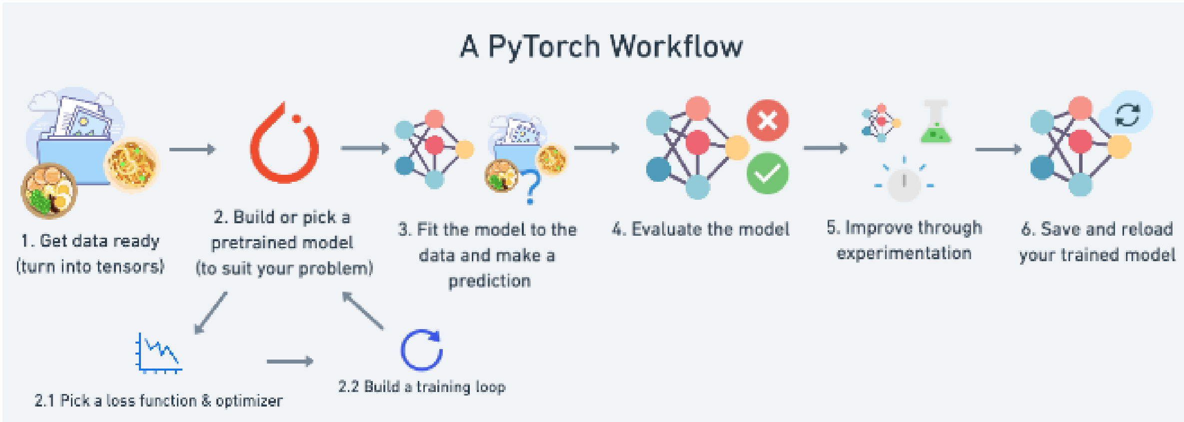
1 .Building Custom Linear Regression Model using Pytorch



In [1]:
```
what_i_am_going_to_learn= {1 : "data (prepare and load)",
                           2 : "build model",
                           3 : "fitting the model to data (training)",
                           4 : "making prediction and evaluating a model (infer
                           5 : "Saving and loading a model",
                           6 : "putting it all together"}
what_i_am_going_to_learn
```

Out[1]:
```
{1: 'data (prepare and load)',
 2: 'build model',
 3: 'fitting the model to data (training)',
 4: 'making prediction and evaluating a model (inference)',
 5: 'Saving and loading a model',
 6: 'putting it all together'}
```

In [2]:
```
import torch
from torch import nn  ## nn conatains all of Pytorch's building block for neura
import matplotlib.pyplot as plt
```

In [3]:
```
torch.__version__
```

Out[3]:
```
'2.0.1+cu118'
```

1. Data (Preparing and loading)

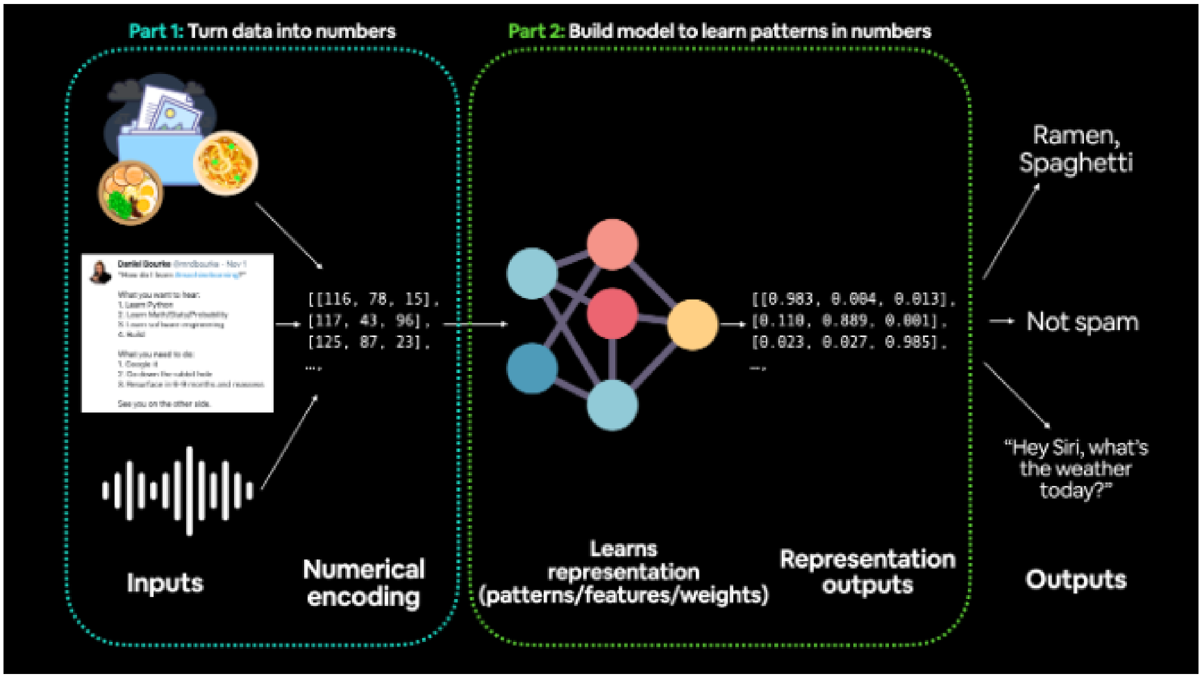
Data can be anything ... in machine learning.

- Excel speadsheet
- Image of any kind
- Video (YouTube has lots of data ...)
- Audio like song or podcast
- DNA

- Text

Machine learning is a game of two parts :

1. Getting data into a numerical representaion.
2. Build a model to learn pattern in that numerical representation



To showcase this let's create some *known* data using the linear Regression formula

In [4]:
```
## Creating  known parameters

weight = 0.7
bias = 0.3

# Create
start = 0
end = 3
step = 0.02
x = torch.arange(start, end, step).unsqueeze(dim=1)
y = weight * x + bias
```

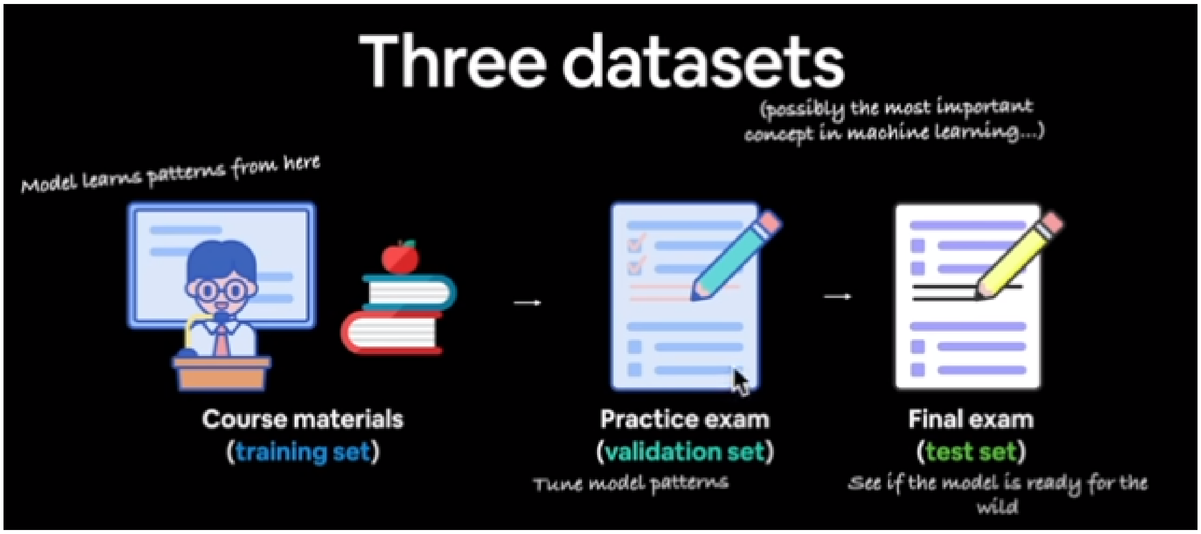
In [5]:
```
print(f"length of x is {len(x)}, and y is {len(y)}")
```

```
length of x is 150, and y is 150
```

