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Факультет «Информатика и системы управления»

Кафедра «Системы обработки информации и управления»

ОТЧЁТ ПО

Лабораторной работе №4

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```
In [1]: import numpy as np
import pandas as pd
import sklearn
from typing import Dict, Tuple
from scipy import stats
from sklearn import datasets
from sklearn import model_selection
from sklearn.datasets import load_digits, load_wine
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classificat
from sklearn.metrics import confusion_matrix
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_square
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.linear_model import SGDClassifier
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR, LinearSV
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

Загрузка и первичный анализ данных

```
In [2]: wine = load_wine()
```

```
In [3]: wine.feature_names
```

```
Out[3]: ['alcohol',
 'malic_acid',
 'ash',
 'alcalinity_of_ash',
 'magnesium',
 'total_phenols',
 'flavanoids',
 'nonflavanoid_phenols',
 'proanthocyanins',
 'color_intensity',
 'hue',
 'od280/od315_of_diluted_wines',
 'proline']
```

```
In [4]: wine.data[:13]
```

```
Out[4]: array([[1.423e+01, 1.710e+00, 2.430e+00, 1.560e+01, 1.270e+02, 2.800e+00,
                3.060e+00, 2.800e-01, 2.290e+00, 5.640e+00, 1.040e+00, 3.920e+00,
                1.065e+03],
               [1.320e+01, 1.780e+00, 2.140e+00, 1.120e+01, 1.000e+02, 2.650e+00,
                2.760e+00, 2.600e-01, 1.280e+00, 4.380e+00, 1.050e+00, 3.400e+00,
                1.050e+03],
               [1.316e+01, 2.360e+00, 2.670e+00, 1.860e+01, 1.010e+02, 2.800e+00,
                3.240e+00, 3.000e-01, 2.810e+00, 5.680e+00, 1.030e+00, 3.170e+00,
                1.185e+03],
               [1.437e+01, 1.950e+00, 2.500e+00, 1.680e+01, 1.130e+02, 3.850e+00,
                3.490e+00, 2.400e-01, 2.180e+00, 7.800e+00, 8.600e-01, 3.450e+00,
                1.480e+03],
               [1.324e+01, 2.590e+00, 2.870e+00, 2.100e+01, 1.180e+02, 2.800e+00,
                2.690e+00, 3.900e-01, 1.820e+00, 4.320e+00, 1.040e+00, 2.930e+00,
                7.350e+02],
               [1.420e+01, 1.760e+00, 2.450e+00, 1.520e+01, 1.120e+02, 3.270e+00,
                3.390e+00, 3.400e-01, 1.970e+00, 6.750e+00, 1.050e+00, 2.850e+00,
                1.450e+03],
               [1.439e+01, 1.870e+00, 2.450e+00, 1.460e+01, 9.600e+01, 2.500e+00,
                2.520e+00, 3.000e-01, 1.980e+00, 5.250e+00, 1.020e+00, 3.580e+00,
                1.290e+03],
               [1.406e+01, 2.150e+00, 2.610e+00, 1.760e+01, 1.210e+02, 2.600e+00,
                2.510e+00, 3.100e-01, 1.250e+00, 5.050e+00, 1.060e+00, 3.580e+00,
                1.295e+03],
               [1.483e+01, 1.640e+00, 2.170e+00, 1.400e+01, 9.700e+01, 2.800e+00,
                2.980e+00, 2.900e-01, 1.980e+00, 5.200e+00, 1.080e+00, 2.850e+00,
                1.045e+03],
               [1.386e+01, 1.350e+00, 2.270e+00, 1.600e+01, 9.800e+01, 2.980e+00,
                3.150e+00, 2.200e-01, 1.850e+00, 7.220e+00, 1.010e+00, 3.550e+00,
                1.045e+03],
               [1.410e+01, 2.160e+00, 2.300e+00, 1.800e+01, 1.050e+02, 2.950e+00,
                3.320e+00, 2.200e-01, 2.380e+00, 5.750e+00, 1.250e+00, 3.170e+00,
                1.510e+03],
               [1.412e+01, 1.480e+00, 2.320e+00, 1.680e+01, 9.500e+01, 2.200e+00,
                2.430e+00, 2.600e-01, 1.570e+00, 5.000e+00, 1.170e+00, 2.820e+00,
                1.280e+03],
               [1.375e+01, 1.730e+00, 2.410e+00, 1.600e+01, 8.900e+01, 2.600e+00,
                2.760e+00, 2.900e-01, 1.810e+00, 5.600e+00, 1.150e+00, 2.900e+00,
                1.320e+03]])
```

```
In [5]: type(wine.data)
```

```
Out[5]: numpy.ndarray
```

```
In [6]: np.unique(wine.target)
```

```
Out[6]: array([0, 1, 2])
```

```
In [7]: wine.target_names
```

```
Out[7]: array(['class_0', 'class_1', 'class_2'], dtype='<U7')
```

```
In [8]: list(zip(np.unique(wine.target), wine.target_names))
```

```
Out[8]: [(0, 'class_0'), (1, 'class_1'), (2, 'class_2')]
```

```
In [9]: # Значения целевого признака
        wine.target
```

```
Out[9]: array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2,
               2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
               2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
               2, 2])
```

```
In [10]: # Размер выборки
wine.data.shape, wine.target.shape
```

```
Out[10]: ((178, 13), (178,))
```

```
In [11]: # Сформируем DataFrame
wine_df = pd.DataFrame(data= np.c_[wine['data'], wine['target']],
                       columns= wine['feature_names'] + ['target'])
```

```
In [12]: # И выведем его статистические характеристики
wine_df.describe()

# Для обучения моделей не обязательно создавать DataFrame
# можно использовать массивы numpy
```

Out[12]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000

Подготовка данных

```
In [13]: # Подготовка данных
wine_x_ds = pd.DataFrame(data=wine['data'], columns=wine['feature_names'])
wine_x_ds_lr = wine_x_ds[['alcohol', 'flavanoids']]
wine_x_ds_lr['x0'] = 1
wine_x_ds_lr['target'] = wine.target
wine_x_ds_lr.head()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\1075460079.py:4: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  wine_x_ds_lr['x0'] = 1
C:\Users\user\AppData\Local\Temp\ipykernel_13056\1075460079.py:5: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  wine_x_ds_lr['target'] = wine.target
```

Out[13]:

	alcohol	flavanoids	x0	target
0	14.23	3.06	1	0
1	13.20	2.76	1	0
2	13.16	3.24	1	0
3	14.37	3.49	1	0
4	13.24	2.69	1	0

In [14]:
```
def convert_target_to_binary(array:np.ndarray, target:int) -> np.ndarray:
    # Если целевой признак совпадает с указанным, то 1 иначе 0
    res = [1 if x==target else 0 for x in array]
    return res
```

In [15]:
```
bin_wine_y = convert_target_to_binary(wine.target, 0)
```

In [16]:
```
wine_x_ds_lr['target_bin'] = bin_wine_y
wine_x_ds_lr.head()
```

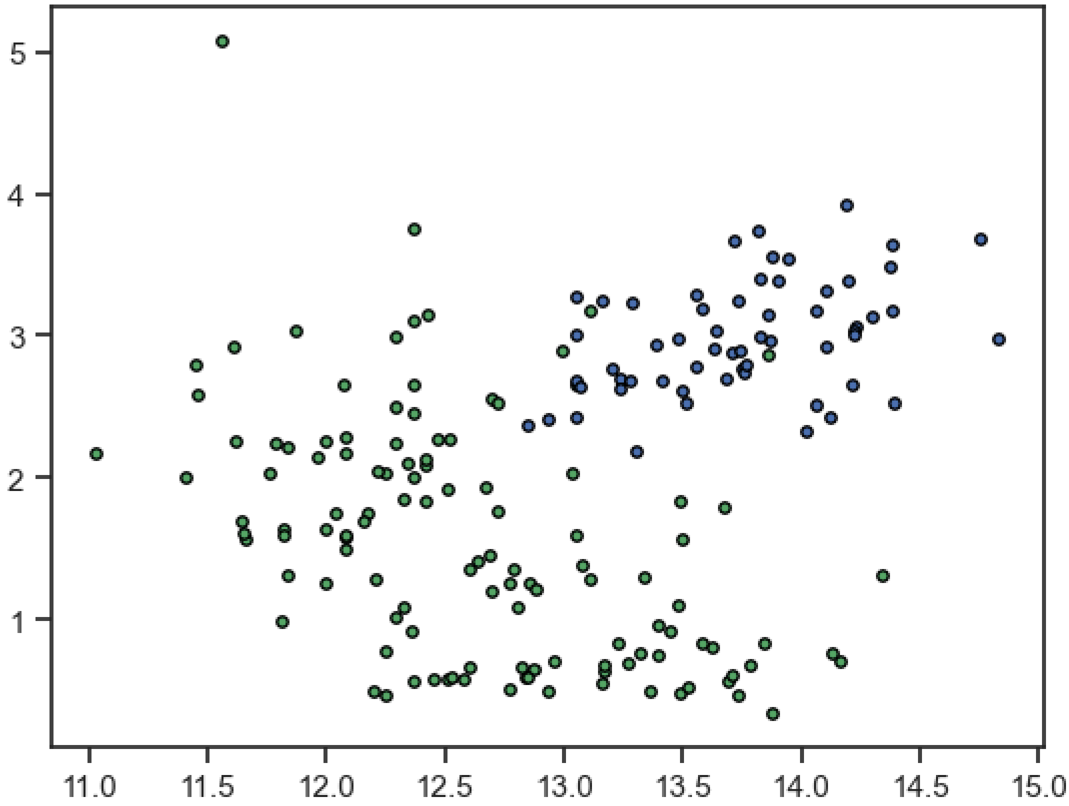
```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\974887079.py:1: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  wine_x_ds_lr['target_bin'] = bin_wine_y
```

