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本实验属于哪门课程?	中国海洋大学25秋《软件工程原理与实践》
实验名称?	实验2：深度学习基础
博客链接:	还没

一、实验内容

在谷歌 Colab 上完成 pytorch 代码练习中的 3.1 pytorch基础练习、3.2螺旋数据分类，关键步骤截图，并附一些自己的想法和解读。

3.1 pytorch 基础练习

基础练习部分包括 pytorch 基础操作，实验指导链接

要求： 把代码输入 colab，在线运行观察效果。

```
import torch

x = torch.tensor(666)
print(x)
```

```
tensor(666)
```

```
x = torch.tensor([1,2,3,4,5,6])
print(x)
```

```
tensor([1, 2, 3, 4, 5, 6])
```

```
x = torch.ones(2,3)
print(x)
```

```
tensor([[1., 1., 1.],
        [1., 1., 1.]])
```

```
x = torch.ones(2,3,4)
print(x)
```

```
tensor([[[1., 1., 1., 1.],
         [1., 1., 1., 1.],
         [1., 1., 1., 1.]],

        [[1., 1., 1., 1.],
         [1., 1., 1., 1.],
         [1., 1., 1., 1.]]])
```

```
x = torch.empty(5,3)
print(x)
```

```
tensor([[0.0000e+00, 0.0000e+00, 0.0000e+00],
        [0.0000e+00, 0.0000e+00, 0.0000e+00],
        [0.0000e+00, 0.0000e+00, 1.4013e-45],
        [0.0000e+00, 0.0000e+00, 0.0000e+00],
        [0.0000e+00, 0.0000e+00, 0.0000e+00]])
```

```
x = torch.rand(5,3)
print(x)
```

```
tensor([[0.6766, 0.6989, 0.8963],
        [0.0302, 0.0896, 0.0751],
        [0.9786, 0.4789, 0.7101],
        [0.9586, 0.4929, 0.4813],
        [0.0616, 0.2381, 0.7769]])
```

```
x = torch.zeros(5,3,dtype=torch.long)
print(x)
```

```
tensor([[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]])
```

```
y = x.new_ones(5,3)
print(y)
```

```
tensor([[1, 1, 1],
        [1, 1, 1],
        [1, 1, 1],
        [1, 1, 1],
        [1, 1, 1]])
```

```
z = torch.randn_like(x,dtype=torch.float)
print(z)
```

```
tensor([[-1.0515,  0.0923,  0.9110],
        [-0.6102, -0.8279,  0.2911],
        [ 0.1451,  0.3776, -0.0953],
        [-0.7434,  0.0706, -0.0993],
        [-1.6713, -0.1680,  0.1495]])
```

```
m = torch.tensor([[2,5,3,7],
          [4,2,1,9]])
print(m.size(0),m.size(1),m.size(),sep=' -- ')
```

```
2 -- 4 -- torch.Size([2, 4])
```

```
print(m.numel())
```

```
8
```

```
print(m[0][2])
```

```
tensor(3)
```

```
print(m[:,1])
```

```
tensor([5, 2])
```

```
print(m[0,:])
```

```
tensor([2, 5, 3, 7])
```

```
v = torch.arange(1,5)
print(v)
```

```
tensor([1, 2, 3, 4])
```

```
m[[0],:] @ v
```

```
tensor([49])
```

```
m + torch.rand(2, 4)
```

```
tensor([[2.2771, 5.6838, 3.4746, 7.3979],
        [4.6423, 2.2614, 1.4216, 9.2961]])
```

```
print(m.t())

print(m.transpose(0, 1))
```

