背景介绍

数据下载

这可能是模式识别文献中最着名的数据库。费舍尔的论文是该领域的经典之作,至今仍被频繁引用。(例如,参见Duda & Hart。)数据集包含3个类别,每个类别50个实例,其中每个类别指的是一种鸢尾花。一类可以与另一类线性判别;后者不能彼此线性判别。

对于三种不同的鸢尾花进行分类任务, **数据集没有缺省的信息**,目标简单明了,通俗易懂。从项目地址下载号我们需要的数据集。

首先解压我们得到的数据,数据中有两个文件 <u>iris.names</u> 和 <u>Iris.data</u> ,前者是对当前数据集的一个简单解释,后者是我们将要训练的数据。

属性信息

下面是每一行数据中,都好分隔开的字段所代表的不同含义。

- 1. 萼片长度cm
- 2. 萼片宽度cm
- 3. 花瓣长度cm
- 4.花瓣宽度cm
- 5.类:
- Iris Setosa
- Iris Versicolour
- Iris Virginica

这里,将分别使用两种方法 LDA 线性判别分析和 SVM 支持向量机。

分析过程

首先先来看一下数据的大体情况吧!

```
Jason@X1:~/flower/Data$ cat Iris.data #观察原始数据集
5.1, 3.5, 1.4, 0.2, 0
4.9,3.0,1.4,0.2,0
4.7,3.2,1.3,0.2,0
4.6, 3.1, 1.5, 0.2, 0
5.0, 3.6, 1.4, 0.2, 0
5.4,3.9,1.7,0.4,0
4.6, 3.4, 1.4, 0.3, 0
5.0, 3.4, 1.5, 0.2, 0
4.4,2.9,1.4,0.2,0
4.9,3.1,1.5,0.1,0
5.4,3.7,1.5,0.2,0
4.8, 3.4, 1.6, 0.2, 0
4.8,3.0,1.4,0.1,0
4.3,3.0,1.1,0.1,0
5.8, 4.0, 1.2, 0.2, 0
5.7, 4.4, 1.5, 0.4, 0
5.4,3.9,1.3,0.4,0
5.1, 3.5, 1.4, 0.3, 0
5.7,3.8,1.7,0.3,0
5.1,3.8,1.5,0.3,0
5.4,3.4,1.7,0.2,0
```

5.1,3.7,1.5,0.4,0 4.6,3.6,1.1,0,0.2,0 5.1,3.3,1.7,0.5,0 4.8,3.4,1.9,0.2,0 5.0,3.4,1.6,0.4,0 5.2,3.5,1.5,0.2,0 5.2,3.5,1.5,0.2,0 5.2,3.4,1.6,0.2,0 5.4,3.4,1.5,0.4,0 5.4,3.4,1.5,0.4,0 5.5,4.2,1.4,0.2,0 4.7,3.2,1.6,0.2,0 5.4,3.4,1.5,0.4,0 5.5,4.2,1.4,0.2,0 4.9,3.1,1.5,0.1,0 5.5,4.2,1.4,0.2,0 4.9,3.1,1.5,0.1,0 5.5,3.5,1.3,0.2,0 5.5,3.5,1.3,0.2,0 6.9,3.1,3.6,0.2,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.5,1.3,0.3,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.0,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.1,4.9,3.1,0 6.9,3.2,4.9,3.1,0 6.9,3.3,4.9,3.1,0 6.9,3.3,4.9,3.1,0 6.9,3.9,4.2,1.5,1 6.9,3.2,4.9,3.1,0 6.9,3.9,4.2,1.5,1 6.9,3.2,4.9,3.1,0 6.9,3.9,4.2,1.5,1 6.9,3.2,4.9,3.1,0 6.9,3.9,4.2,1.5,1 6.9,3.9,5.9,1.7,1 6.9,3.9,5.9,1.7,1 6.9,3.9,5.9,1.7,1 6.9,3.9,5.9,1.7,1 6.9,3.9,5.9,1.7,1 6.9,3.9,9,3.2,4.9,1.3,1 6.9,3.3,9,3.2,4.9,1.3,1 6.9,3.3,9,3.2,4.9,1.3,1 6.9,			
4.6,3.6,1.0,0.2,0 5.1,3.3,1.7,0.5,0 4.8,3.4,1.9,0.2,0 5.0,3.4,1.6,0.2,0 5.0,3.4,1.6,0.2,0 5.2,3.4,1.6,0.2,0 5.2,3.4,1.4,0.2,0 4.8,3.1,1.6,0.2,0 4.8,3.1,1.6,0.2,0 4.8,3.1,1.6,0.2,0 4.8,3.1,1.6,0.2,0 4.9,3.1,1.5,0.4,0 5.2,4.1,1.5,0.4,0 5.2,4.1,1.5,0.4,0 5.2,4.1,1.5,0.4,0 5.2,4.1,1.5,0.4,0 5.3,4.1,0.2,0 4.9,3.1,1.5,0.1,0 5.9,3.2,1.2,0.2,0 4.9,3.1,1.5,0.1,0 4.4,3.0,1.3,0.2,0 5.1,3.4,1.6,0.2,0 5.3,3.5,1.3,0.3,0 4.4,3.2,1.3,0.3,0 4.4,3.2,1.3,0.3,0 4.3,2.1,3.0,2,0 5.1,3.8,1.9,0.4,0 4.3,3.0,1.4,0.3,0 5.1,3.8,1.9,0.4,0 4.3,3.0,1.4,0.3,0 5.1,3.8,1.9,0.4,0 4.3,3.1,1.5,0.2,0 5.0,3.5,1.6,0.2,0 4.6,3.2,1.4,0.2,0 5.0,3.5,1.6,0.2,0 4.6,3.2,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.2,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.2,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.3,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.3,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.3,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.3,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.3,1.4,0.2,0 5.0,3.5,1.3,0.3,0 4.6,3.3,1.4,0.3,0 5.0,3.3,1.4,0.3,0 5.0,3.3,1.4,0.3,0 5.0,3.3,1.4,0.3,0 6.0,3.0,4.2,1.5,1 6.0,2.2,4.4,3.3,1.0,1 6.0,2.2,4.4,3.3,1.0,1 6.1,2.2,4.5,1.5,1 6.1,2.8,4.0,1.3,1 6.1,3.0,1.3,1 6.1,3.0,1.3,1 6.1,3.0,1.3,1 6.1,	5.1,3.7,1.5,0.4,0		
5.1, 3.3, 1.7, 0.5, 0 4.8, 3.4, 1.7, 0.5, 0 5.0, 3.4, 1.6, 0.2, 0 5.0, 3.4, 1.6, 0.2, 0 5.2, 3.5, 1.5, 0.2, 0 5.2, 3.4, 1.4, 0.2, 0 4.7, 3.2, 1.6, 0.2, 0 4.8, 3.1, 1.5, 0.1, 0 5.2, 4.4, 1.5, 0.1, 0 5.5, 4.2, 1.4, 0.2, 0 4.9, 3.1, 1.5, 0.1, 0 5.5, 4.2, 1.4, 0.2, 0 4.9, 3.1, 1.5, 0.1, 0 5.5, 4.2, 1.4, 0.2, 0 4.9, 3.1, 1.5, 0.1, 0 5.5, 4.2, 1.4, 0.2, 0 4.9, 3.1, 1.5, 0.1, 0 5.5, 4.2, 1.4, 0.2, 0 5.5, 3.5, 1.3, 0.2, 0 5.5, 3.5, 1.3, 0.2, 0 5.5, 3.5, 1.3, 0.2, 0 5.5, 3.5, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.6, 3.2, 1.4, 0.2, 0 5.1, 3.8, 1.6, 0.2, 0 5.1, 3.8, 1.6, 0.2, 0 5.3, 3.7, 1.5, 0.2, 0 5.3, 3.7, 1.5, 0.2, 0 5.3, 3.7, 1.5, 0.2, 0 5.3, 3.7, 1.5, 0.2, 0 5.3, 3.3, 4.4, 0.2, 0 7.0, 3.2, 4.7, 1.4, 1 6.4, 3.2, 4.5, 1.5, 1 6.9, 3.1, 4.9, 1.5, 1 5.5, 2.3, 4.9, 1.3, 1 6.5, 2.9, 4.6, 1.3, 1 6.6, 2.9, 4.6, 1.3, 1 6.6, 2.9, 4.6, 1.3, 1 6.7, 3.1, 4.4, 1.4, 1 6.6, 2.2, 4.8, 1.8, 1 6.1, 2.8, 4.7, 1.4, 1 6.6, 2.2, 4.8, 1.8, 1 6.1, 2.8, 4.7, 1.4, 1 6.6, 2.2, 4.8, 1.8, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.9, 4.7, 1.4, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.7, 1.2, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1 6.1, 2.8, 4.3, 1.3, 1			
4.8, 3.4, 1.9, 0.2, 0 5.0, 3.4, 1.6, 0.2, 0 5.0, 3.4, 1.6, 0.2, 0 5.2, 3.5, 1.5, 0.2, 0 5.2, 3.5, 1.5, 0.2, 0 5.2, 3.5, 1.5, 0.2, 0 5.2, 3.4, 1.4, 0.2, 0 4.8, 3.1, 1.6, 0.2, 0 5.2, 4.1, 1.5, 0.4, 0 5.2, 4.1, 1.5, 0.4, 0 5.2, 4.1, 1.5, 0.4, 0 5.2, 4.1, 1.5, 0.4, 0 5.2, 4.1, 1.5, 0.4, 0 5.2, 4.1, 1.5, 0.4, 0 5.2, 4.1, 1.5, 0.4, 0 5.9, 3.2, 1.5, 0.4, 0 5.9, 3.2, 1.5, 0.4, 0 4.9, 3.1, 1.5, 0.1, 0 5.9, 3.2, 1.5, 0.4, 0 4.9, 3.1, 1.5, 0.1, 0 4.4, 3.0, 1.3, 0.2, 0 5.1, 3.4, 1.5, 0.2, 0 5.1, 3.4, 1.5, 0.2, 0 5.0, 3.5, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.3, 0.3, 0 4.4, 3.2, 1.4, 0.2, 0 5.1, 3.8, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0 5.1, 3.1, 1.6, 0.2, 0	4.0,3.0,1.0,0.2,0		
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6.8,2.8,4.8,1.4,1 6.7,3.0,5.0,1.7,1 6.0,2.9,4.5,1.5,1 5.7,2.6,3.5,1.0,1 5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1	6.6,3.0,4.4,1.4,1		
6.7,3.0,5.0,1.7,1 6.0,2.9,4.5,1.5,1 5.7,2.6,3.5,1.0,1 5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1			
6.0,2.9,4.5,1.5,1 5.7,2.6,3.5,1.0,1 5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1			
6.0,2.9,4.5,1.5,1 5.7,2.6,3.5,1.0,1 5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1	6.7,3.0,5.0,1.7,1		
5.7,2.6,3.5,1.0,1 5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1			
5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1			
5.5,2.4,3.8,1.1,1 5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1	5.7,2.6,3.5,1.0,1		
5.5,2.4,3.7,1.0,1 5.8,2.7,3.9,1.2,1			
5.8, 2.7, 3.9, 1.2, 1			
5.8, 2.7, 3.9, 1.2, 1	5.5,2.4,3.7,1.0,1		
0.0, 2.1, 3.1, 1.0, 1			
	0.0,2.7,5.1,1.6,1		