Out[16]:

	alcohol	flavanoids	x0	target	target_bin
0	14.23	3.06	1	0	1
1	13.20	2.76	1	0	1
2	13.16	3.24	1	0	1
3	14.37	3.49	1	0	1
4	13.24	2.69	1	0	1

In [17]:
```
# Визуализация данных
colors = "gb"
#X_viz = iris.data[:, [1,2]]
X_viz = wine_x_ds_lr[['alcohol', 'flavanoids']].values
y_viz = wine_x_ds_lr['target_bin'].values
n_classes = len(np.unique(y_viz))
for i, color in zip(range(n_classes), colors):
    idx = np.where(y_viz == i)
    plt.scatter(X_viz[idx, 0], X_viz[idx, 1],
                c=color,
                cmap=plt.cm.RdYlBu,
                edgecolor='black', s=15)
plt.show()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\3044211854.py:9: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X_viz[idx, 0], X_viz[idx, 1],
```



In [18]:
```
# Реализация градиентного спуска
def sigmoid(x):
    '''
    Функция - сигмоида
    '''
    return 1 / (1 + np.exp(-x))

def proba(b, x):
    '''
    Вероятность единичного класса
    '''
    return sigmoid(np.dot(x,b))

def cost_function(b, x, y):
    '''
    Функция потерь
    '''
```

```python
    k = x.shape[0]
    res = -(1 / k) * np.sum(
        y * np.log(proba(b, x))
        + (1 - y) * np.log(1 - proba(b, x)))
    return res

def gradient(b, x, y):
    '''
    Определение градиента
    '''
    k = x.shape[0]
    res = (1 / k) * np.dot(
        x.T, (proba(b, x) - y))

def optimize_lr(x, y, b):
    '''
    Для оптимизации используется функция
    scipy.optimize.fmin_tnc
    '''
    opt_weights = fmin_tnc(
        func=cost_function,
        x0=b,
        fprime=gradient,
        approx_grad=True,
        args=(x, y))
    return opt_weights[0]
```

In [19]:
```python
opt_x = wine_x_ds_lr[['x0', 'alcohol', 'flavanoids']].values
opt_x[:5]
```

Out[19]:
```
array([[ 1.   , 14.23,  3.06],
       [ 1.   , 13.2 ,  2.76],
       [ 1.   , 13.16,  3.24],
       [ 1.   , 14.37,  3.49],
       [ 1.   , 13.24,  2.69]])
```

In [20]:
```python
opt_y = wine_x_ds_lr['target_bin']
opt_y[:5]
```

Out[20]:
```
0    1
1    1
2    1
3    1
4    1
Name: target_bin, dtype: int64
```

In [21]:
```python
b_init = np.zeros(3)
b_init
```

Out[21]:
```
array([0., 0., 0.])
```

In [22]:
```python
from scipy.optimize import fmin_tnc
b_res = optimize_lr(opt_x, opt_y, b_init)
b_res
```

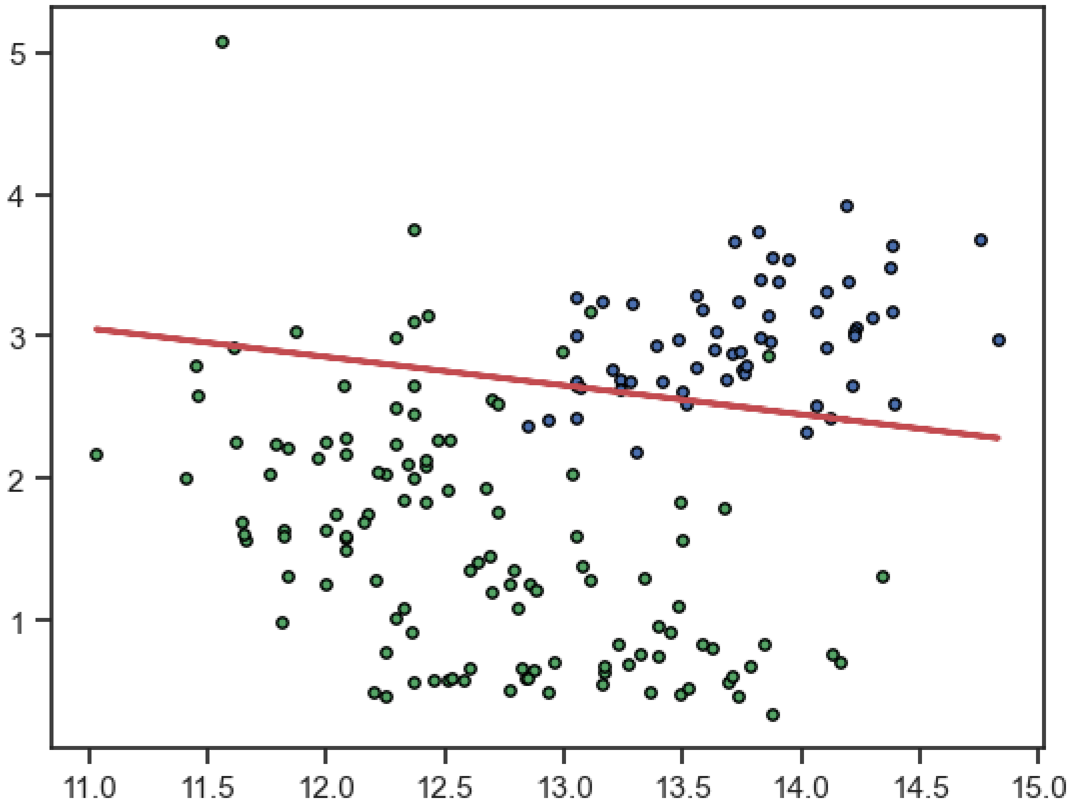
```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\3126456101.py:21: RuntimeWarnin
g: divide by zero encountered in log
  + (1 - y) * np.log(1 - proba(b, x)))
C:\Users\user\AppData\Local\Temp\ipykernel_13056\3126456101.py:21: RuntimeWarnin
g: divide by zero encountered in log
  + (1 - y) * np.log(1 - proba(b, x)))
C:\Users\user\anaconda3\Lib\site-packages\scipy\optimize\_numdiff.py:576: Runtime
Warning: invalid value encountered in subtract
  df = fun(x) - f0
C:\Users\user\AppData\Local\Temp\ipykernel_13056\3126456101.py:21: RuntimeWarnin
g: divide by zero encountered in log
  + (1 - y) * np.log(1 - proba(b, x)))
C:\Users\user\anaconda3\Lib\site-packages\scipy\optimize\_numdiff.py:576: Runtime
Warning: invalid value encountered in subtract
  df = fun(x) - f0
C:\Users\user\AppData\Local\Temp\ipykernel_13056\3126456101.py:21: RuntimeWarnin
g: divide by zero encountered in log
  + (1 - y) * np.log(1 - proba(b, x)))
C:\Users\user\anaconda3\Lib\site-packages\scipy\optimize\_numdiff.py:576: Runtime
Warning: invalid value encountered in subtract
  df = fun(x) - f0
```

Out[22]:
```
array([-11.10840839,   0.42401794,   2.1097742 ])
```

In [23]:
```
def vis_lr(b):
    '''
    Визуализация результата
    '''
    colors = "gb"
    X_viz = wine_x_ds_lr[['alcohol', 'flavanoids']].values
    y_viz = wine_x_ds_lr['target_bin'].values
    n_classes = len(np.unique(y_viz))
    for i, color in zip(range(n_classes), colors):
        idx = np.where(y_viz == i)
        plt.scatter(X_viz[idx, 0], X_viz[idx, 1],
                    c=color,
                    cmap=plt.cm.RdYlBu,
                    edgecolor='black', s=15)

    t1 = wine_x_ds_lr['alcohol'].values
    t2 = -((b[0]+np.dot(b[1], t1))/b[2])
    plt.plot(t1, t2, 'r', linewidth=2.0)
    plt.show()
```

In [24]:
```
vis_lr(b_res)
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\544148779.py:11: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X_viz[idx, 0], X_viz[idx, 1],
```



Разделяем выборку на тестовую и обучающую

In [25]:
```
from sklearn.linear_model import LogisticRegression
```

In [26]:
```
wine_X_train, wine_X_test, wine_y_train, wine_y_test = train_test_split(
    wine_x_ds_lr[['alcohol', 'flavanoids']].values,
    wine_x_ds_lr['target_bin'].values, test_size=0.3, random_state=1)
```

Логистическая регрессия

In [27]:
```
cl1 = LogisticRegression()
```

In [28]:
```
cl1.fit(wine_X_train, wine_y_train)
```

Out[28]:
```
▾ LogisticRegression
LogisticRegression()
```

In [29]:
```
pred_wine_y_test = cl1.predict(wine_X_test)
pred_wine_y_test
```

Out[29]:
```
array([0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1,
       1, 1, 0, 1, 1, 1, 0, 0, 0, 1], dtype=int64)
```