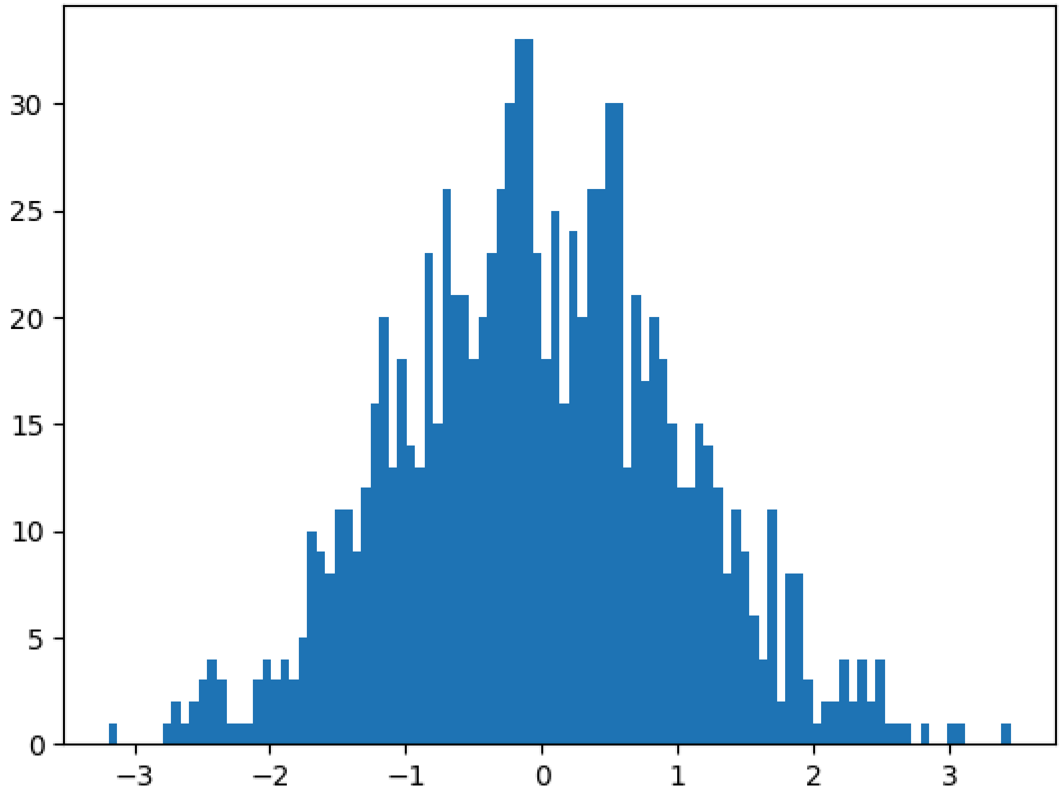
```
tensor([[2, 4],
        [5, 2],
        [3, 1],
        [7, 9]])
tensor([[2, 4],
        [5, 2],
        [3, 1],
        [7, 9]])
```

```
torch.linspace(3, 8, 20)
```

```
tensor([3.0000, 3.2632, 3.5263, 3.7895, 4.0526, 4.3158, 4.5789, 4.8421, 5.1053,
        5.3684, 5.6316, 5.8947, 6.1579, 6.4211, 6.6842, 6.9474, 7.2105, 7.4737,
        7.7368, 8.0000])
```

```python
from matplotlib import pyplot as plt
plt.hist(torch.randn(1000).numpy(),100)
```

