1. Make Classification data and get it ready

```
import sklearn
```

```
from sklearn.datasets import make_circles

n_samples=1000
X,y=make_circles(n_samples,noise=0.03,random_state=42)
```

```
len(X),len(y)
```

```
(1000, 1000)
```

```
print(f"First 5 samples of X: \n{X[:5]}")
print(f"First 5 samples of y: {y[:5]}")
```

```
First 5 samples of X:
[[ 0.75424625  0.23148074]
 [-0.75615888  0.15325888]
 [-0.81539193  0.17328203]
 [-0.39373073  0.69288277]
 [ 0.44220765 -0.89672343]]
First 5 samples of y: [1 1 1 1 0]
```

```
y
```

```
array([1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1,
       0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1,
       1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1,
       1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1,
       1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1,
       0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0,
       0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0,
       1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0,
       1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1,
       1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1,
       1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0,
       1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1,
       0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 1, 0, 0])
```

```
import pandas as pd
circles=pd.DataFrame({"X1":X[:,0],"X2":X[:,1],"label":y})
circles
```

	X1	X2	label
0	0.754246	0.231481	1
1	-0.756159	0.153259	1
2	-0.815392	0.173282	1
3	-0.393731	0.692883	1
4	0.442208	-0.896723	0
...	...	...	...
995	0.244054	0.944125	0
996	-0.978655	-0.272373	0
997	-0.136900	-0.810012	1
998	0.670362	-0.767502	0
999	0.281057	0.963824	0

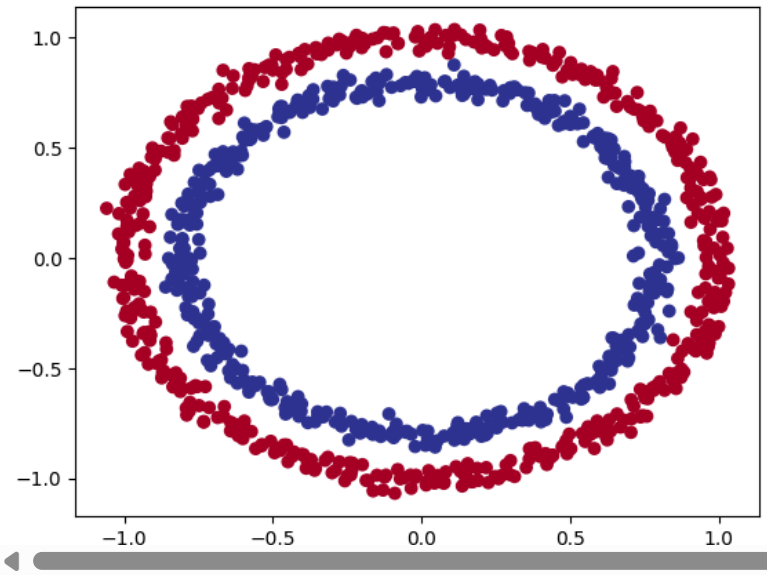
1000 rows × 3 columns

Next steps: Generate code with circles | View recommended plots | New interactive sheet

```
# Check different labels
circles.label.value_counts()
```

label	count
1	500
0	500

```
import matplotlib.pyplot as plt
plt.scatter(X[:,0],X[:,1],c=y,cmap=plt.cm.RdYlBu);
```



Start coding or generate with AI.

1.1 Check input and output shapes

```
X.shape,y.shape
```

```
((1000, 2), (1000,))
```

```
X,X.shape
```

```
(array([[ 0.75424625,  0.23148074],
        [-0.75615888,  0.15325888],
        [-0.81539193,  0.17328203],
        ...,
        [-0.13690036, -0.81001183],
        [ 0.67036156, -0.76750154],
        [ 0.28105665,  0.96382443]]),
 (1000, 2))
```

```
X[100]
```

```
array([-0.71086577,  0.27889325])
```

```
# View the first example of features and labels
x_sample=X[0]
y_sample=y[0]

print(f"Values for one sample of X: {x_sample} and the same for y:{y_sample}")
print(f"Shapes for one samle of X: {x_sample.shape} and the same for y:{y_sample.shape}")
```

```
Values for one sample of X: [0.75424625 0.23148074] and the same for y:1
Shapes for one samle of X: (2,) and the same for y:()
```

1.2 Turn data into tensors and create train and test splits

```
import torch
torch.__version__
```

```
type(X),X.dtype
```

```
(numpy.ndarray, dtype('float64'))
```

```
#turn data into tensors

X=torch.from_numpy(X).type(torch.float)
y=torch.from_numpy(y).type(torch.float)

X[:5],y[:5]
```

```
(tensor([[ 0.7542,  0.2315],
         [-0.7562,  0.1533],
         [-0.8154,  0.1733],
         [-0.3937,  0.6929],
         [ 0.4422, -0.8967]]),
 tensor([1., 1., 1., 1., 0.]))
```

```
X
```

```
tensor([[ 0.7542,  0.2315],
        [-0.7562,  0.1533],
        [-0.8154,  0.1733],
        ...,
        [-0.1369, -0.8100],
        [ 0.6704, -0.7675],
        [ 0.2811,  0.9638]])
```

```
X[:5],y[:5]
```

```
(tensor([[ 0.7542,  0.2315],
         [-0.7562,  0.1533],
         [-0.8154,  0.1733],
         [-0.3937,  0.6929],
         [ 0.4422, -0.8967]]),
 tensor([1., 1., 1., 1., 0.]))
```

```
type(X),type(y),X.dtype,y.dtype
```

```
(torch.Tensor, torch.Tensor, torch.float32, torch.float32)
```

```
# split data into train and test sets
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
```

```
len(X_train),len(X_test),len(y_train),len(y_test)
```

```
(800, 200, 800, 200)
```

```
Start coding or generate with AI.
```

Double-click (or enter) to edit

2. Building a model

Let's build a model to clssify our blue and red dots

To do so , we want to :

1. Setup device agnoistic code so our code will run on accelerator(GPU) if there is one
2. Construct a model(by subclassing nn.modules)
3. Define a loss function and Optimizer
4. Create a training and test loop

```
import torch
from torch import nn
device="cuda" if torch.cuda.is_available() else "cpu"
device
```

```
X_train
```

```
tensor([[ 0.6579, -0.4651],
        [ 0.6319, -0.7347],
        [-1.0086, -0.1240],
        ...,
        [ 0.0157, -1.0300],
        [ 1.0110,  0.1680],
        [ 0.5578, -0.5709]])
```

Now we have setup device agnostic code, let's create a model that:

1. Subclasses nn.modules (almost all modules PyTorch subclass nn.module)
2. Create 2 nn.Linear() layers that are capable of handling the shapes of our data
3. Define a forward() method that outlines the forward pass (of forward computation) of the model
4. Instatiate an instance of out model class and send it to the target device

```
# 1. Construct a model class that subclasses nn.Module


class CircleModelV0(nn.Module):
  def __init__(self):
    super().__init__()
    self.layer_1=nn.Linear(in_features=2,out_features=5)
    self.layer_2=nn.Linear(in_features=5,out_features=1)

  def forward(self,x):
    return self.layer_2(self.layer_1(x))

model_0=CircleModelV0().to(device)
model_0
```

```
CircleModelV0(
      (layer_1): Linear(in_features=2, out_features=5, bias=True)
      (layer_2): Linear(in_features=5, out_features=1, bias=True)
    )
```

```
# Replicate CircleModelV0 with nn.Sequential

model_0= nn.Sequential(
    nn.Linear(in_features=2,out_features=5),
```

```
    nn.Linear(in_features=5,out_features=1)
).to(device)

model_0
```

```
Sequential(
  (0): Linear(in_features=2, out_features=5, bias=True)
  (1): Linear(in_features=5, out_features=1, bias=True)
)
```

```
# Make predictions with the model

untrained_prediction=model_0(X_test.to(device))

print(f"Length of predictions:{len(untrained_prediction)}, Shape:{(untrained_prediction.shape)}")
print(f"Length of test samples:{len(y_test)} and shape:{y_test.shape}")
print(f"\n First 10 samples: {untrained_prediction[:10]}")
print(f"\n First 1- test sampled:{y_test[:10]}")
```

```
Length of predictions:200, Shape:torch.Size([200, 1])
Length of test samples:200 and shape:torch.Size([200])

 First 10 samples: tensor([[0.4075],
        [0.3343],
        [0.4043],
        [0.4092],
        [0.0948],
        [0.0525],
        [0.0918],
        [0.0250],
        [0.4174],
        [0.3260]], grad_fn=<SliceBackward0>)

 First 1- test sampled:tensor([1., 0., 1., 0., 1., 1., 0., 0., 1., 0.])
```

Setup loss and optimizer

```
# create a loss function
loss_fun=nn.BCEWithLogitsLoss()
optimizer=torch.optim.SGD(params=model_0.parameters(),lr=0.1)


# Calculate aacuracy (for classification model)
def accuracy(y_true,y_pred):
  correct=torch.eq(y_true,y_pred).sum().item()
  acc=(correct/len(y_true))*100
  return acc
```