In [30]:
```
pred_wine_y_test_proba = cl1.predict_proba(wine_X_test)
pred_wine_y_test_proba[:10]
```

Out[30]:
```
array([[0.93969011, 0.06030989],
       [0.94033901, 0.05966099],
       [0.13373648, 0.86626352],
       [0.99179808, 0.00820192],
       [0.15318867, 0.84681133],
       [0.96651156, 0.03348844],
       [0.98788521, 0.01211479],
       [0.00857351, 0.99142649],
       [0.99415987, 0.00584013],
       [0.93671187, 0.06328813]])
```

In [31]:
```
# Вероятность принадлежности к 0 классу
[round(x, 4) for x in pred_wine_y_test_proba[:10,0]]
```

Out[31]:
```
[0.9397,
 0.9403,
 0.1337,
 0.9918,
 0.1532,
 0.9665,
 0.9879,
 0.0086,
 0.9942,
 0.9367]
```

In [32]:
```
# Вероятность принадлежности к 1 классу
[round(x, 4) for x in pred_wine_y_test_proba[:10,1]]
```

Out[32]:
```
[0.0603,
 0.0597,
 0.8663,
 0.0082,
 0.8468,
 0.0335,
 0.0121,
 0.9914,
 0.0058,
 0.0633]
```

In [33]:
```
# Сумма вероятностей равна 1
pred_wine_y_test_proba[:10,0] + pred_wine_y_test_proba[:10,1]
```

Out[33]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

Оценка качества

In [34]:
```
accuracy_score(wine_y_test, pred_wine_y_test)
```

Out[34]:
```
0.9814814814814815
```

In [35]:
```
def accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    """
    Вычисление метрики accuracy для каждого класса
    y_true - истинные значения классов
    y_pred - предсказанные значения классов
    Возвращает словарь: ключ - метка класса,
```

```
    значение - Accuracy для данного класса
    """
    # Для удобства фильтрации сформируем Pandas DataFrame
    d = {'t': y_true, 'p': y_pred}
    df = pd.DataFrame(data=d)
    # Метки классов
    classes = np.unique(y_true)
    # Результирующий словарь
    res = dict()
    # Перебор меток классов
    for c in classes:
        # отфильтруем данные, которые соответствуют
        # текущей метке класса в истинных значениях
        temp_data_flt = df[df['t']==c]
        # расчет accuracy для заданной метки класса
        temp_acc = accuracy_score(
            temp_data_flt['t'].values,
            temp_data_flt['p'].values)
        # сохранение результата в словарь
        res[c] = temp_acc
    return res

def print_accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray):
    """
    Вывод метрики accuracy для каждого класса
    """
    accs = accuracy_score_for_classes(y_true, y_pred)
    if len(accs)>0:
        print('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))
```

In [36]:
```
print_accuracy_score_for_classes(wine_y_test, pred_wine_y_test)
```

```
Метка    Accuracy
0        0.967741935483871
1        1.0
```

In [37]:
```
confusion_matrix(wine_y_test, pred_wine_y_test, labels=[0, 1])
```

Out[37]:
```
array([[30,  1],
       [ 0, 23]], dtype=int64)
```

SVM

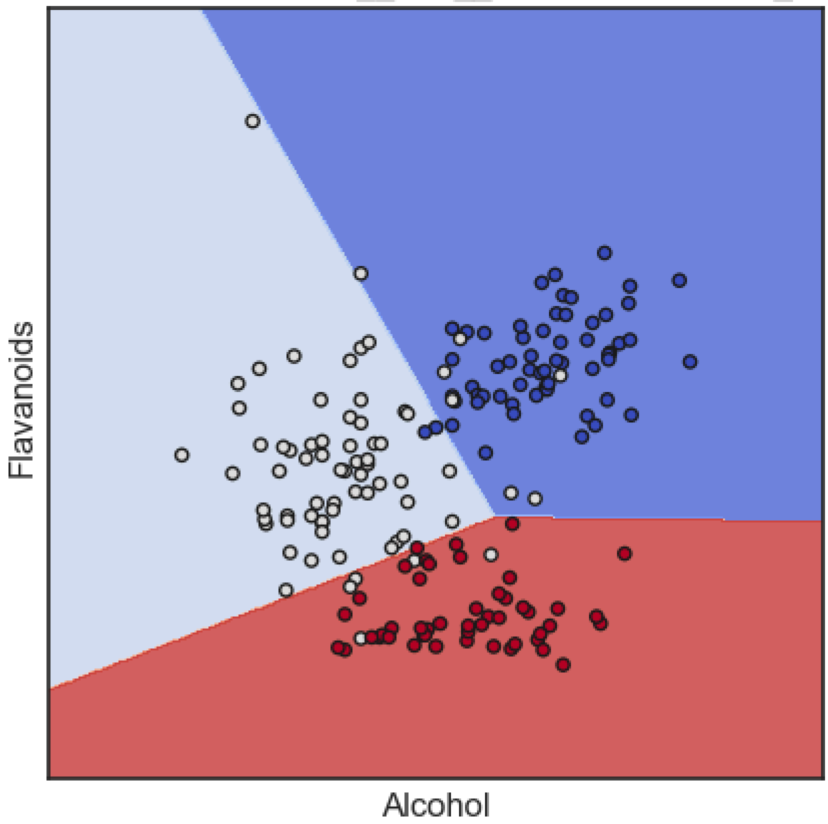
In [38]:
```
wine_X = wine.data[:, [0, 6]]
wine_y = wine.target
```

In [39]:
```
def make_meshgrid(x, y, h=.02):
    """Create a mesh of points to plot in

    Parameters
    ----------
    x: data to base x-axis meshgrid on
    y: data to base y-axis meshgrid on
    h: stepsize for meshgrid, optional
```

```
    Returns
    -------
    xx, yy : ndarray
    """
    x_min, x_max = x.min() - 1, x.max() + 1
    y_min, y_max = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y_min, y_max, h))
    return xx, yy

def plot_contours(ax, clf, xx, yy, **params):
    """Plot the decision boundaries for a classifier.

    Parameters
    ----------
    ax: matplotlib axes object
    clf: a classifier
    xx: meshgrid ndarray
    yy: meshgrid ndarray
    params: dictionary of params to pass to contourf, optional
    """
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    #Можно проверить все ли метки классов предсказываются
    #print(np.unique(Z))
    out = ax.contourf(xx, yy, Z, **params)
    return out


def plot_cl(clf):
    title = clf.__repr__
    clf.fit(wine_X, wine_y)
    fig, ax = plt.subplots(figsize=(5,5))
    X0, X1 = wine_X[:, 0], wine_X[:, 1]
    xx, yy = make_meshgrid(X0, X1)
    plot_contours(ax, clf, xx, yy, cmap=plt.cm.coolwarm, alpha=0.8)
    ax.scatter(X0, X1, c=wine_y, cmap=plt.cm.coolwarm, s=20, edgecolors='k')
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xlabel('Alcohol')
    ax.set_ylabel('Flavanoids')
    ax.set_xticks(())
    ax.set_yticks(())
    ax.set_title(title)
    plt.show()
```

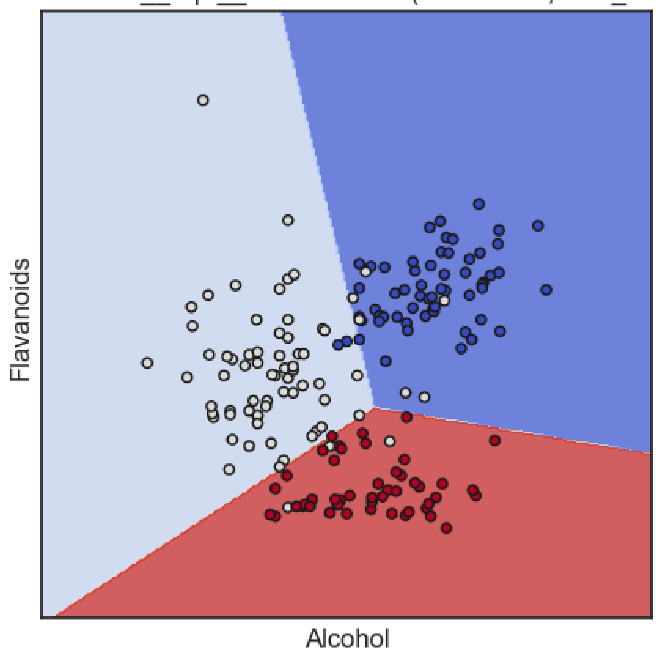
In [40]:
```
plot_cl(LinearSVC(C=1.0, max_iter=10000))
```