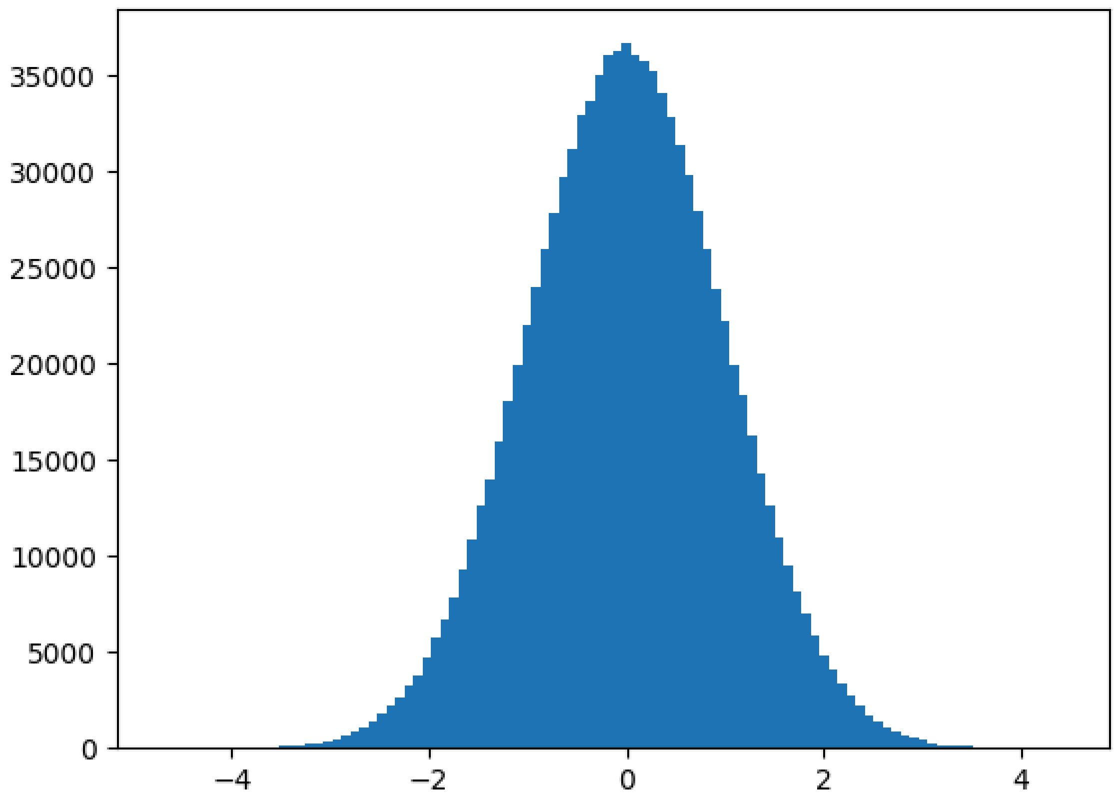
```
(array([ 1.,  0.,  0.,  0.,  0.,  0.,  1.,  2.,  1.,  2.,  3.,  4.,  3.,
         1.,  1.,  1.,  3.,  4.,  3.,  4.,  3.,  5., 10.,  9.,  8., 11.,
        11.,  9., 12., 16., 20., 13., 18., 14., 13., 23., 15., 26., 21.,
        21., 18., 20., 23., 26., 30., 33., 33., 23., 18., 25., 16., 24.,
        20., 26., 26., 30., 30., 13., 21., 17., 20., 18., 15., 12., 12.,
        15., 14., 12.,  8., 11.,  9.,  6.,  4., 11.,  2.,  8.,  8.,  3.,
         1.,  2.,  2.,  4.,  2.,  4.,  2.,  4.,  1.,  1.,  1.,  0.,  1.,
         0.,  0.,  1.,  1.,  0.,  0.,  0.,  0.,  1.]),
 array([-3.18605018e+00, -3.11969924e+00, -3.05334854e+00, -2.98699760e+00,
        -2.92064691e+00, -2.85429597e+00, -2.78794527e+00, -2.72159433e+00,
        -2.65524364e+00, -2.58889270e+00, -2.52254200e+00, -2.45619106e+00,
        -2.38984013e+00, -2.32348943e+00, -2.25713873e+00, -2.19078779e+00,
        -2.12443686e+00, -2.05808616e+00, -1.99173534e+00, -1.92538452e+00,
        -1.85903370e+00, -1.79268289e+00, -1.72633207e+00, -1.65998125e+00,
        -1.59363031e+00, -1.52727950e+00, -1.46092868e+00, -1.39457786e+00,
        -1.32822704e+00, -1.26187623e+00, -1.19552541e+00, -1.12917471e+00,
        -1.06282377e+00, -9.96472836e-01, -9.30122137e-01, -8.63771200e-01,
        -7.97420502e-01, -7.31069565e-01, -6.64718866e-01, -5.98367929e-01,
        -5.32017231e-01, -4.65666294e-01, -3.99315596e-01, -3.32964659e-01,
        -2.66613960e-01, -2.00263023e-01, -1.33912325e-01, -6.75613880e-02,
        -1.21045113e-03,  6.51402473e-02,  1.31491184e-01,  1.97841883e-01,
         2.64192820e-01,  3.30543518e-01,  3.96894455e-01,  4.63245153e-01,
         5.29596090e-01,  5.95946789e-01,  6.62297726e-01,  7.28648424e-01,
         7.94999361e-01,  8.61350298e-01,  9.27700758e-01,  9.94051695e-01,
         1.06040263e+00,  1.12675357e+00,  1.19310451e+00,  1.25945497e+00,
         1.32580590e+00,  1.39215684e+00,  1.45850778e+00,  1.52485824e+00,
         1.59120917e+00,  1.65756011e+00,  1.72391105e+00,  1.79026151e+00,
         1.85661244e+00,  1.92296338e+00,  1.98931432e+00,  2.05566478e+00,
         2.12201571e+00,  2.18836665e+00,  2.25471759e+00,  2.32106853e+00,
         2.38741899e+00,  2.45376992e+00,  2.52012086e+00,  2.58647180e+00,
         2.65282226e+00,  2.71917319e+00,  2.78552413e+00,  2.85187507e+00,
         2.91822553e+00,  2.98457646e+00,  3.05092740e+00,  3.11727834e+00,
         3.18362927e+00,  3.24997973e+00,  3.31633067e+00,  3.38268161e+00,
         3.44903183e+00]),
 <BarContainer object of 100 artists>)
```




```
plt.hist(torch.randn(10**6).numpy(),100)
```

```
(array([2.0000e+00, 1.0000e+00, 0.0000e+00, 2.0000e+00, 3.0000e+00,
        2.0000e+00, 1.3000e+01, 1.4000e+01, 1.8000e+01, 2.5000e+01,
        4.0000e+01, 4.2000e+01, 5.9000e+01, 8.9000e+01, 1.1200e+02,
        1.7000e+02, 2.3100e+02, 2.7400e+02, 3.5600e+02, 4.9400e+02,
        6.6100e+02, 8.5700e+02, 1.1100e+03, 1.3650e+03, 1.7510e+03,
        2.2010e+03, 2.6240e+03, 3.2760e+03, 3.7810e+03, 4.7510e+03,
        5.7350e+03, 6.6740e+03, 7.7970e+03, 9.3070e+03, 1.0905e+04,
        1.2625e+04, 1.4032e+04, 1.5951e+04, 1.8054e+04, 1.9966e+04,
        2.2020e+04, 2.3992e+04, 2.6005e+04, 2.7814e+04, 2.9682e+04,
        3.1159e+04, 3.2962e+04, 3.3675e+04, 3.5076e+04, 3.6132e+04,
        3.6284e+04, 3.6686e+04, 3.6078e+04, 3.5755e+04, 3.5232e+04,
        3.4105e+04, 3.2904e+04, 3.1362e+04, 2.9869e+04, 2.7948e+04,
        2.5966e+04, 2.3897e+04, 2.2177e+04, 1.9942e+04, 1.8372e+04,
        1.6332e+04, 1.4275e+04, 1.2603e+04, 1.0977e+04, 9.5400e+03,
        8.1990e+03, 6.9730e+03, 5.8160e+03, 4.8300e+03, 4.0820e+03,
        3.3670e+03, 2.7040e+03, 2.2090e+03, 1.7450e+03, 1.4010e+03,
        1.0390e+03, 8.1600e+02, 6.2400e+02, 5.3700e+02, 4.0700e+02,
        2.8700e+02, 1.8400e+02, 1.4400e+02, 1.1700e+02, 1.1000e+02,
        6.8000e+01, 4.6000e+01, 3.5000e+01, 1.8000e+01, 1.8000e+01,
        8.0000e+00, 5.0000e+00, 9.0000e+00, 6.0000e+00, 5.0000e+00]),
 array([-4.71457434, -4.62314463, -4.53171492, -4.44028473, -4.34885502,
        -4.25742531, -4.1659956 , -4.07456541, -3.9831357 , -3.89170599,
        -3.80027604, -3.70884633, -3.61741638, -3.52598667, -3.43455696,
        -3.34312701, -3.25169706, -3.16026735, -3.06883764, -2.97740769,
```

```
       -2.88597775, -2.79454803, -2.70311832, -2.61168838, -2.52025867,
       -2.42882872, -2.33739901, -2.24596906, -2.15453935, -2.0631094 ,
       -1.97167969, -1.88024974, -1.78882003, -1.69739032, -1.60596037,
       -1.51453066, -1.42310071, -1.331671  , -1.24024105, -1.14881134,
       -1.05738139, -0.96595168, -0.87452173, -0.78309202, -0.69166231,
       -0.60023212, -0.50880241, -0.4173727 , -0.32594299, -0.23451328,
       -0.1430831 , -0.05165339,  0.03977633,  0.13120604,  0.22263622,
        0.31406593,  0.40549564,  0.49692535,  0.58835554,  0.67978525,
        0.77121496,  0.86264467,  0.95407486,  1.04550457,  1.13693428,
        1.22836399,  1.3197937 ,  1.41122389,  1.5026536 ,  1.59408331,
        1.68551302,  1.77694321,  1.86837292,  1.95980263,  2.05123234,
        2.14266253,  2.23409224,  2.32552195,  2.41695166,  2.50838184,
        2.59981155,  2.69124126,  2.78267097,  2.87410069,  2.96553087,
        3.05696058,  3.14839029,  3.23982   ,  3.33124971,  3.42267942,
        3.51411009,  3.6055398 ,  3.69696951,  3.78839922,  3.87982893,
        3.97125864,  4.06268835,  4.15411806,  4.24554777,  4.33697844,
        4.42840767]),
 <BarContainer object of 100 artists>)
```




```
a=torch.tensor([[1,2,3,4]])
b=torch.tensor([[5,6,7,8]])
print(torch.cat((a,b),0))
```

```
tensor([[1, 2, 3, 4],
        [5, 6, 7, 8]])
```

```
print( torch.cat((a,b),1))
```

```
tensor([[1, 2, 3, 4, 5, 6, 7, 8]])
```

想法：

张量是个好东西。

pytorch相比tensorflow确实有很多不错之处。

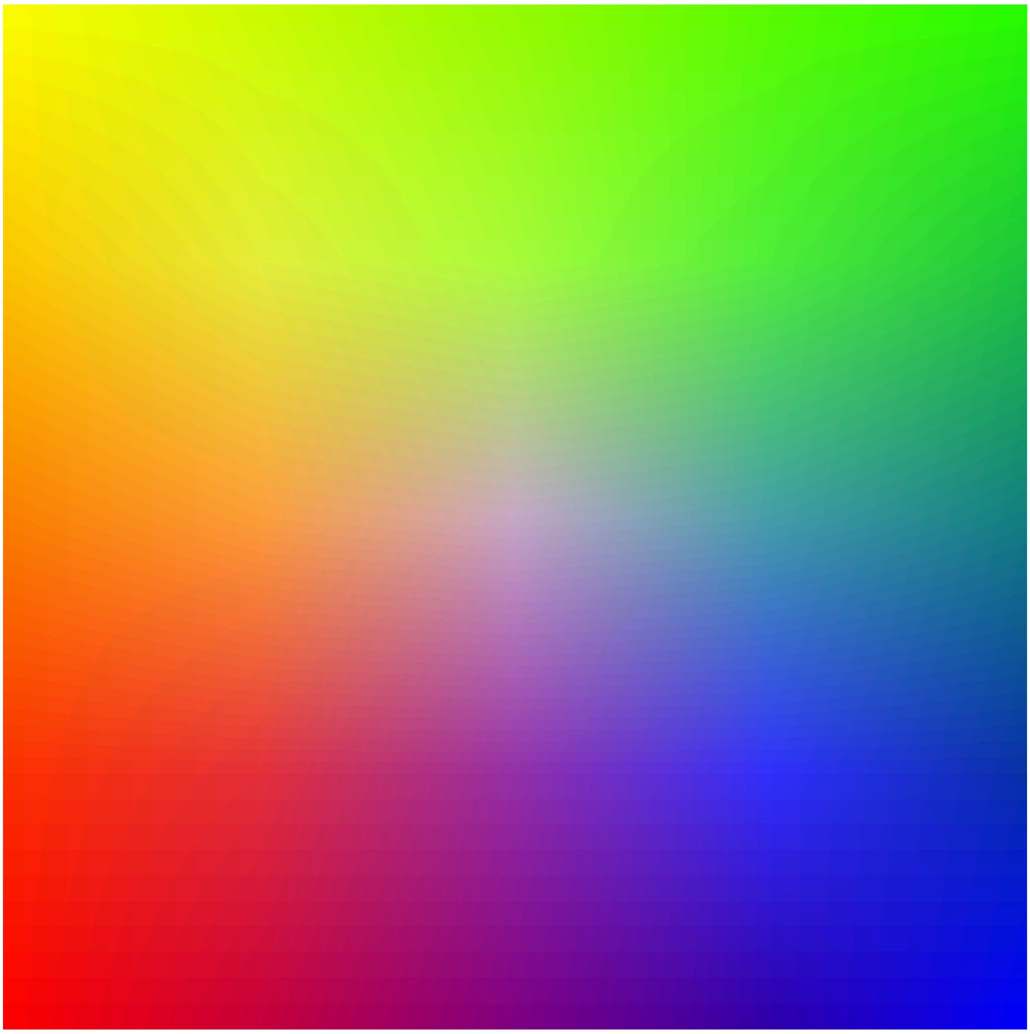
3.2 螺旋数据分类

用神经网络实现简单数据分类，[实验指导链接]

运行代码会发现少了一个图片，原作者移动位置了，新的位置在： https://raw.githubusercontent.com/Atcold/pytorch-Deep-Learning/master/res/ziegler.png

要求： 把代码输入 colab，在线运行观察效果

关键截图：



```
!wget https://raw.githubusercontent.com/Atcold/NYU-DLSP21/refs/heads/master/res/plot_lib.py
```

```
--2025-10-11 15:53:23--  https://raw.githubusercontent.com/Atcold/NYU-
DLSP21/refs/heads/master/res/plot_lib.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)...
185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 4605 (4.5K) [text/plain]
Saving to: ‘plot_lib.py.2’
```

plot_lib.py.2 0%[ ] 0 --.-KB/s
plot_lib.py.2 100%[===================>] 4.50K --.-KB/s in 0s

```
2025-10-11 15:53:24 (71.0 MB/s) - ‘plot_lib.py.2’ saved [4605/4605]
```

```python
import random
import torch
from torch import nn,optim
import math
from IPython import display
from plot_lib import plot_data, plot_model, set_default

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print('device: ', device)
seed = 12345
random.seed(seed)

torch.manual_seed(seed)
N=1000
D=2
C=3
H=100
```

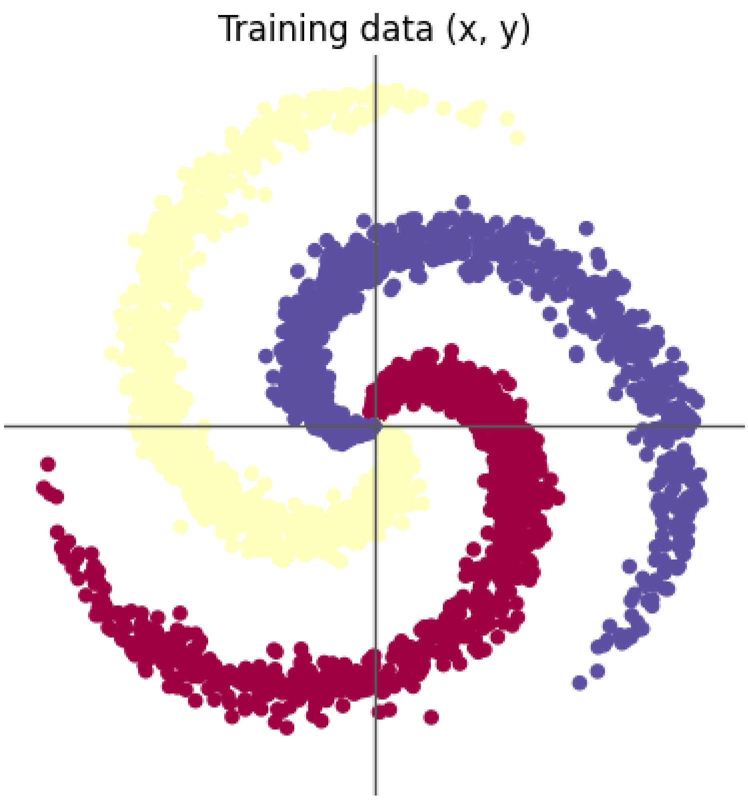
```
device:  cuda:0
```

```
X=torch.zeros(N*C, D).to(device)
Y=torch.zeros(N*C,dtype=torch.long).to(device)
for c in range(C):
    index=0
    t= torch.linspace(0,1,N)
    inner_var = torch.linspace((2*math.pi/C)*c,(2*math.pi/C)*(2+c),N)+
torch.randn(N) * 0.2
    for ix in range(N * c,N *(c + 1)):
        X[ix]= t[index] *
torch.FloatTensor([math.sin(inner_var[index]),math.cos(inner_var[index])])
        Y[ix]=c
        index += 1
print("shapes:")
print("X:", X.size())
print("Y:", Y.size())
```

```
shapes:
X: torch.Size([3000, 2])
Y: torch.Size([3000])
```

```
plot_data(X,Y)
```

```
<matplotlib.collections.PathCollection at 0x7e8090c160c0>
```



模型很有效，这是最有意思的。

二、问题总结与体会

描述实验过程中所遇到的问题，以及是如何解决的。有哪些收获和体会，对于课程的安排有哪些建议。

思考下面的问题：

1、AlexNet有哪些特点？为什么可以比LeNet取得更好的性能？

AlexNet的主要特点是网络层数更深，使用了ReLU激活函数来加快训练速度，采用Dropout技术防止模型过拟合，并且用GPU进行并行训练。这些改进让它能学习更复杂的特征，所以比LeNet性能更好。

2、激活函数有哪些作用？

激活函数的主要作用是给神经网络引入非线性，让网络能够拟合复杂的非线性关系。

3、梯度消失现象是什么？

梯度消失是指在深层网络训练中，误差反向传播时梯度会逐层连乘而变得越来越小，导致靠近输入层的参数更新非常缓慢，使得深层网络难以有效训练。

4、神经网络是更宽好还是更深好？

更深的网络通常比更宽的网络效果更好。深度网络能构建从低层到高层的特征层次，用更少的参数表达更复杂的函数。但网络过深也会带来训练困难。

5、为什么要使用Softmax？

使用Softmax是因为它能把网络输出转化为概率分布，使得各个类别的输出值在0到1之间且总和为1，这样既方便理解模型对每个类别的置信度，也便于计算交叉熵损失。

6、SGD 和 Adam 哪个更有效？

Adam通常收敛更快且对超参数不太敏感，在实践中更常用；而SGD配合恰当的调参可能找到泛化能力更好的解。具体哪个更有效要看具体任务和训练设置。