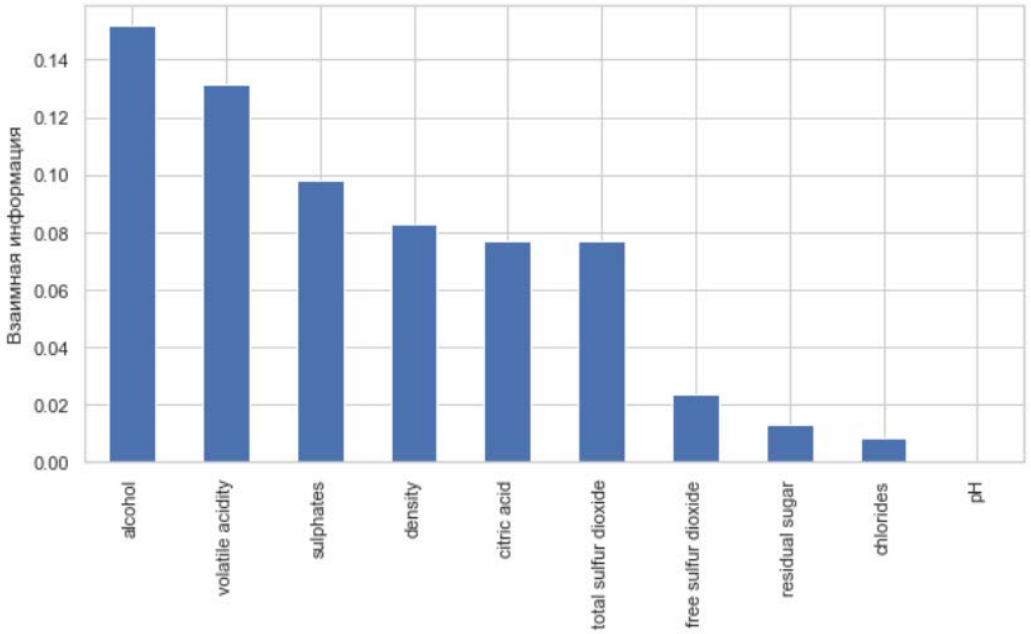
```
def corr_groups(cr):
    grouped_feature_list = []
    correlated_groups = []

    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))
```

```
[]
```

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

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



```
sel_mi = SelectKBest(mutual_info_regression, k=5).fit(data, train_y)

list(zip(features, sel_mi.get_support()))
```

```
[('volatile acidity', True),
 ('citric acid', False),
 ('residual sugar', False),
 ('chlorides', False),
 ('free sulfur dioxide', False),
 ('total sulfur dioxide', True),
 ('density', True),
 ('pH', False),
 ('sulphates', True),
 ('alcohol', True)]
```

```
features[sel_mi.get_support()]
```

```
Index(['volatile acidity', 'total sulfur dioxide', 'density', 'sulphates',
       'alcohol'],
      dtype='object')
```

Список литературы

[1] Гапанюк Ю. Е. Лабораторная работа «Обработка признаков (часть2)» [Электронный ресурс] https://github.com/ugapanyuk/ml_course_2021/wiki/LAB_MMO__FEATURES