5.4,3.0,4.5,1.5,1	
6.0,3.4,4.5,1.6,1	
6.7,3.1,4.7,1.5,1	
6.3, 2.3, 4.4, 1.3, 1	
5.6,3.0,4.1,1.3,1	
5.5, 2.5, 4.0, 1.3, 1	
5.5,2.6,4.4,1.2,1	
6.1,3.0,4.6,1.4,1	
5.8,2.6,4.0,1.2,1	
5.0,2.3,3.3,1.0,1	
5.6,2.7,4.2,1.3,1	
5.7,3.0,4.2,1.2,1	
5.7,2.9,4.2,1.3,1	
6.2,2.9,4.3,1.3,1	
5.1,2.5,3.0,1.1,1	
5.7,2.8,4.1,1.3,1	
6.3,3.3,6.0,2.5,2	
5.8,2.7,5.1,1.9,2	
7.1,3.0,5.9,2.1,2	
6.3,2.9,5.6,1.8,2	
6.5,3.0,5.8,2.2,2	
7.6,3.0,6.6,2.1,2	
4.9,2.5,4.5,1.7,2	
7.3,2.9,6.3,1.8,2	
6.7,2.5,5.8,1.8,2	
7.2,3.6,6.1,2.5,2	
6.5,3.2,5.1,2.0,2	
6.4,2.7,5.3,1.9,2	
6.8,3.0,5.5,2.1,2	
5.7,2.5,5.0,2.0,2	
5.8,2.8,5.1,2.4,2	
6.4,3.2,5.3,2.3,2	
6.5,3.0,5.5,1.8,2	
7.7,3.8,6.7,2.2,2	
7.7,2.6,6.9,2.3,2	
6.0,2.2,5.0,1.5,2	
6.9,3.2,5.7,2.3,2	
5.6,2.8,4.9,2.0,2	
7.7,2.8,6.7,2.0,2	
6.3,2.7,4.9,1.8,2	
6.7,3.3,5.7,2.1,2	
7.2,3.2,6.0,1.8,2	
6.2,2.8,4.8,1.8,2	
6.1,3.0,4.9,1.8,2	
6.4,2.8,5.6,2.1,2	
7.2,3.0,5.8,1.6,2	
7.4,2.8,6.1,1.9,2	
7.9,3.8,6.4,2.0,2	
6.4, 2.8, 5.6, 2.2, 2	
6.4,2.8,5.6,2.2,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2	
6.4,2.8,5.6,2.2,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2 5.8,2.7,5.1,1.9,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2 5.8,2.7,5.1,1.9,2 6.8,3.2,5.9,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2 5.8,2.7,5.1,1.9,2 6.8,3.2,5.9,2.3,2 6.7,3.3,5.7,2.5,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2 5.8,2.7,5.1,1.9,2 6.8,3.2,5.9,2.3,2 6.7,3.3,5.7,2.5,2 6.7,3.0,5.2,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2 5.8,2.7,5.1,1.9,2 6.8,3.2,5.9,2.3,2 6.7,3.3,5.7,2.5,2 6.7,3.0,5.2,2.3,2	
6.4,2.8,5.6,2.2,2 6.3,2.8,5.1,1.5,2 6.1,2.6,5.6,1.4,2 7.7,3.0,6.1,2.3,2 6.3,3.4,5.6,2.4,2 6.4,3.1,5.5,1.8,2 6.0,3.0,4.8,1.8,2 6.9,3.1,5.4,2.1,2 6.7,3.1,5.6,2.4,2 6.9,3.1,5.1,2.3,2 5.8,2.7,5.1,1.9,2 6.8,3.2,5.9,2.3,2 6.7,3.3,5.7,2.5,2	

```
6.5,3.0,5.2,2.0,2
6.2,3.4,5.4,2.3,2
5.9,3.0,5.1,1.8,2
```

很容易理解,这里我们抽出一个字段来看

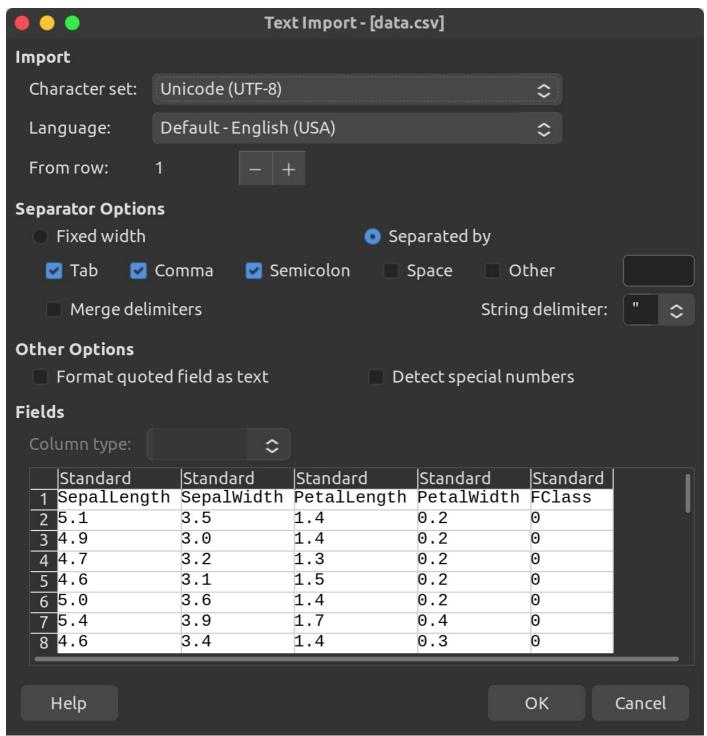
```
5.9 , 3.0 , 5.1 , 1.8 , 2
|萼片长度cm|萼片宽度cm|花瓣长度cm|花瓣宽度cm| 类 |
```

数据预处理

好了既然我们已经知道数据是完整的,这里首先对原始数据预处理一下,改成比较适合的格式,这里可以使用python来完成,但是这里我是使用cut command将数据流重定向至一个信的csv文件,因为python还得编译的搞,不太舒服。

这里需要注意的两点是1.win下txt文件会在换行的时候加一个 AM 符号,虽然丢我们数据的处理可能不会产生影响,但是还是tr command去掉好了;2.在加入数据到csv文件时,不要忘记加入表头,否则一会数据分析的时候就很难看。

```
Jason@X1:~/flower/Dat$ echo SepalLength,SepalWidth,PetalLength,\
> PetalWidth,FClass > data.csv
Jason@X1:~/flower/Data$ cat Iris.data | cut -d',' -f 1,2,3,4,5 >> data.csv
# 没有返回错误信息,原目录下应该完成了转换。
Jason@X1:~/flower/Data$ xdg-open data.csv
```



好,可以看到我们的数据完美的被分隔了到了新建的 data.csv 中,这就非常舒服。

读入数据

利用 pandas 数据分析模块和 numpy 科学计算模块来分析数据。首先读入我们的数据:

```
import pandas as pd
import numpy as np
from pandas import Series, DataFrame

data_train=pd.read_csv('/home/jason/Documents/ML/flower/data.csv', engine =
'python', encoding='UTF-8')
data_train #dataframe格式
```

这里就可以看到data.csv中的数据了。但是只有数据表我们很难从中找出规律。所以接下来通过pandas中的方法来大体 查看一下数据集的全貌。

>>> data_train.info()

运行一下唉

```
Jason@X1:~/flower/Dat$ py3 linear.py
[150 rows x 5 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
SepalLength 150 non-null float64
SepalWidth
             150 non-null float64
PetalLength 150 non-null float64
              150 non-null float64
PetalWidth
              150 non-null int64
FClass
dtypes: float64(4), int64(1)
memory usage: 5.9 KB
None
```

这里可以看到这150条记录都是非空的,并且前四个字段为float,最后一个为int型,看来Fisher没有故意搞我们,确实数据没有缺省。

然后我们再使用describe来看一下

>>> da	ta_train.desc	ribe()				
	SepalLength	SepalWidth	PetalLength	PetalWidth	FClass	
count	150.000000	150.000000	150.000000	150.000000	150.000000	
mean	5.843333	3.054000	3.758667	1.198667	1.000000	
std	0.828066	0.433594	1.764420	0.763161	0.819232	
min	4.300000	2.000000	1.000000	0.100000	0.000000	
25%	5.100000	2.800000	1.600000	0.300000	0.000000	
50%	5.800000	3.000000	4.350000	1.300000	1.000000	
75%	6.400000	3.300000	5.100000	1.800000	2.000000	
max	7.900000	4.400000	6.900000	2.500000	2.000000	

describe() 还是nice啊,我把describe的内容整理成一个表格,这样是不是更清晰一些

	Min	Max	Mean	SD	Class	Correlation
SepalLength	4.3	7.9	5.84	0.83	0.7826	
SepalWidth	2.0	4.4	3.05	0.43	-0.4194	
PetalLength	1.0	6.9	3.76	1.76	0.9490	(high!)
PetalWidth	0.1	2.5	1.20	0.76	0.9565	(high!)

可以观察到,表格中最后两个item中Class的致是最高的,可以假设一下我们的花朵分类应该会跟这两个item关系密切(PS:因为要求用三次二分类做,所以这里我们可以现不用猜测数据简单关系)。

PL和PW与属性结果的关系

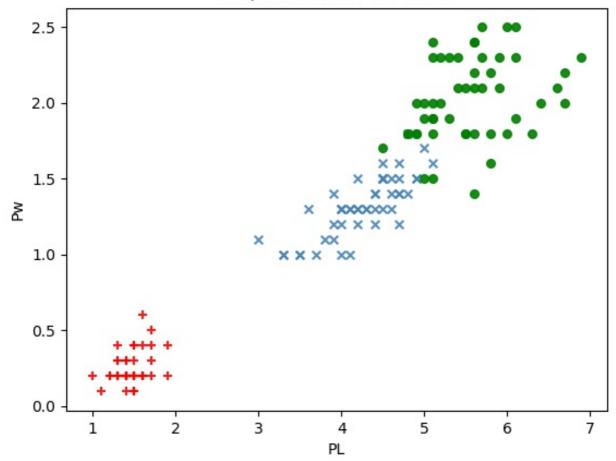
第一个猜想是和PL,PW有关,看一下情况

```
import pandas as pd
```

```
import numpy as np
from pandas import Series, DataFrame
data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
import matplotlib.pyplot as plt
fig = plt.figure()
fig.set(alpha=0.2) #设定图表颜色颜色
plt.scatter(data_train.PetalLength[data_train.FClass==1], # x轴数据为PL
            data_train.PetalWidth[data_train.FClass==1], # y轴数据为PW
            s = 30, # 设置点的大小
           c = 'steelblue', # 设置点的颜色
           marker = 'x', # 设置点的形状
            alpha = 0.9, # 设置点的透明度
plt.scatter(data_train.PetalLength[data_train.FClass==2],
            data_train.PetalWidth[data_train.FClass==2],
            s = 30,
            c = 'green',
           marker = 'o',
            alpha = 0.9,
            )
plt.scatter(data_train.PetalLength[data_train.FClass==0],
            data_train.PetalWidth[data_train.FClass==0],
            s = 30,
           c = 'red',
           marker = '+',
            alpha = 0.9,
plt.ylabel(u"Pw")
plt.title(u"PW,PL realation to FCalss") #标题
plt.xlabel(u"PL")
plt.show()
```

Jason@X1:~/flower/Dat\$ py3 linear.py

PW,PL realation to FCalss

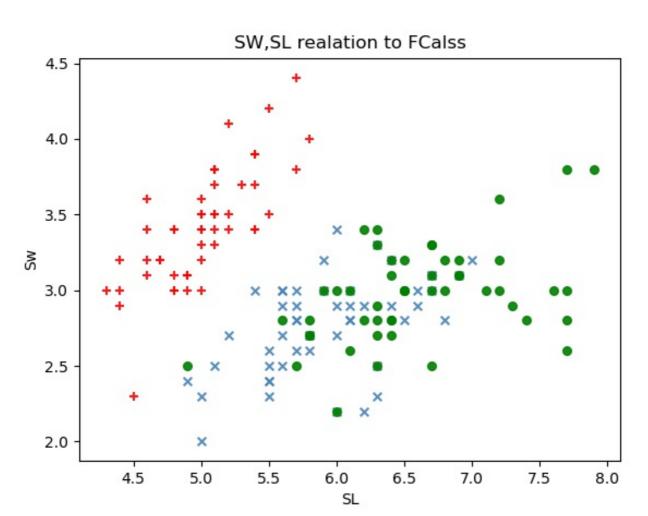


可以看到第一类鸢尾花Iris Setosa可以从后面两种中分离出来。

SL和SW与属性结果的关系

这样还是制作一张散点图

```
import pandas as pd
import numpy as np
from pandas import Series, DataFrame
data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
import matplotlib.pyplot as plt
fig = plt.figure()
fig.set(alpha=0.2) #设定图表颜色颜色
plt.scatter(data_train.SepalLength[data_train.FClass==1], # x轴数据为PL
           data_train.SepalWidth[data_train.FClass==1], # y轴数据为PW
           s = 30, # 设置点的大小
           c = 'steelblue', # 设置点的颜色
           marker = 'x', # 设置点的形状
           alpha = 0.9, # 设置点的透明度
plt.scatter(data_train.SepalLength[data_train.FClass==2],
           data_train.SepalWidth[data_train.FClass==2],
           s = 30,
           c = 'green',
           marker = 'o',
           alpha = 0.9,
```



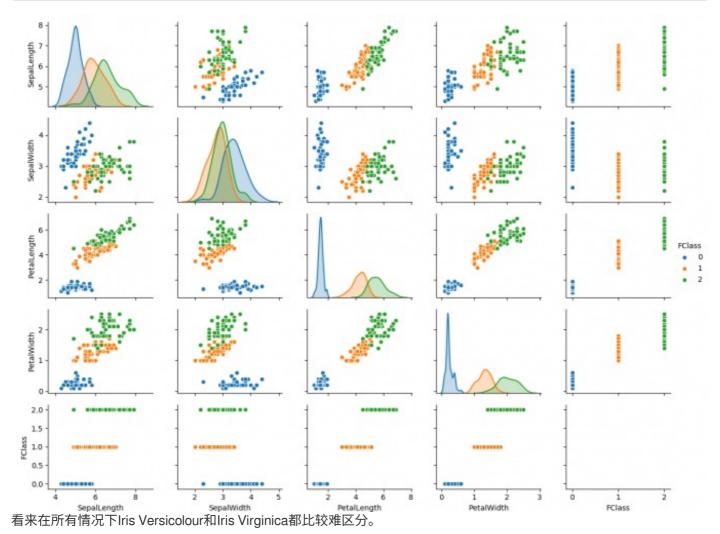
纳尼,看来SW分离不出来什么东西,和第一次是差不多的,看来通过某两对属性组就能分类的想法是不可能了。但是我们可以看出来,第一类鸢尾花无论是花瓣还是花萼都与后面两类差很多,分离出第一种化是比较容易的,重点放在如何分离拆开后两种花朵类型。

下面就要进入瞎猜的环节来看看还有哪些猜想是成立的,这里使用一个库函数帮我们理出所有的可能

```
import pandas as pd
import numpy as np
from pandas import Series, DataFrame

data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
import matplotlib.pyplot as plt
fig = plt.figure()
fig.set(alpha=0.2) #设定图表颜色颜色
```

import seaborn as sns
sns.pairplot(data_train, hue='FClass')
plt.show()



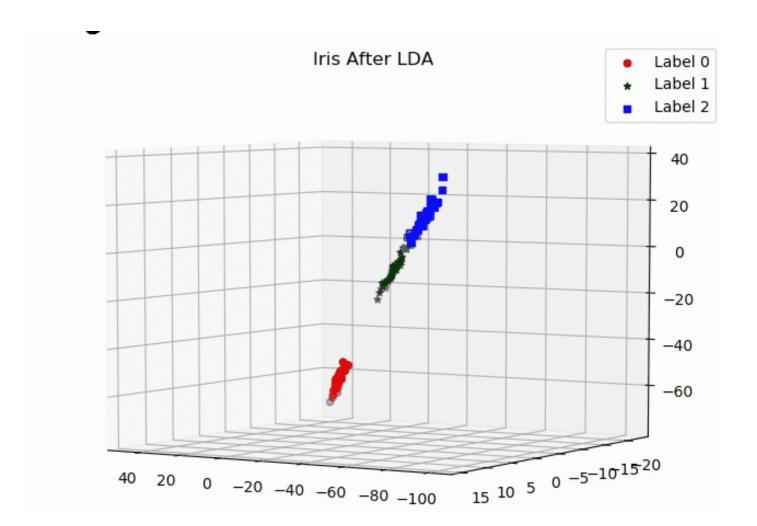
线性判别分析LDA

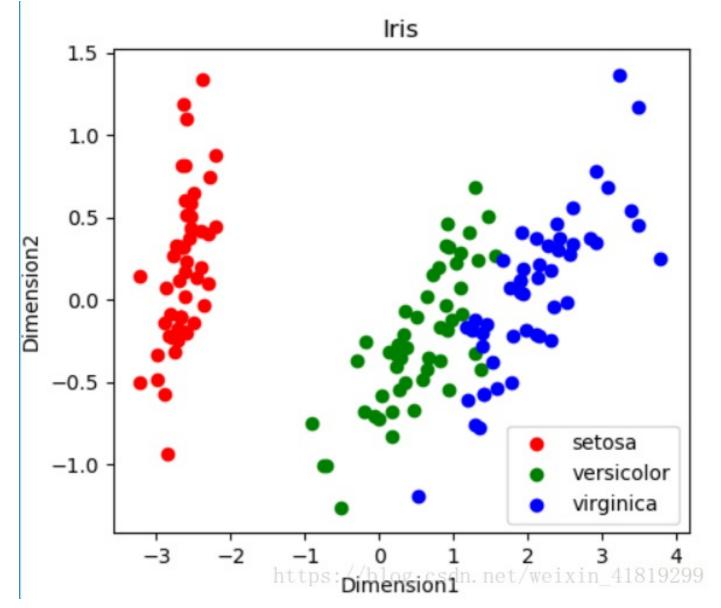
Linear Discriminant Analysis,器最主要的作用我觉得是对数据进行降维,通过将多维数据向更低空间投影,从而能获得一个易于理解的概念模型。

这里我们通过单个二分类问题的概念推到出多类线性判别分析。

低维空间的选择

如何选择一个维度合适的空间,作为我们的特征空间呢?是将一个 d 维数据集投影到一个 k (k<d)维子空间中,如何选择k的大小。比如对于目前我们系哪有的数据集,就有2维或3维这两种降维选择。





这里用到的方法是求特征向量,然后将器归总到类内散度矩阵和类间散度矩阵。 \$\$ \begin{align*} & S_w=\Sigma_0+\Sigma_1=\sum_{x \in X_0}(x-\mu_0)^T+\sum_{x \in X_1}(x-\mu_1)(x-\mu_1)^T \& S_b= (\mu_0-\mu_1)(\mu_0-\mu_1)^T \end{align*} \$\$

每一个特征向量都对应一个特征值, 如果特征值的大小接近就代表我们投影到的空间维度比较合适。

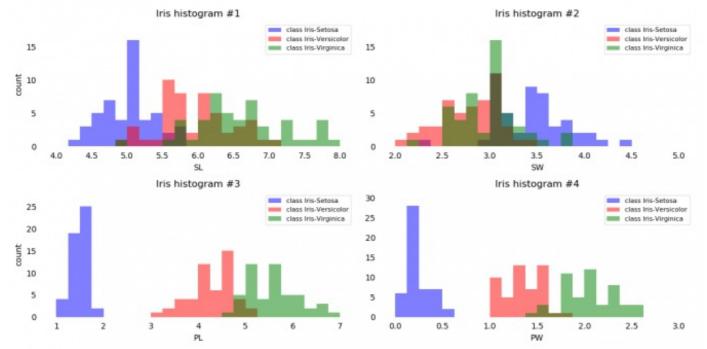
基本方法和步骤

- 计算数据集中不同类别数据的 d 维均值向量。
- 计算散度矩阵,包括类间、类内散度矩阵。
- 计算散度矩阵的特征向量 e1,e2,...,ed 和对应的特征值 λ1,λ2,...,λd。
- 特征向量按特征值大小降序排列,选前 k 个特征值对应的特征向量,组建一个 d×k 维矩阵——每一列就是一个特征 向量。
- 用这个 $d \times k$ -维特征向量矩阵将样本变换到新的子空间。这一步可以写作矩阵乘法 $Y = X \times W$ 。 $X \in \mathbb{R}$ $x \in \mathbb{R}$ 表示 $x \in \mathbb{R}$ 个样本; $x \in \mathbb{R}$ 是变换到子空间后的 $x \in \mathbb{R}$ 化

conjecture

通过前面的一些基本分析,我们已经知道区分花朵类型的在四种特征里面,花瓣的长度、宽度更适合用来区分三种鸢尾 花类别。但这是否正确还是要看一下结果,用直方图做一下映射

```
import pandas as pd
import math
import numpy as np
from pandas import Series, DataFrame
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
feature_dict = {i:label for i,label in zip(range(4),('SL','SW','PL','PW', ))}
data_train = pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
data_train.columns = [l for i,l in sorted(feature_dict.items())] + ['FClass']
X = data_train[['SL', 'SW', 'PL', 'PW']].values
y = data_train['FClass'].values
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12,6))
for ax,cnt in zip(axes.ravel(), range(4)):
    # set bin sizes
    min_b = math.floor(np.min(X[:,cnt]))
    max_b = math.ceil(np.max(X[:,cnt]))
    bins = np.linspace(min_b, max_b, 25)
    # plottling the histograms
    for lab,col in zip(range(1,4), ('blue', 'red', 'green')):
        ax.hist(X[y==lab-1, cnt],
                   color=col,
                   label='class %s' %label_dict[lab-1],
                   bins=bins,
                   alpha=0.5,)
    ylims = ax.get_ylim()
    # plot annotation
    leg = ax.legend(loc='upper right', fancybox=True, fontsize=8)
    leg.get_frame().set_alpha(0.5)
    ax.set_ylim([0, max(ylims)+2])
    ax.set_xlabel(feature_dict[cnt])
    ax.set_title('Iris histogram #%s' %str(cnt+1))
    # hide axis ticks
    ax.tick_params(axis="both", which="both", bottom="off", top="off",
            labelbottom="on", left="off", right="off", labelleft="on")
    # remove axis spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)
    ax.spines["bottom"].set_visible(False)
    ax.spines["left"].set_visible(False)
axes[0][0].set_ylabel('count')
axes[1][0].set_ylabel('count')
fig.tight_layout()
plt.show()
```



