

# Python手搓神经网络

来源于: <https://b23.tv/FvTGUJW>

参考代码: [https://github.com/JunlingWang/Neuronetwork\\_with\\_python/tree/main](https://github.com/JunlingWang/Neuronetwork_with_python/tree/main)

进阶: <https://github.com/ZHE2018/network/blob/master/network3.py>

## 以下是重要内容的笔记

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### 00.Numpy与线性代数

非常重要这里是注意Numpy的数组的切片是原始数组的视图。这意味着数据不会被复制，视图上的任何修改都会直接反映到源数组上。

重要的语法：

矩阵乘法 `np.dot(a, b)`；

轴向平均 `np.mean(a, axis)`；

最值函数 `np.maximum(number, a)`；

最大值 `np.max(a)`；

# 01.神经网络（结构）简介

整个网络：输入层、隐藏层、输出层；  
两个神经元之间为一层：权重矩阵，偏置；  
层的前馈：激活函数；  
反向传播；  
训练（训练集、测试集）、推理；

## 02~09.搭建前馈部分

激活函数ReLU：输入值小于0时输出0，大于0时输出输入值；  
激活函数softmax：将输入值平移到负值区后变为指数再做概率归一化；

## 10~15.反向传播算法

In [1]: # 导入必要的库

```
import numpy as np
import matplotlib.pyplot as plt
import math
import random
import copy
```

In [2]: # 参数

```
NETWORK_SHAPE = [2, 100, 200, 100, 2] # 神经网络的结构
BATCH_SIZE = 30 # 一批次数据的数据总数
LEARNING_RATE = 0.003 # 学习率
LOSS_THRESHOLD = 0.1 # 损失临界值
FORCE_TRAIN_THRESHOLD = 0.05 # 强制训练临界值

force_train = False # 强制训练开关
n_improved = 0
n_not_improved = 0
current_loss = 1
```

In [3]: # 函数

```
# ReLU激活函数
def activation_ReLU(inputs):
    """输入值小于0时输出0，大于0时输出输入值"""
    return np.maximum(0, inputs)

# softmax激活函数
def activation_softmax(inputs):
    """将输入值平移到负值区后变为指数再做概率归一化"""
    max_value = np.max(inputs, axis=1, keepdims=True)
    slided_inputs = inputs - max_value
    exp_value = np.exp(slided_inputs)
    norm_base = np.sum(exp_value, axis=1, keepdims=True)
    norm_values = exp_value / norm_base
    return norm_values

# 归一化函数
def normalize(array):
    """将矩阵进行归一化"""
    max_number = np.max(np.absolute(array), axis=1, keepdims=True)
```

```

scale_rate = np.where(max_number == 0, 1, 1/max_number)
norm = array * scale_rate
return norm

# 分类函数
def classify(probabilities):
    """按照网络的预测结果（第二列）打标签"""
    return np rint(probabilities[:, 1]).reshape(-1, 1)

# 需求函数
def demands(predicted_values, targets_vector):
    """根据网络当次预测结果（也就是最后一层输出,这将是n行2列的矩阵）和标准答案（这将是一个n行1列的向量）来返回一个用于调整参数的demands（这个demands只是最后一层的，还需要向前传递）"""
    demands = np.zeros((len(targets_vector), 2))
    demands[:, 1] = targets_vector
    demands[:, 0] = 1 - targets_vector

    for i in range(len(targets_vector)):
        if np.dot(predicted_values[i], demands[i]) > 0.5 :
            demands[i] = np.array([0, 0])
        else:
            demands[i] = 2 * (demands[i] - 0.5)
    return demands

# 向量标准化函数
def vector_normalize(array):
    max_number = np.max(np.absolute(array))
    scale_rate = np.where(max_number == 0, 1, 1/max_number)
    norm = array * scale_rate
    return norm

# 精确损失函数
def precise_loss_function(predicted, real):
    real_matrix = np.zeros((len(real), 2))
    real_matrix[:, 1] = real
    real_matrix[:, 0] = 1 - real
    product = np.sum(predicted*real_matrix, axis=1)
    return 1 - product

# 损失函数
def loss_function(predicted, real):
    condition = (predicted > 0.5)
    binary_predicted = np.where(condition, 1, 0)
    real_matrix = np.zeros((len(real), 2))
    real_matrix[:, 1] = real
    real_matrix[:, 0] = 1 - real
    product = np.sum(binary_predicted*real_matrix, axis=1)
    return 1 - product

```

In [4]: # 神经网络

```

# 定义一个层类
class Layer:
    """两个神经元之间的层"""
    def __init__(self, n_inputs, n_neurons):
        self.weights = np.random.randn(n_inputs, n_neurons) # 权重矩阵
        self.biases = np.random.randn(n_neurons) # 偏置

    def layer_forward(self, inputs):
        """层的前馈"""
        return np.dot(inputs, self.weights) + self.biases

    def layer_backward(self, prelayer_outputs, currentlayer_demands):
        """层的反向传播，输入前一层的输出结果，和本层的需求；

```

调整矩阵：根据反向传播与梯度下降的想法，根据链式法则，分别输入本层的输入a（也就是返回本层权重矩阵的调整矩阵；

返回归一化的前一层的需求和归一化的本层的调整矩阵"""

# ReLU函数的导数

```
condition = (self.layer_forward(prelayer_outputs) > 0)
derivatives_ReLU = np.where(condition, 1, 0)
```

# 权重的调整矩阵

```
weights_adjust_matrix = np.full(self.weights.shape, 0.0)
for i in range(BATCH_SIZE):
    weights_adjust_matrix = weights_adjust_matrix + (prelayer_outputs * derivatives_ReLU)
weights_adjust_matrix = weights_adjust_matrix / BATCH_SIZE
```

# 前一层的需求

```
prelayer_demands = np.dot((currentlayer_demands * derivatives_ReLU), self.weights)
```

# 归一化

```
norm_prelayer_demands = normalize(prelayer_demands)
norm_weights_adjust_matrix = normalize(weights_adjust_matrix)
```

```
return (norm_prelayer_demands, norm_weights_adjust_matrix)
```

# 定义一个网络类

**class** Network:

"""整个神经网络"""

**def** \_\_init\_\_(self, network\_shape):

self.shape = network\_shape

self.layers = []

**for** i **in** range(len(network\_shape) - 1):

self.layers.append(Layer(network\_shape[i], network\_shape[i + 1]))

**def** network\_forward(self, inputs):

"""前馈运算函数，返回每一层的预测结果"""

outputs = [inputs]

**for** i **in** range(len(self.layers)):

**if** i < len(self.layers) - 1:

layer\_outputs = activation\_ReLU(self.layers[i].layer\_forward(inputs[i]))

layer\_outputs = normalize(layer\_outputs)

**else:**

layer\_outputs = activation\_softmax(self.layers[i].layer\_forward(inputs[i]))

outputs.append(layer\_outputs)

#print(layer\_outputs)

#print('-----')

**return** outputs

**def** network\_backward(self, outputs, targets\_vector):

"""反向传播函数，传入各层预测值和标准答案，对参数做调整，返回调整后的新网络（一个

new\_network = copy.deepcopy(self) # 备用网络

layer\_demands = demands(outputs[-1], targets\_vector) # 最后一层的需求

# 先调整最后一层

final\_layer = new\_network.layers[-1]

# 调整偏置

final\_layer.biases = final\_layer.biases + LEARNING\_RATE \* np.mean(layer\_demands, axis=0)

final\_layer.biases = vector\_normalize(final\_layer.biases)

# 调整权重

final\_weights\_adjust\_matrix = np.full(final\_layer.weights.shape, 0.0)