<bound method BaseEstimator.__repr__ of LinearSVC(max_iter=10000)>



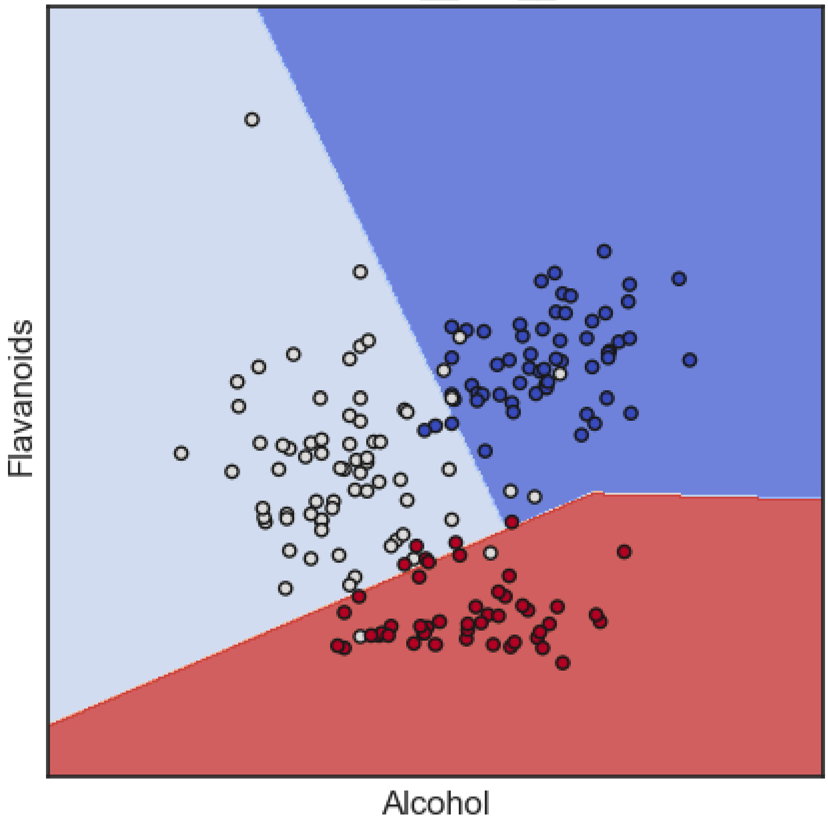
In [41]:
```
plot_cl(LinearSVC(C=1.0, penalty='l1', dual=False, max_iter=10000))
```

<bound method BaseEstimator.__repr__ of LinearSVC(dual=False, max_iter=10000, penalty='l1')>



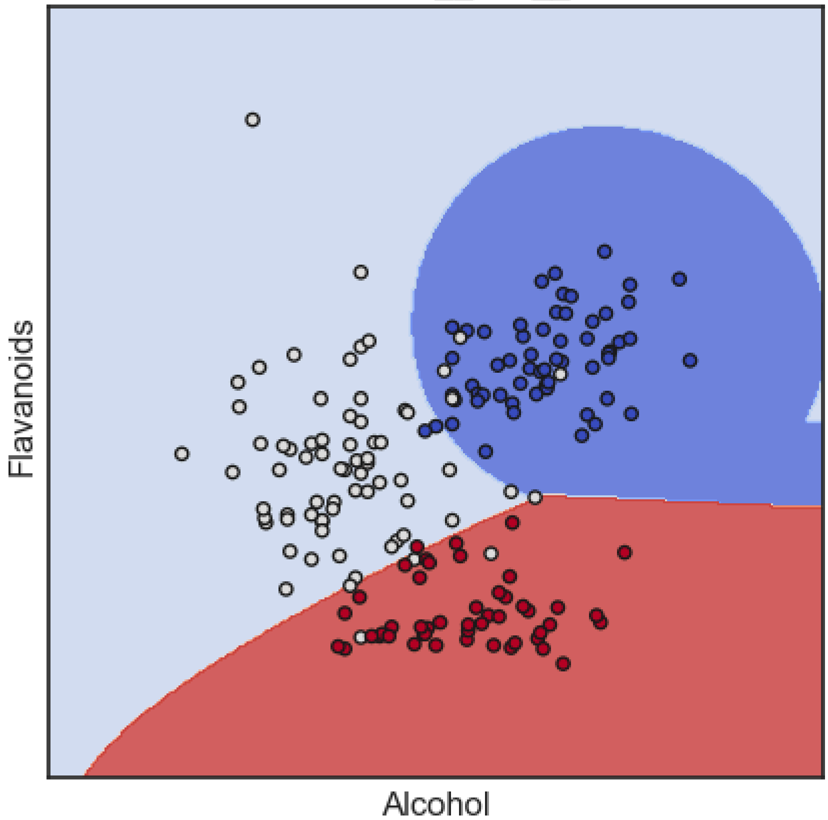
In [42]:
```
plot_cl(SVC(kernel='linear', C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(kernel='linear')>



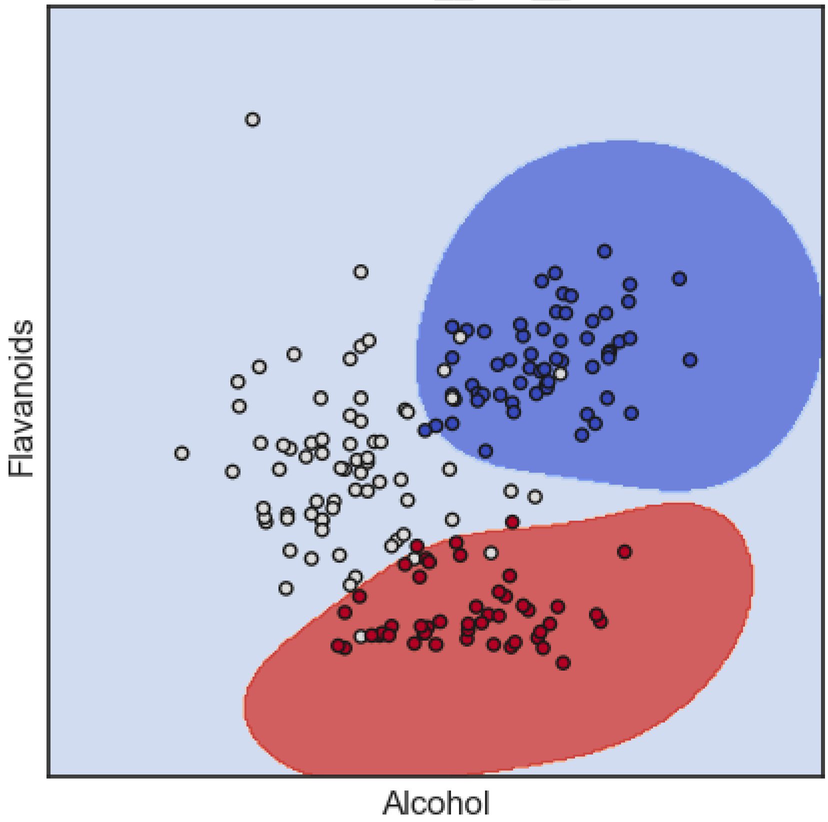
In [43]:
```
plot_cl(SVC(kernel='rbf', gamma=0.2, C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(gamma=0.2)>



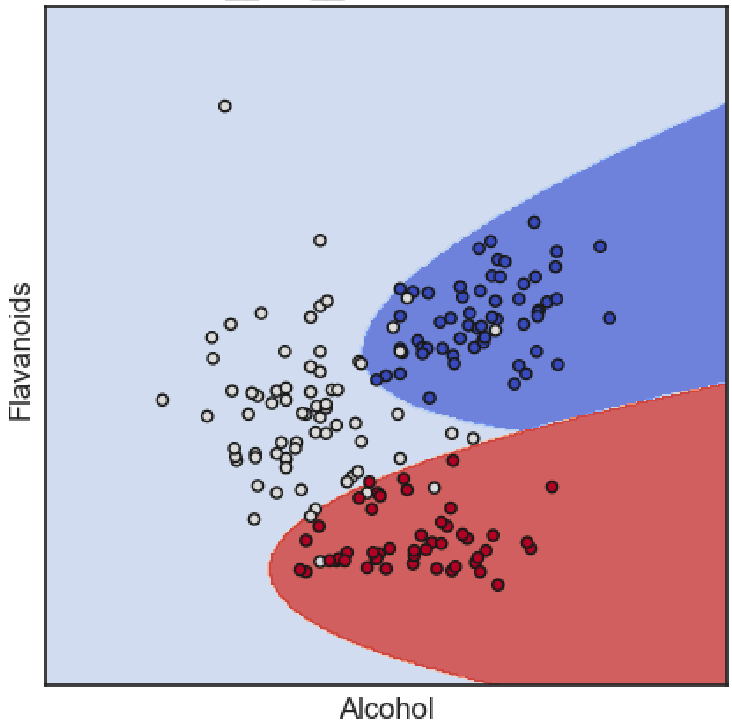
In [44]:
```
plot_cl(SVC(kernel='rbf', gamma=0.9, C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(gamma=0.9)>



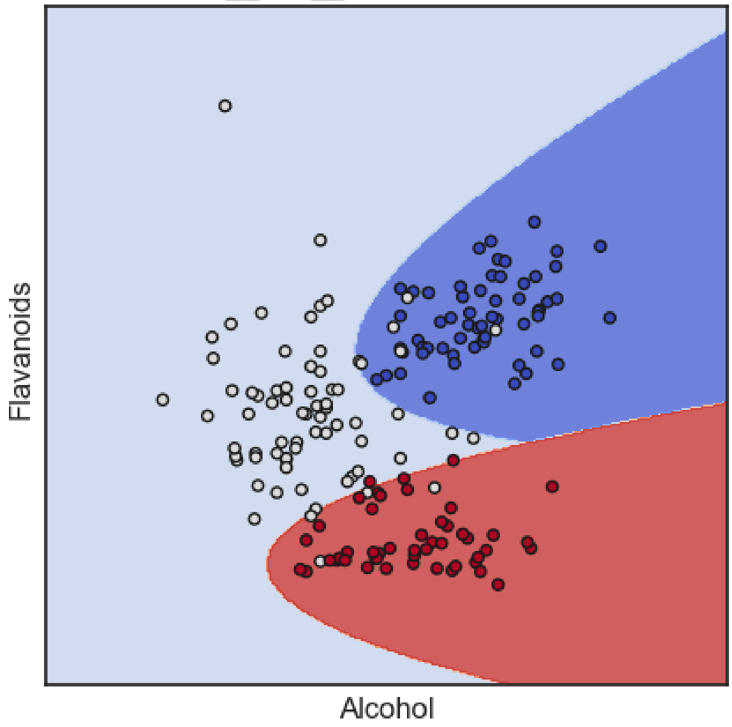
In [45]:
```
plot_cl(SVC(kernel='poly', degree=4, gamma=0.2, C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(degree=4, gamma=0.2, kernel='poly')>



In [46]:
```
plot_cl(SVC(kernel='poly', degree=4, gamma=0.9, C=1.0))
```

<bound method BaseEstimator.__repr__ of SVC(degree=4, gamma=0.9, kernel='poly')>



Дерево решений

In [48]:
```
from io import StringIO
from IPython.display import Image
import graphviz
import pydotplus
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_g
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
%matplotlib inline
```

In [49]:
```
# Визуализация дерева
def get_png_tree(tree_model_param, feature_names_param):
    dot_data = StringIO()
    export_graphviz(tree_model_param, out_file=dot_data, feature_names=feature_n
                    filled=True, rounded=True, special_characters=True)
    graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
    return graph.create_png()
```

In [50]:
```
wine_x_ds = pd.DataFrame(data=wine['data'], columns=wine['feature_names'])
wine_x_ds.head()
```

Out[50]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nc
0	14.23	1.71	2.43	15.6	127.0	2.80	3.06	
1	13.20	1.78	2.14	11.2	100.0	2.65	2.76	
2	13.16	2.36	2.67	18.6	101.0	2.80	3.24	
3	14.37	1.95	2.50	16.8	113.0	3.85	3.49	
4	13.24	2.59	2.87	21.0	118.0	2.80	2.69	

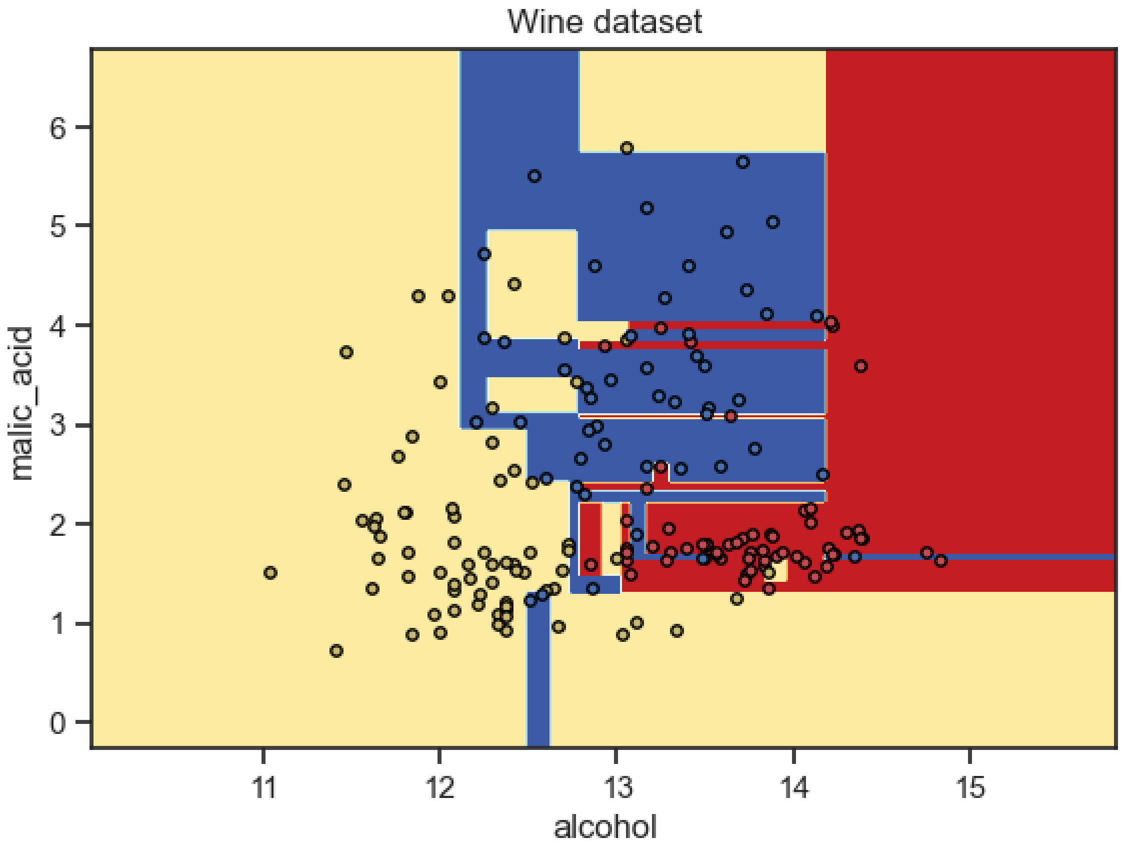
In [51]:

```
def plot_tree_classification(title_param, ds):
    """
    Построение деревьев и вывод графиков для заданного датасета
    """

    n_classes = len(np.unique(ds.target))
    plot_colors = "ryb"
    plot_step = 0.02

    for pairidx, pair in enumerate([[0, 1], [0, 2], [0, 3],
                                    [1, 2], [1, 3], [2, 3]]):
        # We only take the two corresponding features
        X = ds.data[:, pair]
        y = ds.target

        # Train
        clf = DecisionTreeClassifier(random_state=1).fit(X, y)

        plt.title(title_param)

        x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
        y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
        xx, yy = np.meshgrid(np.arange(x_min, x_max, plot_step),
                             np.arange(y_min, y_max, plot_step))
        plt.tight_layout(h_pad=0.5, w_pad=0.5, pad=2.5)

        Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
        Z = Z.reshape(xx.shape)
        cs = plt.contourf(xx, yy, Z, cmap=plt.cm.RdYlBu)

        plt.xlabel(ds.feature_names[pair[0]])
        plt.ylabel(ds.feature_names[pair[1]])

        # Plot the training points
        for i, color in zip(range(n_classes), plot_colors):
            idx = np.where(y == i)
            plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
                        cmap=plt.cm.RdYlBu, edgecolor='black', s=15)

        plt.show()
```

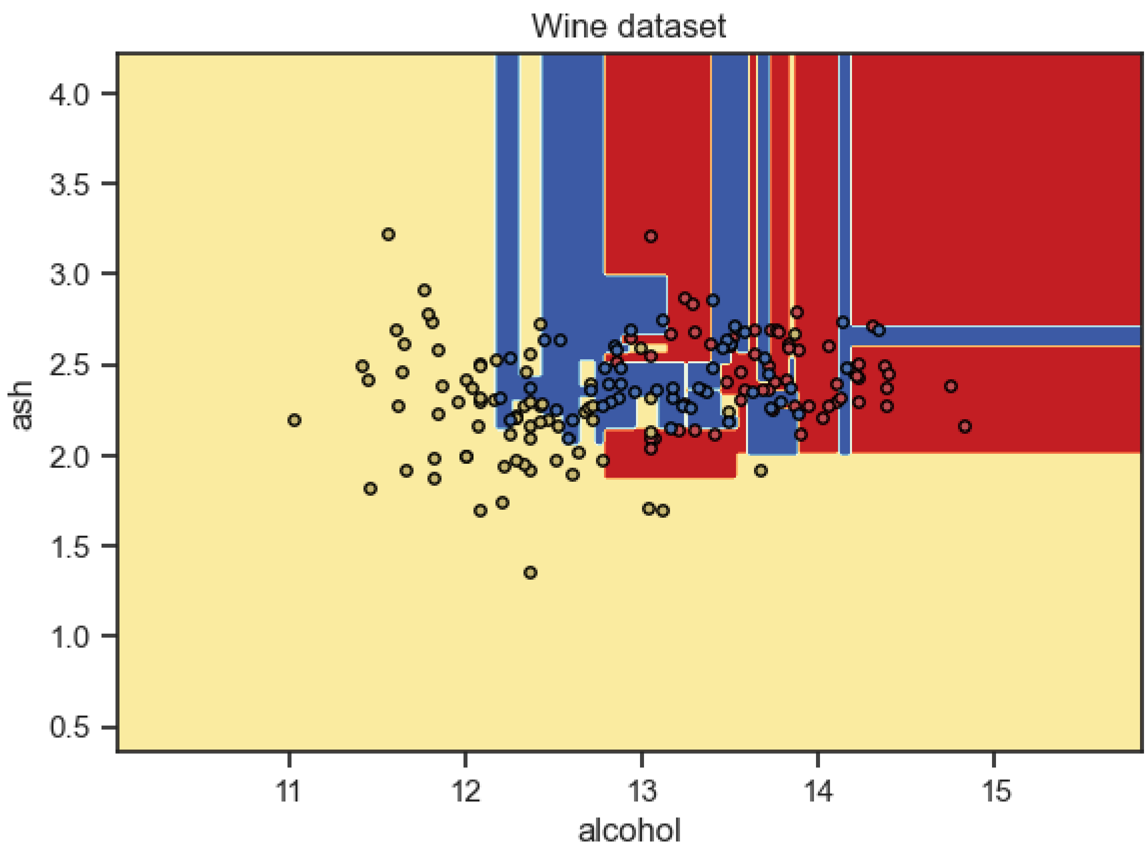
In [52]:

```
plot_tree_classification('Wine dataset', wine)
```