3. Train model

```
# View the frist 5 outputs of the forward pass on the test data
y_logits=model_0(X_test.to(device))[:5]
y_logits
```

```
tensor([[0.4075],
        [0.3343],
        [0.4043],
        [0.4092],
        [0.0948]], grad_fn=<SliceBackward0>)
```

```
# sigmoid on model logits
y_pred=torch.sigmoid(y_logits)
y_pred
```

```
tensor([[0.6005],
        [0.5828],
        [0.5997],
        [0.6009],
        [0.5237]], grad_fn=<SigmoidBackward0>)
```

```
torch.round(y_pred)
```

```
tensor([[1.],
        [1.],
        [1.],
        [1.],
        [1.]], grad_fn=<RoundBackward0>)
```

```
Start coding or generate with AI.
```

Building a training and testing loop

```
# Building a training and testing loop
torch.manual_seed(42)

epochs=100

#put the data to target device
X_train,y_train=X_train.to(device),y_train.to(device)
X_test,y_test=X_test.to(device),y_test.to(device)

for epoch in range(epochs):
  ### Training
  model_0.train()

  #1. Forward pass
  y_logits=model_0(X_train).squeeze() #squeeze to remove extra 1 dimension , this would not work unless model and data are on the s
  y_pred=torch.round(torch.sigmoid(y_logits))  # turn logits-> pred probs -> pred labels

  #2. Calculate loss/accuracy
  loss=loss_fun(y_logits,y_train)
  acc=accuracy(y_true=y_train,y_pred=y_pred)

  #3. Optimizer zero grad
  optimizer.zero_grad()

  #4. Loss Backwards
  loss.backward()

  #5. Optimizer step
  optimizer.step()

  #### Testing

  model_0.eval()
  with torch.inference_mode():
    #1. Forward Pass
    test_logits=model_0(X_test).squeeze()
    test_pred=torch.round(torch.sigmoid(test_logits))
    #2. Calculate loss/accuracy
    test_loss=loss_fun(test_logits,y_test)
    test_acc=accuracy(y_true=y_test,y_pred=test_pred)

  if epoch%10==0:
    print(f"Epoch: {epoch} | Loss:{loss:.5f} | Accuracy: {acc:.5f} | Test Loass: {test_loss:.5f} | Test Accuracy:{test_acc:.5f}")
```

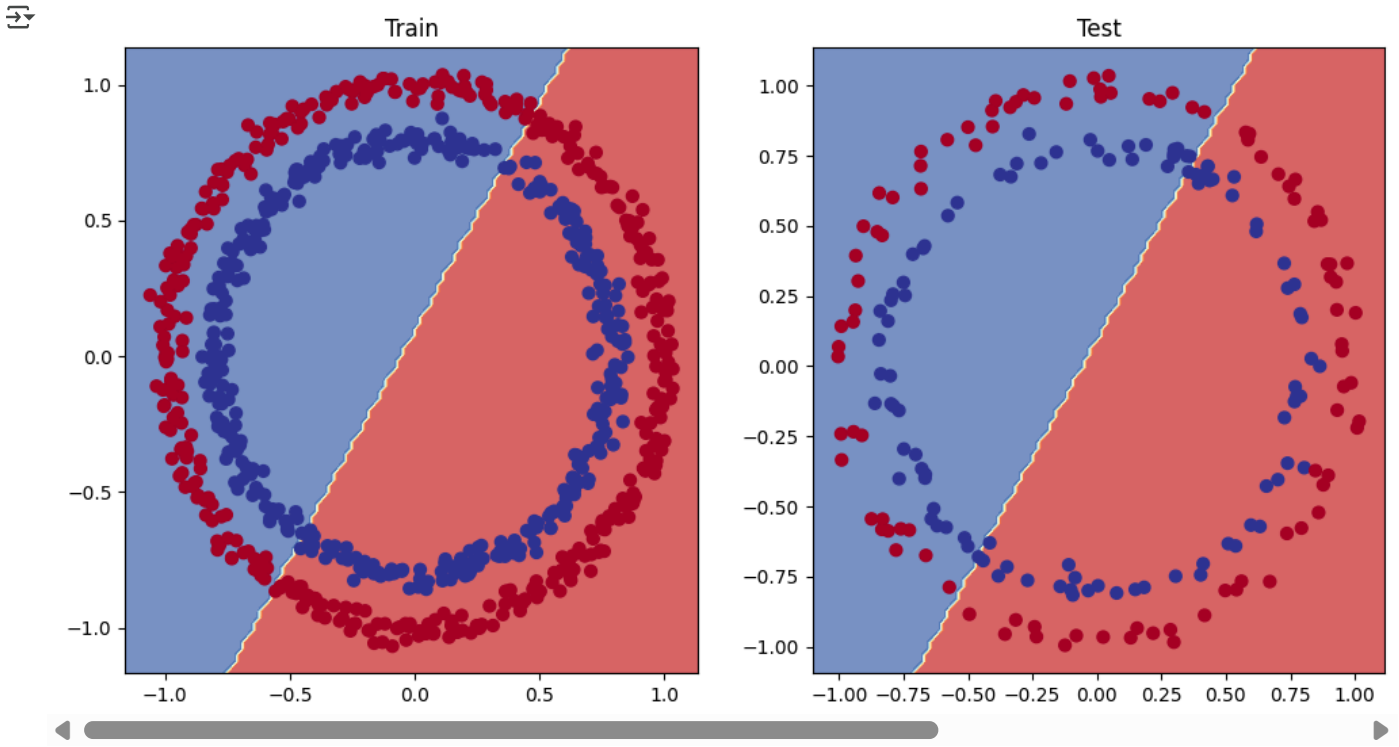
```
Epoch: 0 | Loss:0.70493 | Accuracy: 53.12500 | Test Loass: 0.70295 | Test Accuracy:53.00000
Epoch: 10 | Loss:0.69814 | Accuracy: 53.25000 | Test Loass: 0.69684 | Test Accuracy:54.00000
Epoch: 20 | Loss:0.69587 | Accuracy: 49.87500 | Test Loass: 0.69487 | Test Accuracy:55.50000
Epoch: 30 | Loss:0.69499 | Accuracy: 49.87500 | Test Loass: 0.69419 | Test Accuracy:55.50000
Epoch: 40 | Loss:0.69456 | Accuracy: 49.75000 | Test Loass: 0.69394 | Test Accuracy:50.50000
Epoch: 50 | Loss:0.69430 | Accuracy: 50.12500 | Test Loass: 0.69383 | Test Accuracy:51.00000
Epoch: 60 | Loss:0.69410 | Accuracy: 50.00000 | Test Loass: 0.69379 | Test Accuracy:51.00000
Epoch: 70 | Loss:0.69394 | Accuracy: 49.87500 | Test Loass: 0.69377 | Test Accuracy:50.50000
Epoch: 80 | Loss:0.69381 | Accuracy: 50.00000 | Test Loass: 0.69377 | Test Accuracy:50.00000
Epoch: 90 | Loss:0.69370 | Accuracy: 50.00000 | Test Loass: 0.69378 | Test Accuracy:50.50000
```

4. Make predictions and evaluate the model

```
import requests
from pathlib import Path

# Download helper functions from Learn PyTorch repo (if not already downloaded)
if Path("helper_functions.py").is_file():
  print("helper_functions.py already exists, skipping download")
else:
  print("Downloading helper_functions.py")
  request = requests.get("https://raw.githubusercontent.com/mrdbourke/pytorch-deep-learning/main/helper_functions.py")
  with open("helper_functions.py", "wb") as f:
    f.write(request.content)

from helper_functions import plot_predictions, plot_decision_boundary
```

```
Downloading helper_functions.py
```

```
# Plot decision boundaries for training and test sets
plt.figure(figsize=(12,6))
plt.subplot(1,2,1)
plt.title("Train")
plot_decision_boundary(model_0,X_train,y_train)
plt.subplot(1,2,2)
plt.title("Test")
plot_decision_boundary(model_0,X_test,y_test)
```



Our model is underfitting, meaning it's not learning predictive patterns from the data.