In [6]:
```
x[:5],y[:5]
```

Out[6]:
```
(tensor([[0.0000],
         [0.0200],
         [0.0400],
         [0.0600],
         [0.0800]]),
 tensor([[0.3000],
         [0.3140],
         [0.3280],
         [0.3420],
         [0.3560]]))
```

spliting data into training and testing sets



Split	Purpose	Amount of total data	How often is it used?
Training set	The model learns from this data (like the course materials you study during the semester).	~60-80%	Always
Validation set	The model gets tuned on this data (like the practice exam you take before the final exam).	~10-20%	Often but not always
Testing set	The model gets evaluated on this data to test what it has learned (like the final exam you take at the end of the semester).	~10-20%	Always

In [7]:
```
### Create a train/test split
train_split = int(0.8*len(x))
x_train, y_train = x[:train_split], y[:train_split]
x_test, y_test = x[train_split:], y[train_split:]

len(x_train) , len(y_train), len(x_test), len(y_test)
```

Out[7]:
```
(120, 120, 30, 30)
```

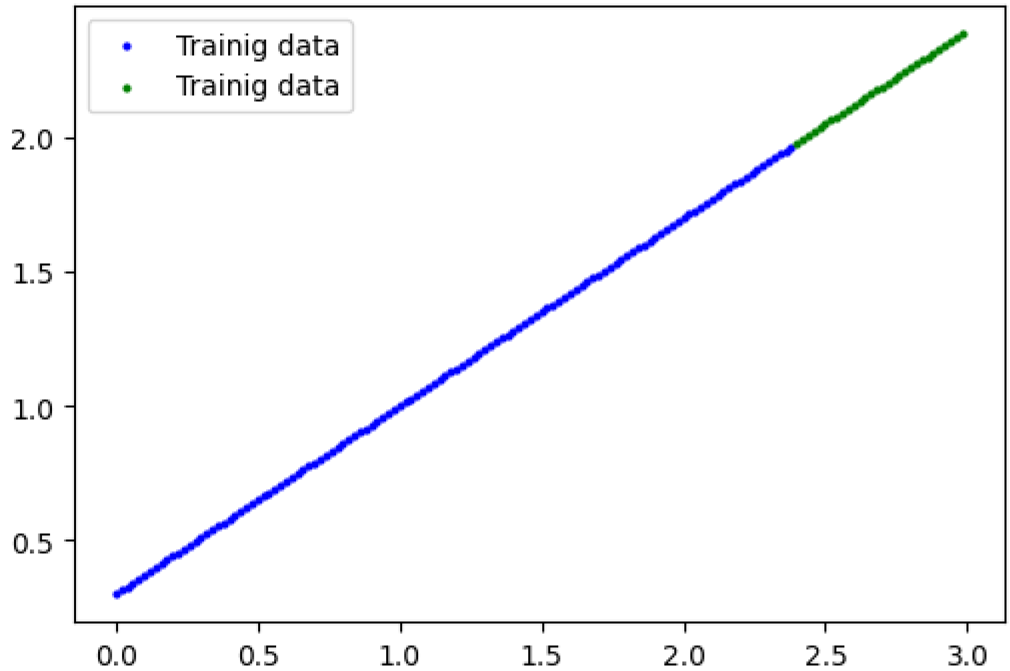
How might we better visualize our data?

This is where the data explore's motto comes in!

"Visulize visulize and visulaize ..... hahaaa"

In [8]:
```
def plot_prediction(train_data = x_train,
                    train_label = y_train,
                    test_data = x_test,
                    test_label = y_test,
                    prediction = None):
  """
  Ploting training data, test data and compare the predictions.
  """
  plt.figure(figsize = (6, 4 ))

  # plot training data in blue
  plt.scatter(train_data, train_label, c='b', s=4, label ='Trainig data')

  ## Plot test data in green
  plt.scatter(test_data, test_label, c='g', s=4, label ='Trainig data')

  #Are there prediction?
  if prediction is not None:
      # Plot the prediction if they exist
      plt.scatter(test_data, prediction, c ='r', s=4, label='Preditions')
  plt.legend()
```

In [9]:
```
plot_prediction()
```



2. Build Model

Our first Pytorch Model... Hahahaaa... ;)

This is very exciting for me ... hahaa.. Let's Do it!

In [10]:
```
torch.randn(1,
          requires_grad= True,
          dtype = torch.float)
```

Out[10]:
```
tensor([-1.3198], requires_grad=True)
```

In [11]:
```
from torch import nn
### Creating a Linear regresion model class
class LinearRegressionModel(nn.Module):
    def __init__(self):
        super().__init__()

        ## Initialize model parameters
        self.weights = nn.Parameter(torch.randn(1,                          ## firs
                                                requires_grad= True,  ## this p
                                                dtype = torch.float)) ## pytorc

        self.bias = nn.Parameter(torch.randn(1,                          ## here als
                                             requires_grad=True,
                                             dtype = torch.float))

        ## Forward method to define the computation in the model
    def forward(self, x:torch.Tensor) -> torch.Tensor:
        return self.weights * x + self.bias ## this is the linear regression fo
```

Checking the contents of our model

So we can chack our model parameters or what's inside our model using `.parameters()`

In [12]:
```
## Creating a random seed
torch.manual_seed(42)
# create an instance of our model (this is a subclass of nn.Model)
model_0 = LinearRegressionModel()

## Let's check out the parameter
list(model_0.parameters())
```

Out[12]:
```
[Parameter containing:
 tensor([0.3367], requires_grad=True),
 Parameter containing:
 tensor([0.1288], requires_grad=True)]
```

In [13]:
```
## List of the named parameters
model_0.state_dict()
```

Out[13]:
```
OrderedDict([('weights', tensor([0.3367])), ('bias', tensor([0.1288]))])
```

In [14]:
```
## my acutal weight and bias
weight, bias
```

Out[14]:
```
(0.7, 0.3)
```

In [15]:
```
## my initial random wight and bias giving this
# ('weights', tensor([0.3367])), ('bias', tensor([0.1288]))
# now i have to my model to adjust this weight and bias
```