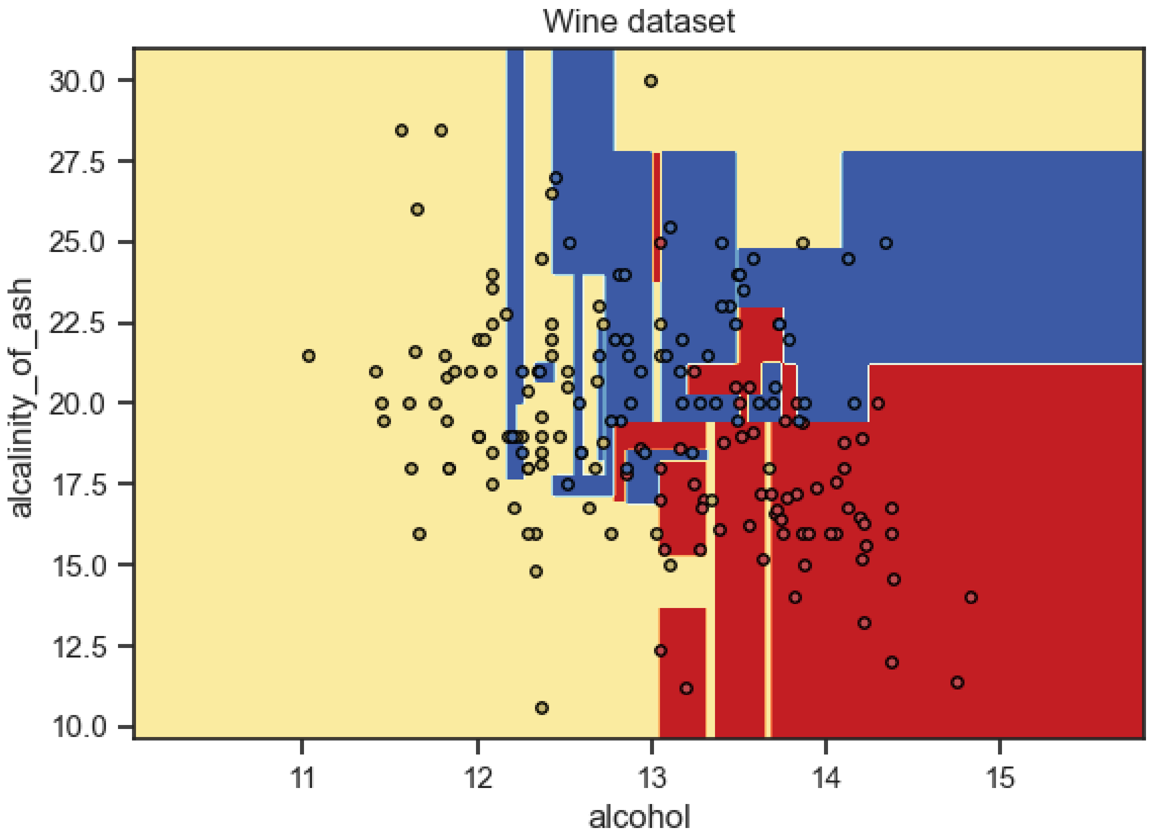
```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\593250511.py:37: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
```



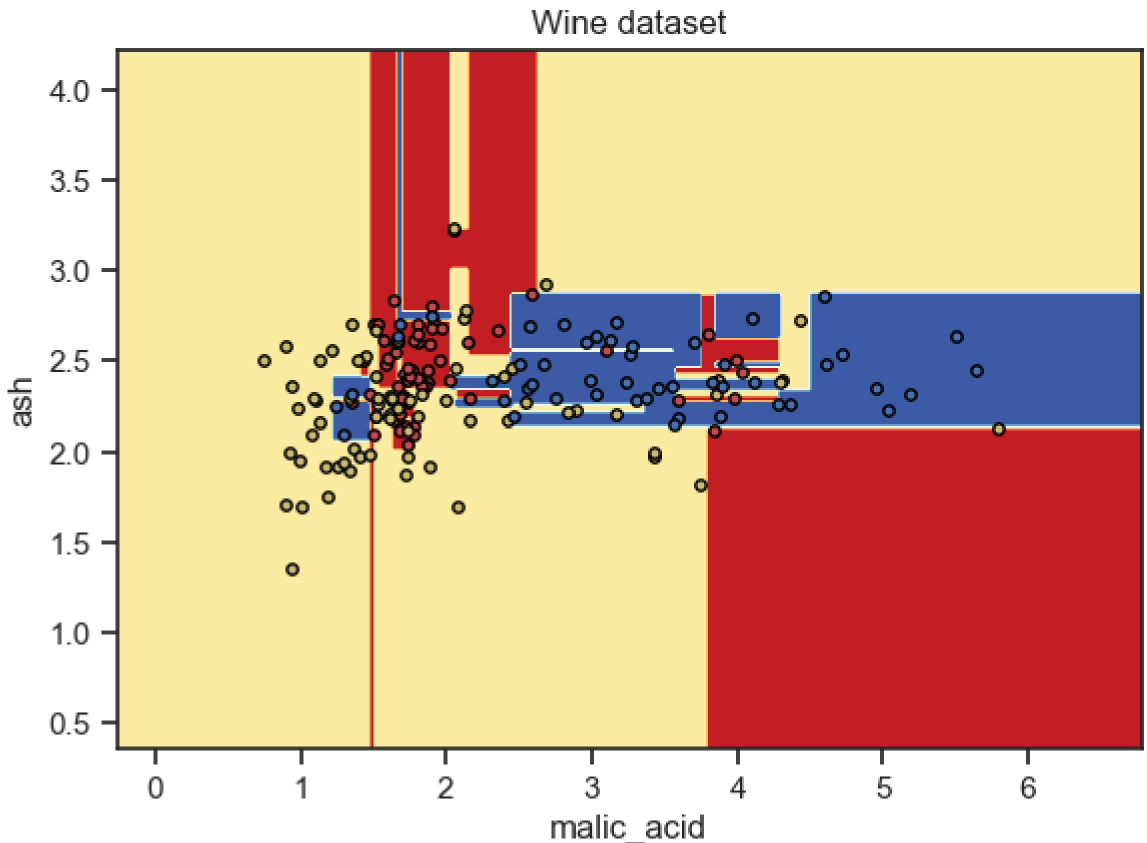

```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\593250511.py:37: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
```



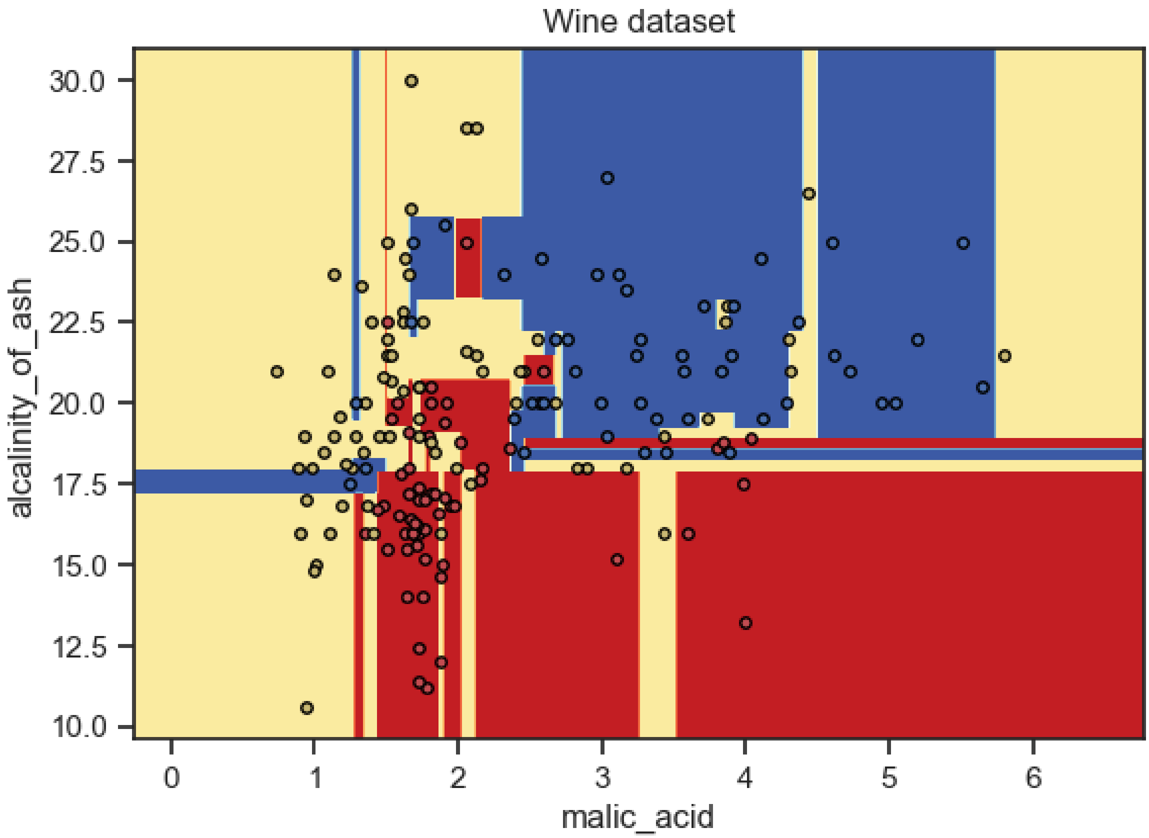

```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\593250511.py:37: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
```