5. Improving a model

Model improvement technique*	What does it do?
Add more layers	Each layer *potentially* increases the learning capabilities of the model with each layer being able to learn some kind of new pattern in the data. More layers are often referred to as making your neural network *deeper*.
Add more hidden units	Similar to the above, more hidden units per layer means a *potential* increase in learning capabilities of the model. More hidden units are often referred to as making your neural network *wider*.
Fitting for longer (more epochs)	Your model might learn more if it had more opportunities to look at the data.
Changing the activation functions	Some data just can't be fit with only straight lines (like what we've seen), using non-linear activation functions can help with this (hint, hint).
Change the learning rate	Less model specific, but still related, the learning rate of the optimizer decides how much a model should change its parameters each step, too much and the model overcorrects, too little and it doesn't learn enough.
Change the loss function	Again, less model specific but still important, different problems require different loss functions. For example, a binary cross entropy loss function won't work with a multi-class classification problem.
Use transfer learning	Take a pretrained model from a problem domain similar to yours and adjust it to your own problem. We cover transfer learning in notebook 06.

```
class CircleModelV1(nn.Module):
  def __init__(self):
    super().__init__()
    self.layer1=nn.Linear(in_features=2,out_features=10)
    self.layer2=nn.Linear(in_features=10,out_features=10)
    self.layer3=nn.Linear(in_features=10,out_features=1)

  def forward(self,x):
    return self.layer3(self.layer2(self.layer1(x)))

model_1=CircleModelV1().to(device)
model_1
```

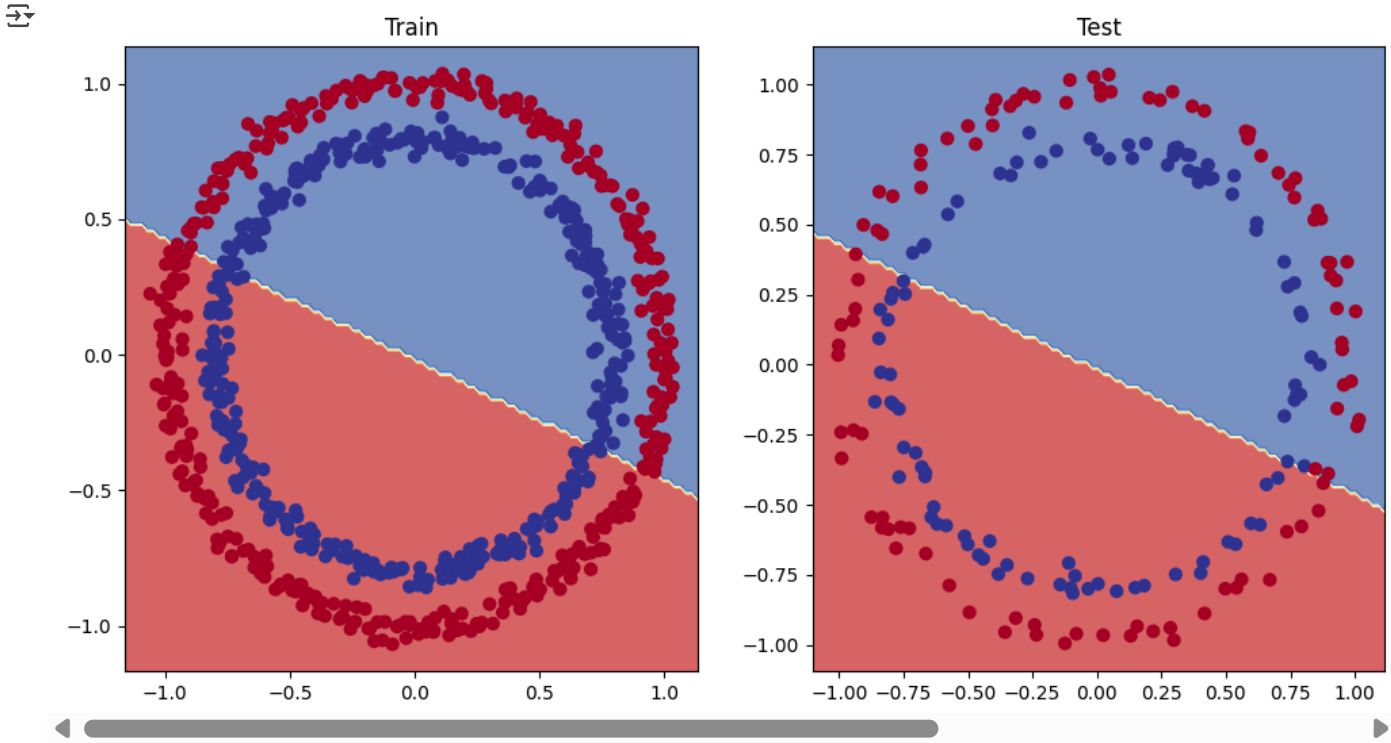
```
CircleModelV1(
  (layer1): Linear(in_features=2, out_features=10, bias=True)
  (layer2): Linear(in_features=10, out_features=10, bias=True)
  (layer3): Linear(in_features=10, out_features=1, bias=True)
)
```

```
# loss_fun=nn.BCELoss() # requires sigmoid on input
loss_fun=nn.BCEWithLogitsLoss()
optimizer=torch.optim.SGD(model_1.parameters(),lr=0.1)


torch.manual_seed(42)

epochs=1000 # train for longer time

X_train,y_train=X_train.to(device),y_train.to(device)
X_test,y_test=X_test.to(device),y_test.to(device)


for epoch in range(epochs):
  ### Training
  # 1. Forward pass
  y_logits=model_1(X_train).squeeze()
```

```
    y_pred=torch.round(torch.sigmoid(y_logits))

    # 2. Calculate loff/accuracy
    loss=loss_fun(y_logits,y_train)
    acc=accuracy(y_train,y_pred)

    # 3. optimizer zero grad
    optimizer.zero_grad()

    # 4. loss backward
    loss.backward()

    # 5. optimizer.step
    optimizer.step()

    ### Testing
    model_1.eval()
    with torch.inference_mode():
      # 1. Forward pass
      test_logits=model_1(X_test).squeeze()
      test_pred=torch.round(torch.sigmoid(test_logits))

      # 2. calculate loss/accuract
      test_loss=loss_fun(test_logits,y_test)
      test_accuracy=accuracy(test_pred,y_test)

    if epoch%100==0:
      print(f"Epoch: {epoch} | Loss: {loss:.5f}, Accuracy: {acc:.2f}% | Test loss: {test_loss:.5f}, Test acc: {test_accuracy:.2f}%")
```

```
Epoch: 0 | Loss: 0.69396, Accuracy: 50.88% | Test loss: 0.69261, Test acc: 51.00%
Epoch: 100 | Loss: 0.69305, Accuracy: 50.38% | Test loss: 0.69379, Test acc: 48.00%
Epoch: 200 | Loss: 0.69299, Accuracy: 51.12% | Test loss: 0.69437, Test acc: 46.00%
Epoch: 300 | Loss: 0.69298, Accuracy: 51.62% | Test loss: 0.69458, Test acc: 45.00%
Epoch: 400 | Loss: 0.69298, Accuracy: 51.12% | Test loss: 0.69465, Test acc: 46.00%
Epoch: 500 | Loss: 0.69298, Accuracy: 51.00% | Test loss: 0.69467, Test acc: 46.00%
Epoch: 600 | Loss: 0.69298, Accuracy: 51.00% | Test loss: 0.69468, Test acc: 46.00%
Epoch: 700 | Loss: 0.69298, Accuracy: 51.00% | Test loss: 0.69468, Test acc: 46.00%
Epoch: 800 | Loss: 0.69298, Accuracy: 51.00% | Test loss: 0.69468, Test acc: 46.00%
Epoch: 900 | Loss: 0.69298, Accuracy: 51.00% | Test loss: 0.69468, Test acc: 46.00%
```

```
# Plot decision boundaries for training and test sets
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.title("Train")
plot_decision_boundary(model_1, X_train, y_train)
plt.subplot(1, 2, 2)
plt.title("Test")
plot_decision_boundary(model_1, X_test, y_test)
```