Making prediction using `torch.inference_mode()`

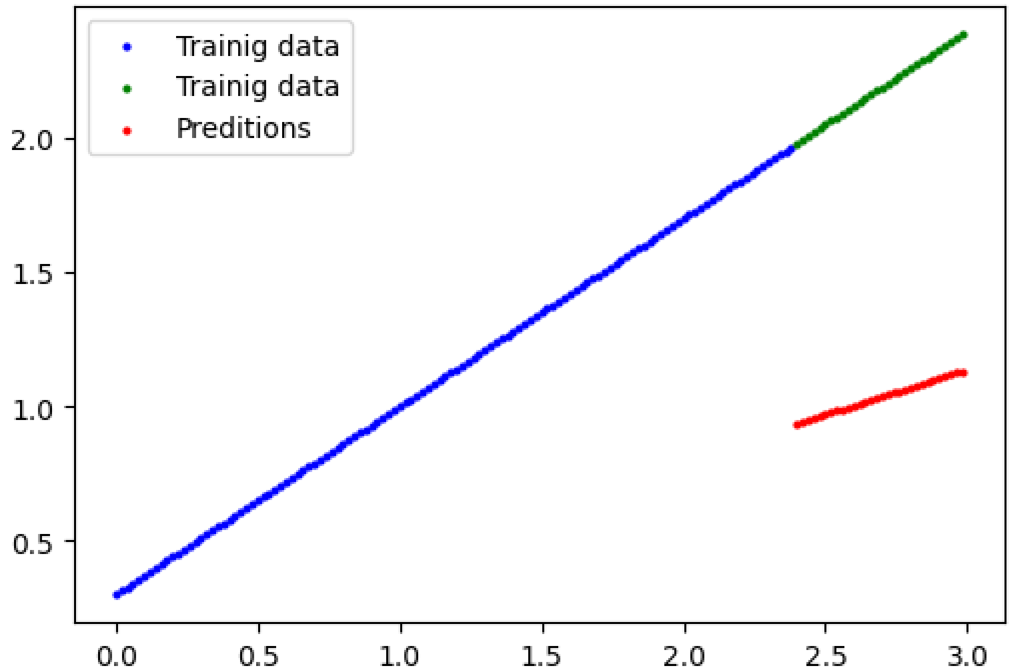
to check our model's predictive power, let's see how well it predicts `y test` based on `x test` .

When we pass data through our model, it's going to run it through the forword method

In [16]:
```
## Make prediction with model

with torch.inference_mode():
  y_preds = model_0(x_test)
y_preds
```

Out[16]:
```
tensor([[0.9369],
        [0.9436],
        [0.9503],
        [0.9571],
        [0.9638],
        [0.9705],
        [0.9773],
        [0.9840],
        [0.9907],
        [0.9975],
        [1.0042],
        [1.0109],
        [1.0177],
        [1.0244],
        [1.0311],
        [1.0379],
        [1.0446],
        [1.0513],
        [1.0581],
        [1.0648],
        [1.0715],
        [1.0783],
        [1.0850],
        [1.0917],
        [1.0985],
        [1.1052],
        [1.1119],
        [1.1187],
        [1.1254],
        [1.1321]])
```

In [17]:
```
## Let's Visulize the prediction
plot_prediction(prediction=y_preds)
```



In [18]:
```
### Why the prediction is so far from actual value,
## becuase i have initilize my wights and bias on the top of small random value
```

3. Training model

The whole idea of training is for a model to move from unknown parameters(these may be random) to some known parameter

or in other words from a poor representaion of the data to a better representaion of the data

We need to train:

- **Loss fuction** : A fuction to measure how wrong your model's predictions are to the ideal outputs, lower is better
- **Optimizer** :Takes into account the loss of a model and adjusts the models parameters (weights and bias)

In [19]:
```
list(model_0.parameters())
```

Out[19]:
```
[Parameter containing:
 tensor([0.3367], requires_grad=True),
 Parameter containing:
 tensor([0.1288], requires_grad=True)]
```

In [20]:
```
model_0.state_dict()
```

Out[20]:
```
OrderedDict([('weights', tensor([0.3367])), ('bias', tensor([0.1288]))])
```

In [21]:
```
## Let's setup  a loss fucntion
loss_fn = nn.L1Loss() ## "L1Loss()" this is nothing but it's a MAE

# Let's setup an optimizer
## OPTIMIZER adust our weight and bias
optimizer = torch.optim.SGD(params = model_0.parameters(),
                            lr=0.001) ## lr learning rate  is most important hy
                            ## learning rate said the--: higher learning rate t
```

Building a training and testing loop

A couple of things we need in training loop:

1. Loop through the data
2. forward pass (this involve data moving through our model's `foward()` fuction) to make a predictions on data - also called forward propagation
3. Calculate the loss (comapre forwad pass prediction to ground truth table)
4. Optimizer zero grad
5. Back Propagation
6. optimizer steps - use the optimizer to adjust our model's parameters to try and improve the loss

In [22]:
```
torch.manual_seed(42)
epochs = 20

# Loop through the data for training
for epoch in range(epochs):
    # Set the model to training mode
    model_0.train()

    # Forward pass
    y_pred = model_0(x_train)

    # Calculate the loss
    loss = loss_fn(y_pred, y_train)
    print(f"Loss :{loss}")

    # Backpropagation
    loss.backward()

    # Optimizer step to update parameters
    optimizer.step()


    model_0.eval() # it trun off gradient tracting
```

```
Loss :0.6035290360450745
Loss :0.601112961769104
Loss :0.5962807536125183
Loss :0.5890324115753174
Loss :0.5793680548667908
Loss :0.5672875046730042
Loss :0.5527908205986023
Loss :0.5358782410621643
Loss :0.5165494084358215
Loss :0.4948045015335083
Loss :0.4706435203552246
Loss :0.4440663754940033
Loss :0.4150732159614563
Loss :0.38366392254829407
Loss :0.349838525056839
Loss :0.31359702348709106
Loss :0.2749393880367279
Loss :0.2338656485080719
Loss :0.19037583470344543
Loss :0.14570392668247223
```

In [23]:
```
## first epoch updation
model_0.state_dict()
```

Out[23]:
```
OrderedDict([('weights', tensor([0.5866])), ('bias', tensor([0.3387]))])
```

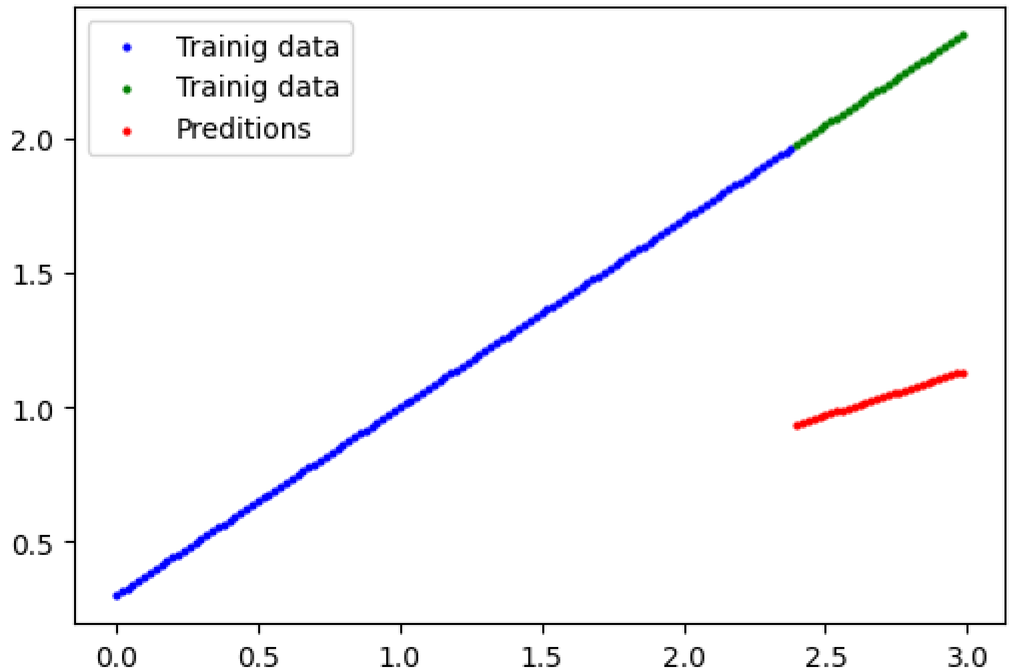
In [24]:
```
# again i run the train looop and print the parameter
model_0.state_dict()
```

