# 机器学习第三章作业

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## 1 第一题

- 1. 当数据集做过归一化时, 不必考虑 b
- 2. 当预测结果 y 只与 x 的线性变换结果有关时, 不必考虑 b

### 2 第三题

通过编程实现对率回归代码如下:

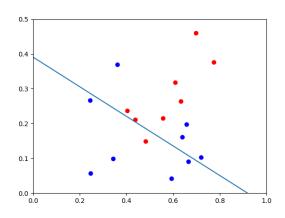


图 1: 实现结果

```
import numpy as np
from matplotlib import pyplot as plt

def load_dataset():
    file = open(r'melon3_dataset.txt')
    dataMat = []
    labelMat = []
    for line in file.readlines():
        lineArr = line.strip().split()
        dataMat.append([1.0, float(lineArr[0]), float(lineArr[1])])
        labelMat.append(int(lineArr[2]))
```

```
return dataMat, labelMat
def sigmoid(inX):
    return 1.0 / (1 + np.exp(-inX))
def mat_plot(dataMatrix, labelMatrix, weights):
   fig = plt.figure()
    ax = fig.add_subplot(111)
   n = np.shape(dataMatrix)[0]
   for i in range(n):
        if labelMatrix[i] == 1:
            ax.scatter(dataMatrix[i, 1], dataMatrix[i, 2], c='r')
            ax.scatter(dataMatrix[i, 1], dataMatrix[i, 2], c='b')
    x = np.arange(0, 1, 0.01)
    y = (-weights[0] - weights[1] * x) / weights[2]
    ax.plot(x, y)
    plt.xlim(0, 1)
    plt.ylim(0, 0.5)
    plt.show()
def model():
    dataMat, labelMat = load_dataset()
    dataMatrix = np.mat(dataMat)
    labelMatrix = np.mat(labelMat).transpose()
   m, n = np.shape(dataMatrix)
   alpha = 0.001
   maxCycles = 500
    weights = np.ones((n, 1))
   for i in range(maxCycles):
        h = sigmoid(dataMatrix * weights)
        error = (labelMatrix - h)
        gradient = dataMatrix.transpose() * error
        weights += alpha * gradient
    mat_plot(dataMatrix, labelMatrix, weights)
if __name__ == '__main__':
    model()
```

#### 3 第五题

通过编程实现线性判别分析 代码如下:

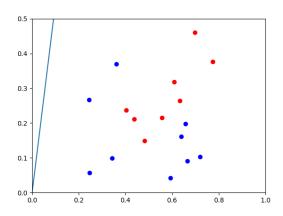


图 2: 实现结果

```
import numpy as np
from matplotlib import pyplot as plt
def load_dataset():
    file = open(r'melon3_dataset.txt')
    dataMat = []
    labelMat = []
    for line in file.readlines():
        lineArr = line.strip().split()
        dataMat.append([float(lineArr[0]), float(lineArr[1])])
        labelMat.append(int(lineArr[2]))
   return dataMat, labelMat
def mat_plot(w, data):
   fig = plt.figure()
    ax = fig.add_subplot(111)
   n = np.shape(data)[0]
    for i in range(n):
        if i < 8:
            ax.scatter(data[i, 0], data[i, 1], c='r')
        else:
            ax.scatter(data[i, 0], data[i, 1], c='b')
    x = np.arange(0, 1, 0.01)
    y = (w[0, 0] / w[1, 0]) * x
    ax.plot(x, y)
    plt.xlim(0, 1)
    plt.ylim(0, 0.5)
    plt.show()
```

```
def model():
    dataMat, labelMat = load_dataset()
    data = np.array(dataMat)
    X_0 = np.array(data[:8])
    X_1 = np.array(data[8:])
    miu_0 = np.mean(X_0, axis=0).reshape((-1, 1))
    miu_1 = np.mean(X_1, axis=0).reshape((-1, 1))
    cov_0 = np.cov(X_0, rowvar=False)
    cov_1 = np.cov(X_1, rowvar=False)
    S_w = np.mat(cov_0 + cov_1)
    Omega = S_w.I * (miu_0 - miu_1)
    mat_plot(Omega, data)

if __name__ == '__main__':
    model()
```

#### 4 第七题

理论最优的 EOOC 编码为:

$$C_1 = +1, +1, +1, +1, +1, +1, +1, +1, +1$$
  
 $C_2 = +1, +1, +1, -1, -1, -1, -1, -1$   
 $C_3 = -1, -1, -1, +1, +1, +1, -1, -1$   
 $C_4 = -1, -1, -1, -1, -1, -1, +1, +1, +1$ 

此时最大海明距离为6

**证明.** 假设存在海明距离为 7 的编码,则此时 EOOC 编码之间  $C_i$  不同的位置至少有 7 个,则有:

$$dif_{ij} = \{x | C_{ix} \neq C_{jx}\} \ge 7$$
$$dif_{jk} = dif_{ij} \cup dif_{ik} - dif_{ij} \cap dif_{ik}$$
$$dif_{jk} = |dif_{ij}| + |dif_{ik}| - 2 * |dif_{ij} \cap dif_{ik}|$$

设  $dif_{xj} = 7$ ,  $dif_{ix} = 7$ , 则有  $dif_{ij} = 6$ 

$$dif_{ix} + duf_{ij} - 2 * |dif_{ix} \cap dif_{ij}| \le 5 < 7$$

因此,显然不成立,得证

#### 5 第九题

因为对 OvR、MvM 来说,由于对每个类进行了相同的处理,其拆解出的二分类任务中类别不平衡的影响会相互抵消,因此通常不需要进行专门处理