5.1 Preparing data to see if our model can model a straight line

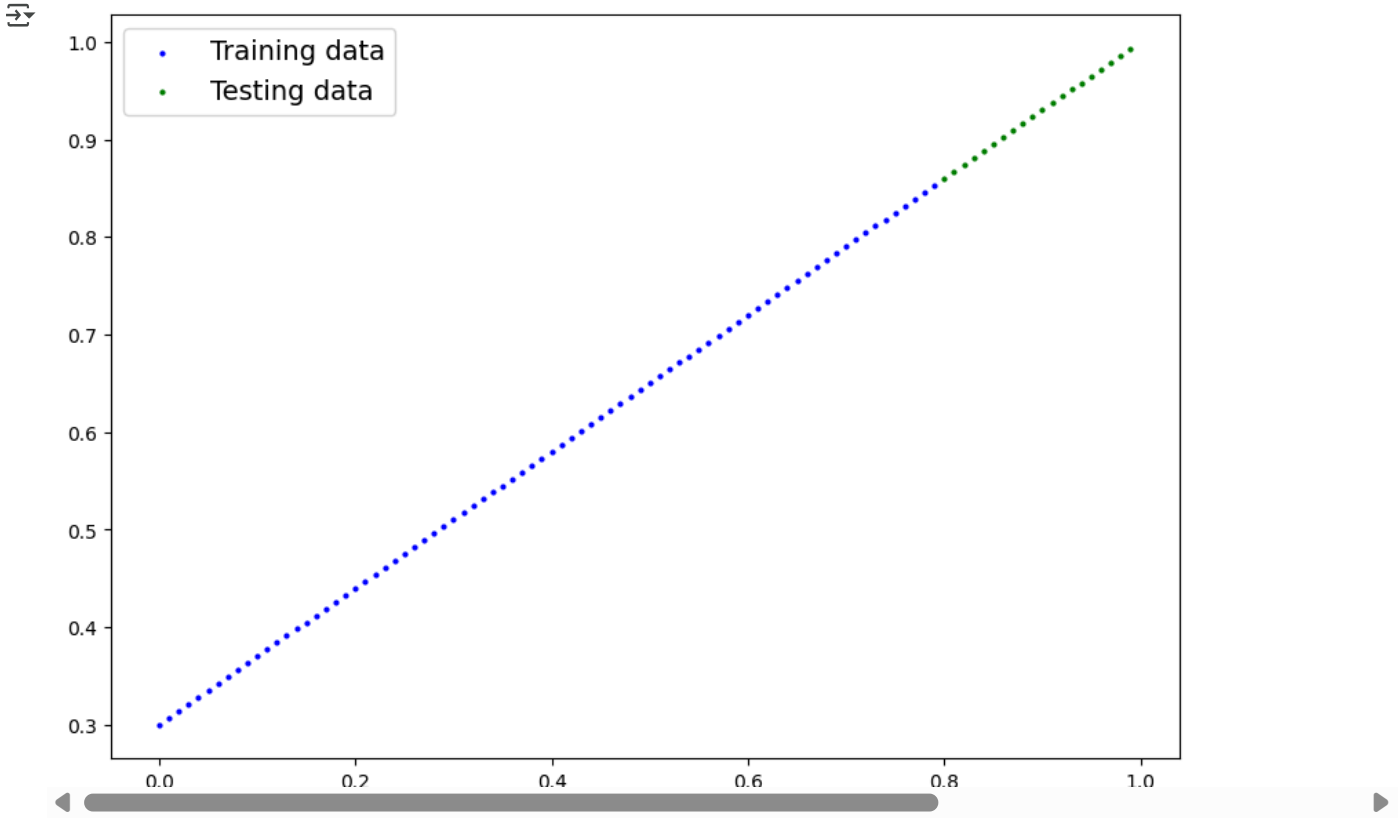
```
# Create some data (same as notebook 01)
weight=0.7
bias=0.3
start=0
end=1
step=0.01

# Create data
X_regression=torch.arange(start,end,step).unsqueeze(dim=1)
y_regression=weight*X_regression+bias

print(len(X_regression))

X_regression[:5],y_regression[:5]
```

```
100
(tensor([[0.0000],
         [0.0100],
         [0.0200],
         [0.0300],
         [0.0400]]),
 tensor([[0.3000],
         [0.3070],
         [0.3140],
         [0.3210],
         [0.3280]]))
```

```
# Create train and test splits
train_split = int(0.8 * len(X_regression)) # 80% of data used for training set
X_train_regression, y_train_regression = X_regression[:train_split], y_regression[:train_split]
X_test_regression, y_test_regression = X_regression[train_split:], y_regression[train_split:]

# Check the lengths of each split
print(len(X_train_regression),
    len(y_train_regression),
    len(X_test_regression),
    len(y_test_regression))
```

```
80 80 20 20
```

```
plot_predictions(train_data=X_train_regression,
    train_labels=y_train_regression,
    test_data=X_test_regression,
    test_labels=y_test_regression
);
```




```
# Same architecture as model_1 (but using nn.Sequential)
model_2 = nn.Sequential(
    nn.Linear(in_features=1, out_features=10),
    nn.Linear(in_features=10, out_features=10),
    nn.Linear(in_features=10, out_features=1)
).to(device)

model_2
```

```
Sequential(
  (0): Linear(in_features=1, out_features=10, bias=True)
  (1): Linear(in_features=10, out_features=10, bias=True)
  (2): Linear(in_features=10, out_features=1, bias=True)
)
```

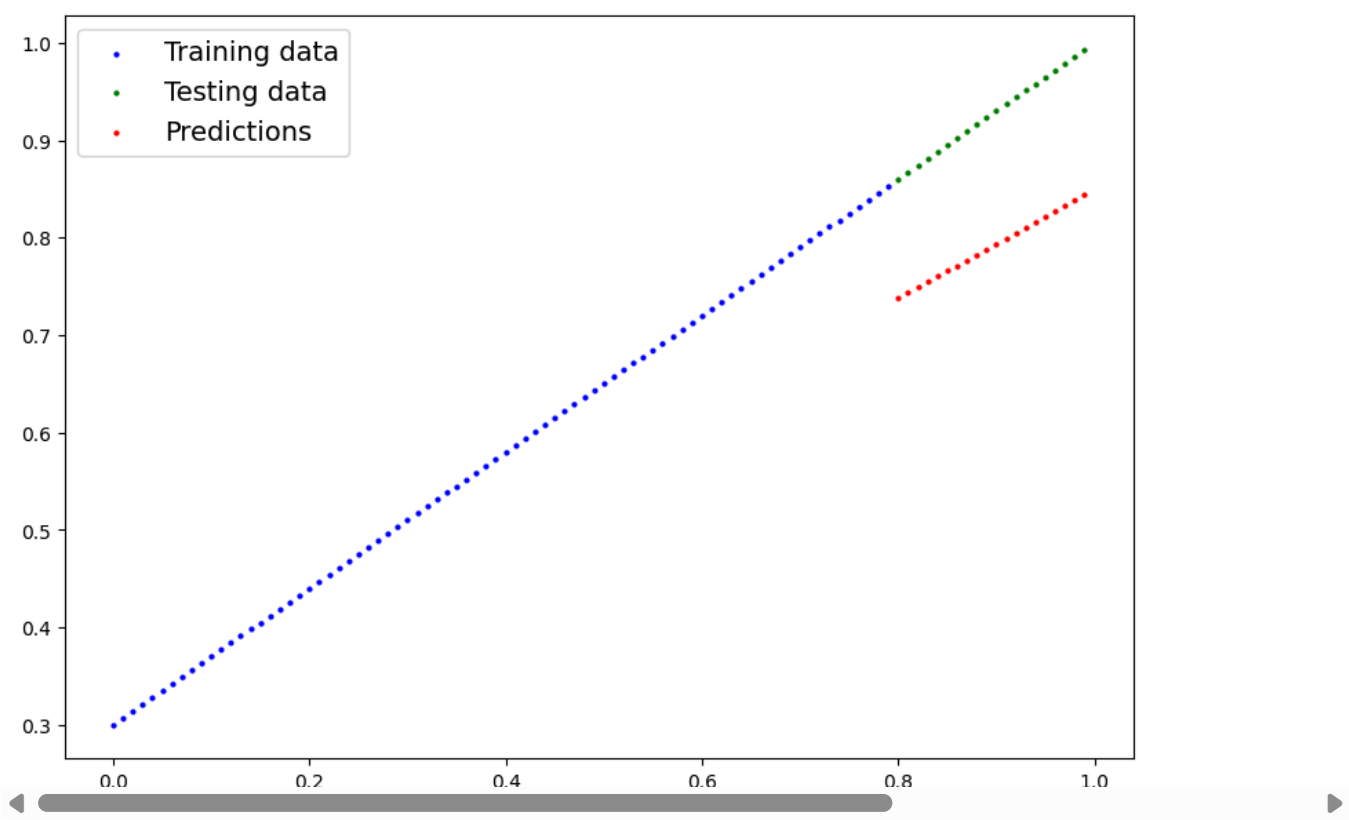
```
# Loss and optimizer
loss_fn = nn.L1Loss()
optimizer = torch.optim.SGD(model_2.parameters(), lr=0.1)


# Train the model
torch.manual_seed(42)

# Set the number of epochs
epochs = 1000

# Put data to target device
X_train_regression, y_train_regression = X_train_regression.to(device), y_train_regression.to(device)
X_test_regression, y_test_regression = X_test_regression.to(device), y_test_regression.to(device)

for epoch in range(epochs):
    ### Training
    # 1. Forward pass
    y_pred = model_2(X_train_regression)

    # 2. Calculate loss (no accuracy since it's a regression problem, not classification)
    loss = loss_fn(y_pred, y_train_regression)

    # 3. Optimizer zero grad
    optimizer.zero_grad()

    # 4. Loss backwards
    loss.backward()

    # 5. Optimizer step
    optimizer.step()
```

```
    ### Testing
    model_2.eval()
    with torch.inference_mode():
      # 1. Forward pass
      test_pred = model_2(X_test_regression)
      # 2. Calculate the loss
      test_loss = loss_fn(test_pred, y_test_regression)

    # Print out what's happening
    if epoch % 100 == 0:
        print(f"Epoch: {epoch} | Train loss: {loss:.5f}, Test loss: {test_loss:.5f}")
```

```
Epoch: 0 | Train loss: 0.75986, Test loss: 0.54143
Epoch: 100 | Train loss: 0.09309, Test loss: 0.02901
Epoch: 200 | Train loss: 0.07376, Test loss: 0.02850
Epoch: 300 | Train loss: 0.06745, Test loss: 0.00615
Epoch: 400 | Train loss: 0.06107, Test loss: 0.02004
Epoch: 500 | Train loss: 0.05698, Test loss: 0.01061
Epoch: 600 | Train loss: 0.04857, Test loss: 0.01326
Epoch: 700 | Train loss: 0.06109, Test loss: 0.02127
Epoch: 800 | Train loss: 0.05600, Test loss: 0.01425
Epoch: 900 | Train loss: 0.05571, Test loss: 0.00603
```