Out[24]:
```
OrderedDict([('weights', tensor([0.5866])), ('bias', tensor([0.3387]))])
```

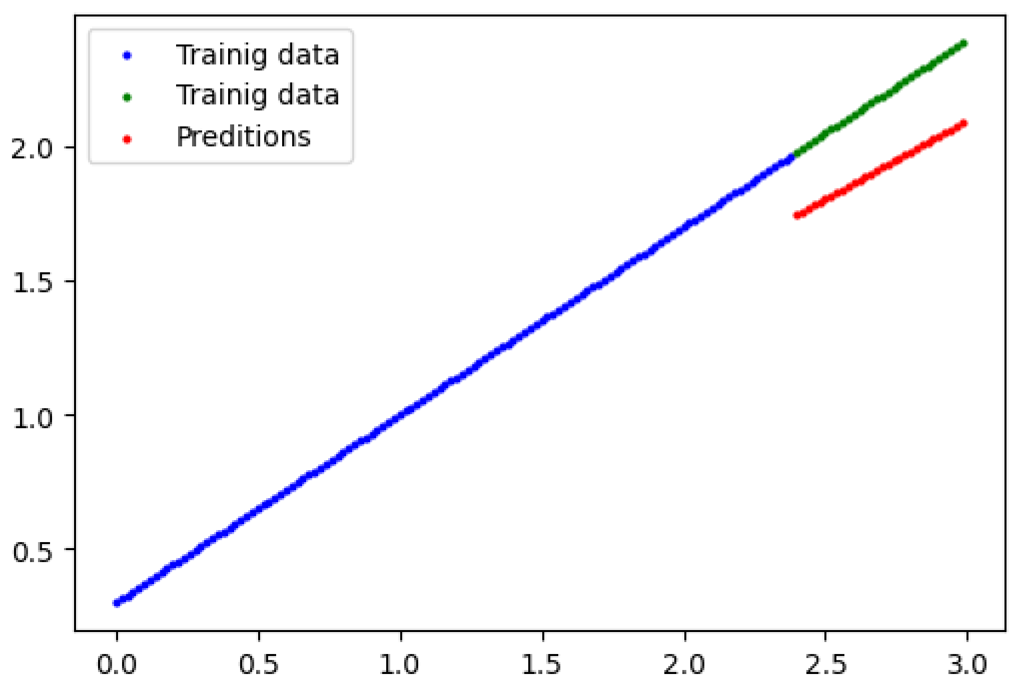
In [25]:
```
# see the updata in weight and bias it's Learning
```

In [26]:
```
with torch.inference_mode():
  y_preds_new = model_0(x_test)
```

In [27]:
```
plot_prediction(prediction=y_preds)
```



In [28]:
```

plot_prediction(prediction=y_preds_new)
```



Suerb our Model is adjusting after some epochs

let's re-run our code and train on random epochs

In [29]:
```
## Creating a random seed
torch.manual_seed(40)
# create an instance of our model (this is a subclass of nn.Model)
model_1 = LinearRegressionModel()

## Let's check out the parameter
list(model_1.parameters())
```

Out[29]:
```
[Parameter containing:
 tensor([0.9307], requires_grad=True),
 Parameter containing:
 tensor([-0.3482], requires_grad=True)]
```

In [30]:
```
## Let's setup  a loss fucntion
loss_fn = nn.L1Loss() ## "L1Loss()" this is nothing but it's a MAE

# Let's setup an optimizer
## OPTIMIZER adust our weight and bias
optimizer = torch.optim.SGD(params = model_0.parameters(),
                            lr=0.00001)
```

In [31]:
```
torch.manual_seed(42)
epochs = 100

## Track Different values
epoch_count = []
loss_values = []
test_loss_values = []

# Loop through the data for training
for epoch in range(epochs):
    # Set the model to training mode
    model_0.train()

    # Forward pass
    y_pred_epochs = model_0(x_train)

    # Calculate the loss
    loss = loss_fn(y_pred_epochs, y_train)

    # Backpropagation
    loss.backward()

    # Optimizer step to update parameters
    optimizer.step()

    ## Testing
    model_0.eval() # (different settings in the model not needed for evluation)

    with torch.inference_mode():  # Use torch.no_grad() to turn off gradient tr
        # 1. Do the forward pass
        test_pred = model_0(x_test)

        # Calculate the loss
        test_loss = loss_fn(test_pred, y_test)
        # 2. Calculate the loss
        test_loss = loss_fn(test_pred,  y_test)

        #Let's print what happing every 10 epochs
        if epoch %10==0:
            epoch_count.append(epoch)
            loss_values.append(loss)
            test_loss_values.append(test_loss)
            print(f"Epoch :{epoch} | Loss :{loss} | Test loss :{test_loss}")
            print(model_0.state_dict())
```