仅凭这些简单的图形化展示,已经足以让我们得出结论:在四种特征里面,花瓣的长度、宽度更适合用来区分三种鸢尾 花类别。

实际应用中,比起通过投影降维(此处即LDA),另一种比较好的办法是做特征筛选。像鸢尾花这样的低维数据集,看一眼直方图就能得到很多信息了。

LDA

• 计算数据的 d 维均值向量

```
import numpy as np
import math
import pandas as pd
from pandas import Series, DataFrame
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
feature_dict = {i:label for i,label in zip(range(4),('SL','SW','PL','PW', ))}
data_train = pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
data_train.columns = [l for i,l in sorted(feature_dict.items())] + ['FClass']
#print (data_train.tail())
X_src = data_train[['SL', 'SW', 'PL', 'PW']].values
y_src = data_train['FClass'].values
X, X_spl, y, y_spl = train_test_split(X_src, y_src, test_size=0.3,
random_state=42, stratify=y_src)
#print (X.tail(),y.tail())
np.set_printoptions(precision=4)
mean_vectors = []
for clo in range(1,4):
    mean_vectors.append(np.mean(X[y==clo-1],axis=0))
    print('Mean Vector FClass %s: %s\n' %(clo-1, mean_vectors[clo-1]))
```

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```
Jason@X1:~/flower/Data$ py3 LDA.py
Mean Vector FClass 0: [4.9886 3.4114 1.4886 0.2371]

Mean Vector FClass 1: [5.9486 2.7314 4.2371 1.3086]

Mean Vector FClass 2: [6.6829 3.0086 5.6314 2.0686]
```

● 计算散度矩阵 \$\$ S_w=\Sigma_0+\Sigma_1=\sum_{x \in X_0}(x-\mu_0)^T+\sum_{x \in X_1}(x-\mu_1)(x-\mu_1)^T \$\$

```
S_W = np.zeros((4,4)) #4x4的矩阵
for clo,mv in zip(range(1,4), mean_vectors):
    class_sc_mat = np.zeros((4,4))
    for row in X[y == clo-1]:
        row, mv = row.reshape(4,1), mv.reshape(4,1)
        class_sc_mat += (row-mv).dot((row-mv).T)
    S_W += class_sc_mat
print('类内散度矩阵:\n', S_W)
```

ру一下

```
Jason@X1:~/flower/Data$ py3 LDA.py
类内散度矩阵:
[[26.9126 9.7063 17.5711 3.2614]
[ 9.7063 13.2583 5.7343 3.0851]
[17.5711 5.7343 19.4926 4.0283]
[ 3.2614 3.0851 4.0283 3.8246]]
```

 $S_b=(\mu_0-\mu_1)(\mu_0-\mu_1)^T$

```
overall_mean = np.mean(X, axis=0)

S_B = np.zeros((4,4))
for i,mean_vec in enumerate(mean_vectors):
    n = X[y==i,:].shape[0]
    mean_vec = mean_vec.reshape(4,1)
    overall_mean = overall_mean.reshape(4,1)
    S_B += n * (mean_vec - overall_mean).dot((mean_vec - overall_mean).T)

print('类间散度矩阵:\n', S_B)
```

ру一下

• 求解矩阵的广义特征值

```
eig_vals, eig_vecs = np.linalg.eig(np.linalg.inv(S_W).dot(S_B))

for i in range(len(eig_vals)):
    eigvec_sc = eig_vecs[:,i].reshape(4,1)
    print('\n特征向量 {}: \n{}'.format(i+1, eigvec_sc.real))
    print('特征值 {:}: {:.2e}'.format(i+1, eig_vals[i].real))
```

ру一下

```
Jason@X1:~/flower/Data$ py3 LDA.py
特征向量 1:
[[-0.1895]
 [-0.3302]
 [0.5051]
 [ 0.7746]]
特征值 1: 3.23e+01
特征向量 2:
[[ 0.0448]
 [ 0.5551]
 [-0.2891]
 [ 0.7786]]
特征值 2: 3.72e-01
特征向量 3:
[[ 0.4887]
 [ 0.1004]
 [ 0.1842]
 [-0.8468]]
特征值 3: -4.92e-15
特征向量 4:
[[ 0.7403]
 [-0.3929]
 [-0.4662]
 [ 0.2834]]
特征值 4: 2.78e-15
```

特征向量和特征值代表了一个线性变换的形变程度,特征向量是形变的方向,特征值是形变的大小。

• 选择线性判别器构成新的特征子空间

将特征向量根据特征值的大小从高到低排序,然后选择前 k 个本征向量:

```
eig_pairs = [(np.abs(eig_vals[i]), eig_vecs[:,i]) for i in range(len(eig_vals))]
eig_pairs = sorted(eig_pairs, key=lambda k: k[0], reverse=True)
print('特征值:\n')
for i in eig_pairs:
    print(i[0])
```

ру一下

```
Jason@X1:~/flower/Data$ py3 LDA.py
特征值:
32.34182135648737
0.37171378445332187
4.915564356595094e-15
2.7775787346756613e-15
```

我们将4d空间投影到2d空间上,所以选择前两个特征向量。在LDA中,线性判别器的数目最多是 c–1,c 是总的类别数,这是因为类内散布矩阵 SB 是 c 个秩为1或0的矩阵的和。

按特征值的大小得到降序排列的本征对之后,现在就可以组建我们的 k×d-维特征向量矩阵 W 了(此时大小为 4×2),

```
W = np.hstack((eig_pairs[0][1].reshape(4,1), eig_pairs[1][1].reshape(4,1)))
print('矩阵 W:\n', W.real)
```

ру一下

```
Jason@X1:~/flower/Data$ py3 LDA.py
矩阵 W:
[[-0.1895    0.0448]
[-0.3302    0.5551]
[ 0.5051 -0.2891]
[ 0.7746    0.7786]]
```

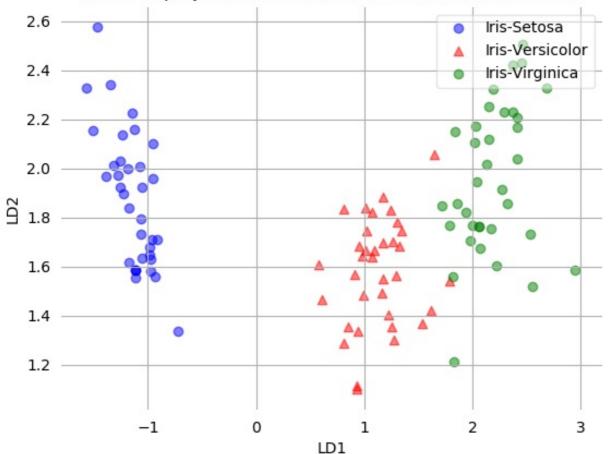
• 将样本变换到新的子空间中

使用上一步刚刚计算出的 4×2-维矩阵 W, 将样本变换到新的特征空间上:

```
X_lda = X.dot(W)
label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
def plot_step_lda():
    ax = plt.subplot(111)
    for label, marker, color in zip(
        range(1,4),('o', '^', 'o'),('blue', 'red', 'green')):
        plt.scatter(x=X_lda[:,0].real[y == label-1],
                y=X_lda[:,1].real[y == label-1],
                marker=marker,
                color=color,
                alpha=0.5,
                label=label_dict[label-1]
    plt.xlabel('LD1')
    plt.ylabel('LD2')
    leg = plt.legend(loc='upper right', fancybox=True)
    leg.get_frame().set_alpha(0.5)
    plt.title('LDA: Iris projection onto the first 2 linear discriminants')
    # hide axis ticks
    plt.tick_params(axis="both", which="both", bottom="off", top="off",
            labelbottom="on", left="off", right="off", labelleft="on")
    # remove axis spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)
    ax.spines["bottom"].set_visible(False)
    ax.spines["left"].set_visible(False)
    plt.grid()
    plt.tight_layout
    plt.show()
plot_step_lda()
```

结果绘图





上方散点图展示了我们通过 LDA 构建的新的特征子空间。可以看到第一个线性判别器"LD1"把不同类数据区分得不错, 第二个线性判别器就不行了。其原因在上面已经做了简单解释。

预测

然后就是对样本结果集的预测了。

```
X_lda = X.dot(W)
label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
def plot_step_lda():
    ax = plt.subplot(111)
    for label, marker, color in zip(
        range(1,4),('o', '^', 'o'),('blue', 'red', 'green')):
        plt.scatter(x=X_lda[:,0].real[y == label-1],
                y=X_lda[:,1].real[y == label-1],
                marker=marker,
                color=color,
                alpha=0.5,
                label=label_dict[label-1]
    plt.xlabel('LD1')
    plt.ylabel('LD2')
    leg = plt.legend(loc='upper right', fancybox=True)
    leg.get_frame().set_alpha(0.5)
    plt.title('LDA: Iris projection onto the first 2 linear discriminants')
```

比较

下面比较一下我们的模型和实际的测试集有多大的误差

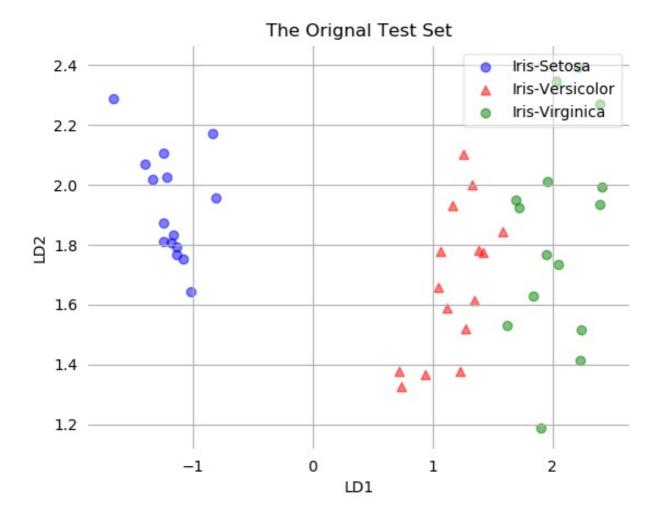
```
import numpy as np
import math
import pandas as pd
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
feature_dict = {i:label for i,label in zip(range(4),('SL','SW','PL','PW', ))}
data_train = pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
data_train.columns = [l for i,l in sorted(feature_dict.items())] + ['FClass']
#print (data_train.tail())
X_src = data_train[['SL', 'SW', 'PL', 'PW']].values
y_src = data_train['FClass'].values
X, X_spl, y, y_spl = train_test_split(X_src, y_src, test_size=0.3,
random_state=42, stratify=y_src)
np.set_printoptions(precision=4)
mean_vectors = []
for clo in range(1,4):
    mean_vectors.append(np.mean(X[y==clo-1],axis=0))
    print('Mean Vector FClass %s: %s\n' %(clo-1, mean_vectors[clo-1]))
S_W = np.zeros((4,4)) #4x4的矩阵
for clo, mv in zip(range(1,4), mean_vectors):
    class\_sc\_mat = np.zeros((4,4))
    for row in X[y == clo-1]:
        row, mv = row.reshape(4,1), mv.reshape(4,1)
        class_sc_mat += (row-mv).dot((row-mv).T)
    S_W += class_sc_mat
print('类内散度矩阵:\n', S_W)
overall_mean = np.mean(X, axis=0)
S_B = np.zeros((4,4))
for i, mean_vec in enumerate(mean_vectors):
    n = X[y==i,:].shape[0]
```

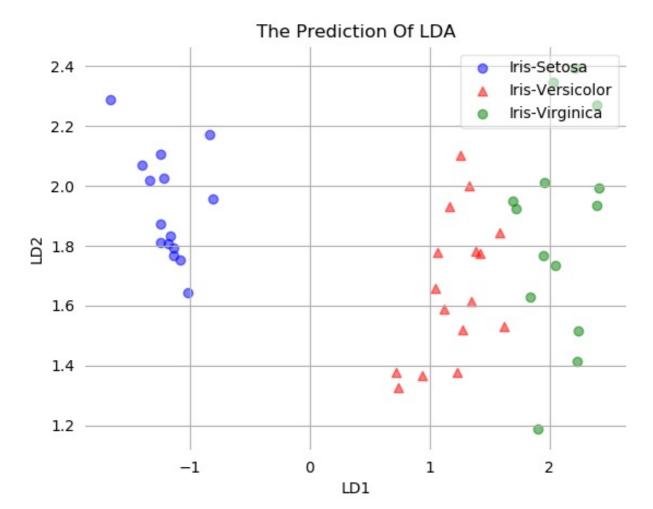
```
mean_vec = mean_vec.reshape(4,1)
    overall_mean = overall_mean.reshape(4,1)
    S_B += n * (mean_vec - overall_mean).dot((mean_vec - overall_mean).T)
print('类间散度矩阵:\n', S_B)
eig_vals, eig_vecs = np.linalg.eig(np.linalg.inv(S_W).dot(S_B))
for i in range(len(eig_vals)):
    eigvec_sc = eig_vecs[:,i].reshape(4,1)
    print('\n特征向量 {}: \n{}'.format(i+1, eigvec_sc.real))
    print('特征值 {:}: {:.2e}'.format(i+1, eig_vals[i].real))
eig_pairs = [(np.abs(eig_vals[i]), eig_vecs[:,i]) for i in range(len(eig_vals))]
eig_pairs = sorted(eig_pairs, key=lambda k: k[0], reverse=True)
print('特征值:\n')
for i in eig_pairs:
    print(i[0])
W = np.hstack((eig\_pairs[0][1].reshape(4,1), eig\_pairs[1][1].reshape(4,1)))
print('矩阵 W:\n', W.real)
X_{lda} = X_{spl.dot(W)}
label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
def plot_step_lda(argX, argy, title):
    ax = plt.subplot(111)
    for label, marker, color in zip(
        range(1,4),('o', '^', 'o'),('blue', 'red', 'green')):
        plt.scatter(x=argX[:,0].real[argy == label-1],
                y=argX[:,1].real[argy == label-1],
                marker=marker,
                color=color,
                alpha=0.5,
                label=label_dict[label-1]
    plt.xlabel('LD1')
    plt.ylabel('LD2')
    leg = plt.legend(loc='upper right', fancybox=True)
    leg.get_frame().set_alpha(0.5)
    plt.title(title)
    # hide axis ticks
    plt.tick_params(axis="both", which="both", bottom="off", top="off",
            labelbottom="on", left="off", right="off", labelleft="on")
    # remove axis spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)
    ax.spines["bottom"].set_visible(False)
    ax.spines["left"].set_visible(False)
    plt.grid()
    plt.tight_layout
    plt.show()
y_pred=y_spl
```

```
#print (data_train.tail())
#print (X.tail())

plot_step_lda(X_lda,y_spl,"The Orignal Test Set")
for i in range(0,45):
    if X_lda[i][0]<=0:
        y_pred[i]=0
    elif X_lda[i][0]>0 and X_lda[i][0]<=1.69:
        y_pred[i]=1
    elif X_lda[i][0]>1.69:
        y_pred[i]=2

#print(y_pred)
plot_step_lda(X_lda,y_pred,"The Prediction Of LDA")
```





可以看到我们只有一个数据点出现了误差。

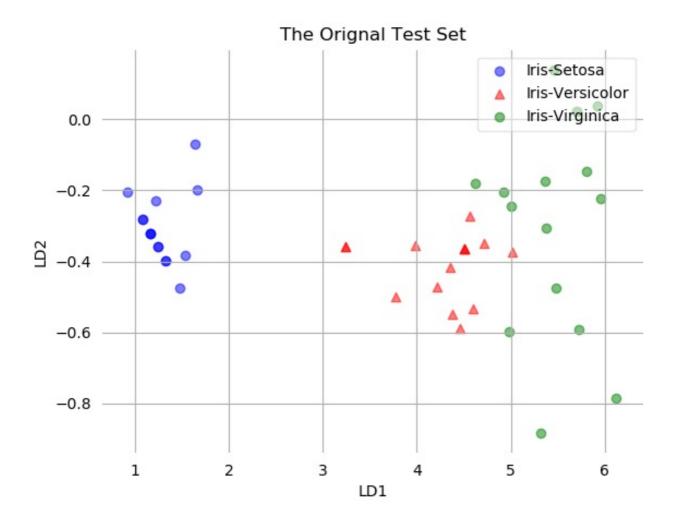
猜想验证

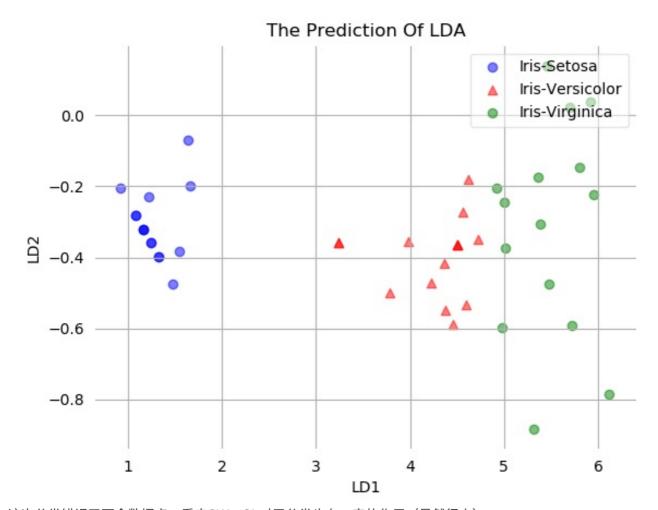
```
import numpy as np
import math
import pandas as pd
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
feature_dict = {i:label for i,label in zip(range(4),('SL','SW','PL','PW', ))}
data_train = pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
data_train.columns = [l for i,l in sorted(feature_dict.items())] + ['FClass']
#print (data_train.tail())
X_src = data_train[['PL', 'PW']].values
y_src = data_train['FClass'].values
X, X_spl, y, y_spl = train_test_split(X_src, y_src, test_size=0.3,
random_state=42, stratify=y_src)
np.set_printoptions(precision=4)
mean_vectors = []
for clo in range(1,2):
    mean_vectors.append(np.mean(X[y==clo-1],axis=0))
    print('Mean Vector FClass %s: %s\n' %(clo-1, mean_vectors[clo-1]))
```

```
S_W = np.zeros((2,2)) #2x2的矩阵
for clo, mv in zip(range(1,2), mean_vectors):
    class\_sc\_mat = np.zeros((2,2))
    for row in X[y == clo-1]:
        row, mv = row.reshape(2,1), mv.reshape(2,1)
        class_sc_mat += (row-mv).dot((row-mv).T)
    S W += class sc mat
print('类内散度矩阵:\n', S_W)
overall_mean = np.mean(X, axis=0)
S_B = np.zeros((2,2))
for i, mean_vec in enumerate(mean_vectors):
    n = X[y==i,:].shape[0]
    mean_vec = mean_vec.reshape(2,1)
    overall_mean = overall_mean.reshape(2,1)
    S_B += n * (mean_vec - overall_mean).dot((mean_vec - overall_mean).T)
print('类间散度矩阵:\n', S_B)
eig_vals, eig_vecs = np.linalg.eig(np.linalg.inv(S_W).dot(S_B))
for i in range(len(eig_vals)):
    eigvec_sc = eig_vecs[:,i].reshape(2,1)
    print('\n特征向量 {}: \n{}'.format(i+1, eigvec_sc.real))
    print('特征值 {:}: {:.2e}'.format(i+1, eig_vals[i].real))
eig_pairs = [(np.abs(eig_vals[i]), eig_vecs[:,i]) for i in range(len(eig_vals))]
eig_pairs = sorted(eig_pairs, key=lambda k: k[0], reverse=True)
print('特征值:\n')
for i in eig_pairs:
    print(i[0])
W = np.hstack((eig\_pairs[0][1].reshape(2,1), eig\_pairs[1][1].reshape(2,1)))
print('矩阵 W:\n', W.real)
X_lda = X_spl.dot(W)
label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
def plot_step_lda(argX, argy, title):
    ax = plt.subplot(111)
    for label, marker, color in zip(
        range(1,4),('o', '^', 'o'),('blue', 'red', 'green')):
        plt.scatter(x=argX[:,0].real[argy == label-1],
                y=argX[:,1].real[argy == label-1],
                marker=marker,
                color=color,
                alpha=0.5,
                label=label_dict[label-1]
    plt.xlabel('LD1')
    plt.ylabel('LD2')
    leg = plt.legend(loc='upper right', fancybox=True)
    leg.get_frame().set_alpha(0.5)
    plt.title(title)
```

```
# hide axis ticks
    plt.tick_params(axis="both", which="both", bottom="off", top="off",
            labelbottom="on", left="off", right="off", labelleft="on")
    # remove axis spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)
    ax.spines["bottom"].set_visible(False)
    ax.spines["left"].set_visible(False)
    plt.grid()
    plt.tight_layout
    plt.show()
y_pred=y_spl
#print (data_train.tail())
#print (X.tail())
plot_step_lda(X_lda,y_spl,"The Orignal Test Set")
for i in range(0,45):
    if X_lda[i][0]<=2.5:</pre>
        y_pred[i]=0
    elif X_lda[i][0]>2.5 and X_lda[i][0]<=4.9:</pre>
        y_pred[i]=1
    elif X_lda[i][0]>4.9:
        y_pred[i]=2
#print(y_pred)
plot_step_lda(X_lda,y_pred,"The Prediction Of LDA")
Jason@X1:~/flower/Dat$ py3 conj.py
```

```
Mean Vector FClass 0: [1.4886 0.2371]
类内散度矩阵:
 [[0.7954 0.1149]
 [0.1149 0.3417]]
类间散度矩阵:
 [[184.6903 77.7966]
 [ 77.7966 32.77 ]]
特征向量 1:
[[0.7997]
 [0.6003]]
特征值 1: 2.76e+02
特征向量 2:
[[-0.3882]
[ 0.9216]]
特征值 2: 0.00e+00
特征值:
275.7224210820924
0.0
矩阵 W:
 [[ 0.7997 -0.3882]
 [ 0.6003 0.9216]]
```





这次分类错误了两个数据点,看来SW,SL对于分类也有一定的作用(虽然很小)

PCA

主成分分析(PCA)是一种统计过程,它使用正交变换将可能相关变量的一组观察值(每个实体都采用各种数值)转换为一组称为主成分的线性不相关变量值。如果有 ñ 观察与 p 变量,然后是不同主成分的数量 min(n-1,p)。这种转换的定义方式是第一主成分具有尽可能大的方差(即,尽可能多地考虑数据的可变性),并且每个后续成分依次在约束下具有最高的方差。它与前面的组件正交。得到的矢量(每个是变量的线性组合并包含n个观测值)是不相关的正交基组。PCA对原始变量的相对缩放敏感。

```
import pandas as pd
import math
import numpy as np
from pandas import Series,DataFrame
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt

label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
feature_dict = {i:label for i,label in zip(range(4),('SL','SW','PL','PW', ))}

data_train = pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')

data_train.columns = [l for i,l in sorted(feature_dict.items())] + ['FClass']

X = data_train[['SL','SW','PL','PW']].values
y = data_train[['SL','SW','PL','PW']].values
#X_src = data_train[['SL','SW','PL','PW']].values
```

```
#y_src = data_train['FClass'].values
#X, X_spl, y, y_spl = train_test_split(X_src, y_src, test_size=0.3,
random_state=42, stratify=y_src)
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
target_names = label_dict
pca = PCA(n_components=2)
X_r = pca.fit(X).transform(X)
\#X_p = pca.predict(X_spl)
lda = LDA(n_components=2)
X_r2 = Ida.fit(X, y).transform(X)
X_p = lda.predict(X)
label_dict = {0: 'Iris-Setosa', 1: 'Iris-Versicolor', 2:'Iris-Virginica'}
def plot_step_lda(X, title):
    ax = plt.subplot(111)
    for label, marker, color in zip(
        range(1,4),('o', '^', 'o'),('blue', 'red', 'green')):
        plt.scatter(x=X[:,0].real[y == label-1],
                y=X[:,1].real[y == label-1],
                marker=marker,
                color=color,
                alpha=0.5,
                label=label_dict[label-1]
    plt.xlabel('LD1')
    plt.ylabel('LD2')
    leg = plt.legend(loc='upper right', fancybox=True)
    leg.get_frame().set_alpha(0.5)
    plt.title(title)
    # hide axis ticks
    plt.tick_params(axis="both", which="both", bottom="off", top="off",
            labelbottom="on", left="off", right="off", labelleft="on")
    # remove axis spines
    ax.spines["top"].set_visible(False)
    ax.spines["right"].set_visible(False)
    ax.spines["bottom"].set_visible(False)
    ax.spines["left"].set_visible(False)
    plt.grid()
    plt.tight_layout
    plt.show()
plot_step_lda(X_r, 'PCA')
plot_step_lda(X_r2, 'LDA')
# Percentage of variance explained for each components
print('explained variance ratio (first two components): %s'
      % str(pca.explained_variance_ratio_))
plt.figure()
```

支持向量机SVM

数据集分割

这里每个化的种类由50个item,所以我们抽出40个进行训练,剩下的10个做测试集,这里使用train test split函数

```
import pandas as pd
from pandas import Series, DataFrame
from sklearn.model_selection import train_test_split

data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')

x = data_train[["SepalLength", "SepalWidth", "PetalLength", "PetalWidth"]]
y = data_train["FClass"]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42, stratify=y)
```

回归

直接调用sklearn中的函数即可,完全不需要写逻辑。其实LDA也是,但是为了理解内容我们还是稍微写一下LDA的。

```
import pandas as pd
from pandas import Series, DataFrame
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')

x =data_train[["SepalLength", "SepalWidth", "PetalLength", "PetalWidth"]]
y = data_train["FClass"]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42, stratify=y)

classifier = LogisticRegression()
classifier.fit(x_train, y_train)
```

最后py运行一下

性能评估

```
import pandas as pd
from pandas import Series, DataFrame
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')

x =data_train[["SepalLength", "SepalWidth", "PetalLength", "PetalWidth"]]
y = data_train["FClass"]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42, stratify=y)
# 这里本来是像使用40-10来分类的,结果发现这样使用后直接精度到0.98没太有优化空间了,所以改为35-15
classifier = LogisticRegression()
classifier.fit(x_train, y_train)
```

```
prdt_y = classifier.predict(x_test)
print (metrics.classification_report(y_test,prdt_y))
print (metrics.accuracy_score(y_test,prdt_y))
```

ру一下

Jason@X1:~/fl		py3 sdfs.p recall	•	support
0	1.00	1.00	1.00	15
1	1.00	0.73	0.85	15
2	0.79	1.00	0.88	15
micro avg	0.91	0.91	0.91	45
macro avg	0.93	0.91	0.91	45
weighted avg	0.93	0.91	0.91	45
0.9111111111	11111			

可以看到对于Iris Setosa - Iris Versicolour - Iris Virginica三种不同的花,我们分类的精度,召回率, \$F1\$,最后显示的正确率。

模型改进

正确率只有0.9啊,太捞了。我们能不能继续优化一下来。

软间隔与正则化

women知道优化目标中的第一项用来描述超平面的间隔大小,另一项 $\sum_{i=1} \int \int (f(x_i), y_i) \ \ \,$ 用来表示训练集上的误差,课些微更一般的形式

 $\$ \min \limits_f \Omega(f) + C \sum_{i=1}^{m} \iota(f(x_i),y_i) \$\$

线性判别中, \$C\$ 这个正则化常数,用于对经验风险和结构风险进行折中,而我们的 LogisticRegression() 方法中也可以设置这个参数。我们长将正则化的程度降低,看看会有什么不一样的结果。

```
>>> classifier = LogisticRegression(C=1e3)
```

再次py一下我们可以发现正确率果然提高了一些

Jas	son@X1:~/fl	ower/Dat\$ py3.		f1-score	support
	0	1.00	1.00	1.00	15
	1	0.83	1.00	0.91	15
	2	1.00	0.80	0.89	15
	micro avg	0.93	0.93	0.93	45
	macro avg	0.94	0.93	0.93	45
we	ighted avg	0.94	0.93	0.93	45
0.9	93333333333	33333			

solver参数

LogisticRegression() 包含的参数当然不仅仅只有C,我们还可以选择其他的优化方法,这里就要用到我们的solver 参数了。

```
>>> classifier = LogisticRegression(C=1e3, solver='lbfgs')
#将优化器改为L-BFGS梯度下降优化
```

可以自己py一下看看结果,这里就不再赘述了,但是需要注意的是,方法之间没有高低,根据第一章中的"没有免费午餐"定理,只有适合的才是最好的。下面是不同优化器:

```
'liblinear', 'newton-cg', 'lbfgs', 'sag', 'saga'
```

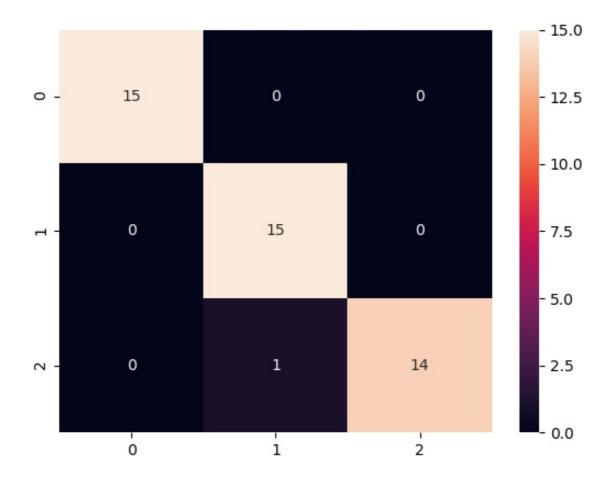
multi_class参数

这个参数的默认值为'ovr',也就是将一个类的样例当作正例,其它类作为反例,来训练多个二分类器,和我们的思路是一样的;'multinomial'表示最小化多项式损失满足整个概率分布,也就是Softmax分类器。

```
>>> classifier = LogisticRegression(C=1e3, solver='sags', multi_class='multinomial') #优化器改为随机平均梯度下降, multi改为Softmax
```

这样处理之后,我们的精度达到了0.98,这样就十分可以了,继续处理有可能会出现过拟合的情况。

观察



观察一下混淆矩阵,我们的模型只在一个测试上分类错误!

复制参数

将我们训练的模型放入一个3*4的矩阵中,通过这个矩阵我们可以得到三个二元逻辑回归模型,系数矩阵就是coef,截距就是intercept。

```
import pandas as pd
from pandas import Series, DataFrame
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
data_train=pd.read_csv('/home/jason/Documents/ML/flower/Data/data.csv')
x =data_train[["SepalLength", "SepalWidth", "PetalLength", "PetalWidth"]]
y = data_train["FClass"]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,
random_state=42, stratify=y)
classifier = LogisticRegression(C=1e3)
classifier.fit(x_train, y_train)
prdt_y = classifier.predict(x_test)
coef = pd.DataFrame(classifier.coef_,columns=data_train.columns[0:4])
coef["intercept"] = classifier.intercept_
print (coef.round(2))
```

py一下,

```
Jason@X1:~/flower/Dat$ py3 args.py
   SepalLength SepalWidth PetalLength PetalWidth intercept
0
          1.31
                      2.91
                                  -3.99
                                               -1.96
                                                           0.68
          0.97
                     -0.22
                                   -0.25
                                               -1.77
                                                           1.61
1
2
         -2.28
                     -2.69
                                   4.24
                                                3.72
                                                          -2.29
```

也就得到了三个线性回归方程 \$\$ \begin{align*} & P(FClass==0)=\sigma(1.31SL+2.91SW-3.99PL-1.96PW+0.68) \\ & P(FClass==0)=\sigma(0.97SL-0.22SW-0.25PL-1.77PW+1.61) \\ & P(FClass==0)=\sigma(-2.28SL-2.69SW+4.24PL+3.72PW-2.29) \\ \\ \end{align*} \$\$

相关论文与参考资料:

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- Dasarathy,BV(1980)"邻近地区:在部分暴露环境中识别的新系统结构和分类规则"。IEEE模式分析和机器智能交易,卷。PAMI-2,No.1,67-71。 网站链接
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