**for** i **in** range(BATCH\_SIZE):

```

        #print(outputs[-2][i].reshape(len(outputs[-2][i]), 1))
        #print(layer_demands[i])
        #print("outputs[-2][i] shape:", outputs[-2][i].shape)
        #print("layer_demands[i] shape:", layer_demands[i].shape)

        final_weights_adjust_matrix = final_weights_adjust_matrix + (out
final_weights_adjust_matrix = final_weights_adjust_matrix / BATCH_S
norm_final_weights_adjust_matrix = normalize(final_weights_adjust_ma
final_layer.weights = final_layer.weights + LEARNING_RATE * norm_fir
final_layer.weights = normalize(final_layer.weights)

# 调整其它层
layer_demands = normalize(np.dot(layer_demands, final_layer.weights

for i in range(len(new_network.layers) - 1):
    layer = new_network.layers[-(i + 2)]

    #print(layer_demands)
    #print('-----')
    #print("layer_demands[i] shape:", layer_demands[i].shape)
    #print('-----')
    #print(np.mean(layer_demands, axis=0))

    # 调整偏置
    layer.biases = layer.biases + LEARNING_RATE * np.mean(layer_dema
    layer.biases = vector_normalize(layer.biases)

    # 获得前一层的需求和本层的权重调整矩阵
    layer_demands, weights_adjust_matrix = layer.layer_backward(outp

    # 调整权重
    layer.weights = layer.weights + LEARNING_RATE * weights_adjust_r
    layer.weights = normalize(layer.weights)

return new_network

def one_batch_training(self, data_batch):
    """进行单批次训练"""
    global force_train, n_improved, n_not_improved

    inputs = data_batch[:, (0, 1)]
    targets_vector = copy.deepcopy(data_batch[:, 2]).astype(int) # 标准答
    outputs = self.network_forward(inputs)
    precise_loss = precise_loss_function(outputs[-1], targets_vector) #
    loss = loss_function(outputs[-1], targets_vector) # 损失

    if np.mean(loss) <= LOSS_THRESHOLD:
        print('No need for training') # 不需要进行进一步训练
        return 0

    else:
        # 进行训练, 生成新网络
        new_network = self.network_backward(outputs, targets_vector)
        new_outputs = new_network.network_forward(inputs)
        new_precise_loss = precise_loss_function(new_outputs[-1], target
        new_loss = loss_function(new_outputs[-1], targets_vector)

        # 利用两种损失比较新旧网络的准确度, 若新网络更好则将旧网络替换为新网络
        if np.mean(precise_loss) >= np.mean(new_precise_loss) or np.mean
            for i in range(len(self.layers)):
                self.layers[i].weights = new_network.layers[i].weights.c
                self.layers[i].biases = new_network.layers[i].biases.co
            #print('Improved')
            n_improved += 1

```

```

# print('-----')

else:
    if force_train:
        for i in range(len(self.layers)):
            self.layers[i].weights = new_network.layers[i].weights
            self.layers[i].biases = new_network.layers[i].biases
        print('Force train')
    else:
        # print('No improvement')
        n_not_improved += 1
    # print('-----')

def train(self, n_entries):
    """多批次训练"""
    global force_train, n_improved, n_not_improved
    n_improved = 0
    n_not_improved = 0

    # 训练集
    n_batches = n_entries // BATCH_SIZE + 1
    for i in range(n_batches):
        data_batch = generate_data(BATCH_SIZE)
        self.one_batch_training(data_batch)
        if self.one_batch_training(data_batch) == 0:
            break

    improvement_rate = n_improved / (n_improved + n_not_improved)
    print('improvement_rate is')
    print(improvement_rate)
    # print('-----')
    print('-----')

    if improvement_rate <= FORCE_TRAIN_THRESHOLD:
        force_train = True
    else:
        force_train = False

    # 测试集
    data = generate_data(1000)
    inputs = data[:, (0, 1)]
    outputs = self.network_forward(inputs)
    classification = classify(outputs[-1])
    data[:, 2] = classification.T
    plot_data(data, 'After Training')

```

In [5]: # 生成数据与可视化

```

def tag_entry(x, y):
    """打标函数，在单位圆外标为1，反之标为0"""
    if x**2 + y**2 > 1:
        tag = 1
    else:
        tag = 0
    return tag

def generate_data(num_of_data):
    """随机生成数据"""
    entry_list = []
    for i in range(num_of_data):
        x = random.uniform(-2, 2)
        y = random.uniform(-2, 2)
        tag = tag_entry(x, y)
        entry = [x, y, tag]

```

```

        entry_list.append(entry)
    return np.array(entry_list)

def plot_data(data, title):
    """将数据可视化"""
    color = []
    for i in data[:, 2]:
        if i == 0:
            color.append('orange')
        else:
            color.append('blue')
    plt.scatter(data[:, 0], data[:, 1], c=color)
    plt.title(title)
    plt.show()