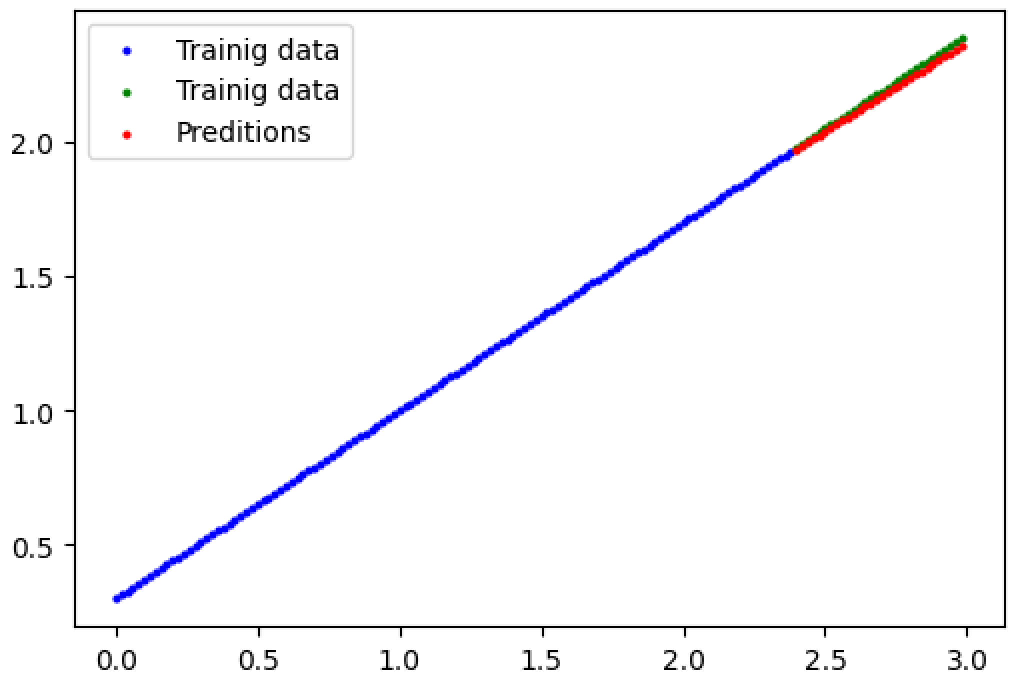
```
Epoch :0 | Loss :0.10209652781486511 | Test loss :0.26552122831344604
OrderedDict([('weights', tensor([0.5868])), ('bias', tensor([0.3389]))])
Epoch :10 | Loss :0.09703473746776581 | Test loss :0.2546893358230591
OrderedDict([('weights', tensor([0.5900])), ('bias', tensor([0.3413]))])
Epoch :20 | Loss :0.09034940600395203 | Test loss :0.24013684689998627
OrderedDict([('weights', tensor([0.5942])), ('bias', tensor([0.3445]))])
Epoch :30 | Loss :0.08222953230142593 | Test loss :0.22194547951221466
OrderedDict([('weights', tensor([0.5996])), ('bias', tensor([0.3482]))])
Epoch :40 | Loss :0.07293810695409775 | Test loss :0.20022781193256378
OrderedDict([('weights', tensor([0.6060])), ('bias', tensor([0.3526]))])
Epoch :50 | Loss :0.06286042183637619 | Test loss :0.17513741552829742
OrderedDict([('weights', tensor([0.6135])), ('bias', tensor([0.3574]))])
Epoch :60 | Loss :0.052583400160074234 | Test loss :0.14691190421581268
OrderedDict([('weights', tensor([0.6221])), ('bias', tensor([0.3627]))])
Epoch :70 | Loss :0.04301953688263893 | Test loss :0.11590401083230972
OrderedDict([('weights', tensor([0.6315])), ('bias', tensor([0.3684]))])
Epoch :80 | Loss :0.03566855192184448 | Test loss :0.08267594873905182
OrderedDict([('weights', tensor([0.6417])), ('bias', tensor([0.3742]))])
Epoch :90 | Loss :0.03311769291758537 | Test loss :0.048183780163526535
OrderedDict([('weights', tensor([0.6524])), ('bias', tensor([0.3799]))])
```

In [32]:
```
with torch.inference_mode():
    y_pred_epochs = model_0(x_test)
```

In [33]:
```
model_0.state_dict()
```

Out[33]:
```
OrderedDict([('weights', tensor([0.6620])), ('bias', tensor([0.3846]))])
```

In [34]:
```
plot_prediction(prediction=y_pred_epochs)
```



Let's Plot the loss curve

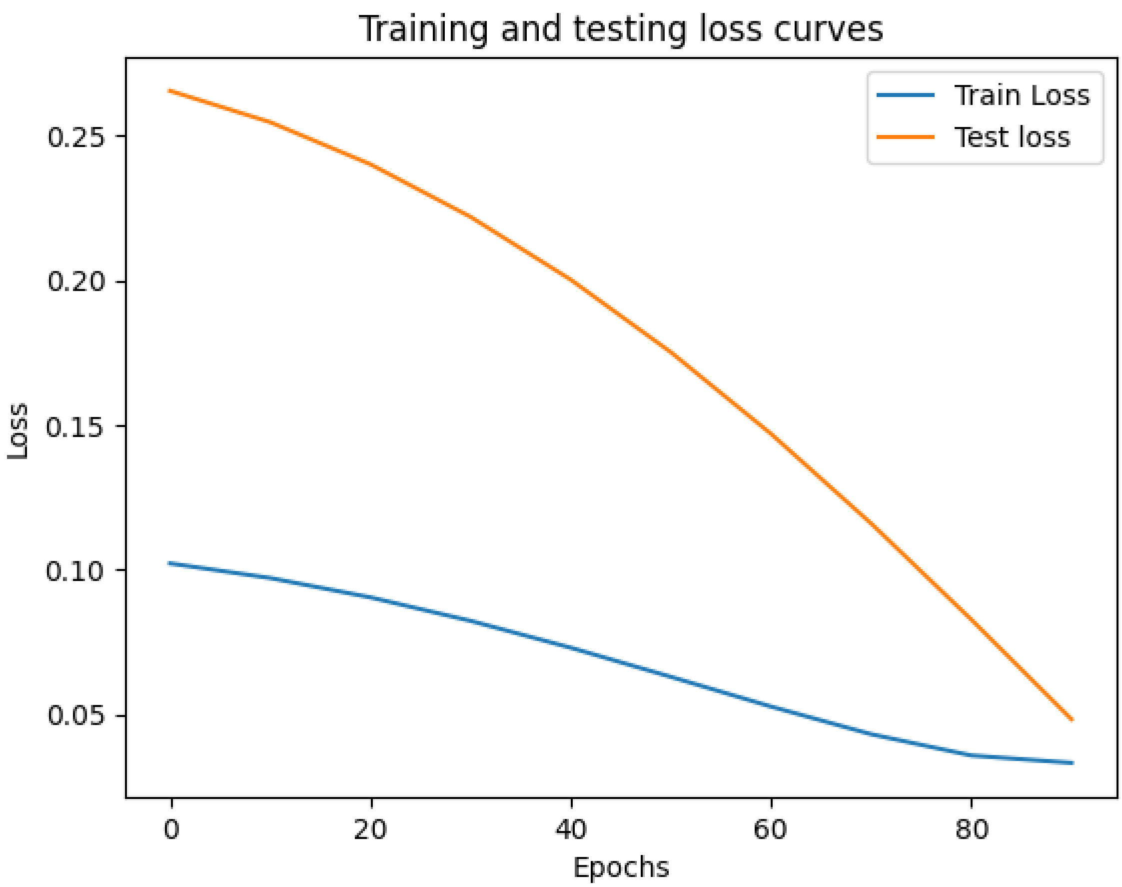
In [35]:
```
loss_values, test_loss_values
```

Out[35]:
```
([tensor(0.1021, grad_fn=<MeanBackward0>),
  tensor(0.0970, grad_fn=<MeanBackward0>),
  tensor(0.0903, grad_fn=<MeanBackward0>),
  tensor(0.0822, grad_fn=<MeanBackward0>),
  tensor(0.0729, grad_fn=<MeanBackward0>),
  tensor(0.0629, grad_fn=<MeanBackward0>),
  tensor(0.0526, grad_fn=<MeanBackward0>),
  tensor(0.0430, grad_fn=<MeanBackward0>),
  tensor(0.0357, grad_fn=<MeanBackward0>),
  tensor(0.0331, grad_fn=<MeanBackward0>)],
 [tensor(0.2655),
  tensor(0.2547),
  tensor(0.2401),
  tensor(0.2219),
  tensor(0.2002),
  tensor(0.1751),
  tensor(0.1469),
  tensor(0.1159),
  tensor(0.0827),
  tensor(0.0482)])
```

