In [1]:
```
import sys; sys.path.append('../..') ; sys.path.append('..') ; from my_utils

import torch
import torch.nn as nn
import torch.utils.data as data
import torch.optim as optim
# dummy trainloader
trainloader = data.DataLoader(data.TensorDataset(torch.Tensor(1), torch.Tens
device = torch.device('cpu')

import matplotlib.pyplot as plt
```

In this homework, there are three different datasets consisting of 2-dimensional input features and binary class labels, and you will be asked to implement machine learning classifiers.

Let's begin by importing some libaries.

Next, we set a random seed for reproducibility.

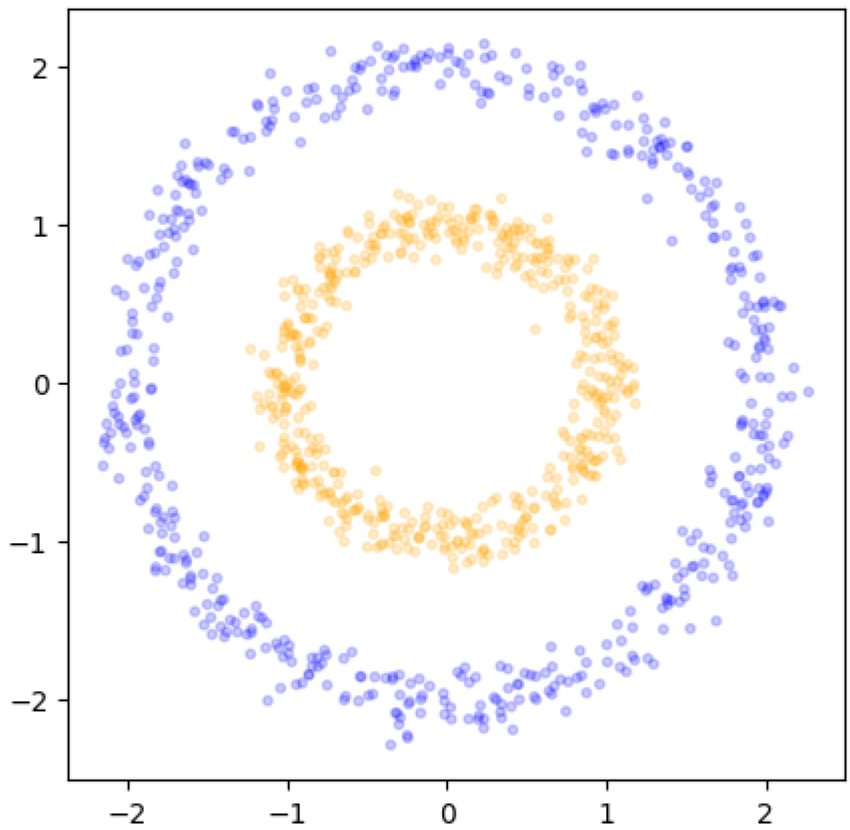
In [2]:
```
import numpy as np
import random

seed = 0
np.random.seed(seed)
torch.random.manual_seed(seed)
random.seed(seed)
```

Concentric annuli

In [3]:
```
X, y = sample_annuli()
fig, ax = plt.subplots(1,1, figsize=(5,5))
print(X.shape)
plot_scatter(ax, X, y)
```

```
torch.Size([1024, 2])
```



[2pt] Let's start by implmenting a logistic regression model. Fill the template below to complete the logisitc regression model. Use the binary cross entropy loss, torch.nn.BCELoss.

(i) Complete the model, (ii) finish the training loop, (iii) present the results with a figure (see the example below) and the classification accuracy

In [4]:
```
class Model(nn.Module):
    def __init__(self,device="cpu"):
        super(Model, self).__init__()
        self.linear = nn.Linear(2, 1)
        self.sigmoid = nn.Sigmoid()


    def forward(self, x):
        layer = self.linear(x)
        y = self.sigmoid(layer)
        return y
```

In [5]:
```
model = Model().to(device)
```

In [6]:
```
optimizer = optim.AdamW(model.parameters(), lr=1e-2, weight_decay=1e-6)
```

In [7]:
```
criterion = nn.BCELoss()

# complete the following training loop.
for itr in range(1, 1001):
```

Loading [MathJax]/extensions/Safe.js

```python
    optimizer.zero_grad()
    yh = model(X) # forward pass
    y = y.float().view(-1, 1)
    loss = criterion(yh, y)
    loss.backward()  # Backward pass
    optimizer.step()
```