Okay, unlike model_1 on the classification data, it looks like model_2's loss is actually going down

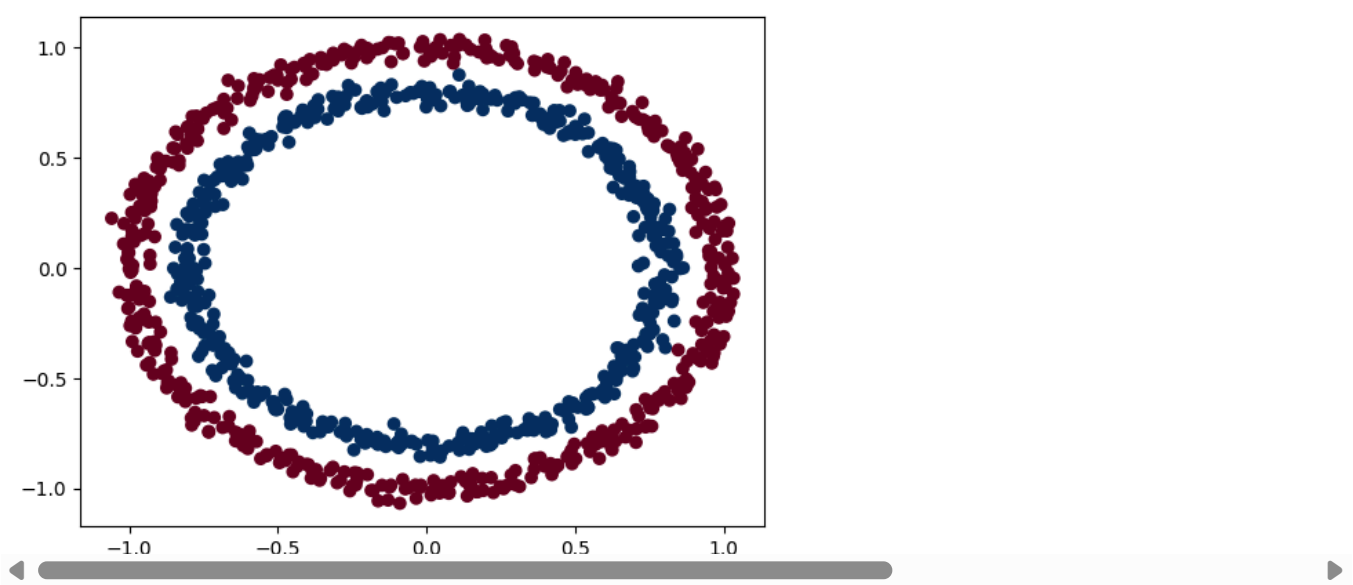
```
# Turn on evaluation mode
model_2.eval()

# Make predictions (inference)
with torch.inference_mode():
    y_preds = model_2(X_test_regression)

# Plot data and predictions with data on the CPU (matplotlib can't handle data on the GPU)
# (try removing .cpu() from one of the below and see what happens)
plot_predictions(train_data=X_train_regression.cpu(),
                 train_labels=y_train_regression.cpu(),
                 test_data=X_test_regression.cpu(),
                 test_labels=y_test_regression.cpu(),
                 predictions=y_preds.cpu());
```



6. The missing piece: non-linearity

```
# Make and plot data
import matplotlib.pyplot as plt
from sklearn.datasets import make_circles
```

```
n_samples = 1000

X, y = make_circles(n_samples=1000,
    noise=0.03,
    random_state=42,
)

plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.RdBu);
```




```
# Convert to tensors and split into train and test sets
import torch
from sklearn.model_selection import train_test_split

# Turn data into tensors
X = torch.from_numpy(X).type(torch.float)
y = torch.from_numpy(y).type(torch.float)

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.2,
                                                    random_state=42
)

X_train[:5], y_train[:5]
```

```
(tensor([[ 0.6579, -0.4651],
         [ 0.6319, -0.7347],
         [-1.0086, -0.1240],
         [-0.9666, -0.2256],
         [-0.1666,  0.7994]]),
 tensor([1., 0., 0., 0., 1.]))
```

```
# Build model with non-linear activation function
from torch import nn
class CircleModelV2(nn.Module):
    def __init__(self):
        super().__init__()
        self.layer_1 = nn.Linear(in_features=2, out_features=10)
        self.layer_2 = nn.Linear(in_features=10, out_features=10)
        self.layer_3 = nn.Linear(in_features=10, out_features=1)
        self.relu = nn.ReLU() # <- add in ReLU activation function
        # Can also put sigmoid in the model
        # This would mean you don't need to use it on the predictions
        # self.sigmoid = nn.Sigmoid()

    def forward(self, x):
      # Intersperse the ReLU activation function between layers
       return self.layer_3(self.relu(self.layer_2(self.relu(self.layer_1(x)))))

model_3 = CircleModelV2().to(device)
print(model_3)
```

```
CircleModelV2(
  (layer_1): Linear(in_features=2, out_features=10, bias=True)
  (layer_2): Linear(in_features=10, out_features=10, bias=True)
```

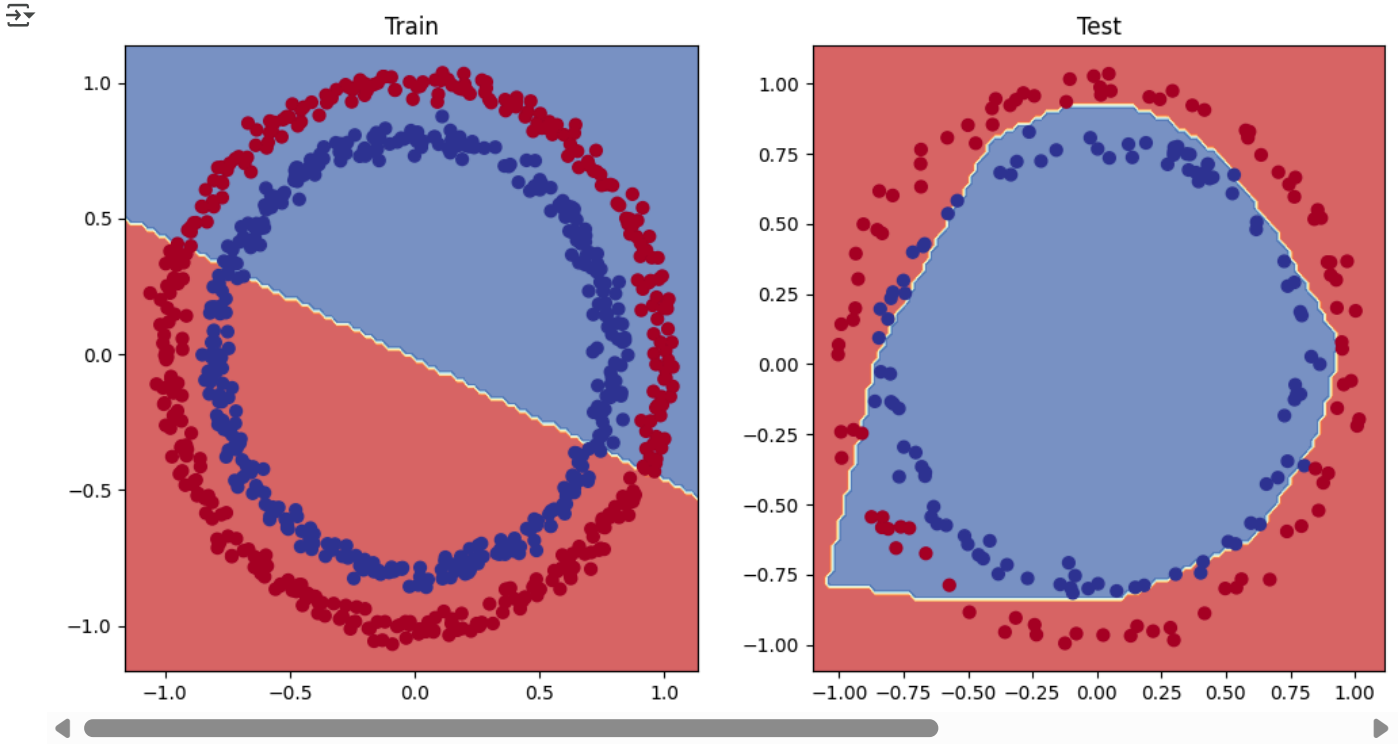
```
        (layer_3): Linear(in_features=10, out_features=1, bias=True)
        (relu): ReLU()
      )


# Setup loss and optimizer
loss_fn = nn.BCEWithLogitsLoss()
optimizer = torch.optim.SGD(model_3.parameters(), lr=0.1)


# Fit the model
torch.manual_seed(42)
epochs = 1000

# Put all data on target device
X_train, y_train = X_train.to(device), y_train.to(device)
X_test, y_test = X_test.to(device), y_test.to(device)

for epoch in range(epochs):
    # 1. Forward pass
    y_logits = model_3(X_train).squeeze()
    y_pred = torch.round(torch.sigmoid(y_logits)) # logits -> prediction probabilities -> prediction labels

    # 2. Calculate loss and accuracy
    loss = loss_fn(y_logits, y_train) # BCEWithLogitsLoss calculates loss using logits
    acc = accuracy(y_true=y_train,
                   y_pred=y_pred)

    # 3. Optimizer zero grad
    optimizer.zero_grad()

    # 4. Loss backward
    loss.backward()

    # 5. Optimizer step
    optimizer.step()

    ### Testing
    model_3.eval()
    with torch.inference_mode():
      # 1. Forward pass
      test_logits = model_3(X_test).squeeze()
      test_pred = torch.round(torch.sigmoid(test_logits)) # logits -> prediction probabilities -> prediction labels
      # 2. Calculate loss and accuracy
      test_loss = loss_fn(test_logits, y_test)
      test_acc = accuracy(y_true=y_test,
                          y_pred=test_pred)

    # Print out what's happening
    if epoch % 100 == 0:
        print(f"Epoch: {epoch} | Loss: {loss:.5f}, Accuracy: {acc:.2f}% | Test Loss: {test_loss:.5f}, Test Accuracy: {test_acc:.2f}
```

```
Epoch: 0 | Loss: 0.69295, Accuracy: 50.00% | Test Loss: 0.69319, Test Accuracy: 50.00%
Epoch: 100 | Loss: 0.69115, Accuracy: 52.88% | Test Loss: 0.69102, Test Accuracy: 52.50%
Epoch: 200 | Loss: 0.68977, Accuracy: 53.37% | Test Loss: 0.68940, Test Accuracy: 55.00%
Epoch: 300 | Loss: 0.68795, Accuracy: 53.00% | Test Loss: 0.68723, Test Accuracy: 56.00%
Epoch: 400 | Loss: 0.68517, Accuracy: 52.75% | Test Loss: 0.68411, Test Accuracy: 56.50%
Epoch: 500 | Loss: 0.68102, Accuracy: 52.75% | Test Loss: 0.67941, Test Accuracy: 56.50%
Epoch: 600 | Loss: 0.67515, Accuracy: 54.50% | Test Loss: 0.67285, Test Accuracy: 56.00%
Epoch: 700 | Loss: 0.66659, Accuracy: 58.38% | Test Loss: 0.66322, Test Accuracy: 59.00%
Epoch: 800 | Loss: 0.65160, Accuracy: 64.00% | Test Loss: 0.64757, Test Accuracy: 67.50%
Epoch: 900 | Loss: 0.62362, Accuracy: 74.00% | Test Loss: 0.62145, Test Accuracy: 79.00%
```

```
# Make predictions
model_3.eval()
with torch.inference_mode():
    y_preds = torch.round(torch.sigmoid(model_3(X_test))).squeeze()
y_preds[:10], y[:10] # want preds in same format as truth labels
```

```
(tensor([1., 0., 1., 0., 0., 1., 0., 0., 1., 0.]),
 tensor([1., 1., 1., 1., 0., 1., 1., 1., 1., 0.]))
```

```
# Plot decision boundaries for training and test sets
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.title("Train")
plot_decision_boundary(model_1, X_train, y_train) # model_1 = no non-linearity
plt.subplot(1, 2, 2)
plt.title("Test")
plot_decision_boundary(model_3, X_test, y_test) # model_3 = has non-linearity
```

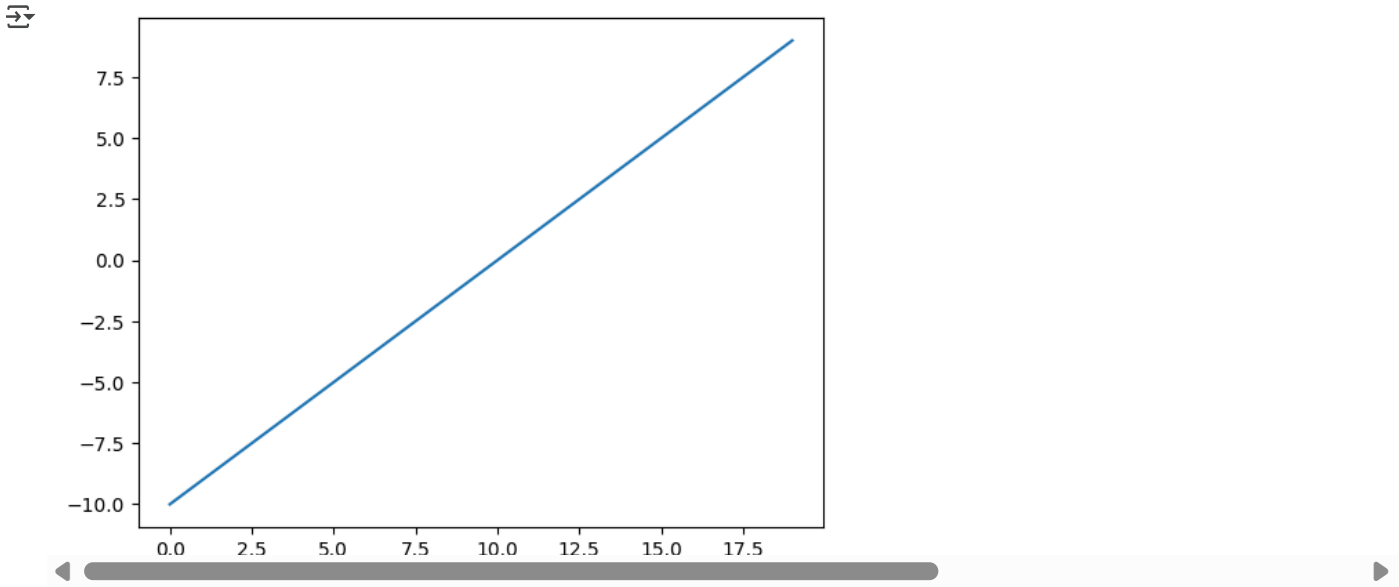


7. Replicating non-linear activation functions

```
# Create a toy tensor (similar to the data going into our model(s))
A = torch.arange(-10, 10, 1, dtype=torch.float32)
A
```

```
tensor([-10.,  -9.,  -8.,  -7.,  -6.,  -5.,  -4.,  -3.,  -2.,  -1.,   0.,   1.,
          2.,   3.,   4.,   5.,   6.,   7.,   8.,   9.])
```

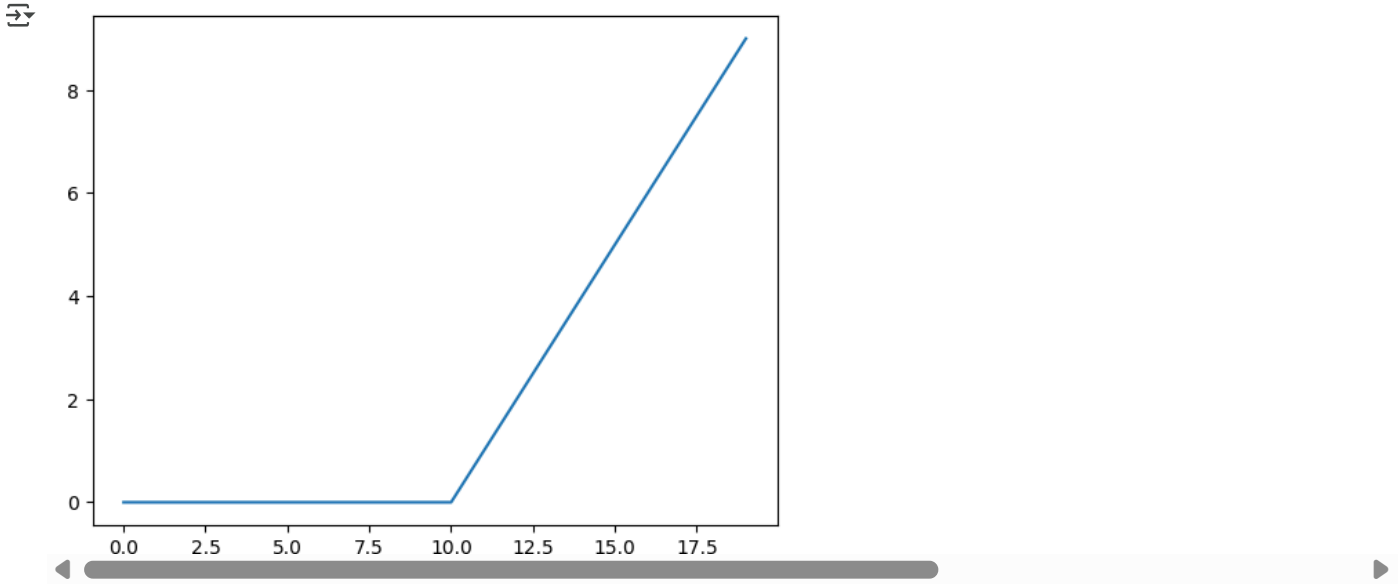
```
# Visualize the toy tensor
plt.plot(A);
```



```
# Create ReLU function by hand
def relu(x):
  return torch.maximum(torch.tensor(0),x) # inputs must be tensors

# Pass toy tensor through ReLU function
relu(A)
```

```
tensor([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 2., 3., 4., 5., 6., 7.,
        8., 9.])
```

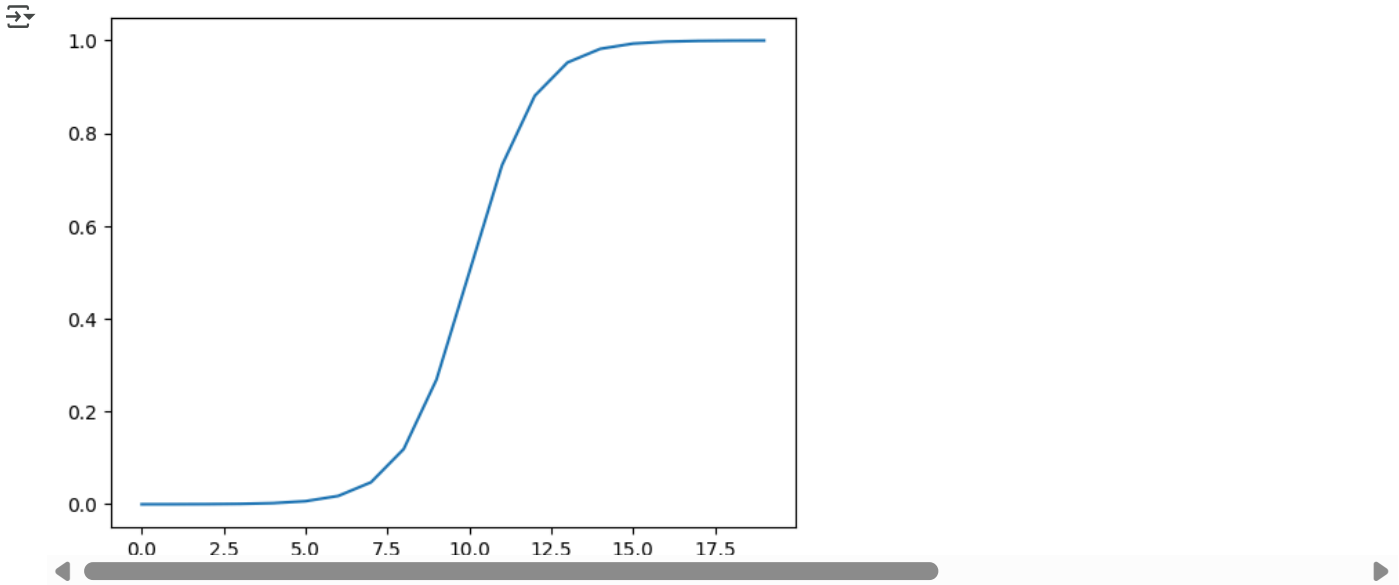
```
# Plot ReLU activated toy tensor
plt.plot(relu(A));
```




```
# Create a custom sigmoid function
def sigmoid(x):
  return 1/(1+torch.exp(-x))

# Test custom sigmoid on toy tensor
sigmoid(A)
```

```
tensor([4.5398e-05, 1.2339e-04, 3.3535e-04, 9.1105e-04, 2.4726e-03, 6.6929e-03,
        1.7986e-02, 4.7426e-02, 1.1920e-01, 2.6894e-01, 5.0000e-01, 7.3106e-01,
        8.8080e-01, 9.5257e-01, 9.8201e-01, 9.9331e-01, 9.9753e-01, 9.9909e-01,
        9.9966e-01, 9.9988e-01])
```

```
# Plot sigmoid activated toy tensor
plt.plot(sigmoid(A));
```