In [36]:
```
## let's convert into in numpy
import numpy as np
loss_values = np.array(torch.tensor(loss_values))
test_loss_values = np.array(torch.tensor(test_loss_values))
```

In [37]:
```
import matplotlib.pyplot as plt
plt.plot(epoch_count, loss_values, label='Train Loss')
plt.plot(epoch_count, test_loss_values, label='Test loss')
plt.title("Training and testing loss curves")
plt.ylabel('Loss')
plt.xlabel('Epochs')
plt.legend()
```

Out[37]:
```
<matplotlib.legend.Legend at 0x797ff7828d00>
```



Let's save our model

There are there main methods, with the help of these methods we can save and load our models in pytorch

1. `torch.save()` - this is allows us to save our model in pickel formate
2. `torch.load()` -allows us to load a saved pytorch object
3. `torch.nn.Model.load.stat_dict()` -this allows to load a model's saved stae dictionary

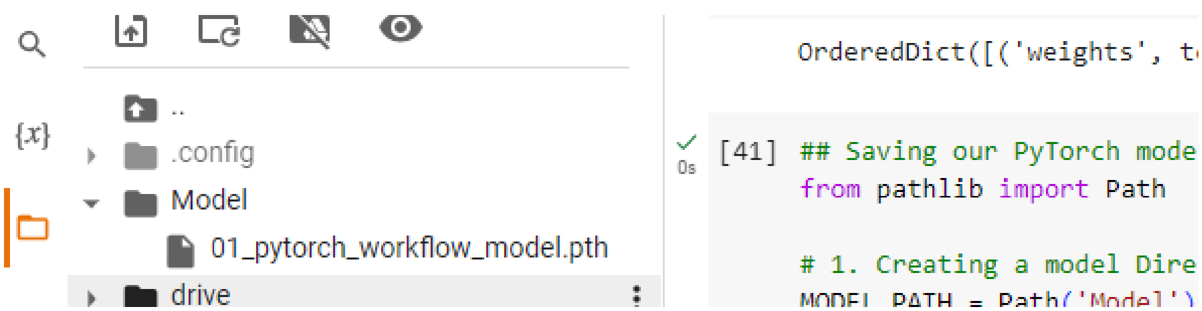
In [38]:
```
model_0.state_dict()
```

Out[38]:
```
OrderedDict([('weights', tensor([0.6620])), ('bias', tensor([0.3846]))])
```

In [39]:
```
## Saving our PyTorch model
from pathlib import Path

# 1. Creating a model Directroy
MODEL_PATH = Path('Model')
MODEL_PATH.mkdir(parents = True, exist_ok=True)

# 2. Creating model save path
MODEL_NAME = '01_pytorch_workflow_model.pth'
MODEL_SAVE_PATH = MODEL_PATH / MODEL_NAME

# 3. Saveing model state_dict() formate

print(f"Saving model to :{MODEL_SAVE_PATH}")
torch.save(obj = model_0.state_dict(),
           f = MODEL_SAVE_PATH)
```

```
Saving model to :Model/01_pytorch_workflow_model.pth
```

We successfully saved our model, and we're now celebrating with cheers of triumph!



In [40]:
```
!ls -l Model
```

```
total 4
-rw-r--r-- 1 root root 1199 Sep 28 09:46 01_pytorch_workflow_model.pth
```

Let's Load our model

In [41]:
```
## To load in saved state_dict we have to instanctiate a new instance of our mo
loaded_model_0 = LinearRegressionModel()

loaded_model_0.load_state_dict(torch.load(f=MODEL_SAVE_PATH))
```

Out[41]:
```
<All keys matched successfully>
```

In [42]:
```
loaded_model_0.state_dict()
```

Out[42]:
```
OrderedDict([('weights', tensor([0.6620])), ('bias', tensor([0.3846]))])
```

In [43]:
```
## Let's make some prediction with our loaded model
loaded_model_0.eval()
with torch.inference_mode():
    loaded_model_preds = loaded_model_0(x_test)
```

In [44]:
```
loaded_model_preds = loaded_model_preds.detach().numpy().tolist()
```

In [45]:
```
y_test = y_test.detach().numpy().tolist()
```

In [46]:
```
import pandas as pd
df = pd.DataFrame({'Predicted': loaded_model_preds, 'Actual': y_test})

# Print the DataFrame
print(df)
```

```
               Predicted                Actual
0   [1.9735325574874878]  [1.9800000190734863]
1   [1.9867732524871826]    [1.99399995803833]
2    [2.000013828277588]   [2.008000135421753]
3   [2.0132546424865723]  [2.0220000743865967]
4   [2.0264952182769775]  [2.0360000133514404]
5    [2.039735794067383]   [2.049999952316284]
6    [2.052976608276367]   [2.063999891281128]
7   [2.0662174224853516]   [2.078000068664551]
8    [2.079457998275757]  [2.0920000076293945]
9    [2.092698574066162]  [2.1059999465942383]
10  [2.1059393882751465]   [2.119999885559082]
11   [2.119180202484131]   [2.133999824523926]
12   [2.132420778274536]  [2.1480000019073486]
13  [2.1456613540649414]  [2.1619999408721924]
14   [2.158902168273926]   [2.175999879837036]
15    [2.17214298248291]   [2.190000057220459]
16  [2.1853837966918945]  [2.2039999961853027]
17  [2.1986241340637207]  [2.2179999351501465]
18   [2.211864948272705]  [2.2319998741149902]
19  [2.2251057624816895]   [2.246000051498413]
20  [2.2383463382720947]   [2.259999990463257]
21      [2.251586914062]  [2.2739999294281006]
22  [2.2648277282714844]  [2.2879998683929443]
23  [2.2780685424804688]   [2.302000045776367]
24   [2.291309356689453]   [2.315999984741211]
25  [2.3045499324798584]  [2.3299999237060547]
26  [2.3177905082702637]  [2.3439998626708984]
27   [2.331031322479248]  [2.3580000400543213]
28  [2.3442721366882324]   [2.371999979019165]
29   [2.357512712478637]   [2.385999917984009]
```

2. Creating a Model Using PyTorch's `nn.Module` Library

2.1 Data

In [47]:
```
import torch
import matplotlib.pyplot as plt
```

In [48]:
```
## Again i am creating same data which i created earlier for regrassion model
weight = 0.7
bias = 0.3

x = torch.arange(0, 5, step=0.2).unsqueeze(1)
y = weight * x + bias
```

In [49]:
```
len(x),len(y)
```

Out[49]:
```
(25, 25)
```

In [50]:
```
x[:5], y[:5]
```

Out[50]:
```
(tensor([[0.0000],
         [0.2000],
         [0.4000],
         [0.6000],
         [0.8000]]),
 tensor([[0.3000],
         [0.4400],
         [0.5800],
         [0.7200],
         [0.8600]]))
```