```

In [6]: # 训练流程控制

```

def main():
    global current_loss
    data = generate_data(1000) # 生成数据
    plot_data(data, "Right Classification")

    # 选择起始网络
    use_this_network = 'n' # No
    while use_this_network != 'Y' and use_this_network != 'y':
        network = Network(NETWORK_SHAPE)
        inputs = data[:, (0, 1)]
        outputs = network.network_forward(inputs)
        classification = classify(outputs[-1])
        data[:, 2] = classification.T
        plot_data(data, "Choose Network")
        use_this_network = input("Use this network? Y to yes, N to No \n")

    # 进行训练
    do_train = input("Train? Y to yes, N to No \n")
    while do_train == 'Y' or do_train == 'y' or do_train.isnumeric() == True:
        if do_train.isnumeric() == True:
            n_entries = int(do_train)
        else:
            n_entries = int(input("Enter the number of data entries used to"))

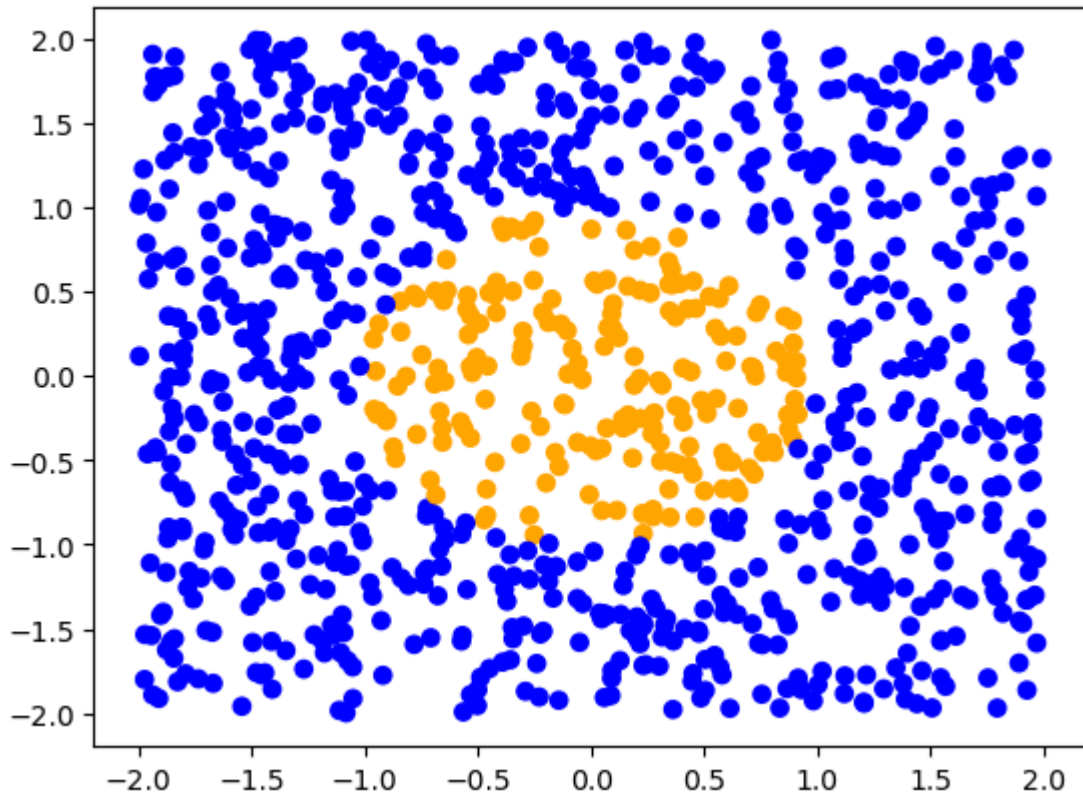
        network.train(n_entries)
        do_train = input("Train? Y to yes, N to No \n")

    # 演示训练效果
    inputs = data[:, (0, 1)]
    outputs = network.network_forward(inputs)
    classification = classify(outputs[-1])
    data[:, 2] = classification.T
    plot_data(data, "After training")
    print("谢谢, 再见! ")

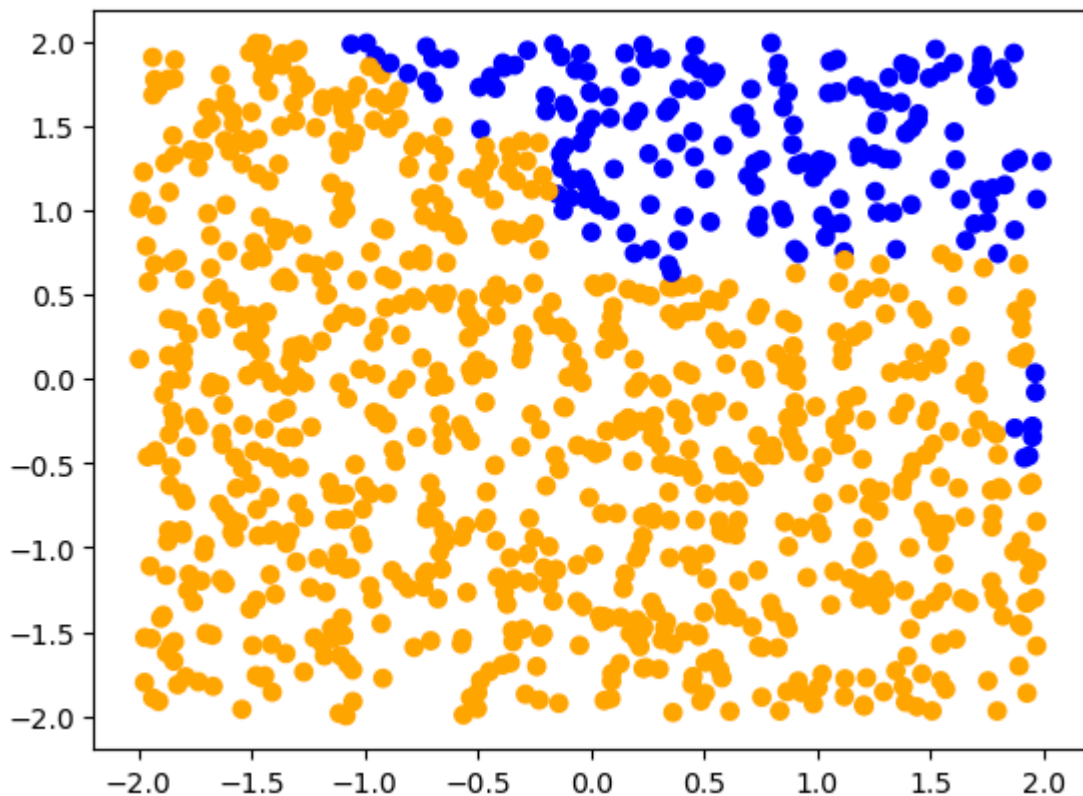
```

In [7]: main()

Right Classification



Choose Network



Use this network? Y to yes, N to No

y

Train? Y to yes, N to No

y

Enter the number of data entries used to train.

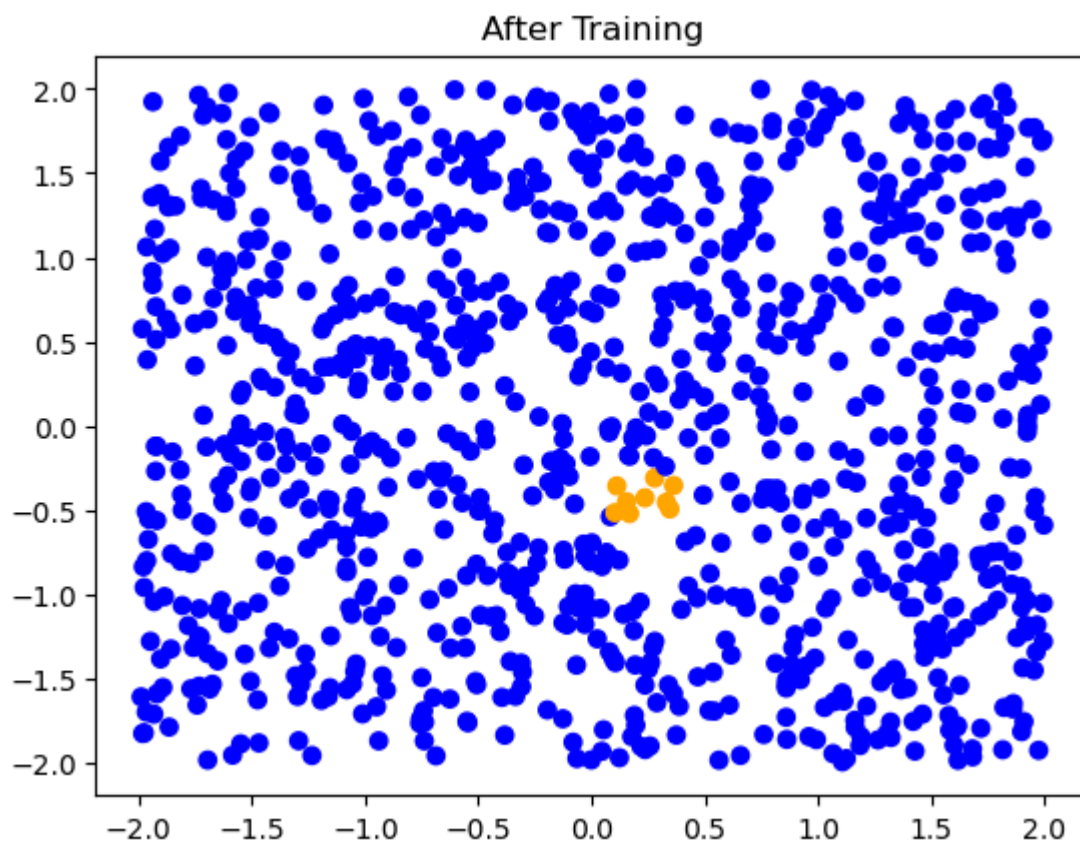
2500

```
/var/folders/7l/1kcst3m15b3f1jyrwvsyrckw0000gn/T/ipykernel_15134/144325295
2.py:22: RuntimeWarning: divide by zero encountered in divide
  scale_rate = np.where(max_number == 0, 1, 1/max_number)
```



