## • 编程作业:

Iris 数据集是常用的分类实验数据集,由Fisher, 1936收集整理。 Iris也称鸢尾花卉数据集,是一类多重变量分析的数据集。数据集包含 150 个数据样本,分为3类,每类50个数据,每个数据包含4个属性。可通过花萼长度,花萼宽度,花瓣长度,花瓣宽度 4 个属性预测鸢尾花卉属于(Setosa VersicolourVirginica)三个种类中的哪一类。

- 数据下载: <a href="http://archive.ics.uci.edu/ml/datasets/iris">http://archive.ics.uci.edu/ml/datasets/iris</a>
- 编程设计三层 BP 神经网络实现 Iris 数据集的分类

```
1 from sklearn.datasets import load_iris
 2
    import math
 3
    import numpy as np
    import matplotlib.pyplot as plt
 4
 5
    iris = load_iris()
   dataset=iris.data
    dataset_label=iris.target
8
    order = np.random.permutation(np.arange(150))
9
    shuffled_dataset = dataset[order, :]
10
    shuffled_labels = dataset_label[order]
   trainset = list(shuffled_dataset[:120, :])
11
12
    train_label = list(shuffled_labels[:120])
13 | testset = list(shuffled_dataset[120:, :])
   test_label = list(shuffled_labels[120:])
14
```

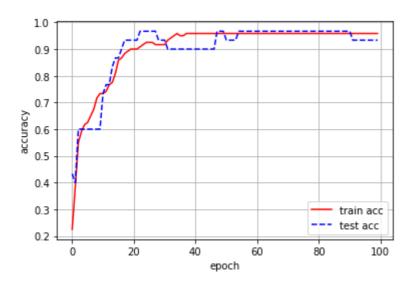
```
1 def sigmoid(x):
2 return 1/(1+math.exp(-x))
```

```
1 def dsigmoid(x):
2 return sigmoid(x)*(1-sigmoid(x))
```

```
class Neuralnet:
 1
 2
        def __init__(self, ni, nh, no):
 3
            self.ni=ni
 4
            self.nh=nh
 5
            self.no=no
            self.ai=[0.0] * ni
 6
 7
            self.ah=[0.0] * nh
            self.ao=[0.0] * no
 8
 9
            self.wi= list(np.random.rand(ni, nh))
            self.wo= list(np.random.rand(nh, no))
10
11
12
        def forward(self, inputs):
            """前向传播"""
13
14
            if len(inputs) != self.ni:
                raise ValueError('与输入层节点数不符!')
15
16
17
            # 激活输入层
18
            for i in range(self.ni):
19
                self.ai[i] = inputs[i]
20
21
            # 激活隐藏层
22
            for j in range(self.nh):
```

```
23
                sum = 0.0
24
                for i in range(self.ni):
25
                     sum = sum + self.ai[i] * self.wi[i][j]
26
                self.ah[j] = sigmoid(sum)
27
            # 激活输出层
28
29
            for k in range(self.no):
30
                sum = 0.0
                for j in range(self.nh):
31
32
                    sum = sum + self.ah[j] * self.wo[j][k]
33
                self.ao[k] = sigmoid(sum)
34
            return self.ao[:]
35
36
37
        def backPropagate(self, target, lr):
            """ 反向传播 """
38
39
            # 计算输出层的误差
            output_deltas = [0.0] * self.no
40
41
            if target==0:
42
                targets=[1, 0, 0]
43
            elif target==1:
                targets=[0, 1, 0]
44
45
            else:
46
                targets=[0, 0, 1]
47
48
            for k in range(self.no):
49
                error = targets[k] - self.ao[k]
                output_deltas[k] = dsigmoid(self.ao[k]) * error
50
51
52
            # 计算隐藏层的误差
            hidden_deltas = [0.0] * self.nh
53
54
            for j in range(self.nh):
55
                error = 0.0
                for k in range(self.no):
56
57
                     error = error + output_deltas[k] * self.wo[j][k]
58
                hidden_deltas[j] = dsigmoid(self.ah[j]) * error
59
            # 更新输出层权重
60
            for j in range(self.nh):
61
62
                for k in range(self.no):
                    change = output_deltas[k] * self.ah[j]
63
64
                     self.wo[j][k] = self.wo[j][k] + lr * change
65
            # 更新输入层权重
66
67
            for i in range(self.ni):
68
                for j in range(self.nh):
69
                     change = hidden_deltas[j] * self.ai[i]
70
                    self.wi[i][j] = self.wi[i][j] + lr * change
71
72
            # 计算误差
73
            error = 0.0
74
            for k in range(self.no):
                error += 0.5 * (targets[k] - self.ao[k]) ** 2
75
76
77
            return error
```

```
2
    1r=0.1
 3
    trian_acc=[0.0]*epoch
    test_acc=[0.0]*epoch
 5
    X = Neuralnet(4, 25, 3)
 6
    for i in range(epoch):
 7
        correct_amount=0
 8
        test_correct_amount=0
 9
        for j in range(len(train_label)):
10
            result=X.forward(trainset[j])
11
            X.backPropagate(train_label[j], lr)
            if list(np.where(result==np.max(result)))==train_label[j]:
12
13
                correct\_amount+=1
14
        trian_acc[i]=correct_amount/len(train_label)
15
        for 1 in range(len(test_label)):
16
            result1=X.forward(testset[]])
17
            if list(np.where(result1==np.max(result1)))==test_label[]:
18
                test\_correct\_amount+=1
19
        test_acc[i]=test_correct_amount/len(test_label)
20 \mid x = np.arange(epoch)
    y = np.array(trian_acc)
21
    z= np.array(test_acc)
22
23
    plt.xlabel("epoch")
24
    plt.ylabel("accuracy")
25 plt.plot(x, y, '-r', label = 'train acc')
    plt.plot(x, z, '--b', label = 'test acc')
26
    plt.grid()
27
28 plt.legend()
29
    plt.show()
```



更高,较好地实现了分类的目标。

## • 实验结论: 从最后得到的实验结果可以看到经过100个epoch后,训练精度和测试精度都达到0.9以上甚至