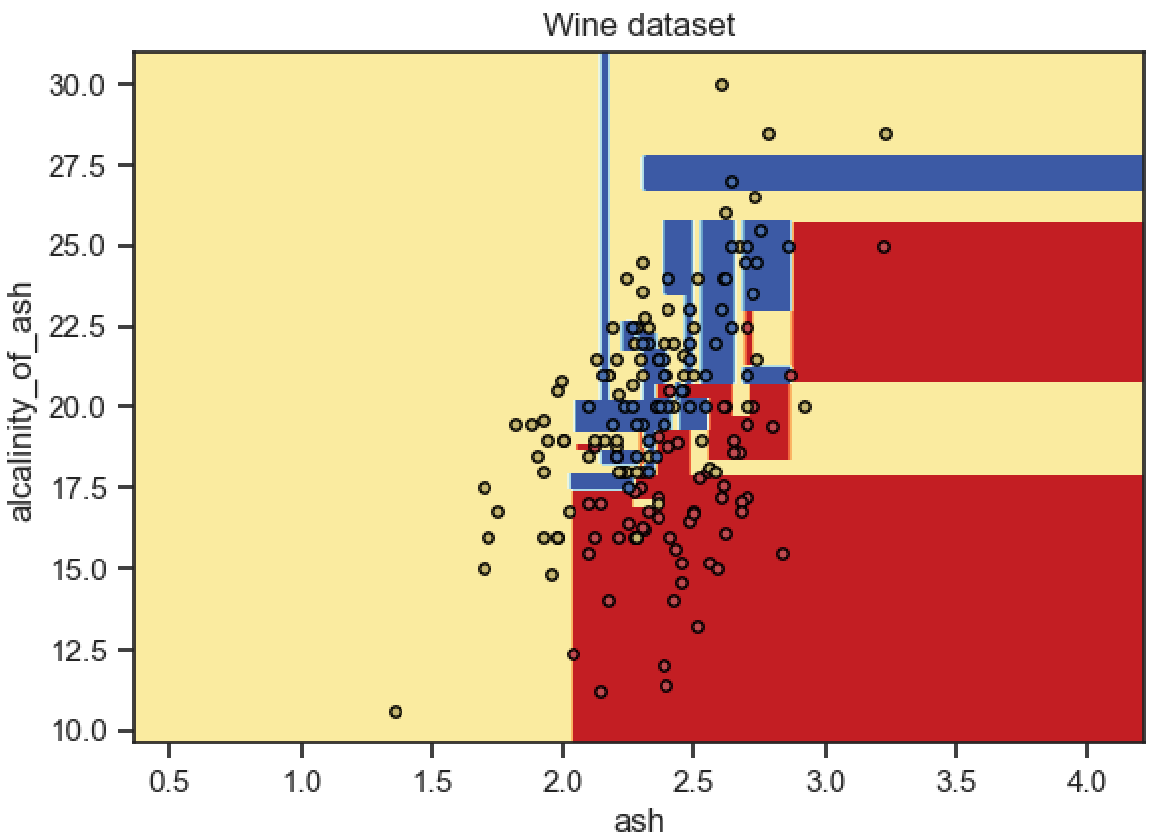

```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\593250511.py:37: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
```




```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\593250511.py:37: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
```




```
C:\Users\user\AppData\Local\Temp\ipykernel_13056\593250511.py:37: UserWarning: No
data for colormapping provided via 'c'. Parameters 'cmap' will be ignored
  plt.scatter(X[idx, 0], X[idx, 1], c=color, label=ds.target_names[i],
```



In [53]:
```
# Обучим дерево на всех признаках
wine_tree_cl = DecisionTreeClassifier(random_state=1)
wine_tree_cl.fit(wine_x_ds, wine.target)
wine_tree_cl
```

Out[53]:

▾ DecisionTreeClassifier

DecisionTreeClassifier(random_state=1)

In [54]:

```
from IPython.core.display import HTML
from sklearn.tree import export_text
tree_rules = export_text(wine_tree_cl, feature_names=list(wine_x_ds.columns))
HTML('<pre>' + tree_rules + '</pre>')
```

Out[54]:

```
|--- proline <= 755.00
|   |--- od280/od315_of_diluted_wines <= 2.11
|   |   |--- hue <= 0.94
|   |   |   |--- flavanoids <= 1.58
|   |   |   |   |--- class: 2
|   |   |   |--- flavanoids >  1.58
|   |   |   |   |--- class: 1
|   |   |--- hue >  0.94
|   |   |   |--- malic_acid <= 2.39
|   |   |   |   |--- class: 1
|   |   |   |--- malic_acid >  2.39
|   |   |   |   |--- class: 2
|   |--- od280/od315_of_diluted_wines >  2.11
|   |   |--- flavanoids <= 0.80
|   |   |   |--- class: 2
|   |   |--- flavanoids >  0.80
|   |   |   |--- alcohol <= 13.17
|   |   |   |   |--- class: 1
|   |   |   |--- alcohol >  13.17
|   |   |   |   |--- magnesium <= 98.50
|   |   |   |   |   |--- class: 1
|   |   |   |   |--- magnesium >  98.50
|   |   |   |   |   |--- class: 0
|--- proline >  755.00
|   |--- flavanoids <= 2.17
|   |   |--- flavanoids <= 0.90
|   |   |   |--- class: 2
|   |   |--- flavanoids >  0.90
|   |   |   |--- class: 1
|   |--- flavanoids >  2.17
|   |   |--- magnesium <= 135.50
|   |   |   |--- class: 0
|   |   |--- magnesium >  135.50
|   |   |   |--- class: 1
```

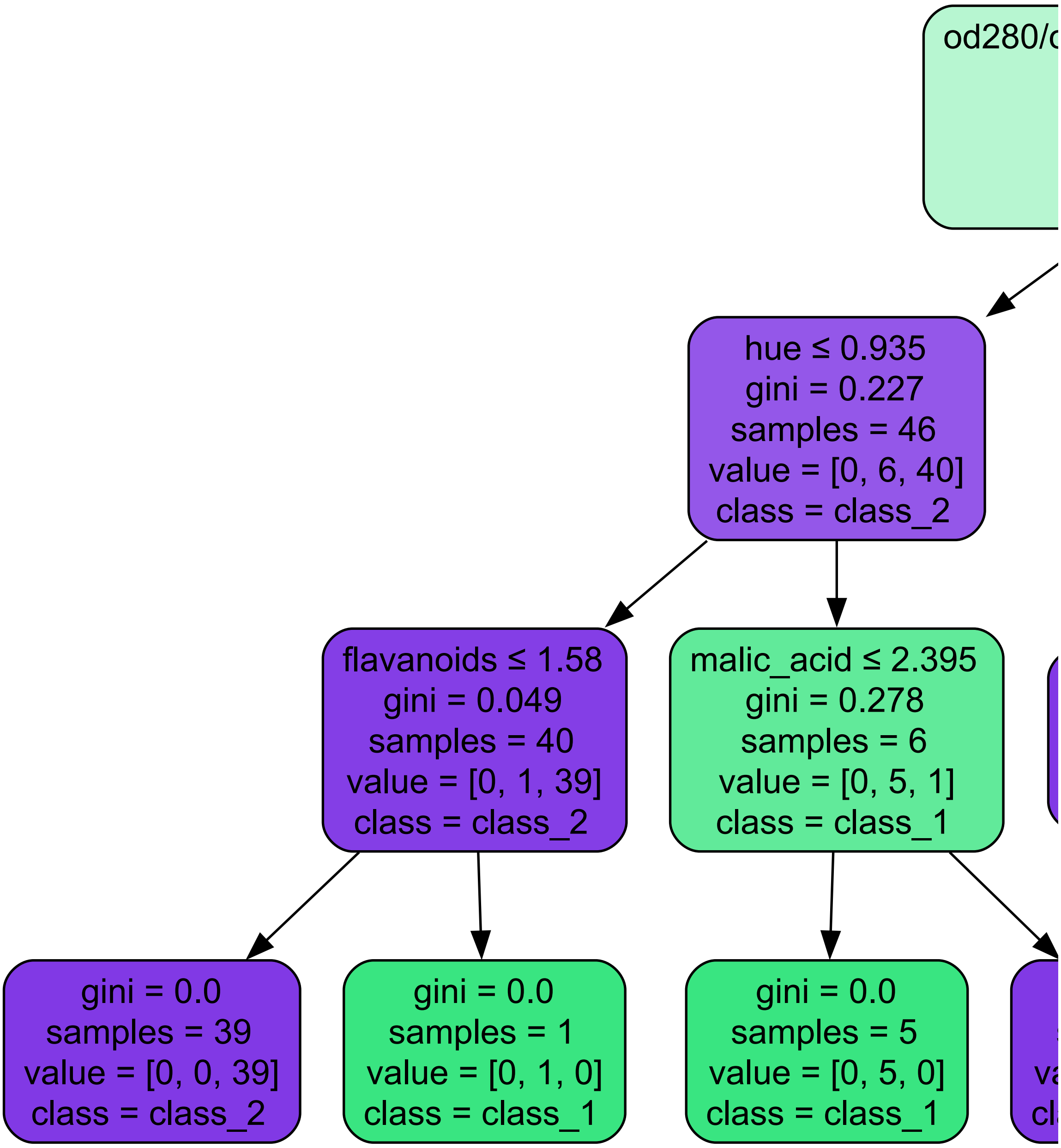
In [55]:

```
wine.feature_names
```

Out[55]:
```
['alcohol',
 'malic_acid',
 'ash',
 'alcalinity_of_ash',
 'magnesium',
 'total_phenols',
 'flavanoids',
 'nonflavanoid_phenols',
 'proanthocyanins',
 'color_intensity',
 'hue',
 'od280/od315_of_diluted_wines',
 'proline']
```

In [56]:
```
dot_data = export_graphviz(wine_tree_cl, out_file=None,
                           feature_names=wine.feature_names,
                           class_names=wine.target_names,
                           filled=True, rounded=True, special_characters=True)
graph = graphviz.Source(dot_data)
graph
```

Out[56]:



Важность признаков

In [57]:
```python
# Важность признаков
list(zip(wine_x_ds.columns.values, wine_tree_cl.feature_importances_))
```

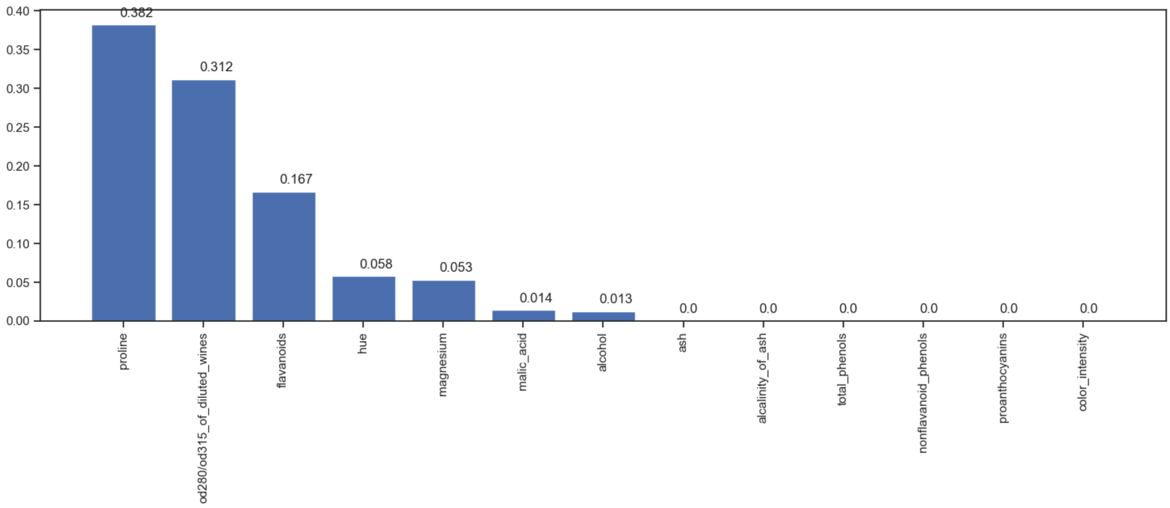
Out[57]:
```
[('alcohol', 0.012570564071187309),
 ('malic_acid', 0.014223159778821876),
 ('ash', 0.0),
 ('alcalinity_of_ash', 0.0),
 ('magnesium', 0.0534597951279922),
 ('total_phenols', 0.0),
 ('flavanoids', 0.16704836491408806),
 ('nonflavanoid_phenols', 0.0),
 ('proanthocyanins', 0.0),
 ('color_intensity', 0.0),
 ('hue', 0.058185091460406506),
 ('od280/od315_of_diluted_wines', 0.3120425747831769),
 ('proline', 0.38247044986432716)]
```

In [58]:
```python
# Важность признаков в сумме дает единицу
sum(wine_tree_cl.feature_importances_)
```

Out[58]:
```
1.0
```

In [59]:
```python
from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, figsize=(18,5)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.feature_importa
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
    # Названия признаков
    labels = [x for x,_ in sorted_list]
    # Важности признаков
    data = [x for _,x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a,b in zip(ind, data):
        plt.text(a-0.05, b+0.01, str(round(b,3)))
    plt.show()
    return labels, data
```

In [60]:
```python
wine_tree_cl_fl, wine_tree_cl_fd = draw_feature_importances(wine_tree_cl, wine_x
```



In [61]:
```
# Список признаков, отсортированный на основе важности, и значения важности
wine_tree_cl_fl, wine_tree_cl_fd
```

Out[61]:
```
(['proline',
  'od280/od315_of_diluted_wines',
  'flavanoids',
  'hue',
  'magnesium',
  'malic_acid',
  'alcohol',
  'ash',
  'alcalinity_of_ash',
  'total_phenols',
  'nonflavanoid_phenols',
  'proanthocyanins',
  'color_intensity'],
 [0.38247044986432716,
  0.3120425747831769,
  0.16704836491408806,
  0.058185091460406506,
  0.0534597951279922,
  0.014223159778821876,
  0.012570564071187309,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0])
```

In [62]:
```
wine_x_ds.head()
```

Out[62]:

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nc
0	14.23	1.71	2.43	15.6	127.0	2.80	3.06	
1	13.20	1.78	2.14	11.2	100.0	2.65	2.76	
2	13.16	2.36	2.67	18.6	101.0	2.80	3.24	
3	14.37	1.95	2.50	16.8	113.0	3.85	3.49	
4	13.24	2.59	2.87	21.0	118.0	2.80	2.69	

In [63]:

```
# Пересортируем признаки на основе важности
wine_x_ds_sorted = wine_x_ds[wine_tree_cl_fl]
wine_x_ds_sorted.head()
```

Out[63]:

	proline	od280/od315_of_diluted_wines	flavanoids	hue	magnesium	malic_acid	alc
0	1065.0	3.92	3.06	1.04	127.0	1.71	1
1	1050.0	3.40	2.76	1.05	100.0	1.78	1
2	1185.0	3.17	3.24	1.03	101.0	2.36	1
3	1480.0	3.45	3.49	0.86	113.0	1.95	1
4	735.0	2.93	2.69	1.04	118.0	2.59	1

In [64]:

```
# Разделим выборку на обучающую и тестовую
wine_X_train, wine_X_test, wine_y_train, wine_y_test = train_test_split(
    wine_x_ds_sorted, wine.target, test_size=0.3, random_state=1)
wine_X_train.shape, wine_X_test.shape
```

Out[64]: ((124, 13), (54, 13))

In [65]:

```
# Обучим дерево и предскажем результаты на всех признаках
wine_tree_cl_feat_1 = DecisionTreeClassifier(random_state=1).fit(wine_X_train, w
wine_y_test_predict = wine_tree_cl_feat_1.predict(wine_X_test)
wine_y_test_predict.shape
```

Out[65]: (54,)

Оценка качества

In [66]:

```
# Проверим точность по классам
print_accuracy_score_for_classes(wine_y_test, wine_y_test_predict)
```

```
Метка    Accuracy
0        0.9130434782608695
1        0.9473684210526315
2        0.9166666666666666
```

In [67]:

```
confusion_matrix(wine_y_test, pred_wine_y_test, labels=[0, 1])
```

Out[67]:

```
array([[ 0, 23],
       [18,  1]], dtype=int64)
```

In [68]:
```
# Обучим дерево и предскажем результаты на единственном самом важном признаке
wine_tree_cl_feat_2 = DecisionTreeClassifier(random_state=1).fit(wine_X_train[[w
wine_y_test_predict_2 = wine_tree_cl_feat_2.predict(wine_X_test[[wine_tree_cl_fl
wine_y_test_predict_2.shape
```

Out[68]:
```
(54,)
```

Оценка качества

In [69]:
```
# Проверим точность по классам
print_accuracy_score_for_classes(wine_y_test, wine_y_test_predict_2)
```

```
Метка    Accuracy
0        0.8695652173913043
1        0.6842105263157895
2        0.3333333333333333
```

In [70]:
```
confusion_matrix(wine_y_test, pred_wine_y_test, labels=[0, 1])
```

Out[70]:
```
array([[ 0, 23],
       [18,  1]], dtype=int64)
```

Вывод: Самое высокое качество у модели логистической регрессии.