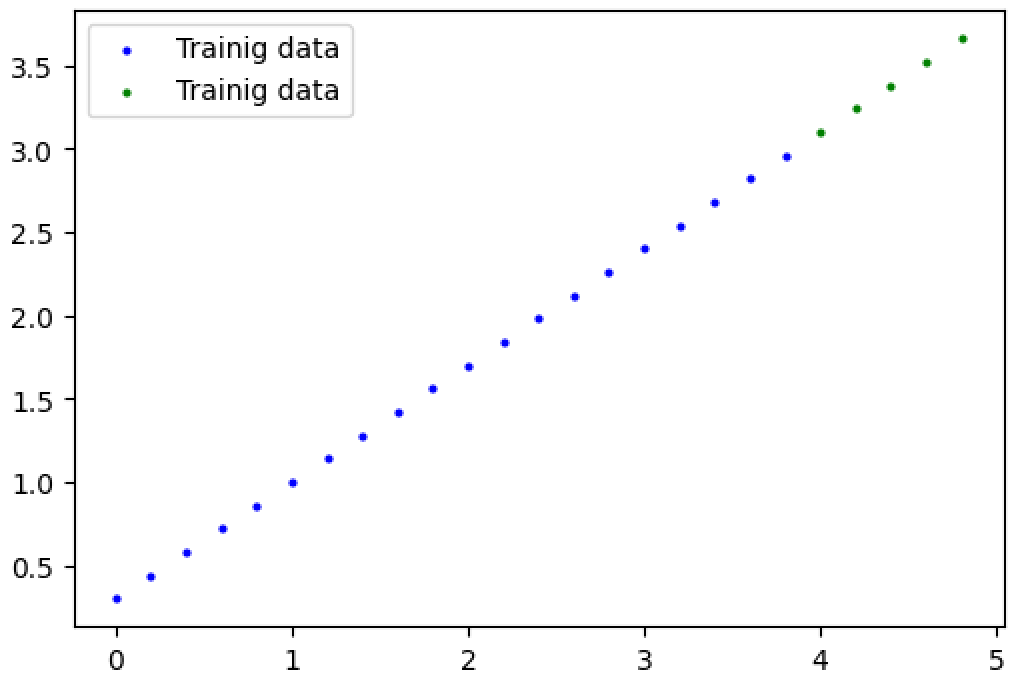
In [51]:
```
## split the data
train_split = int(0.8 * len(x))

x_train, y_train = x[:train_split], y[:train_split]
x_test, y_test = x[train_split:], y[train_split:]
```

In [52]:
```
print(f"train data shape : {x_train.shape} {y_train.shape}")
print(f"test data shape : {x_test.shape} {y_test.shape}")
```

```
train data shape : torch.Size([20, 1]) torch.Size([20, 1])
test data shape : torch.Size([5, 1]) torch.Size([5, 1])
```

In [53]:
```
def plot_prediction(train_data = x_train,
                    train_label = y_train,
                    test_data = x_test,
                    test_label = y_test,
                    prediction = None):
  """
  Ploting training data, test data and compare the predictions.
  """
  plt.figure(figsize = (6, 4 ))

  # plot training data in blue
  plt.scatter(train_data, train_label, c='b', s=4, label ='Trainig data')

  ## Plot test data in green
  plt.scatter(test_data, test_label, c='g', s=4, label ='Trainig data')

  #Are there prediction?
  if prediction is not None:
      # Plot the prediction if they exist
      plt.scatter(test_data, prediction, c ='r', s=4, label='Preditions')
  plt.legend()
```

In [54]:
```
plot_prediction()
```



Building a pytorch model

In [55]:
```
print("X_train shape:", x_train.size())
print("X_test shape:", x_test.size())
print("y_train:", y_train.size())
print("y_test:", y_test.size())
```

```
X_train shape: torch.Size([20, 1])
X_test shape: torch.Size([5, 1])
y_train: torch.Size([20, 1])
y_test: torch.Size([5, 1])
```

In [56]:
```
import torch
import torch.nn as nn

# Creating a linear model by subclassing nn.Module
class LinearRegressionModel(nn.Module):
    def __init__(self):
        super().__init__()
        # Using nn.Linear() to create the model parameters
        self.linear_layer = nn.Linear(in_features=1, # input feature
                                      out_features=1 # output layer
                                     )
        ## nn.Linear() applies a linear transformation to the incoming data "y

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

# Let's set the manual seed
torch.manual_seed(0)
model_1 = LinearRegressionModel()
model_1, model_1.state_dict()
```

Out[56]:
```
(LinearRegressionModel(
   (linear_layer): Linear(in_features=1, out_features=1, bias=True)
 ),
 OrderedDict([('linear_layer.weight', tensor([[-0.0075]])),
              ('linear_layer.bias', tensor([0.5364]))]))
```

Let's train this model

For training we need:

- Loss Function
- Optimizer
- Training Loop
- Testing Loop

In [57]:
```
## set a loss fuction
loss_fn = nn.L1Loss()

#setup our Optimizer
optimizer = torch.optim.SGD(params=model_1.parameters(),
                            lr= 0.001)
```