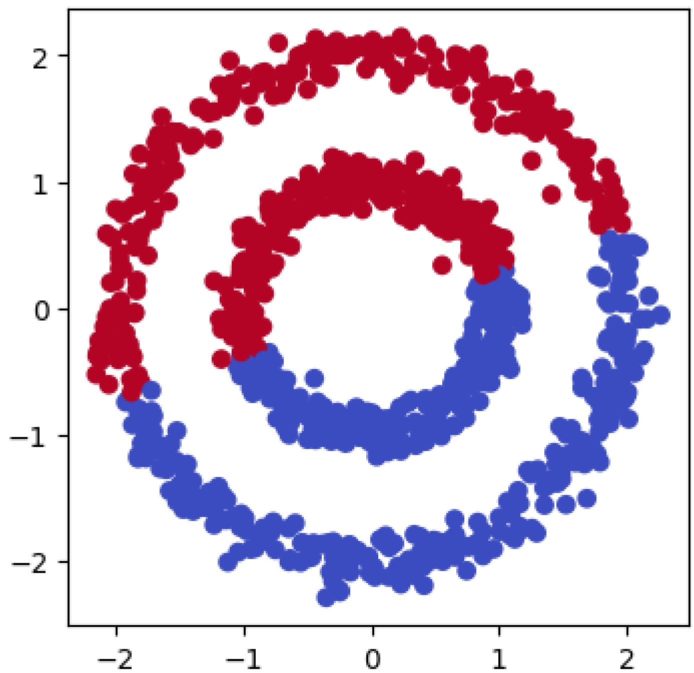
In [8]:
```python
# visualize the result and report the accuracy
with torch.no_grad():
    fig = plt.figure(figsize=(4,4))

    yh_test = model(X)  # X_test should contain your test data
    predicted_labels = (yh_test >= 0.5).float()  # Convert predicted probabi

    # Calculate accuracy
    print(predicted_labels, y)
    correct_predictions = (predicted_labels == y.float().view(-1, 1)).sum().
    total_samples = len(y)
    accuracy = correct_predictions / total_samples
    print(accuracy)

    # Visualization
    fig, ax = plt.subplots(figsize=(4, 4))
    ax.scatter(X.numpy()[:, 0], X.numpy()[:, 1], c=predicted_labels.numpy().
```

```
tensor([[0.],
        [1.],
        [0.],
        ...,
        [0.],
        [0.],
        [1.]]) tensor([[1.],
        [1.],
        [1.],
        ...,
        [0.],
        [0.],
        [0.]])
0.52734375
<Figure size 400x400 with 0 Axes>
```



It is obvious that the logistic regression would not be able to distinguish two classes (not linearly separate data). You will have to build another model.

[3pt] In the class template below, implement your own model that will achieve 100% accuracy in classifying the data poitns in training set. There is one restriction; you are allowed to use "one" linear layer for your implementation as in the logistic regression model above. But you are allowed to use as many nonlinear functions as needed.

In [18]:
```
class Model(nn.Module):
    def __init__(self,device="cpu"):
        super(Model, self).__init__()
        self.linear = nn.Linear(2,1)
        self.silu = nn.SiLU()
        self.bn = nn.BatchNorm1d(2)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        y = self.bn(x)
        y = self.silu(y)
        y = self.bn(y)
        y = self.linear(y)
        y = self.sigmoid(y)
        return y
```

In [19]:
```
model = Model().to(device)
```

In [20]:
```
optimizer = optim.AdamW(model.parameters(), lr=1e-2, weight_decay=1e-6)
criterion = nn.BCELoss()
```

In [21]:
```
for itr in range(1, 3001):
    optimizer.zero_grad()
    yh = model(X) # forward pass
    y = y.float().view(-1, 1)
    loss = criterion(yh, y)
    loss.backward()  # Backward pass
    optimizer.step()
```

