Лабораторная работа №7.

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Вариант 4

1. Считаем заданный набор данных из репозитария UCI

In [1]:
```
import pandas as pd
import numpy as np
url = \
"https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data"
data_set = pd.read_csv( url, header=None )
data_set = data_set.replace('?',np.NaN)
data_set
data_set[1] = data_set[1].astype('float64', copy=False)
for i in range(18, 26):
    data_set[i] = data_set[i].astype('float64', copy=False)
titles = {
    1 : "symboling",
    2 : "normalized-losses",
    3 : "make",
    4 : "aspiration",
    5 : "num-of-doors",
    6 : "body-style",
    7 : "symboling",
    8 : "drive-wheels",
    9 : "engine-location",
    10 : "wheel-base",
    11 : "length",
    12 : "width",
    13 : "height",
    14 : "curb-weight",
    15 : "engine-type",
    16 : "num-of-cylinders",
    17 : "engine-size",
    18 : "fuel-system",
    19 : "bore",
    20 : "stroke",
    21 : "compression-ratio",
    22 : "horsepower",
    23 : "peak-rpm",
    24 : "city-mpg",
    25 : "highway-mpg",
    26 : "price",
}
data_set
```

Out[1]:

	0	1	2	3	4	5	6	7	8	9	...	16	17	18	19	20
0	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0
1	3	NaN	alfa-romero	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0
2	1	NaN	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0
3	2	164.0	audi	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0

4	2	164.0	audi	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
200	-1	95.0	volvo	gas	std	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5
201	-1	95.0	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	8.7
202	-1	95.0	volvo	gas	std	four	sedan	rwd	front	109.1	...	173	mpfi	3.58	2.87	8.8
203	-1	95.0	volvo	diesel	turbo	four	sedan	rwd	front	109.1	...	145	idi	3.01	3.40	23.0
204	-1	95.0	volvo	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5

205 rows × 26 columns

1. Произведем препроцессинг данных

In [2]:

```
from sklearn.preprocessing import LabelEncoder
lb_make = LabelEncoder()
data_setX = data_set.loc[:, 1:]
data_setY = data_set[0]
for i in data_setX:
    if data_setX[i].dtype == "object":
        data_setX[i] = lb_make.fit_transform(data_setX[i])
    else:
        data_setX[i] = data_setX[i].fillna(data_setX[i].median());
data_setX
```

Out[2]:

	1	2	3	4	5	6	7	8	9	10	...	16	17	18	19	20	21	22	23	24
0	115.0	0	1	0	1	0	2	0	88.6	168.8	...	130	5	3.47	2.68	9.0	111.0	5000.0	21.0	27.0
1	115.0	0	1	0	1	0	2	0	88.6	168.8	...	130	5	3.47	2.68	9.0	111.0	5000.0	21.0	27.0
2	115.0	0	1	0	1	2	2	0	94.5	171.2	...	152	5	2.68	3.47	9.0	154.0	5000.0	19.0	26.0
3	164.0	1	1	0	0	3	1	0	99.8	176.6	...	109	5	3.19	3.40	10.0	102.0	5500.0	24.0	30.0
4	164.0	1	1	0	0	3	0	0	99.4	176.6	...	136	5	3.19	3.40	8.0	115.0	5500.0	18.0	22.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
200	95.0	21	1	0	0	3	2	0	109.1	188.8	...	141	5	3.78	3.15	9.5	114.0	5400.0	23.0	28.0
201	95.0	21	1	1	0	3	2	0	109.1	188.8	...	141	5	3.78	3.15	8.7	160.0	5300.0	19.0	25.0
202	95.0	21	1	0	0	3	2	0	109.1	188.8	...	173	5	3.58	2.87	8.8	134.0	5500.0	18.0	23.0
203	95.0	21	0	1	0	3	2	0	109.1	188.8	...	145	3	3.01	3.40	23.0	106.0	4800.0	26.0	27.0
204	95.0	21	1	1	0	3	2	0	109.1	188.8	...	141	5	3.78	3.15	9.5	114.0	5400.0	19.0	25.0

205 rows × 25 columns

1. Используя метод отбора на основе важности признаков класса ExtraTreesClassifier, определим и оставим в наборе наиболее важные признаки (я оставил 7 признаков).

In [3]:

```
X = data_setX.values
y = data_setY.values
n_features = 9
```

In [4]:

```
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
```

```
model.fit(X, y)
z = model.feature_importances_
z_s = sorted(z)[-n_features:]
z_s
```

Out[4]:

```
[0.047924461318993694,
 0.052033865508015226,
 0.05323898609373501,
 0.05661543609873136,
 0.059603500223753124,
 0.06996431860750811,
 0.07573999390924623,
 0.07597495120354576,
 0.07865920699104104]
```

In [5]:

```
indexes = []
max_indexes = []
for i in range(len(z)):
    if z[i] in z_s[-n_features:-2]:
        indexes.append(i+1)
    if z[i] in z_s[-2:]:
        max_indexes.append(i+1)
data_setX = data_setX.loc[:][indexes + max_indexes]
data_setX.columns = [i for i in range(n_features)]
max_indexes_title = [titles[max_indexes[0] + 1], titles[max_indexes[1] + 1]]
data_setX
```

Out[5]:

	0	1	2	3	4	5	6	7	8
0	0	0	88.6	168.8	64.1	48.8	3.47	115.0	1
1	0	0	88.6	168.8	64.1	48.8	3.47	115.0	1
2	0	2	94.5	171.2	65.5	52.4	2.68	115.0	1
3	1	3	99.8	176.6	66.2	54.3	3.19	164.0	0
4	1	3	99.4	176.6	66.4	54.3	3.19	164.0	0
...	...	...	...	...	...	...	...	...	...
200	21	3	109.1	188.8	68.9	55.5	3.78	95.0	0
201	21	3	109.1	188.8	68.8	55.5	3.78	95.0	0
202	21	3	109.1	188.8	68.9	55.5	3.58	95.0	0
203	21	3	109.1	188.8	68.9	55.5	3.01	95.0	0
204	21	3	109.1	188.8	68.9	55.5	3.78	95.0	0

205 rows × 9 columns

In [6]:

```
indexes = [i for i in range(len(data_setX.columns) - 2)]
max_indexes = [i for i in range(len(data_setX.columns) - 2,len(data_setX.columns))]
x_plot = data_setX.loc[:][max_indexes].values
```

1. Разделим данные на тестовые и обущающие

In [7]:

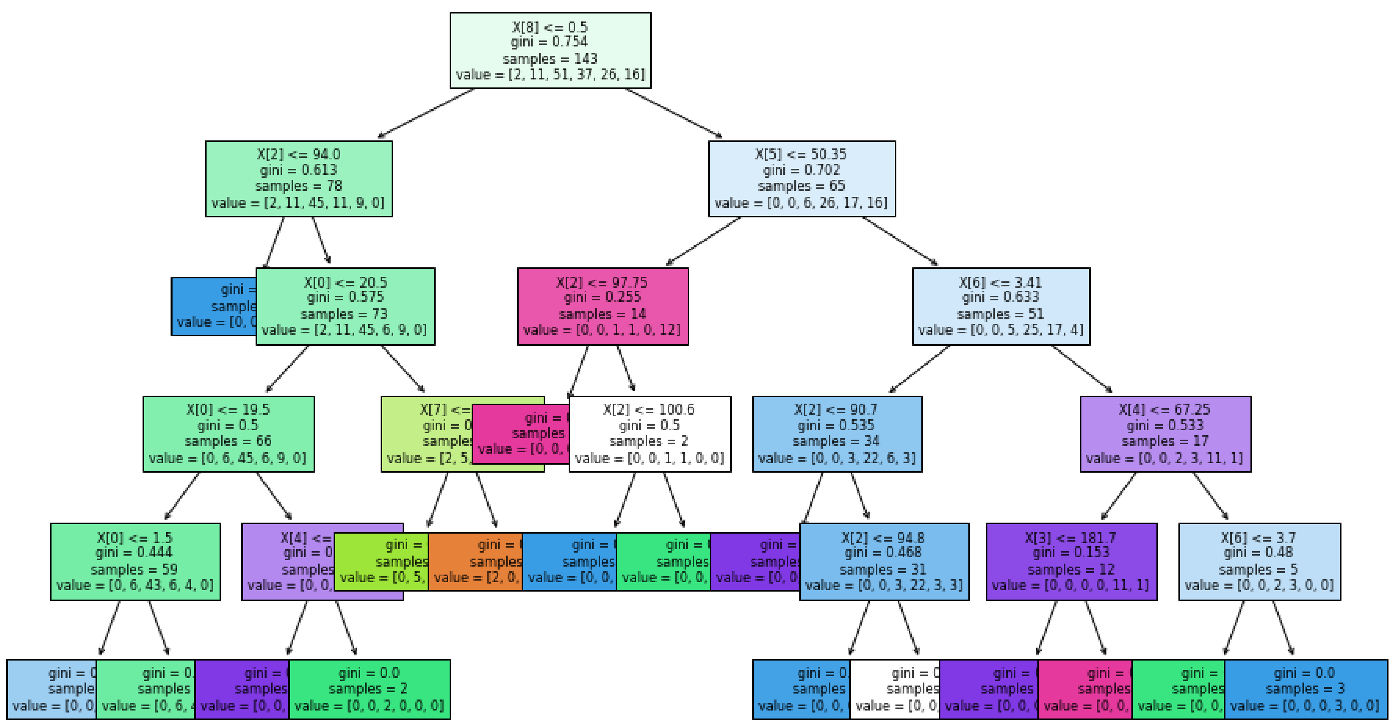
```
from sklearn.model_selection import train_test_split
X = data_setX.values
y = data_setY.values
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.3)
```

1. Создадим и обучим классификатор на основе деревьев решений с глубиной дерева 5,

определим точность классификации и визуализируем границу принятия решений и построим дерево решений. При визуализации границы принятия решений использовали 2 наиболее важных признака

In [8]:
```python
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
dt_clf = DecisionTreeClassifier(max_depth=5)
dt_clf.fit(X_train, y_train);
```

In [9]:
```python
plt.figure(figsize=(15, 9))
plot_tree(dt_clf, filled=True, fontsize=8);
```



In [10]:
```python
dt_clf.score(X_test,y_test)
```

Out[10]:
```
0.5806451612903226
```

In [11]:
```python
from math import floor
def helper(x0, l):
    z  = np.repeat(x0, floor(l / len(x0)))
    while len(z) < l:
        z = np.append(z, z[-1])
    return z.ravel()

def plot_decision_boundary(model, X_data, X_test_data, text):
    max_indexes = X_data.columns[-2:]
    another_indexes = X_data.columns[:-2]
    x1 = np.amin(X_data[max_indexes[0]], axis=0)
    x2 = np.amax(X_data[max_indexes[0]], axis=0)
    y1 = np.amin(X_data[max_indexes[1]], axis=0)
    y2 = np.amax(X_data[max_indexes[1]], axis=0)
    axis = [x1,x2,y1,y2]
    x_max1, x_max2 = np.meshgrid(
        np.linspace(axis[0], axis[1], int((axis[1]-axis[0])*100)).reshape(-1, 1),
        np.linspace(axis[2], axis[3], int((axis[3]-axis[2])*100)).reshape(-1, 1),
    )
    X_new = np.c_[x_max1.ravel(), x_max2.ravel()]
```

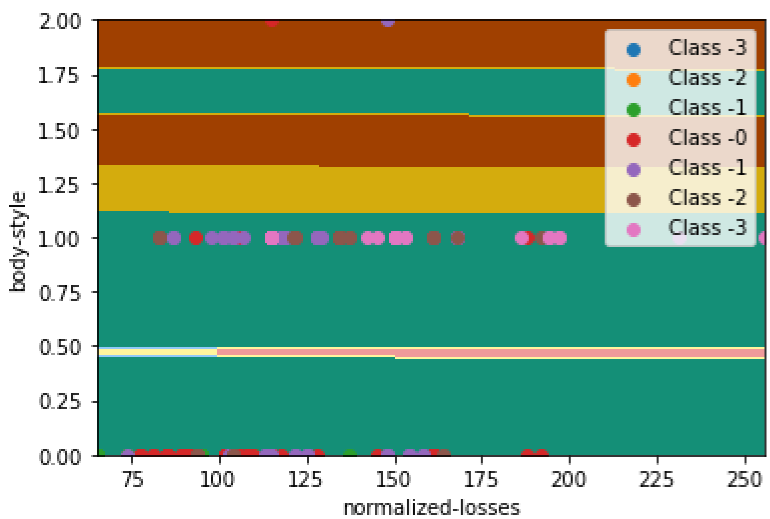
```
    l = len(X_new[:, 0])

    tmp = [helper(X_test_data[i], l) for i in range(len(another_indexes))]
    X_new = tmp[0]
    for i in range(1, len(tmp)):
        X_new = np.c_[X_new, tmp[i]]

    X_new = np.c_[X_new, x_max1.ravel(), x_max2.ravel()]
    y_predict = model.predict(X_new)

    zz = y_predict.reshape(x_max1.shape)
    from matplotlib.colors import ListedColormap
    custom_cmap = ListedColormap(['#EF9A9A','#FFF59D','#90CAF9', '#9B59B6','#2471A3','#1
    plt.contourf(x_max1, x_max2, zz, cmap=custom_cmap)
    plt.xlabel(text[0])
    plt.ylabel(text[1])
```

In [12]:
```
plot_decision_boundary(dt_clf, data_setX, X_train, max_indexes_title)
plt.scatter(x_plot[y==-3,0], x_plot[y==-3,1], label='Class -3')
plt.scatter(x_plot[y==-2,0], x_plot[y==-2,1], label='Class -2')
plt.scatter(x_plot[y==-1,0], x_plot[y==-1,1], label='Class -1')
plt.scatter(x_plot[y==0,0], x_plot[y==0,1], label='Class -0')
plt.scatter(x_plot[y==1,0], x_plot[y==1,1], label='Class -1')
plt.scatter(x_plot[y==2,0], x_plot[y==2,1], label='Class -2')
plt.scatter(x_plot[y==3,0], x_plot[y==3,1], label='Class -3')
plt.legend()
plt.show()
```



1. Построим на основе классификатора деревьев решений ансамблевые классификаторы

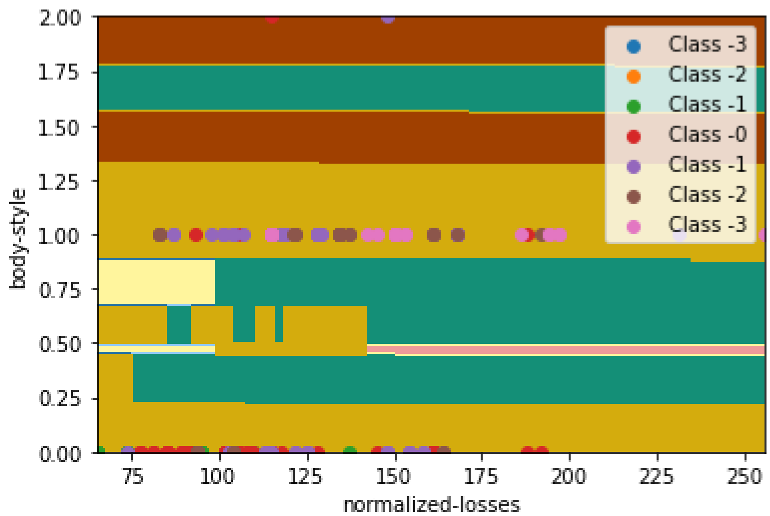
In [13]:
```
class_scores = {}
```

In [14]:
```
from sklearn.ensemble import BaggingClassifier

bagging_clf = BaggingClassifier(DecisionTreeClassifier(),
                           n_estimators=50, max_samples=100,
                           bootstrap=True)
bagging_clf.fit(X_train, y_train)
class_scores["BaggingClassifier"] = bagging_clf.score(X_test, y_test)
```

In [15]:
```
plot_decision_boundary(bagging_clf, data_setX, X_train, max_indexes_title)
plt.scatter(x_plot[y==-3,0], x_plot[y==-3,1], label='Class -3')
plt.scatter(x_plot[y==-2,0], x_plot[y==-2,1], label='Class -2')
plt.scatter(x_plot[y==-1,0], x_plot[y==-1,1], label='Class -1')
plt.scatter(x_plot[y==0,0], x_plot[y==0,1], label='Class -0')
```

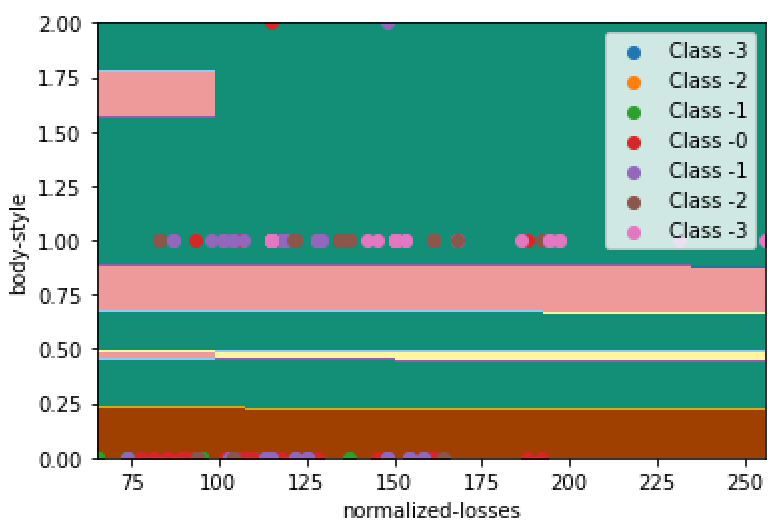
```
plt.scatter(x_plot[y==1,0], x_plot[y==1,1], label='Class -1')
plt.scatter(x_plot[y==2,0], x_plot[y==2,1], label='Class -2')
plt.scatter(x_plot[y==3,0], x_plot[y==3,1], label='Class -3')
plt.legend()
plt.show()
```



In [16]:
```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(n_estimators=50, oob_score=True,
                                random_state=666, n_jobs=-1)
rf_clf.fit(X, y);
class_scores["RandomForestClassifier"] = rf_clf.oob_score_
```

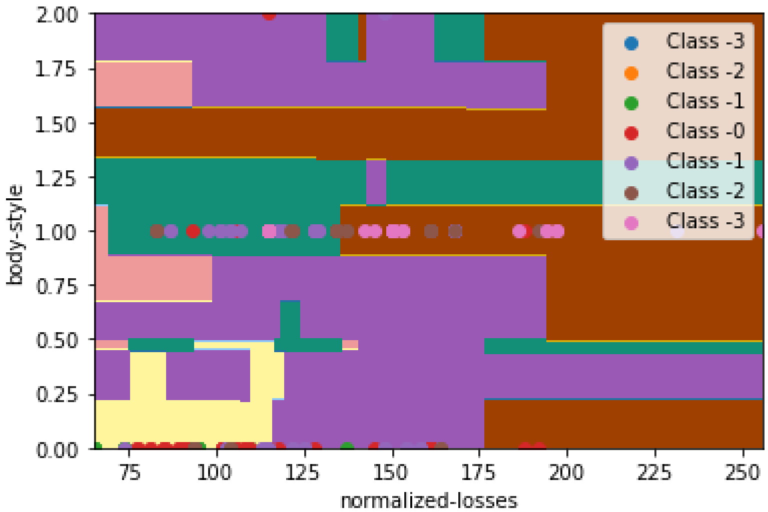
In [17]:
```
plot_decision_boundary(rf_clf, data_setX, X_train, max_indexes_title)
plt.scatter(x_plot[y==-3,0], x_plot[y==-3,1], label='Class -3')
plt.scatter(x_plot[y==-2,0], x_plot[y==-2,1], label='Class -2')
plt.scatter(x_plot[y==-1,0], x_plot[y==-1,1], label='Class -1')
plt.scatter(x_plot[y==0,0], x_plot[y==0,1], label='Class -0')
plt.scatter(x_plot[y==1,0], x_plot[y==1,1], label='Class -1')
plt.scatter(x_plot[y==2,0], x_plot[y==2,1], label='Class -2')
plt.scatter(x_plot[y==3,0], x_plot[y==3,1], label='Class -3')
plt.legend()
plt.show()
```



In [18]:
```
from sklearn.ensemble import AdaBoostClassifier

ada_clf = AdaBoostClassifier(
    DecisionTreeClassifier(max_depth=5), n_estimators=50)
ada_clf.fit(X_train, y_train)
class_scores["AdaBoostClassifier"] = ada_clf.score(X_test, y_test)
```

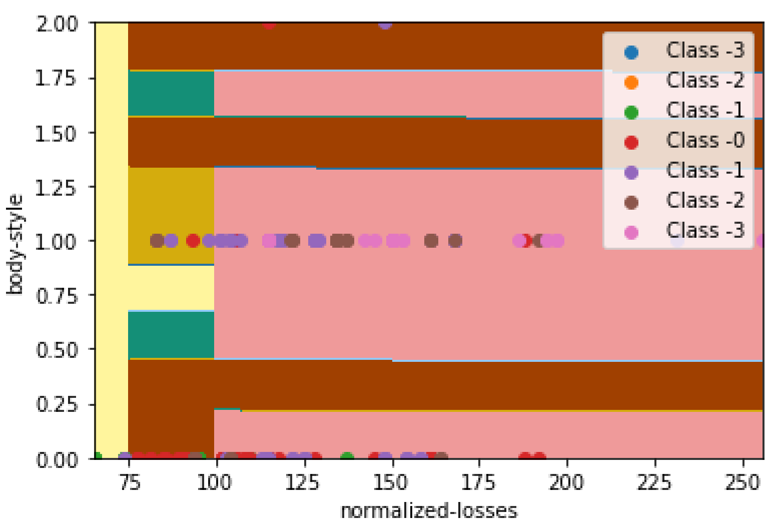
In [19]:
```
plot_decision_boundary(ada_clf, data_setX, X_train, max_indexes_title)
plt.scatter(x_plot[y==-3,0], x_plot[y==-3,1], label='Class -3')
plt.scatter(x_plot[y==-2,0], x_plot[y==-2,1], label='Class -2')
plt.scatter(x_plot[y==-1,0], x_plot[y==-1,1], label='Class -1')
plt.scatter(x_plot[y==0,0], x_plot[y==0,1], label='Class -0')
plt.scatter(x_plot[y==1,0], x_plot[y==1,1], label='Class -1')
plt.scatter(x_plot[y==2,0], x_plot[y==2,1], label='Class -2')
plt.scatter(x_plot[y==3,0], x_plot[y==3,1], label='Class -3')
plt.legend()
plt.show()
```



In [20]:
```
from sklearn.ensemble import GradientBoostingClassifier

gb_clf = GradientBoostingClassifier(max_depth=5, n_estimators=50)
gb_clf.fit(X_train, y_train)
class_scores["GradientBoostingClassifier"] = gb_clf.score(X_test, y_test)
```

In [21]:
```
plot_decision_boundary(gb_clf, data_setX, X_train, max_indexes_title)
plt.scatter(x_plot[y==-3,0], x_plot[y==-3,1], label='Class -3')
plt.scatter(x_plot[y==-2,0], x_plot[y==-2,1], label='Class -2')
plt.scatter(x_plot[y==-1,0], x_plot[y==-1,1], label='Class -1')
plt.scatter(x_plot[y==0,0], x_plot[y==0,1], label='Class -0')
plt.scatter(x_plot[y==1,0], x_plot[y==1,1], label='Class -1')
plt.scatter(x_plot[y==2,0], x_plot[y==2,1], label='Class -2')
plt.scatter(x_plot[y==3,0], x_plot[y==3,1], label='Class -3')
plt.legend()
plt.show()
```



1. Определим лучший классификатор, дающий наиболее высокую точность классификации.

In [22]:
```
max_elem = max(class_scores, key=class_scores.get)
print("Лучший классификатор, дающий наиболее высокую точность классификации: {}({})".for
```

```
Лучший классификатор, дающий наиболее высокую точность классификации: RandomForestClassi
fier(0.848780487804878)
```