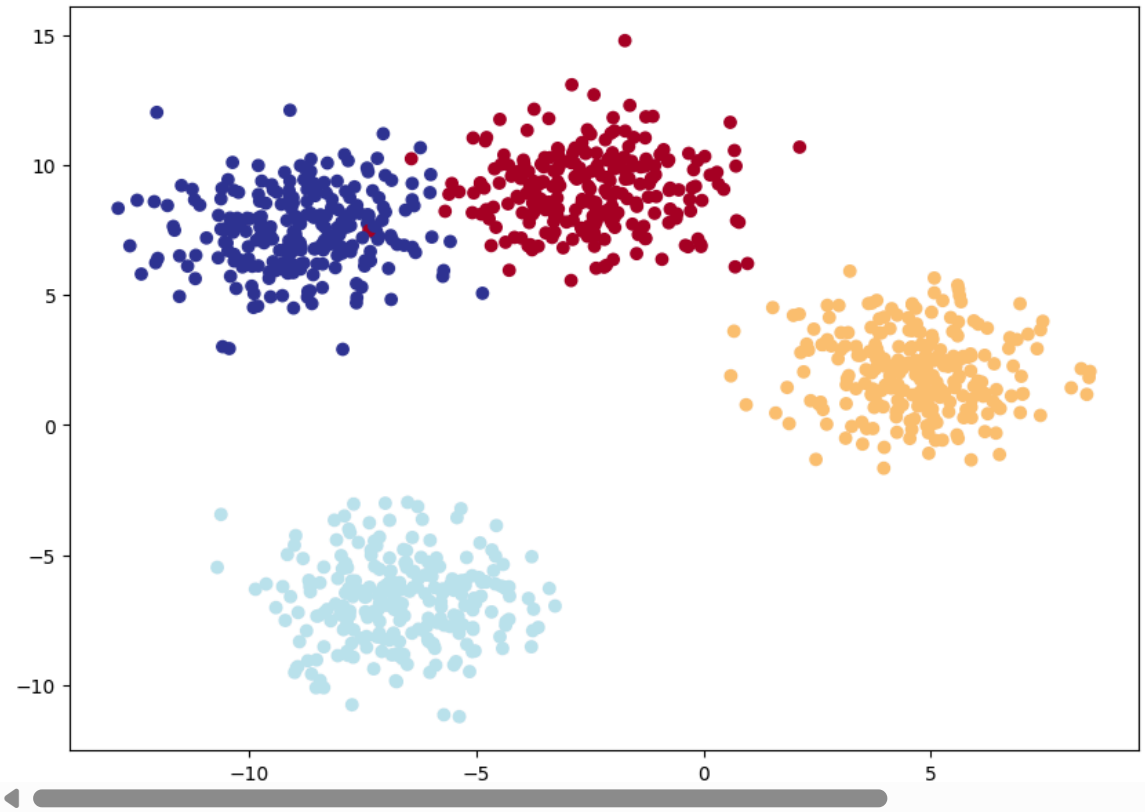


8. Multi-class classification using Pytorch

```
# Import dependencies
import torch
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from sklearn.model_selection import train_test_split

# Set the hyperparameters for data creation
NUM_CLASSES = 4
NUM_FEATURES = 2
RANDOM_SEED = 42

# 1. Create multi-class data
X_blob, y_blob = make_blobs(n_samples=1000,
    n_features=NUM_FEATURES, # X features
```

```
    centers=NUM_CLASSES, # y labels
    cluster_std=1.5, # give the clusters a little shake up (try changing this to 1.0, the default)
    random_state=RANDOM_SEED
)

# 2. Turn data into tensors
X_blob=torch.from_numpy(X_blob).type(torch.float)
y_blob=torch.from_numpy(y_blob).type(torch.LongTensor)
print(X_blob[:5],y_blob[:5])

# 3. Split into train and test sets
X_blob_train, X_blob_test, y_blob_train, y_blob_test = train_test_split(X_blob,
    y_blob,
    test_size=0.2,
    random_state=RANDOM_SEED
)

# 4. Plot data
plt.figure(figsize=(10, 7))
plt.scatter(X_blob[:, 0], X_blob[:, 1], c=y_blob, cmap=plt.cm.RdYlBu);
```

```
tensor([[-8.4134,  6.9352],
        [-5.7665, -6.4312],
        [-6.0421, -6.7661],
        [ 3.9508,  0.6984],
        [ 4.2505, -0.2815]]) tensor([3, 2, 2, 1, 1])
```




```
# Create device agnostic code
device="cuda" if torch.cuda.is_available() else "cpu"
device
```

```
from torch import nn

# Build model
class BlobModel(nn.Module):
    def __init__(self, input_features, output_features, hidden_units=8):
        """Initializes all required hyperparameters for a multi-class classification model.

        Args:
            input_features (int): Number of input features to the model.
            out_features (int): Number of output features of the model
              (how many classes there are).
            hidden_units (int): Number of hidden units between layers, default 8.
        """
        super().__init__()
        self.linear_layer_stack = nn.Sequential(
```

```
            nn.Linear(in_features=input_features, out_features=hidden_units),
            # nn.ReLU(), # <- does our dataset require non-linear layers? (try uncommenting and see if the results change)
            nn.Linear(in_features=hidden_units, out_features=hidden_units),
            # nn.ReLU(), # <- does our dataset require non-linear layers? (try uncommenting and see if the results change)
            nn.Linear(in_features=hidden_units, out_features=output_features), # how many classes are there?
        )

    def forward(self, x):
        return self.linear_layer_stack(x)

# Create an instance of BlobModel and send it to the target device
model_4 = BlobModel(input_features=NUM_FEATURES,
                    output_features=NUM_CLASSES,
                    hidden_units=8).to(device)
model_4
```

```
BlobModel(
  (linear_layer_stack): Sequential(
    (0): Linear(in_features=2, out_features=8, bias=True)
    (1): Linear(in_features=8, out_features=8, bias=True)
    (2): Linear(in_features=8, out_features=4, bias=True)
  )
)
```

```
# Create loss and optimizer
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model_4.parameters(),
                            lr=0.1) # exercise: try changing the learning rate here and seeing what happens to the model's performa
```

```
# Perform a single forward pass on the data (we'll need to put it to the target device for it to work)
model_4(X_blob_train.to(device))[:5]
```

```
tensor([[-1.2711, -0.6494, -1.4740, -0.7044],
        [ 0.2210, -1.5439,  0.0420,  1.1531],
        [ 2.8698,  0.9143,  3.3169,  1.4027],
        [ 1.9576,  0.3125,  2.2244,  1.1324],
        [ 0.5458, -1.2381,  0.4441,  1.1804]], grad_fn=<SliceBackward0>)
```

```
# How many elements in a single prediction sample?
model_4(X_blob_train.to(device))[0].shape, NUM_CLASSES
```

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

```
# Make prediction logits with model
y_logits = model_4(X_blob_test.to(device))

# Perform softmax calculation on logits across dimension 1 to get prediction probabilities
y_pred_probs = torch.softmax(y_logits, dim=1)
print(y_logits[:5])
print(y_pred_probs[:5])
```

```
tensor([[-1.2549, -0.8112, -1.4795, -0.5696],
        [ 1.7168, -1.2270,  1.7367,  2.1010],
        [ 2.2400,  0.7714,  2.6020,  1.0107],
        [-0.7993, -0.3723, -0.9138, -0.5388],
        [-0.4332, -1.6117, -0.6891,  0.6852]], grad_fn=<SliceBackward0>)
tensor([[0.1872, 0.2918, 0.1495, 0.3715],
        [0.2824, 0.0149, 0.2881, 0.4147],
        [0.3380, 0.0778, 0.4854, 0.0989],
        [0.2118, 0.3246, 0.1889, 0.2748],
        [0.1945, 0.0598, 0.1506, 0.5951]], grad_fn=<SliceBackward0>)
```

```
# Sum the first sample output of the softmax activation function
torch.sum(y_pred_probs[0])
```

```
tensor(1., grad_fn=<SumBackward0>)
```

```
# Which class does the model think is *most* likely at the index 0 sample?
print(y_pred_probs[0])
print(torch.argmax(y_pred_probs[0]))
```

```
tensor([0.1872, 0.2918, 0.1495, 0.3715], grad_fn=<SelectBackward0>)
tensor(3)
```

```
# Fit the model
torch.manual_seed(42)
```

```
# Set number of epochs
epochs = 100

# Put data to target device
X_blob_train, y_blob_train = X_blob_train.to(device), y_blob_train.to(device)
X_blob_test, y_blob_test = X_blob_test.to(device), y_blob_test.to(device)

for epoch in range(epochs):
    ### Training
    model_4.train()

    # 1. Forward pass
    y_logits = model_4(X_blob_train) # model outputs raw logits
    y_pred = torch.softmax(y_logits, dim=1).argmax(dim=1) # go from logits -> prediction probabilities -> prediction labels
    # print(y_logits)
    # 2. Calculate loss and accuracy
    loss = loss_fn(y_logits, y_blob_train)
    acc = accuracy(y_true=y_blob_train,
                   y_pred=y_pred)

    # 3. Optimizer zero grad
    optimizer.zero_grad()

    # 4. Loss backwards
    loss.backward()

    # 5. Optimizer step
    optimizer.step()

    ### Testing
    model_4.eval()
    with torch.inference_mode():
      # 1. Forward pass
      test_logits = model_4(X_blob_test)
      test_pred = torch.softmax(test_logits, dim=1).argmax(dim=1)
      # 2. Calculate test loss and accuracy
      test_loss = loss_fn(test_logits, y_blob_test)
      test_acc = accuracy(y_true=y_blob_test,
                          y_pred=test_pred)

    # Print out what's happening
    if epoch % 10 == 0:
        print(f"Epoch: {epoch} | Loss: {loss:.5f}, Acc: {acc:.2f}% | Test Loss: {test_loss:.5f}, Test Acc: {test_acc:.2f}%")
```

```
Epoch: 0 | Loss: 1.04324, Acc: 65.50% | Test Loss: 0.57861, Test Acc: 95.50%
Epoch: 10 | Loss: 0.14398, Acc: 99.12% | Test Loss: 0.13037, Test Acc: 99.00%
Epoch: 20 | Loss: 0.08062, Acc: 99.12% | Test Loss: 0.07216, Test Acc: 99.50%
Epoch: 30 | Loss: 0.05924, Acc: 99.12% | Test Loss: 0.05133, Test Acc: 99.50%
Epoch: 40 | Loss: 0.04892, Acc: 99.00% | Test Loss: 0.04098, Test Acc: 99.50%
Epoch: 50 | Loss: 0.04295, Acc: 99.00% | Test Loss: 0.03486, Test Acc: 99.50%
Epoch: 60 | Loss: 0.03910, Acc: 99.00% | Test Loss: 0.03083, Test Acc: 99.50%
Epoch: 70 | Loss: 0.03643, Acc: 99.00% | Test Loss: 0.02799, Test Acc: 99.50%
Epoch: 80 | Loss: 0.03448, Acc: 99.00% | Test Loss: 0.02587, Test Acc: 99.50%
Epoch: 90 | Loss: 0.03300, Acc: 99.12% | Test Loss: 0.02423, Test Acc: 99.50%
```

```
# Make predictions
model_4.eval()
with torch.inference_mode():
    y_logits = model_4(X_blob_test)

# View the first 10 predictions
y_logits[:10]
```

```
tensor([[  4.3377,  10.3539, -14.8948,  -9.7642],
        [  5.0142, -12.0371,   3.3860,  10.6699],
        [ -5.5885, -13.3448,  20.9894,  12.7711],
        [  1.8400,   7.5599,  -8.6016,  -6.9942],
        [  8.0727,   3.2906, -14.5998,  -3.6186],
        [  5.5844, -14.9521,   5.0168,  13.2891],
        [ -5.9739, -10.1913,  18.8655,   9.9179],
        [  7.0755,  -0.7601,  -9.5531,   0.1736],
        [ -5.5918, -18.5990,  25.5310,  17.5799],
        [  7.3142,   0.7197, -11.2017,  -1.2011]])
```

```
# Turn predicted logits in prediction probabilities
y_pred_probs = torch.softmax(y_logits, dim=1)

# Turn prediction probabilities into prediction labels
y_preds = y_pred_probs.argmax(dim=1)
```

```
# Compare first 10 model preds and test labels
print(f"Predictions: {y_preds[:10]}\nLabels: {y_blob_test[:10]}")
print(f"Test accuracy: {accuracy(y_true=y_blob_test, y_pred=y_preds)}%")
```

```
Predictions: tensor([1, 3, 2, 1, 0, 3, 2, 0, 2, 0])
Labels: tensor([1, 3, 2, 1, 0, 3, 2, 0, 2, 0])
Test accuracy: 99.5%
```

```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.title("Train")
plot_decision_boundary(model_4, X_blob_train, y_blob_train)
plt.subplot(1, 2, 2)
plt.title("Test")
plot_decision_boundary(model_4, X_blob_test, y_blob_test)
```