In [58]:
```
torch.manual_seed(43)
epochs = 24
## Track Different values
epoch_count = []
loss_values = []
test_loss_values = []

# Loop through the data for training
for epoch in range(epochs):
    # Set the model to training mode
    model_1.train()

    # Forward pass
    y_pred_epochs = model_1(x_train)

    # Calculate the loss
    loss = loss_fn(y_pred_epochs, y_train)

    # Backpropagation
    loss.backward()

    # Optimizer step to update parameters
    optimizer.step()

    ## Testing
    model_1.eval() # (different settings in the model not needed for evluation)

    with torch.inference_mode():  # Use torch.no_grad() to turn off gradient tr
        # 1. Do the forward pass
        test_pred = model_1(x_test)

        # Calculate the loss
        test_loss = loss_fn(test_pred, y_test)
        # 2. Calculate the loss
        test_loss = loss_fn(test_pred,  y_test)

        #Let's print what happing every 10 epochs

        epoch_count.append(epoch)
        loss_values.append(loss)
        test_loss_values.append(test_loss)
        print(f"Epoch :{epoch} | Loss :{loss} | Test loss :{test_loss}")
        print(model_1.state_dict())
```

```
Epoch :0 | Loss :1.1409204006195068 | Test loss :2.8674263954162598
OrderedDict([('linear_layer.weight', tensor([[-0.0056]])), ('linear_layer.bia
s', tensor([0.5372]))])
Epoch :1 | Loss :1.1367460489273071 | Test loss :2.8492822647094727
OrderedDict([('linear_layer.weight', tensor([[-0.0018]])), ('linear_layer.bia
s', tensor([0.5388]))])
Epoch :2 | Loss :1.1283972263336182 | Test loss :2.822066307067871
OrderedDict([('linear_layer.weight', tensor([[0.0038]])), ('linear_layer.bia
s', tensor([0.5412]))])
Epoch :3 | Loss :1.1158738136291504 | Test loss :2.785778045654297
OrderedDict([('linear_layer.weight', tensor([[0.0113]])), ('linear_layer.bia
s', tensor([0.5444]))])
Epoch :4 | Loss :1.099176287651062 | Test loss :2.7404181957244873
OrderedDict([('linear_layer.weight', tensor([[0.0207]])), ('linear_layer.bia
s', tensor([0.5484]))])
Epoch :5 | Loss :1.0783042907714844 | Test loss :2.685986280441284
OrderedDict([('linear_layer.weight', tensor([[0.0320]])), ('linear_layer.bia
s', tensor([0.5532]))])
Epoch :6 | Loss :1.053257942199707 | Test loss :2.6224820613861084
OrderedDict([('linear_layer.weight', tensor([[0.0452]])), ('linear_layer.bia
s', tensor([0.5588]))])
Epoch :7 | Loss :1.0240371227264404 | Test loss :2.5499062538146973
OrderedDict([('linear_layer.weight', tensor([[0.0602]])), ('linear_layer.bia
s', tensor([0.5652]))])
Epoch :8 | Loss :0.9915741086006165 | Test loss :2.468534231185913
OrderedDict([('linear_layer.weight', tensor([[0.0771]])), ('linear_layer.bia
s', tensor([0.5723]))])
Epoch :9 | Loss :0.9555447697639465 | Test loss :2.378366231918335
OrderedDict([('linear_layer.weight', tensor([[0.0958]])), ('linear_layer.bia
s', tensor([0.5801]))])
Epoch :10 | Loss :0.9156400561332703 | Test loss :2.279402256011963
OrderedDict([('linear_layer.weight', tensor([[0.1164]])), ('linear_layer.bia
s', tensor([0.5886]))])
Epoch :11 | Loss :0.8718595504760742 | Test loss :2.171642303466797
OrderedDict([('linear_layer.weight', tensor([[0.1388]])), ('linear_layer.bia
s', tensor([0.5978]))])
Epoch :12 | Loss :0.8242036700248718 | Test loss :2.055086612701416
OrderedDict([('linear_layer.weight', tensor([[0.1630]])), ('linear_layer.bia
s', tensor([0.6077]))])
Epoch :13 | Loss :0.7726720571517944 | Test loss :1.929734468460083
OrderedDict([('linear_layer.weight', tensor([[0.1891]])), ('linear_layer.bia
s', tensor([0.6183]))])
Epoch :14 | Loss :0.7184436321258545 | Test loss :1.7959502935409546
OrderedDict([('linear_layer.weight', tensor([[0.2169]])), ('linear_layer.bia
s', tensor([0.6295]))])
Epoch :15 | Loss :0.662132740020752 | Test loss :1.6537342071533203
OrderedDict([('linear_layer.weight', tensor([[0.2466]])), ('linear_layer.bia
s', tensor([0.6413]))])
Epoch :16 | Loss :0.6022936105728149 | Test loss :1.5030860900878906
OrderedDict([('linear_layer.weight', tensor([[0.2780]])), ('linear_layer.bia
s', tensor([0.6537]))])
Epoch :17 | Loss :0.5405397415161133 | Test loss :1.3444582223892212
OrderedDict([('linear_layer.weight', tensor([[0.3111]])), ('linear_layer.bia
s', tensor([0.6666]))])
Epoch :18 | Loss :0.4777856767177582 | Test loss :1.1778502464294434
OrderedDict([('linear_layer.weight', tensor([[0.3459]])), ('linear_layer.bia
s', tensor([0.6800]))])
```

```
Epoch :19 | Loss :0.41448941826820374 | Test loss :1.0038020610809326
OrderedDict([('linear_layer.weight', tensor([[0.3824]])), ('linear_layer.bia
s', tensor([0.6938]))])
Epoch :20 | Loss :0.35196417570114136 | Test loss :0.8229421377182007
OrderedDict([('linear_layer.weight', tensor([[0.4203]])), ('linear_layer.bia
s', tensor([0.7079]))])
Epoch :21 | Loss :0.29327192902565 | Test loss :0.6359861493110657
OrderedDict([('linear_layer.weight', tensor([[0.4595]])), ('linear_layer.bia
s', tensor([0.7222]))])
Epoch :22 | Loss :0.24157361686229706 | Test loss :0.44373816251754 76
OrderedDict([('linear_layer.weight', tensor([[0.4999]])), ('linear_layer.bia
s', tensor([0.7366]))])
Epoch :23 | Loss :0.20373372733592987 | Test loss :0.24807004630565643
OrderedDict([('linear_layer.weight', tensor([[0.5411]])), ('linear_layer.bia
s', tensor([0.7509]))])
```

In [59]:
```
model_1.state_dict()
```

Out[59]:
```
OrderedDict([('linear_layer.weight', tensor([[0.5411]])),
             ('linear_layer.bias', tensor([0.7509]))])
```

In [60]:
```
with torch.inference_mode():
    y_pred = model_1(x_test)
```

In [61]:
```
len(x_test),len(y_pred)
```

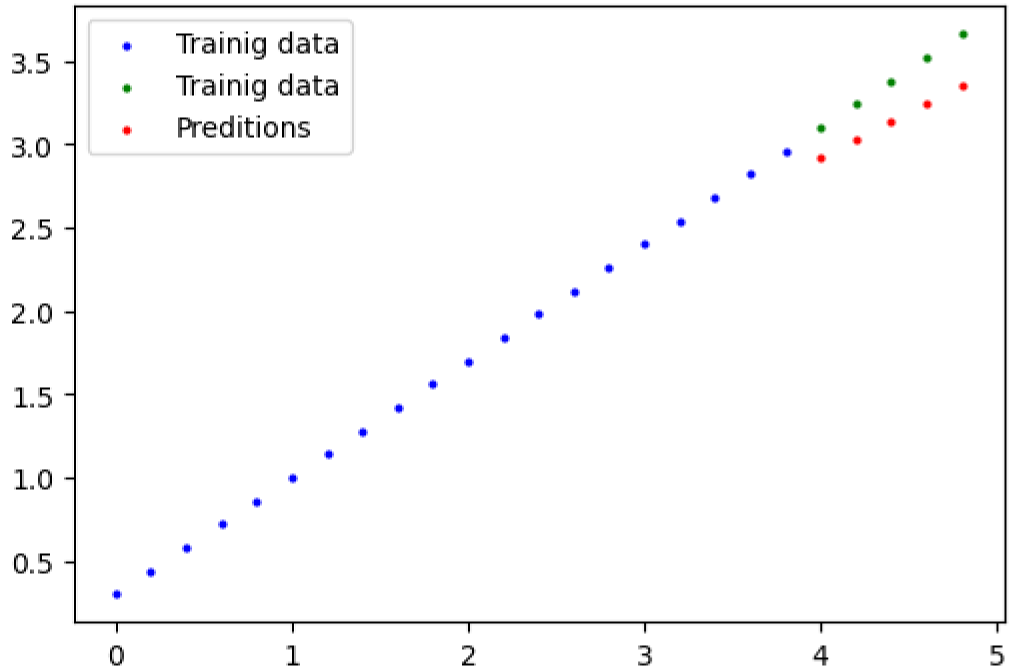
Out[61]:
```
(5, 5)
```

In [62]:
```
## Let's convert into in numpy
import numpy as np
loss_values = np.array(torch.tensor(loss_values))
test_loss_values = np.array(torch.tensor(test_loss_values))
```

In [63]:
```
import matplotlib.pyplot as plt
plt.plot(epoch_count, loss_values, label='Train Loss')
plt.plot(epoch_count, test_loss_values, label='Test loss')
plt.title("Training and testing loss curves")
plt.ylabel('Loss')
plt.xlabel('Epochs')
plt.legend()
```

Out[63]:
```
<matplotlib.legend.Legend at 0x797fe345f1f0>
```

In [64]:
```
plot_prediction(prediction=y_pred)
```



In [64]: