<机器学习>课程 Lecture2 实验

高斯判别性分析

给定一组数据,其输入维度为2,输出维度为1,完成二分类任务.

请使用高斯判别性分析来进行分类并绘制类别分界面.

首先加载数据.

In [29]:
```python
import numpy as np
from sklearn.model_selection import train_test_split

data_filename = "cls_data_0303_1007_2.npy"
cls_data = np.load(data_filename)
x_data, y_data = cls_data[:, :-1], cls_data[:, -1]

x_train, x_test, y_train, y_test = train_test_split(
    x_data, y_data,
    train_size=0.8, shuffle=True,
    stratify=y_data
)

# x_data in [b, c_in]
c_in = x_data.shape[1]
# y_data in [b, c_out]
c_out = 1

# print(x_train.shape)
# print(y_train.shape)
```

定义高斯判别性分析.

在fit函数中分别统计不同类别的数据的均值和协方差.

在predict中根据均值和协方差矩阵计算概率,并选择概率最大的类别作为输出.

In [30]:
```python
import numpy as np
from scipy.stats import multivariate_normal

class GaussianDiscriminantAnalysis():
    """
    高斯判别性分析
    """
    def __init__(self,
        same_cov: bool=False
    ) -> None:
        """
        same_cov 是否具有相同的协方差
        """
        self.c_in = None
        self.classes = None
        self.means = None
```

```
        self.covs = None
        self.same_cov = same_cov

    def fit(self,
        x: np.ndarray, y:np.ndarray
    )->None:
        assert len(x.shape) == 2
        assert x.shape[0] == y.shape[0]

        self.c_in = x.shape[1]
        self.classes = np.unique(y)
        # print(self.classes)

        # 对于每一个类别,分别计算数据的均值和方差
        n_classes = len(self.classes)
        self.means = np.zeros((n_classes, self.c_in))  # 每个类别的均值
        self.covs = np.zeros((n_classes, self.c_in, self.c_in))  # 每个类别的协方
        # 使用高斯函数拟合数据分布
        for i, cc in enumerate(self.classes):
            # mean = ?
            # cov = ?
            mean = np.mean(x[y == cc], axis=0)
            cov = np.cov(x[y == cc], rowvar=False)
            self.means[i] = mean
            self.covs[i] = cov

        assert self.means.shape[0] == len(self.classes)
        assert self.means.shape[1] == self.c_in
        assert self.covs.shape[0] == len(self.classes)

        # 假定不同类别的数据有相同的协方差
        if self.same_cov:
            # self.covs = ?
            pass

    def predict(self,
        x: np.ndarray
    )->np.ndarray:

        n_samples = x.shape[0]
        n_classes = len(self.classes)
        probs = np.zeros((n_samples, n_classes))  # 存储每个样本的类别概率

        # 对于每一个类别计算预测概率
        for idx, cc in enumerate(self.classes):
            mean = self.means[idx]  # 当前类别的均值
            cov = self.covs[idx]    # 当前类别的协方差矩阵

            # 计算多元高斯分布的概率密度
            diff = x - mean  # 样本与均值的差值
            inv_cov = np.linalg.inv(cov)  # 协方差矩阵的逆
            exponent = -0.5 * np.sum(diff @ inv_cov * diff, axis=1)  # 指数部分
            normalization = 1 / np.sqrt((2 * np.pi) ** self.c_in * np.linalg.det
            prob = normalization * np.exp(exponent)  # 概率密度

            probs[:, idx] = prob  # 将概率存储到对应列

        assert probs.shape[0] == x.shape[0]
        assert probs.shape[1] == len(self.classes)
```

```python
        return probs.argmax(axis=1)
```

In [31]:
```python
from matplotlib import pyplot as plt
from matplotlib.colors import ListedColormap
import numpy as np

#可视化函数
def plot_decision_regions(x, y, classifier, resolution=0.02):
    markers = ['s', 'o', '^', 'v']
    colors = ['r', 'g', 'b', 'cyan']
    cmap = ListedColormap(colors[:len(np.unique(y))])

    x1_min, x1_max = x[:, 0].min() - 1, x[:, 0].max() + 1
    x2_min, x2_max = x[:, 1].min() - 1, x[:, 1].max() + 1
    xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution), np.arange(x2_m
    grid = np.array([xx1.ravel(), xx2.ravel()]).T

    # == 对于生成meshgrid的每一个点计算降维和分类结果 ==
    z = classifier.predict(grid)
    z = z.reshape(xx1.shape)
    plt.contourf(xx1, xx2, z, alpha=0.4, cmap=cmap)

    for idx, cc in enumerate(np.unique(y)):
        plt.scatter(x=x[y[:, 0] == cc, 0],
                    y=x[y.ravel() == cc, 1],
                    alpha=0.6,
                    c=cmap(idx),
                    edgecolor='black',
                    marker=markers[idx],
                    label=cc)
```

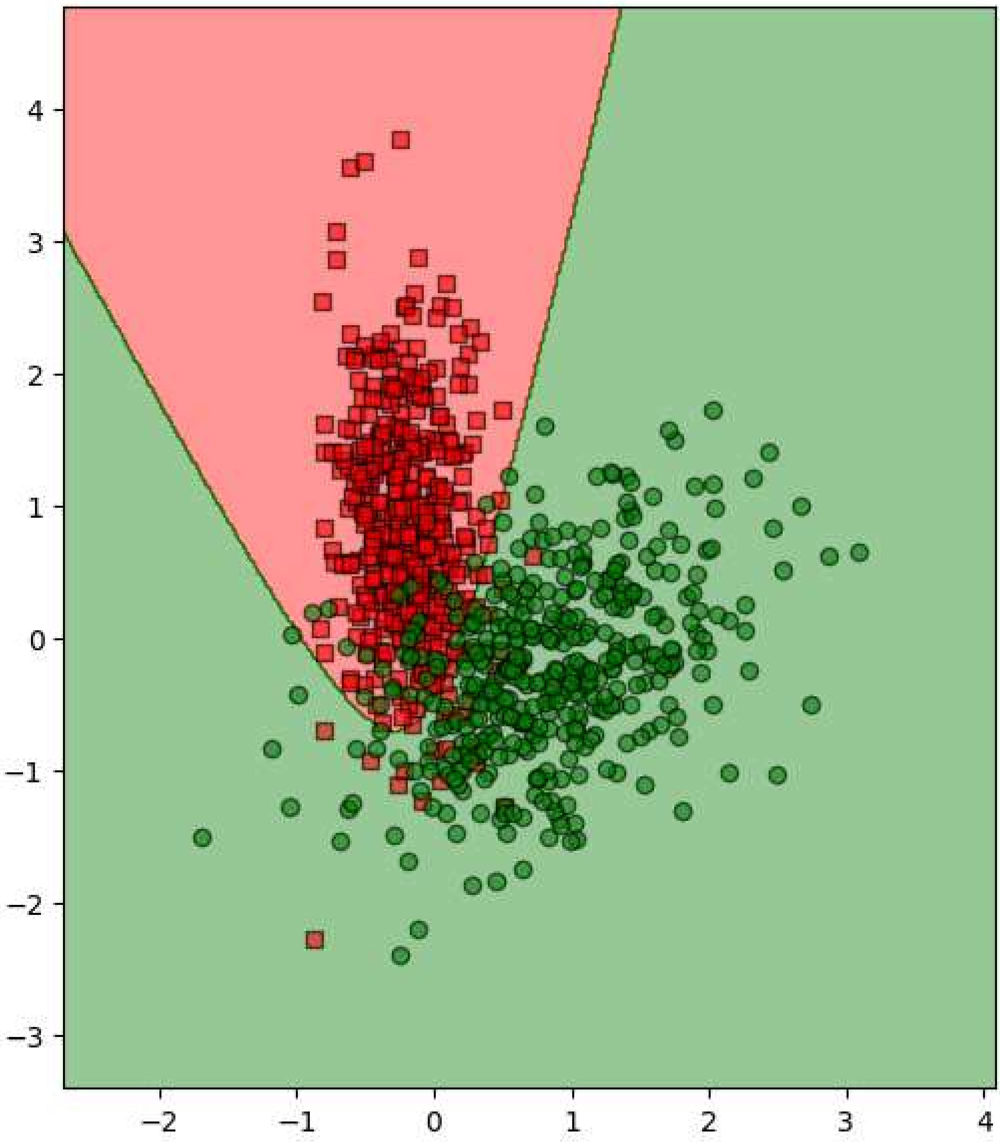
In [32]:
```python
model = GaussianDiscriminantAnalysis(same_cov=True)
model.fit(x_train, y_train)

res = model.predict(x_test)
accuracy = np.sum(res == y_test) / x_test.shape[0]
print(accuracy)

plt.figure(figsize=(6, 7), dpi=100)
plot_decision_regions(x_train, y_train[:, np.newaxis], classifier=model)
plt.show()
```

```
0.935
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_13464\3909362245.py:22: UserWarning:
*c* argument looks like a single numeric RGB or RGBA sequence, which should be av
oided as value-mapping will have precedence in case its length matches with *x* &
*y*.  Please use the *color* keyword-argument or provide a 2D array with a single
row if you intend to specify the same RGB or RGBA value for all points.
  plt.scatter(x=x[y[:, 0] == cc, 0],
```



In [33]:
```
model = GaussianDiscriminantAnalysis(same_cov=False)
model.fit(x_train, y_train)

res = model.predict(x_test)
accuracy = np.sum(res == y_test) / x_test.shape[0]
print(accuracy)

plt.figure(figsize=(6, 7), dpi=100)
plot_decision_regions(x_train, y_train[:, np.newaxis], classifier=model)
plt.show()
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  plt.scatter(x=x[y[:, 0] == cc, 0],
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```

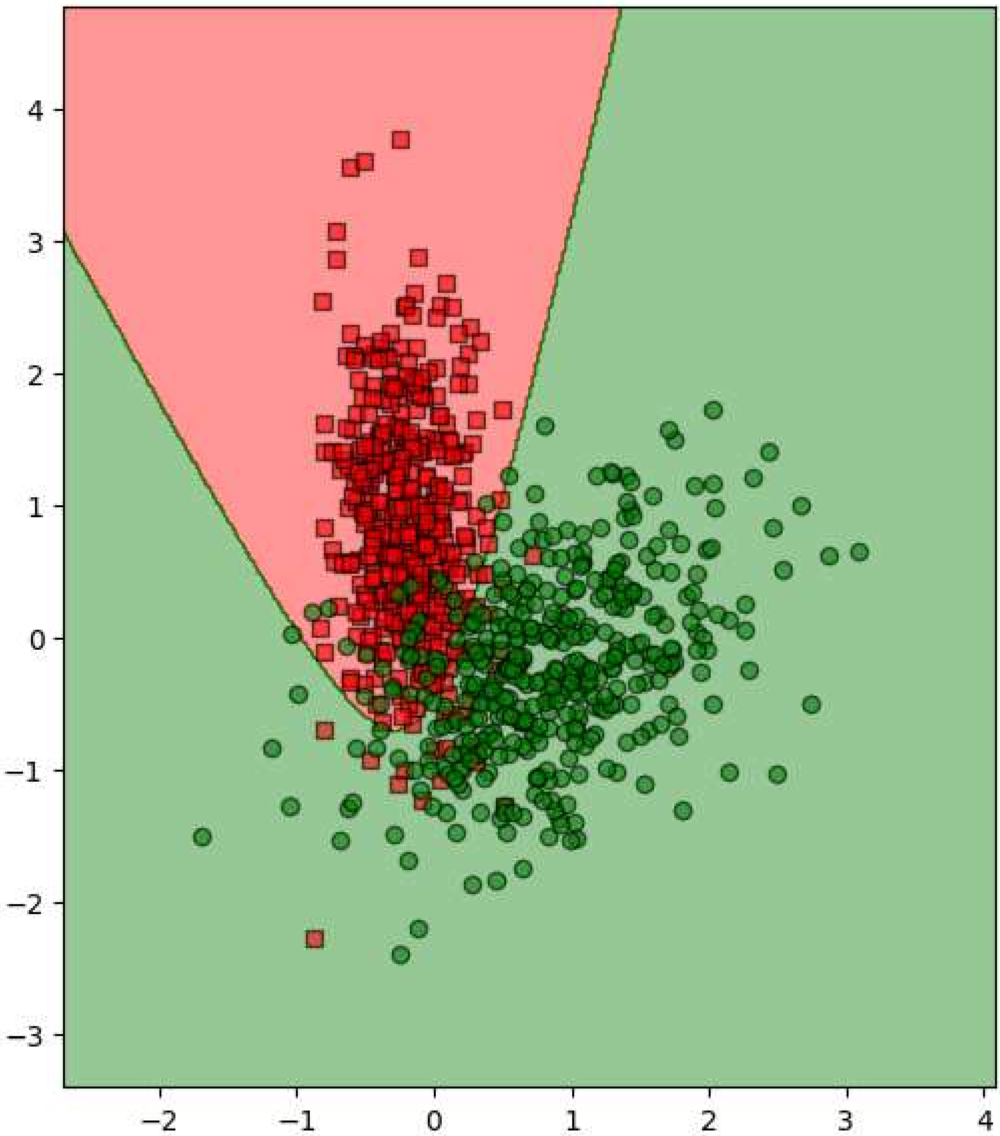

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