In [22]:
```
print(loss.item())
```

```
0.05006854608654976
```

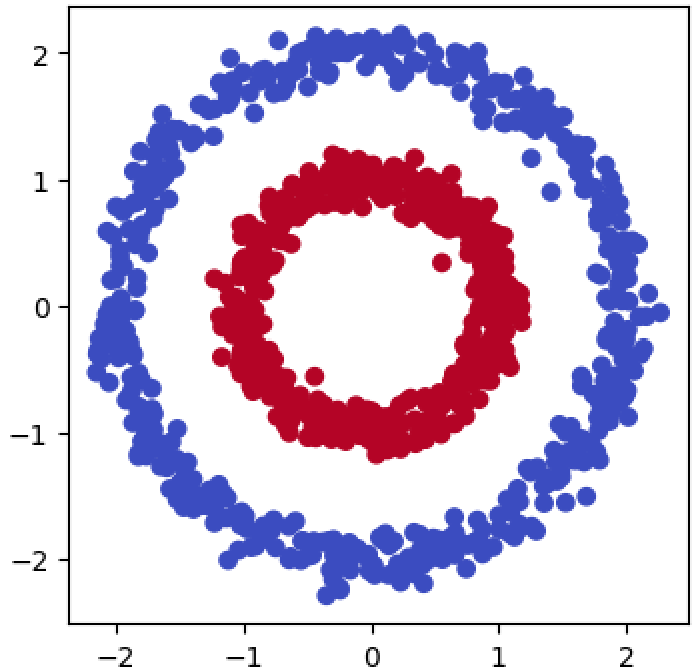
In [24]:
```
import tensorflow as tf
#print(y)
with torch.no_grad():
    fig = plt.figure(figsize=(4,4))

    yh_test = model(X)
    predicted_labels = (yh_test > 0.5).float()  # Convert predicted probabil

    # Calculate accuracy
    print(predicted_labels, y)
    correct_predictions = (predicted_labels == y.float().view(-1, 1)).sum().
    total_samples = len(y)
    accuracy = correct_predictions / total_samples
    print(accuracy)

    # Visualization
    fig, ax = plt.subplots(figsize=(4, 4))
    ax.scatter(X.numpy()[:, 0], X.numpy()[:, 1], c=predicted_labels.numpy().
```

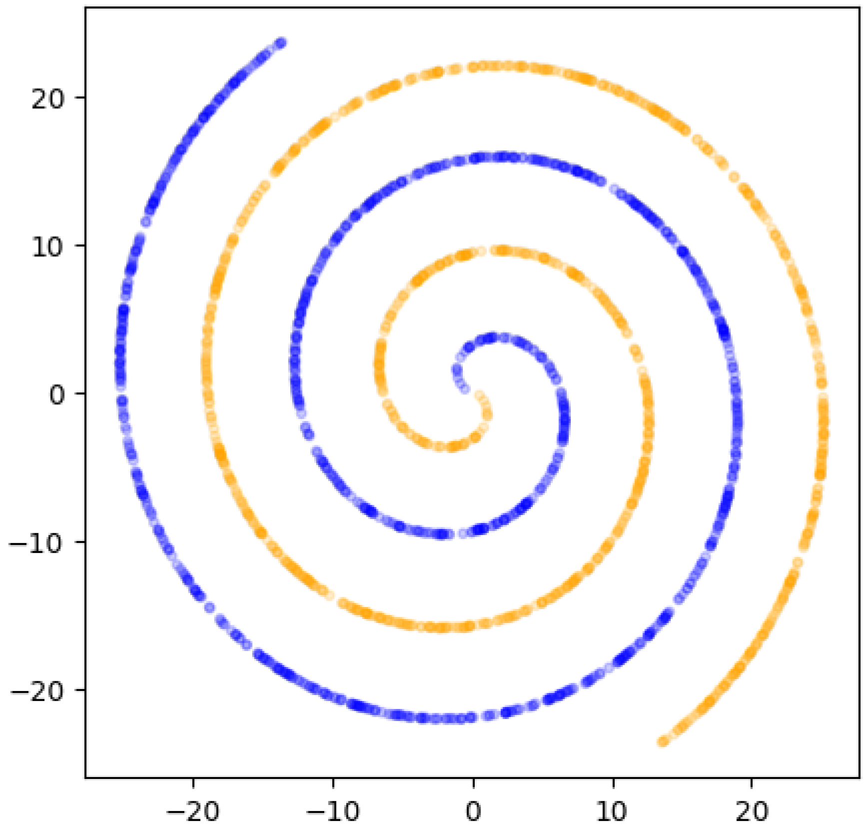
```
tensor([[1.],
        [1.],
        [1.],
        ...,
        [0.],
        [0.],
        [0.]]) tensor([[1.],
        [1.],
        [1.],
        ...,
        [0.],
        [0.],
        [0.]])
1.0
<Figure size 400x400 with 0 Axes>
```



Spiral dataset

In [15]:
```
X, y = sample_spiral()
print(X.shape)
print(y)
fig, ax = plt.subplots(1,1, figsize=(5,5))
plot_scatter(ax, X, y)
```

```
torch.Size([2048, 2])
tensor([0, 0, 0,  ..., 1, 1, 1])
```



It's obvious that neither the logistic regression nor the model you developed for the second dataset would not work for this dataset.

[2pt] implemented a neural network of your choice and achieve 100% classification accuracy

In [16]:
```
class Model(nn.Module):
    def __init__(self,device="cpu"):
        super(Model, self).__init__()

        self.net = nn.Sequential(
            nn.Linear(2,50),
            nn.Tanh(),
            nn.Linear(50,50),
            nn.Tanh(),
            nn.Linear(50,1))
        #for p in self.linear_layer.parameters(): torch.nn.init.zeros_(p)

    def forward(self, x):
        y = self.net(x)
        y = torch.sigmoid(y)
        return y
```

In [17]:
```
model = Model().to(device)
```

In [18]:
```
optimizer = optim.AdamW(model.parameters(), lr=1e-2, weight_decay=1e-6)
```

In [19]:
```
for itr in range(1, 1001):
    optimizer.zero_grad()
#    x0, y = sample_annuli(device=device, n_samples=1024)

    yh = model(X)
    loss = nn.BCELoss()(yh.squeeze(), y.float())
    print(itr,loss.item())
    #loss_traj[itr-1] = loss.item()
    loss.backward()
    optimizer.step()
```

1 0.686331570148468
2 0.7187483906745911
3 0.6712204813957214
4 0.6821600794792175
5 0.6861546039581299
6 0.6722385883331299
7 0.6652229428291321
8 0.6684250235557556
9 0.671859860420227
10 0.6701979637145996
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52 0.6061080694198608
53 0.6059073209762573
54 0.600985050201416
55 0.603423535823822
56 0.601421131362915

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63 0.5935441851615906
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67 0.5931817889213562
68 0.5928484797477722
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71 0.5894709825515747
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73 0.5897322297096252
74 0.5864490866661072
75 0.5873163342475891
76 0.5870151519775391
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79 0.5842284560203552
80 0.5826447606086731
81 0.5838415622711182
82 0.581992506980896
83 0.581304669380188
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98 0.5730525255203247
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110 0.5668889284133911
111 0.5677401423454285
112 0.5692542195320129
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118 0.5635136961936951
119 0.5598823428153992
120 0.5587342381477356
121 0.559718668460846
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124 0.5554752945899963
125 0.5554963946342468
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136 0.5420005321502686
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```

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```
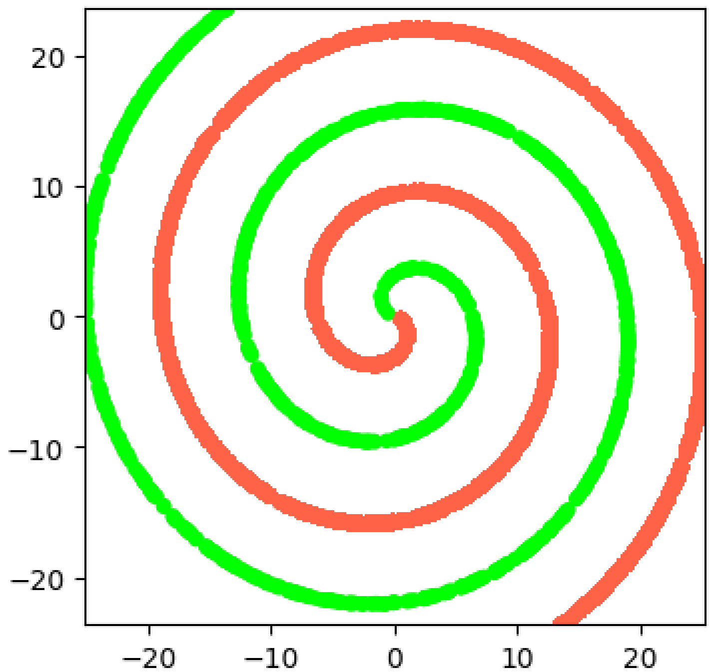

In [20]:
```
with torch.no_grad():
    fig = plt.figure(figsize=(4,4))
    axes = []
    axes.append(fig.add_subplot(1,1,1))#,sharex=True,sharey=True))
    xs, ys = X, y#sample_gaussian(n_samples=200) ; s = torch.linspace(0, 1,
    y_pred = model(xs)
    print(y_pred.shape)
```

```
    label = (y_pred[:,0] >= 0.5).long()
    print(label)
    colors = ['lime','tomato']
    for i in range(1024):
        axes[0].scatter(xs[i,0], xs[i,1], c=colors[label[i]], edgecolor='nor
        axes[0].scatter(xs[i+1024:,0], xs[i+1024:,1], c=colors[label[i+1024]
    axes[0].set_xlim(xs[:,0].min(), xs[:,0].max()) ; axes[0].set_ylim(xs[:,1
    plt.show()

    print(xs.shape)
    err = torch.sum(torch.abs(label - y))
    print(err)
```

```
torch.Size([2048, 1])
tensor([0, 0, 0,  ..., 1, 1, 1])
```




```
torch.Size([2048, 2])
tensor(0)
```

In [ ]:

```

```