improvement\_rate is  
0.07142857142857142

---



Train? Y to yes, N to No

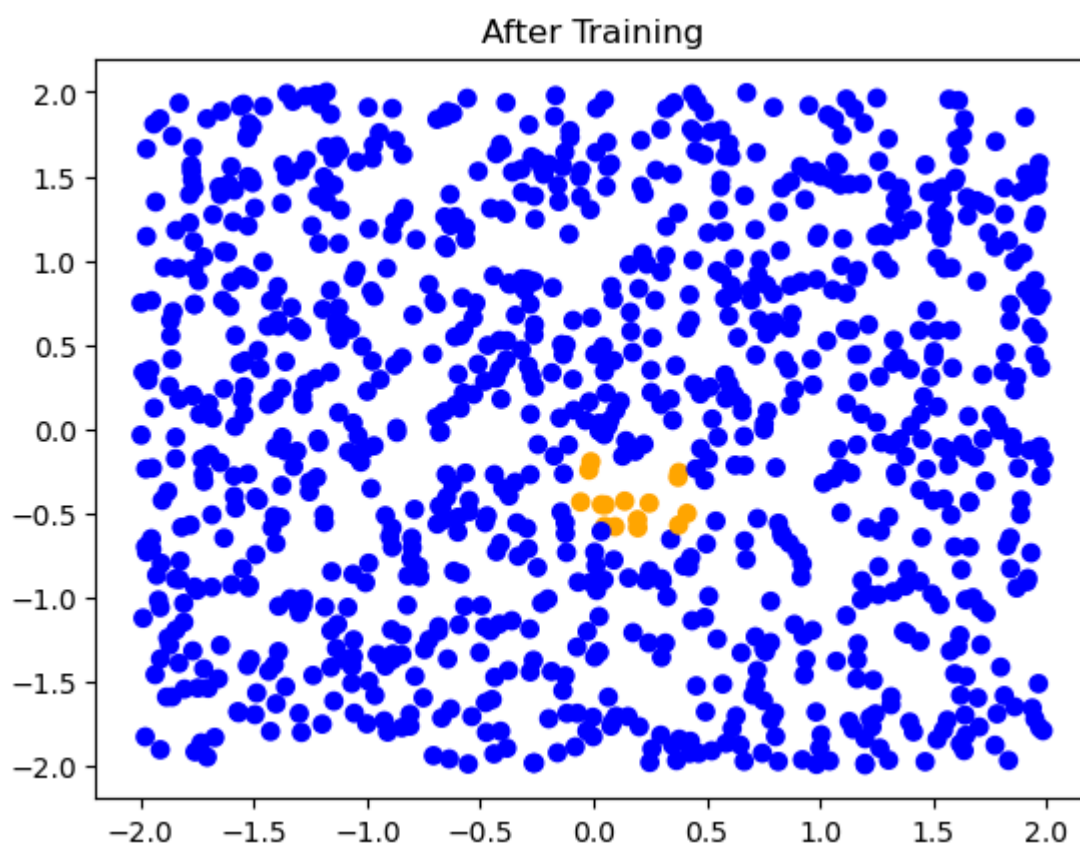
y

Enter the number of data entries used to train.

3000

improvement\_rate is  
0.019801980198019802

---



Train? Y to yes, N to No

y

Enter the number of data entries used to train.

3000

Force train

Force train

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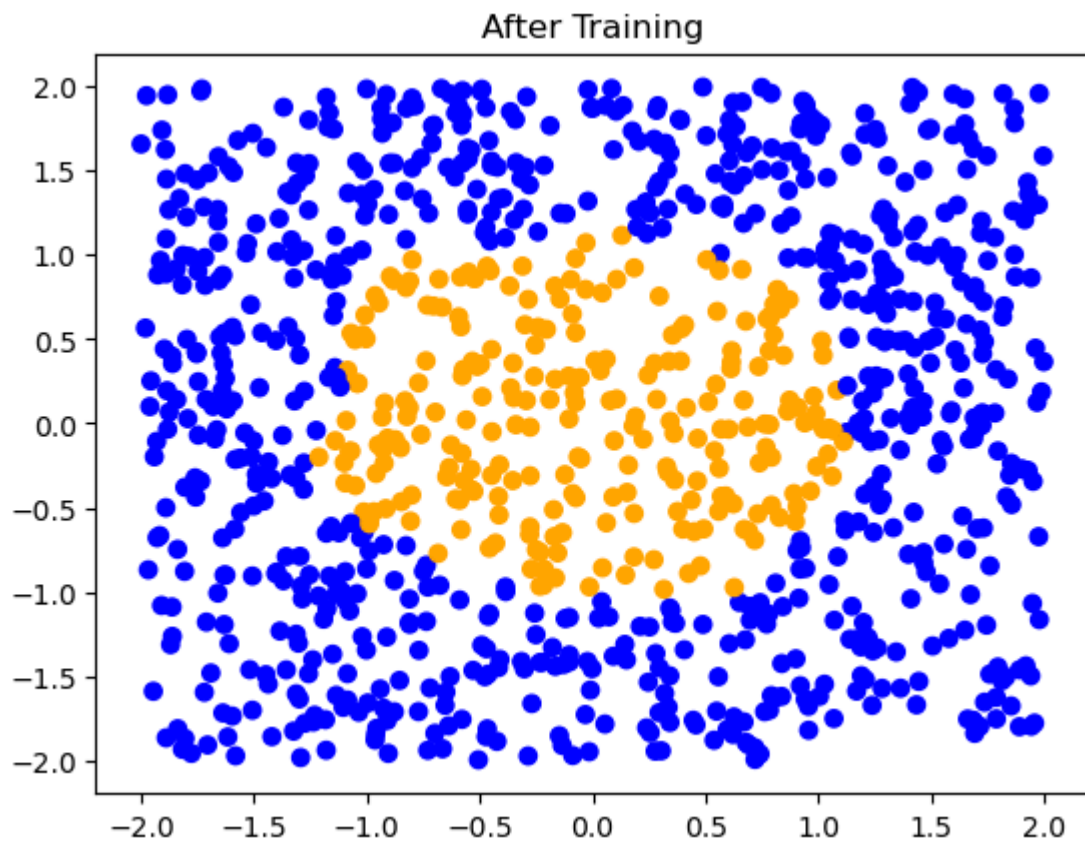
Force train

Force train

improvement\_rate is

1.0

-----



Train? Y to yes, N to No

y

Enter the number of data entries used to train.

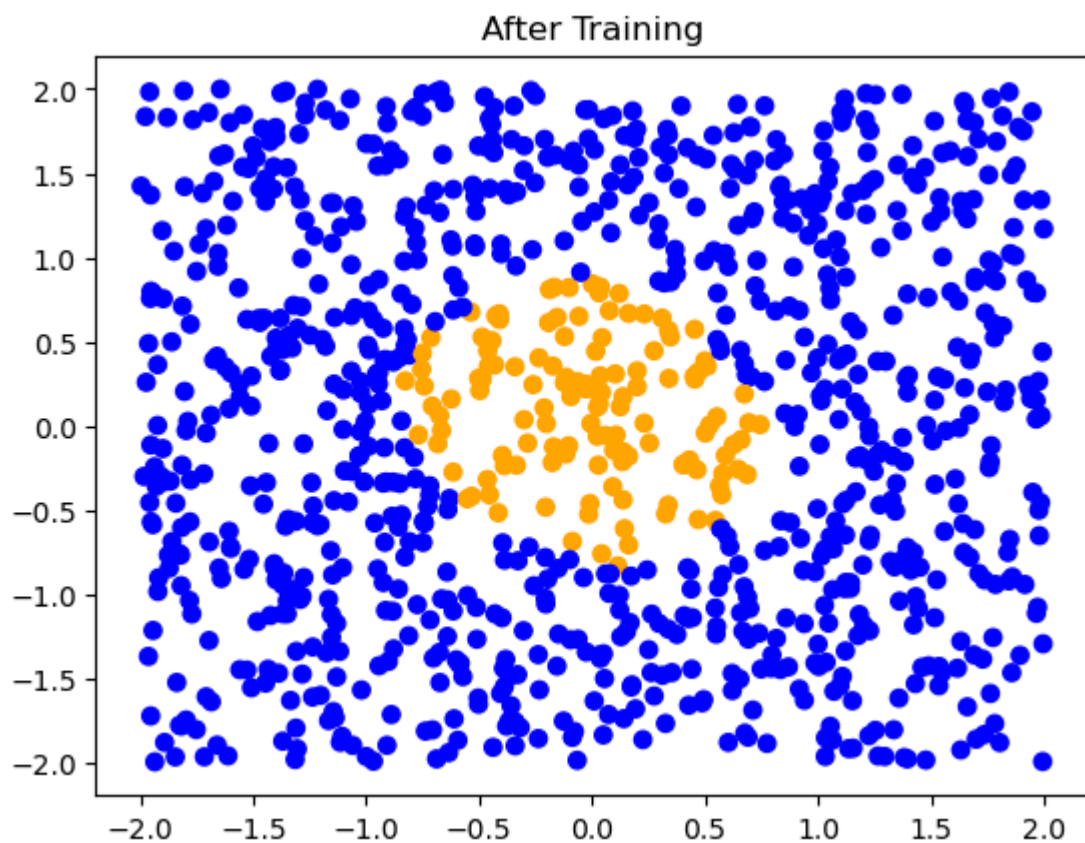
1000

No need for training

improvement\_rate is

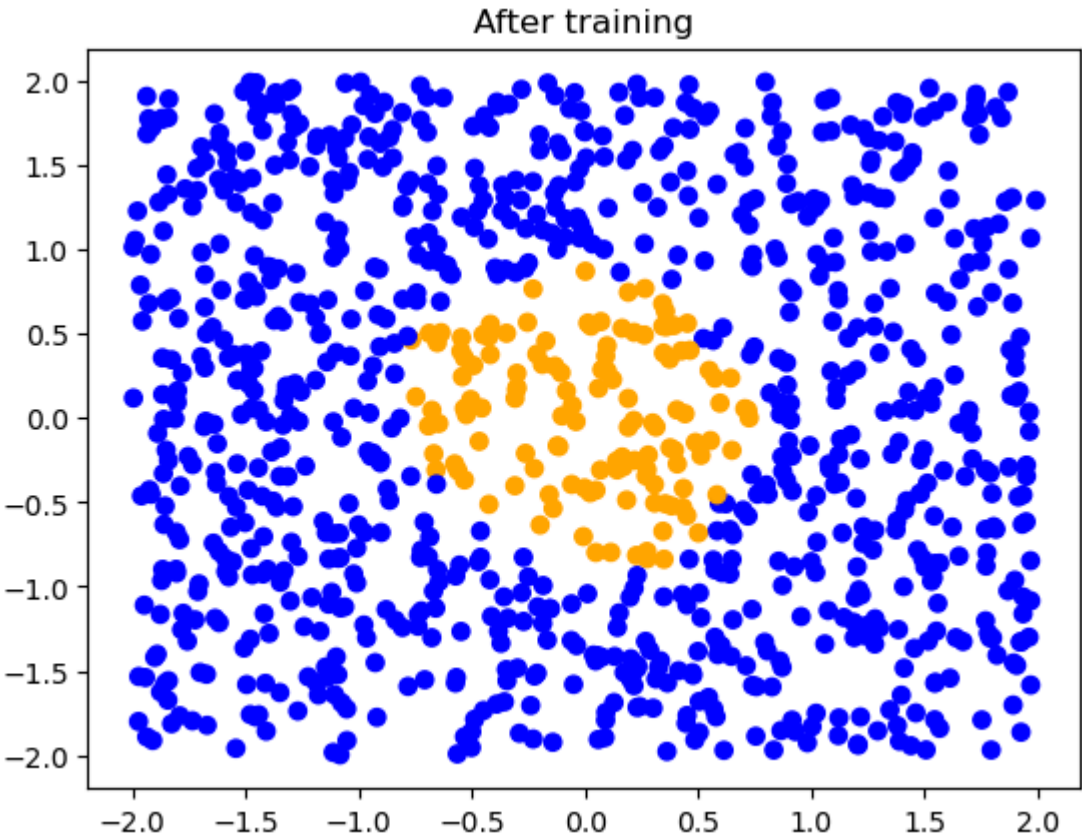
0.2727272727272727

---



Train? Y to yes, N to No

n



谢谢，再见！

In [ ]: