

# Lecture\_17\_TensorFlow\_code

October 7, 2024

Introduction to TensorFlow

## 1 1. Tensors

### 1.0.1 Checking the version of Tensorflow

```
[1]: import tensorflow as tf # now import the tensorflow module
      print(tf.__version__) # make sure the version is 2.x
```

2.13.0

```
[2]: # you would also need numpy for tensorflow programming. Use pip install numpy
      import numpy as np
      from matplotlib import pyplot as plt
```

Tensorflow programming starts with **Tensors**. A tensor has a data type (e.g., float32, int32, string, etc.), a rank, and a shape (dimensionality of the matrix or array).

You simply define the value of the tensor and the datatype and you are good to go! It's worth mentioning that usually we deal with tensors of numeric data, it is quite rare to see string tensors.

### 1.0.2 Scalar tensors, or rank 0 tensors (i.e. they don't have dimensions)

```
[3]: number_tensor = tf.constant(324, dtype = tf.int32)
      float_tensor = tf.constant(3.567, dtype = tf.float64)

      print("number_tensor", number_tensor)
      print("float_tensor", float_tensor)
```

```
number_tensor tf.Tensor(324, shape=(), dtype=int32)
float_tensor tf.Tensor(3.567, shape=(), dtype=float64)
```

### 1.0.3 Vector tensors, or rank 1 tensors

```
[4]: rank1_tensor = tf.constant([1.0,2,3])
      print(rank1_tensor)
```

```
tf.Tensor([1. 2. 3.], shape=(3,), dtype=float32)
```

#### 1.0.4 Matrix tensors, or rank 2 tensors

```
[5]: rank2_tensor = tf.constant([[1,2], [3,4]])  
     print(rank2_tensor)
```

```
tf.Tensor(  
  [[1 2]  
   [3 4]], shape=(2, 2), dtype=int32)
```

#### 1.0.5 Tensor Shape and Rank

The rank of a tensor is the number of dimensions the tensor has, e.g. vector has 1 axis and is rank 1, matrix is rank 2, etc. The rank of a tensor is directly related to the deepest level of nested lists. You can see that `number_tensor` doesn't have any depth and therefore, its rank is 0. Also, you can see the `rank1_tensor [1.0,2,3]` is a rank 1 tensor as the deepest level of nesting is 1 where the `rank2_tensor [[1, 2], [3, 4]]` is a rank 2 tensor as the deepest level of nesting is 2

To determine the rank of a tensor, you can call the `rank` function.

```
[6]: print(tf.rank(rank1_tensor))
```

```
tf.Tensor(1, shape=(), dtype=int32)
```

```
[7]: print(tf.rank(rank2_tensor))
```

```
tf.Tensor(2, shape=(), dtype=int32)
```

The **shape of a tensor** is the number of elements that exist in each dimension. TensorFlow will try to determine the shape of a tensor but sometimes it may be unknown. To **get the shape** of a tensor we use the `shape` attribute.

```
[8]: rank2_tensor.shape
```

```
[8]: TensorShape([2, 2])
```

#### 1.0.6 Rank 3 tensor

```
[9]: rank_3_tensor = tf.constant([  
    [[0, 1, 2, 3, 4],  
     [5, 6, 7, 8, 9]],  
    [[10, 11, 12, 13, 14],  
     [15, 16, 17, 18, 19]],  
    [[20, 21, 22, 23, 24],  
     [25, 26, 27, 28, 29]],])  
  
print(rank_3_tensor)
```

```
tf.Tensor(  
  [[[ 0  1  2  3  4]  
    [ 5  6  7  8  9]]  
   [[10 11 12 13 14]  
    [15 16 17 18 19]]  
   [[20 21 22 23 24]  
    [25 26 27 28 29]]])
```

```
[[10 11 12 13 14]
 [15 16 17 18 19]]

[[20 21 22 23 24]
 [25 26 27 28 29]]], shape=(3, 2, 5), dtype=int32)
```

### 1.0.7 Tensor Creation

```
[10]: # Creating an tensor where all entries is 1. Note here [2,2] is the shape of
      ↪ the tensor
all_one_tensor = tf.ones([2,2])

# Creating an tensor where all entries is 0. Note here [2,2] is the shape of
      ↪ the tensor
all_zero_tensor = tf.zeros([2,2])

# Creating an tensor from nparray, (nested) lists.
nparray = np.array([1,2])
tensor_from_nparray = tf.constant(nparray)
```

### 1.0.8 Changing the Tensor Shape

The number of elements of a tensor is the product of the sizes of all its shapes. There are often many shapes that have the same number of elements, making it convient to be able to change the shape of a tensor.

The following example shows how to change the shape of a tensor.

```
[11]: # tf.ones() creates a shape [1,2,3] tensor full of ones
tensor1 = tf.ones([1,2,3])
# reshape existing data to shape [2,3,1]
tensor2 = tf.reshape(tensor1, [2,3,1])

# -1 tells the tensor to calculate the size of the dimension in that place
# this will reshape the tensor to [3,2]
tensor3 = tf.reshape(tensor2, [3, -1])

# The numer of elements in the reshaped tensor MUST match the number in the
      ↪ original
```

```
[12]: print(tensor1)
      print ('\n')
      print(tensor2)
      print ('\n')
      print(tensor3)
      # Notice the changes in shape
```

```
tf.Tensor(
[[[1. 1. 1.]
  [1. 1. 1.]]], shape=(1, 2, 3), dtype=float32)
```

```
tf.Tensor(
[[[1.]
  [1.]
  [1.]]

 [[1.]
  [1.]
  [1.]]], shape=(2, 3, 1), dtype=float32)
```

```
tf.Tensor(
[[1. 1.]
 [1. 1.]
 [1. 1.]], shape=(3, 2), dtype=float32)
```

### 1.0.9 Slicing Tensors

You may be familiar with the term slice in python and its use on lists, tuples etc. Well the slice operator can be used on tensors to select specific axes or elements.

When we slice or select elements from a tensor, we can use comma seperated values inside the set of square brackets. Each subsequent value references a different dimension of the tensor.

Ex: tensor[dim1, dim2, dim3]

```
[13]: # Creating a 2D tensor
matrix = [[1,2,3,4,5],
          [6,7,8,9,10],
          [11,12,13,14,15],
          [16,17,18,19,20]]

tensor = tf.constant(matrix, dtype=tf.int32)
print(tf.rank(tensor))
print(tensor.shape)
```

```
tf.Tensor(2, shape=(), dtype=int32)
(4, 5)
```

```
[14]: # Now lets select some different rows and columns from our tensor

three = tensor[0,2] # selects the 3rd element from the 1st row
print(three) # -> 3

row1 = tensor[0] # selects the first row
```

```
print(row1)

column1 = tensor[:, 0] # selects the first column
print(column1)
```

```
tf.Tensor(3, shape=(), dtype=int32)
tf.Tensor([1 2 3 4 5], shape=(5,), dtype=int32)
tf.Tensor([ 1  6 11 16], shape=(4,), dtype=int32)
```

```
[15]: row_2_and_4 = tensor[1::2] # selects second and fourth row
print(row_2_and_4)

column_1_in_row_2_and_3 = tensor[1:3, 0]
print(column_1_in_row_2_and_3)
```

```
tf.Tensor(
[[ 6  7  8  9 10]
 [16 17 18 19 20]], shape=(2, 5), dtype=int32)
tf.Tensor([ 6 11], shape=(2,), dtype=int32)
```

### 1.0.10 Tensor Operations

```
[16]: # We can also have common operations between tensors
vector_1 = tf.constant([1,2])
vector_2 = tf.constant([3,4])
sum = vector_1+vector_2
print('sum = ', sum)

# elementwise_product
elementwise_product = vector_1*vector_2
print('elementwise_product = ', elementwise_product)

# dot product with tensordot
dot_product = tf.tensordot(vector_1,vector_2,axes = 1)
print('dot_product = ', dot_product) # 1*3 + 2*4

# another way to do dot product
dot_product_2 = tf.squeeze( tf.expand_dims(vector_1,0) @ tf.
    ↪expand_dims(vector_2,1) )
print('dot_product_2 = ', dot_product_2) # 1*3 + 2*4

# matrix vector product
matrix_1 = tf.constant( [[1,1],[2,2]])
matrix_vector_product = tf.tensordot(matrix_1,vector_1, axes=1)
print("matrix_vector_product = ",matrix_vector_product) # [1+2, 2+4]

# Alternative way to do matrix vector product
```

```

matrix_vector_product_2 = tf.squeeze(matrix_1@tf.expand_dims(vector_1,1))
print("matrix_vector_product_2 = ",matrix_vector_product_2) # [1+2, 2+4]

# matrix matrix product
matrix_2 = tf.constant([[1,2],[1,2]])
matrix_product = matrix_1@matrix_2
print("matrix_product = ",matrix_product)

```

```

sum = tf.Tensor([4 6], shape=(2,), dtype=int32)
elementwise_product = tf.Tensor([3 8], shape=(2,), dtype=int32)
dot_product = tf.Tensor(11, shape=(), dtype=int32)
dot_product_2 = tf.Tensor(11, shape=(), dtype=int32)
matrix_vector_product = tf.Tensor([3 6], shape=(2,), dtype=int32)
matrix_vector_product_2 = tf.Tensor([3 6], shape=(2,), dtype=int32)
matrix_product = tf.Tensor(
[[2 4]
 [4 8]], shape=(2, 2), dtype=int32)

```

## 2 2. Building ML Models with Keras API

### 2.1 2.1 Linear Regression Model

#### 2.1.1 Prepare training data

Consider fitting a linear curve to a data set where there is one feature of numeric type, and the output (target) is also a numeric type. Let's use the following synthetic data as an example.

```

[17]: import matplotlib.pyplot as plt
import numpy as np

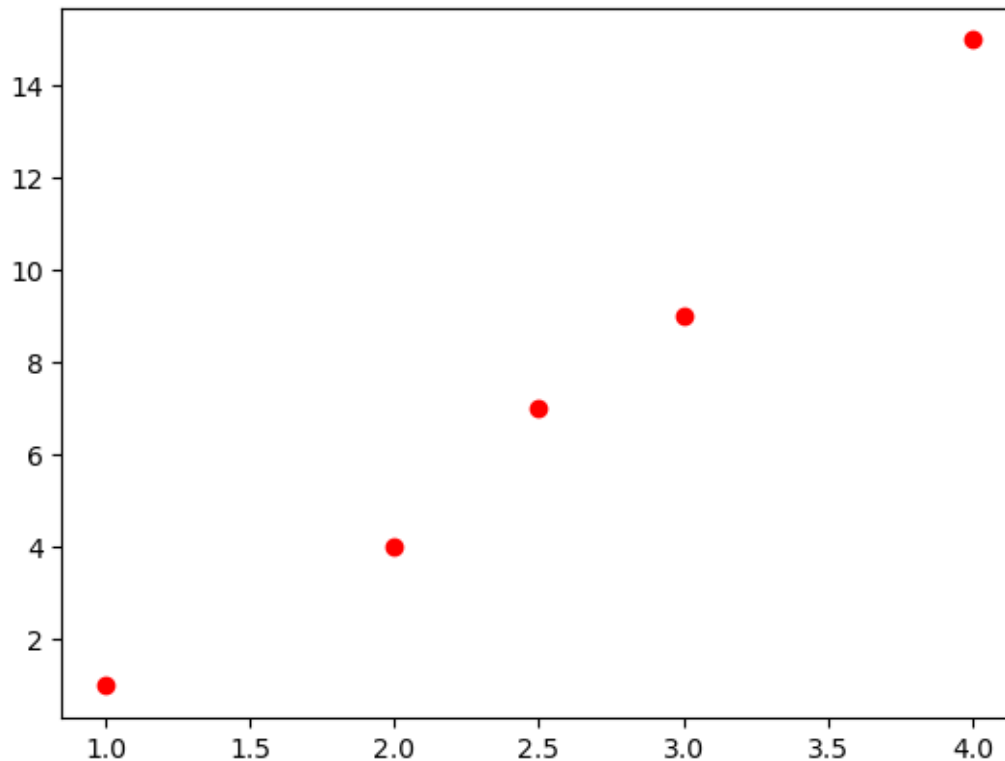
x = np.array([ 1, 2, 2.5, 3, 4],dtype=float)
x = tf.constant(x[:,np.newaxis],dtype=float)
y = np.array([1, 4, 7, 9, 15],dtype=float)
y = tf.constant(y[:,np.newaxis],dtype=float)
plt.plot(x, y, 'ro')

```

```

[17]: [<matplotlib.lines.Line2D at 0x2822824f0>]

```



### 2.1.2 Creating `keras.Sequential()` model

One simple way to create a keras model is the `keras.Sequential()` API. We will first create an empty `Sequential` model. For the purpose of linear regression, we will add a `Dense(1)` layer, here the 1 means the output of this layer is only 1 dimensional (as our target output is only a scalar). We don't need to specify the input dimension - the input dimension will be automatically inferred at runtime.

```
[18]: from tensorflow import keras
      # create a sequential layer to conduct linear regression

      model = keras.Sequential()
      model.add(keras.layers.Dense(1))
```

```
[19]: # You shouldn't run model.summary() until you have pass a data to the model.
      # Without passing the data to the model, the model does not know its input
      ↪ dimension and is not 'built'.
      # model.summary()
```

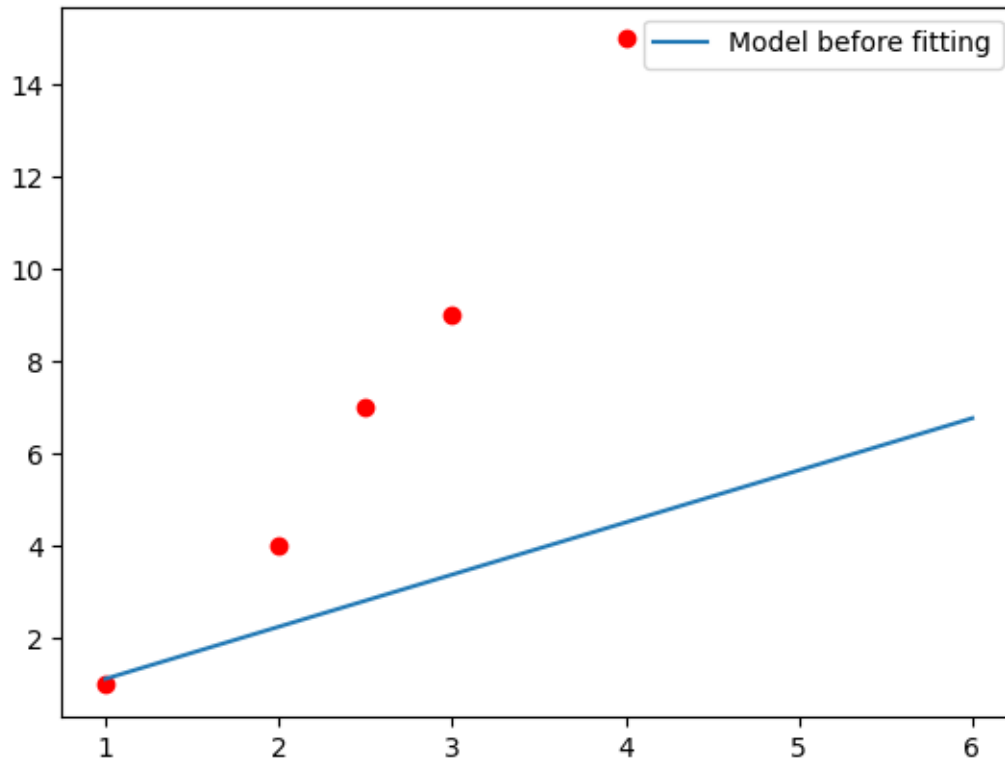
```
[19]: # Let's check out what the prediction of the model looks like (Note: we haven't
      ↪ trained the model yet)
```

```

x_mesh = np.linspace(1,6,100) # generate 100 input values between 1 and 6
x_mesh = tf.constant( x_mesh[:,np.newaxis])
y_pred_mesh = model(x_mesh) # get the output of our model
plt.plot(x, y, 'ro')
plt.plot(x_mesh, y_pred_mesh , label = "Model before fitting")
plt.legend()

```

[19]: <matplotlib.legend.Legend at 0x2824e0df0>



[21]: *# model.summary() is a useful tool to visualize the structure of the model*

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(100, 1)	2

Total params: 2 (8.00 Byte)

Trainable params: 2 (8.00 Byte)



Non-trainable params: 0 (0.00 Byte)

-----

### 2.1.3 Train the model

Training a keras model consists of two steps. The first step is `compile`, in which you need to specify the optimizer and the loss. Then, we call the `fit` method.

```
[20]: model.compile(optimizer = keras.optimizers.SGD(), loss = keras.losses.  
      ↪MeanSquaredError())  
      model.fit(x,y,epochs=30)
```

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at `tf.keras.optimizers.legacy.SGD`.

WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e., `tf.keras.optimizers.legacy.SGD`.

```
Epoch 1/30  
1/1 [=====] - 0s 109ms/step - loss: 32.3518  
Epoch 2/30  
1/1 [=====] - 0s 1ms/step - loss: 23.9135  
Epoch 3/30  
1/1 [=====] - 0s 1ms/step - loss: 17.9901  
Epoch 4/30  
1/1 [=====] - 0s 1ms/step - loss: 13.8304  
Epoch 5/30  
1/1 [=====] - 0s 1ms/step - loss: 10.9078  
Epoch 6/30  
1/1 [=====] - 0s 1ms/step - loss: 8.8528  
Epoch 7/30  
1/1 [=====] - 0s 997us/step - loss: 7.4064  
Epoch 8/30  
1/1 [=====] - 0s 1ms/step - loss: 6.3867  
Epoch 9/30  
1/1 [=====] - 0s 2ms/step - loss: 5.6664  
Epoch 10/30  
1/1 [=====] - 0s 2ms/step - loss: 5.1561  
Epoch 11/30  
1/1 [=====] - 0s 1ms/step - loss: 4.7930  
Epoch 12/30  
1/1 [=====] - 0s 1ms/step - loss: 4.5333  
Epoch 13/30  
1/1 [=====] - 0s 1ms/step - loss: 4.3461  
Epoch 14/30  
1/1 [=====] - 0s 1ms/step - loss: 4.2098  
Epoch 15/30  
1/1 [=====] - 0s 1ms/step - loss: 4.1091
```

```

Epoch 16/30
1/1 [=====] - 0s 1ms/step - loss: 4.0336
Epoch 17/30
1/1 [=====] - 0s 1ms/step - loss: 3.9756
Epoch 18/30
1/1 [=====] - 0s 1ms/step - loss: 3.9300
Epoch 19/30
1/1 [=====] - 0s 1ms/step - loss: 3.8931
Epoch 20/30
1/1 [=====] - 0s 2ms/step - loss: 3.8623
Epoch 21/30
1/1 [=====] - 0s 2ms/step - loss: 3.8358
Epoch 22/30
1/1 [=====] - 0s 2ms/step - loss: 3.8124
Epoch 23/30
1/1 [=====] - 0s 1ms/step - loss: 3.7911
Epoch 24/30
1/1 [=====] - 0s 1000us/step - loss: 3.7714
Epoch 25/30
1/1 [=====] - 0s 959us/step - loss: 3.7528
Epoch 26/30
1/1 [=====] - 0s 1ms/step - loss: 3.7350
Epoch 27/30
1/1 [=====] - 0s 1ms/step - loss: 3.7178
Epoch 28/30
1/1 [=====] - 0s 1ms/step - loss: 3.7010
Epoch 29/30
1/1 [=====] - 0s 1ms/step - loss: 3.6846
Epoch 30/30
1/1 [=====] - 0s 1ms/step - loss: 3.6684

```

[20]: <keras.src.callbacks.History at 0x282634ac0>

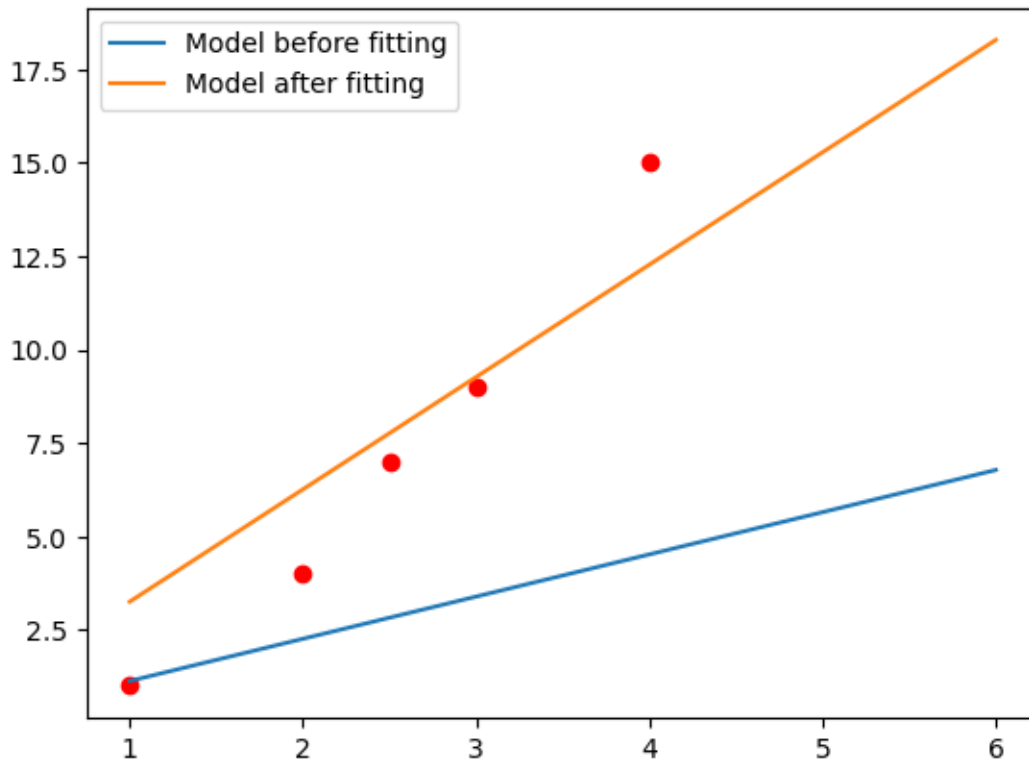
[21]: *### Let's see how the model looks like after training*

```

y_pred_mesh_afterfitting = model(x_mesh)
plt.plot(x, y, 'ro')
plt.plot(x_mesh, y_pred_mesh, label = "Model before fitting")
plt.plot(x_mesh, y_pred_mesh_afterfitting, label = "Model after fitting")
plt.legend()

```

[21]: <matplotlib.legend.Legend at 0x2826dbeb0>



## 2.2 2.2 Building Simple Neural Network with Keras

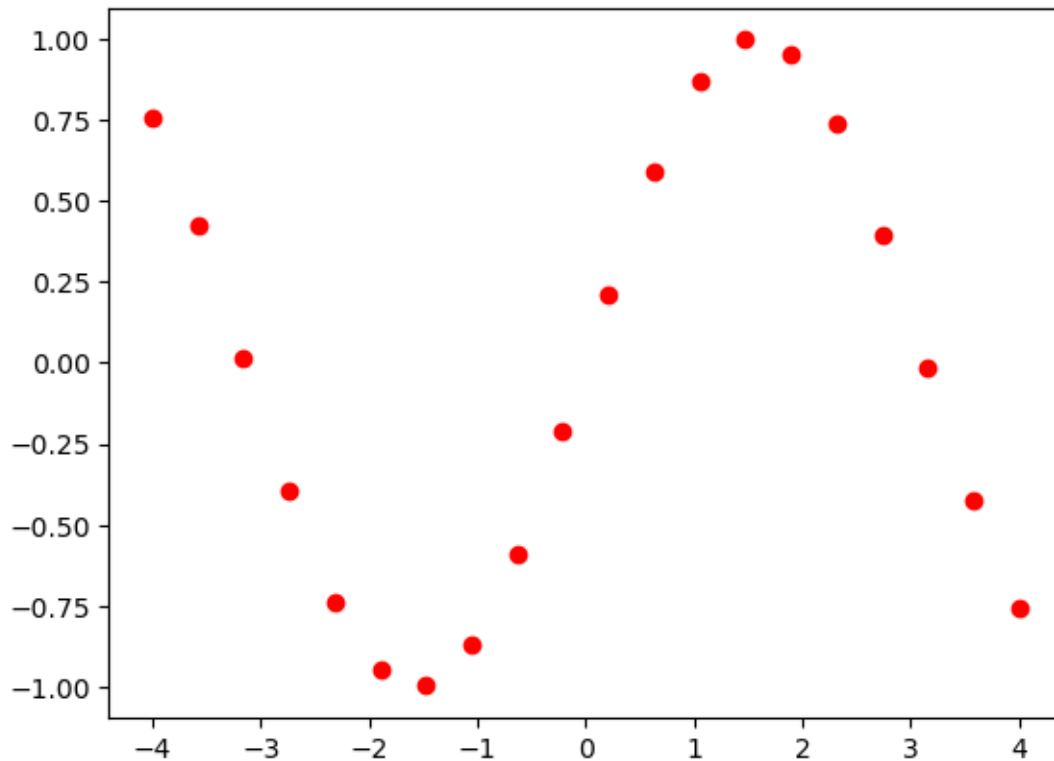
### 2.2.1 Prepare training data

Let's use a neural network to fit a nonlinear function. We create the training data first which is a sinusoidal curve.

```
[22]: x = np.linspace(-4,4,20)
x = x[:,np.newaxis]
y = np.sin(x)

plt.figure()
plt.plot(x,y, 'ro')

x = tf.constant(x)
y = tf.constant(y)
```



### 2.2.2 Creating keras.Sequential() model

To create a neural network, you just need to keep adding layers to the sequential model. In each layer, you need to specify the dimension of the output (in other words, the width of this layer), and the activation, which we use 'relu'.

```
[23]: model = keras.Sequential()

model.add(keras.layers.Dense(20,activation='relu'))
model.add(keras.layers.Dense(20,activation='relu'))
model.add(keras.layers.Dense(20,activation='relu'))

model.add(keras.layers.Dense(1))
```

### 2.2.3 Creating keras.Sequential() model - method 2

```
[24]: model2 = keras.Sequential(layers=[keras.layers.Dense(20,activation='relu'),
    keras.layers.Dense(20,activation='relu'),
    keras.layers.Dense(20,activation='relu'),
    keras.layers.Dense(1)])
```

## 2.2.4 Creating keras model with functional API

```
[25]: input = keras.Input(shape = (1))

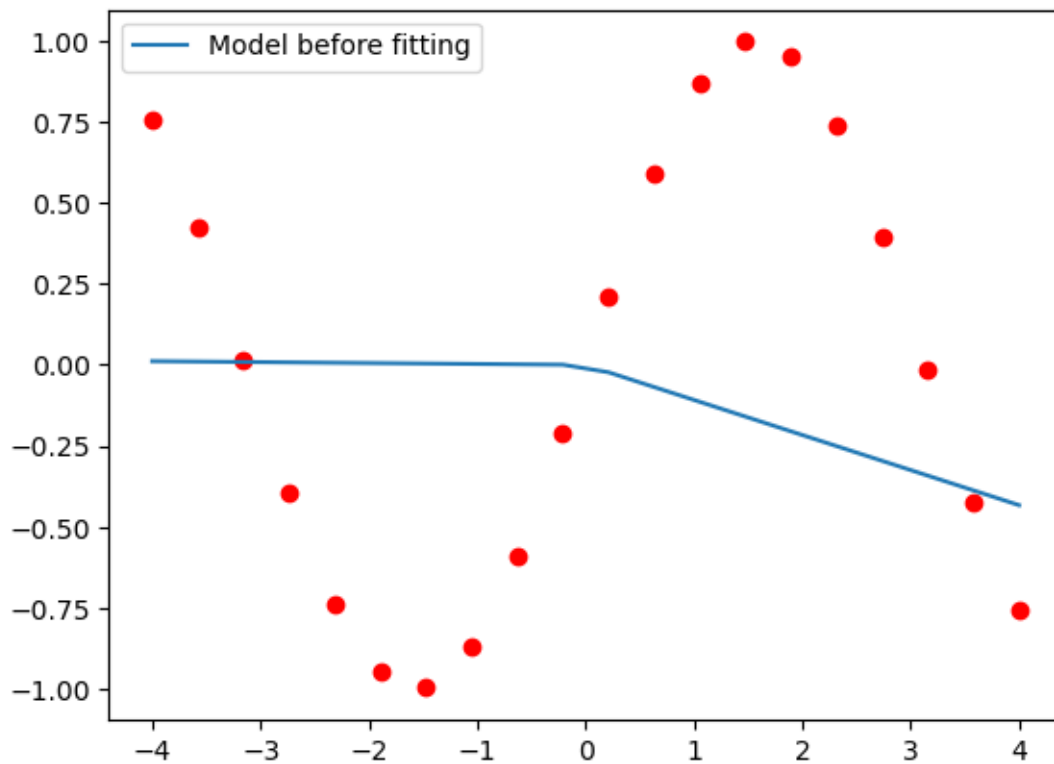
intermediate_1 = keras.layers.Dense(20,activation='relu')(input)
intermediate_2 = keras.layers.Dense(20,activation='relu')(intermediate_1)
intermediate_3 = keras.layers.Dense(20,activation='relu')(intermediate_2)

output = keras.layers.Dense(1)(intermediate_3)

model3 = keras.Model(inputs = input,outputs = output)
```

```
[26]: y_pred_before_training = model(x) # get the output of our model
plt.plot(x, y, 'ro')
plt.plot(x, y_pred_before_training , label = "Model before fitting")
plt.legend()
```

```
[26]: <matplotlib.legend.Legend at 0x28380abb0>
```



```
[27]: model.summary()
```

```
Model: "sequential_1"
```

---

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(20, 20)	40
dense_2 (Dense)	(20, 20)	420
dense_3 (Dense)	(20, 20)	420
dense_4 (Dense)	(20, 1)	21

```

=====
Total params: 901 (3.52 KB)
Trainable params: 901 (3.52 KB)
Non-trainable params: 0 (0.00 Byte)
-----

```

```

[28]: # training the model by calling the compile and the fit function
model.compile(optimizer = keras.optimizers.SGD(),loss=keras.losses.
    ↪MeanSquaredError())
model.fit(x,y,epochs=1000)

```

```

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.SGD`.
WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on
M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e.,
`tf.keras.optimizers.legacy.SGD`.

```

```

Epoch 1/1000
1/1 [=====] - 0s 105ms/step - loss: 0.5137
Epoch 2/1000
1/1 [=====] - 0s 1ms/step - loss: 0.5028
Epoch 3/1000
1/1 [=====] - 0s 1ms/step - loss: 0.4931
Epoch 4/1000
1/1 [=====] - 0s 2ms/step - loss: 0.4844
Epoch 5/1000
1/1 [=====] - 0s 1ms/step - loss: 0.4767
Epoch 6/1000
1/1 [=====] - 0s 2ms/step - loss: 0.4697
Epoch 7/1000
1/1 [=====] - 0s 2ms/step - loss: 0.4636
Epoch 8/1000
1/1 [=====] - 0s 2ms/step - loss: 0.4584
Epoch 9/1000
1/1 [=====] - 0s 2ms/step - loss: 0.4538
Epoch 10/1000
1/1 [=====] - 0s 1ms/step - loss: 0.4498

```

Epoch 11/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4467  
Epoch 12/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4440  
Epoch 13/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4416  
Epoch 14/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4397  
Epoch 15/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4379  
Epoch 16/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4361  
Epoch 17/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4346  
Epoch 18/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4332  
Epoch 19/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4319  
Epoch 20/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4306  
Epoch 21/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4294  
Epoch 22/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4282  
Epoch 23/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4268  
Epoch 24/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4255  
Epoch 25/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4244  
Epoch 26/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4233  
Epoch 27/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4222  
Epoch 28/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4212  
Epoch 29/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4201  
Epoch 30/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4191  
Epoch 31/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4181  
Epoch 32/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4172  
Epoch 33/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.4162  
Epoch 34/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4153

Epoch 35/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4143  
Epoch 36/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4134  
Epoch 37/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4124  
Epoch 38/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4114  
Epoch 39/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4104  
Epoch 40/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.4093  
Epoch 41/1000  
1/1 [=====] - 0s 10ms/step - loss: 0.4083  
Epoch 42/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4074  
Epoch 43/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4066  
Epoch 44/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4058  
Epoch 45/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4051  
Epoch 46/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.4043  
Epoch 47/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4035  
Epoch 48/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4027  
Epoch 49/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4019  
Epoch 50/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4011  
Epoch 51/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.4004  
Epoch 52/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3996  
Epoch 53/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3989  
Epoch 54/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3981  
Epoch 55/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3974  
Epoch 56/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3966  
Epoch 57/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3959  
Epoch 58/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3951



Epoch 59/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3944  
Epoch 60/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3936  
Epoch 61/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3929  
Epoch 62/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3922  
Epoch 63/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3916  
Epoch 64/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3908  
Epoch 65/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3902  
Epoch 66/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3895  
Epoch 67/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3888  
Epoch 68/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3881  
Epoch 69/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3874  
Epoch 70/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3867  
Epoch 71/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3860  
Epoch 72/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3852  
Epoch 73/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3845  
Epoch 74/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3838  
Epoch 75/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3831  
Epoch 76/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3824  
Epoch 77/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3816  
Epoch 78/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3808  
Epoch 79/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3801  
Epoch 80/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3793  
Epoch 81/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3785  
Epoch 82/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3776

Epoch 83/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3768  
Epoch 84/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3760  
Epoch 85/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3752  
Epoch 86/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3745  
Epoch 87/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3738  
Epoch 88/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3731  
Epoch 89/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3724  
Epoch 90/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3717  
Epoch 91/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3710  
Epoch 92/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3703  
Epoch 93/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3696  
Epoch 94/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3688  
Epoch 95/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3681  
Epoch 96/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3674  
Epoch 97/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3667  
Epoch 98/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3660  
Epoch 99/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3653  
Epoch 100/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3646  
Epoch 101/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3639  
Epoch 102/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3632  
Epoch 103/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3625  
Epoch 104/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3618  
Epoch 105/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3611  
Epoch 106/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3603

Epoch 107/1000  
1/1 [=====] - 0s 10ms/step - loss: 0.3596  
Epoch 108/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.3589  
Epoch 109/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3582  
Epoch 110/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3575  
Epoch 111/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3568  
Epoch 112/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3561  
Epoch 113/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3554  
Epoch 114/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3547  
Epoch 115/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3540  
Epoch 116/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3533  
Epoch 117/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3527  
Epoch 118/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3520  
Epoch 119/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3513  
Epoch 120/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3506  
Epoch 121/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3499  
Epoch 122/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3493  
Epoch 123/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3486  
Epoch 124/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3479  
Epoch 125/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3472  
Epoch 126/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3466  
Epoch 127/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3459  
Epoch 128/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3452  
Epoch 129/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3445  
Epoch 130/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3438

Epoch 131/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3431  
Epoch 132/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3424  
Epoch 133/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3418  
Epoch 134/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3411  
Epoch 135/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3404  
Epoch 136/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3397  
Epoch 137/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3390  
Epoch 138/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3383  
Epoch 139/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3376  
Epoch 140/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3369  
Epoch 141/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3362  
Epoch 142/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3355  
Epoch 143/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3348  
Epoch 144/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.3341  
Epoch 145/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3334  
Epoch 146/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3327  
Epoch 147/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3320  
Epoch 148/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3313  
Epoch 149/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3306  
Epoch 150/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3298  
Epoch 151/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3291  
Epoch 152/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3284  
Epoch 153/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3277  
Epoch 154/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3270

Epoch 155/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3263  
Epoch 156/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3255  
Epoch 157/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3248  
Epoch 158/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3241  
Epoch 159/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3233  
Epoch 160/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3226  
Epoch 161/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3219  
Epoch 162/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3211  
Epoch 163/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3204  
Epoch 164/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3197  
Epoch 165/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3189  
Epoch 166/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3182  
Epoch 167/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3175  
Epoch 168/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3167  
Epoch 169/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3160  
Epoch 170/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3152  
Epoch 171/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3145  
Epoch 172/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3137  
Epoch 173/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3130  
Epoch 174/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3122  
Epoch 175/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3115  
Epoch 176/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3107  
Epoch 177/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3100  
Epoch 178/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3092

Epoch 179/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3085  
Epoch 180/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3077  
Epoch 181/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3069  
Epoch 182/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3062  
Epoch 183/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3054  
Epoch 184/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.3047  
Epoch 185/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3039  
Epoch 186/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3032  
Epoch 187/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.3024  
Epoch 188/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.3016  
Epoch 189/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3008  
Epoch 190/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.3000  
Epoch 191/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2992  
Epoch 192/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2984  
Epoch 193/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2976  
Epoch 194/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2969  
Epoch 195/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2960  
Epoch 196/1000  
1/1 [=====] - 0s 25ms/step - loss: 0.2953  
Epoch 197/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.2945  
Epoch 198/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2937  
Epoch 199/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2929  
Epoch 200/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2921  
Epoch 201/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2912  
Epoch 202/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2905

Epoch 203/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2896  
Epoch 204/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.2888  
Epoch 205/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.2880  
Epoch 206/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2872  
Epoch 207/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2863  
Epoch 208/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2855  
Epoch 209/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2846  
Epoch 210/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2838  
Epoch 211/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2829  
Epoch 212/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2820  
Epoch 213/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2812  
Epoch 214/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2803  
Epoch 215/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2795  
Epoch 216/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2785  
Epoch 217/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2776  
Epoch 218/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2767  
Epoch 219/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2758  
Epoch 220/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2749  
Epoch 221/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2740  
Epoch 222/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2730  
Epoch 223/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2721  
Epoch 224/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2711  
Epoch 225/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2702  
Epoch 226/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2693

Epoch 227/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2683  
Epoch 228/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2674  
Epoch 229/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2665  
Epoch 230/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2656  
Epoch 231/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2647  
Epoch 232/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2639  
Epoch 233/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2630  
Epoch 234/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2622  
Epoch 235/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2613  
Epoch 236/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2605  
Epoch 237/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2597  
Epoch 238/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2589  
Epoch 239/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2580  
Epoch 240/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2572  
Epoch 241/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2564  
Epoch 242/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2555  
Epoch 243/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2547  
Epoch 244/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2539  
Epoch 245/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2530  
Epoch 246/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2522  
Epoch 247/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2514  
Epoch 248/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2506  
Epoch 249/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2497  
Epoch 250/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2489



Epoch 251/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2481  
Epoch 252/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2472  
Epoch 253/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2464  
Epoch 254/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2455  
Epoch 255/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2447  
Epoch 256/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2439  
Epoch 257/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2430  
Epoch 258/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2422  
Epoch 259/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2413  
Epoch 260/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2405  
Epoch 261/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.2397  
Epoch 262/1000  
1/1 [=====] - 0s 26ms/step - loss: 0.2388  
Epoch 263/1000  
1/1 [=====] - 0s 13ms/step - loss: 0.2380  
Epoch 264/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.2371  
Epoch 265/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.2363  
Epoch 266/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.2354  
Epoch 267/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2346  
Epoch 268/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2338  
Epoch 269/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2329  
Epoch 270/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2321  
Epoch 271/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2312  
Epoch 272/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2304  
Epoch 273/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2295  
Epoch 274/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2287

Epoch 275/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2278  
Epoch 276/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2270  
Epoch 277/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2262  
Epoch 278/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2253  
Epoch 279/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2245  
Epoch 280/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2236  
Epoch 281/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.2228  
Epoch 282/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2220  
Epoch 283/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2211  
Epoch 284/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2203  
Epoch 285/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2194  
Epoch 286/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2186  
Epoch 287/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2177  
Epoch 288/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2169  
Epoch 289/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2160  
Epoch 290/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2152  
Epoch 291/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2143  
Epoch 292/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2135  
Epoch 293/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2126  
Epoch 294/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2118  
Epoch 295/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2109  
Epoch 296/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2100  
Epoch 297/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2092  
Epoch 298/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.2083

Epoch 299/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2075  
Epoch 300/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2066  
Epoch 301/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2057  
Epoch 302/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2048  
Epoch 303/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2040  
Epoch 304/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2031  
Epoch 305/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.2022  
Epoch 306/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.2014  
Epoch 307/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.2005  
Epoch 308/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1997  
Epoch 309/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1988  
Epoch 310/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1979  
Epoch 311/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1971  
Epoch 312/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1963  
Epoch 313/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1954  
Epoch 314/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1946  
Epoch 315/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1937  
Epoch 316/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1929  
Epoch 317/1000  
1/1 [=====] - 0s 18ms/step - loss: 0.1920  
Epoch 318/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.1912  
Epoch 319/1000  
1/1 [=====] - 0s 6ms/step - loss: 0.1904  
Epoch 320/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1895  
Epoch 321/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1887  
Epoch 322/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1878

Epoch 323/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1870  
Epoch 324/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1862  
Epoch 325/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.1853  
Epoch 326/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1845  
Epoch 327/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1837  
Epoch 328/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1829  
Epoch 329/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1820  
Epoch 330/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1812  
Epoch 331/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1804  
Epoch 332/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1796  
Epoch 333/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1787  
Epoch 334/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1779  
Epoch 335/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1771  
Epoch 336/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1763  
Epoch 337/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1755  
Epoch 338/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1746  
Epoch 339/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1738  
Epoch 340/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1730  
Epoch 341/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1722  
Epoch 342/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1714  
Epoch 343/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1706  
Epoch 344/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1698  
Epoch 345/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1690  
Epoch 346/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1682

Epoch 347/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1674  
Epoch 348/1000  
1/1 [=====] - 0s 6ms/step - loss: 0.1666  
Epoch 349/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.1658  
Epoch 350/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1650  
Epoch 351/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1642  
Epoch 352/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1634  
Epoch 353/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1626  
Epoch 354/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1618  
Epoch 355/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.1610  
Epoch 356/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1602  
Epoch 357/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1594  
Epoch 358/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1586  
Epoch 359/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1579  
Epoch 360/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1571  
Epoch 361/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1563  
Epoch 362/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1555  
Epoch 363/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1547  
Epoch 364/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1540  
Epoch 365/1000  
1/1 [=====] - 0s 23ms/step - loss: 0.1532  
Epoch 366/1000  
1/1 [=====] - 0s 6ms/step - loss: 0.1524  
Epoch 367/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1517  
Epoch 368/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1509  
Epoch 369/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1501  
Epoch 370/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1494

Epoch 371/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1486  
Epoch 372/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1479  
Epoch 373/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1471  
Epoch 374/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1463  
Epoch 375/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.1456  
Epoch 376/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1448  
Epoch 377/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1441  
Epoch 378/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1433  
Epoch 379/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1426  
Epoch 380/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1418  
Epoch 381/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1411  
Epoch 382/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1404  
Epoch 383/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1396  
Epoch 384/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1389  
Epoch 385/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1381  
Epoch 386/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1374  
Epoch 387/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1367  
Epoch 388/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1359  
Epoch 389/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1352  
Epoch 390/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1345  
Epoch 391/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1338  
Epoch 392/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1330  
Epoch 393/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1323  
Epoch 394/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1316

Epoch 395/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1309  
Epoch 396/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1302  
Epoch 397/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1295  
Epoch 398/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1288  
Epoch 399/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1281  
Epoch 400/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1274  
Epoch 401/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1267  
Epoch 402/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1260  
Epoch 403/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1253  
Epoch 404/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1246  
Epoch 405/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1239  
Epoch 406/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1232  
Epoch 407/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1225  
Epoch 408/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1218  
Epoch 409/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1212  
Epoch 410/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1205  
Epoch 411/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1198  
Epoch 412/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1191  
Epoch 413/1000  
1/1 [=====] - 0s 22ms/step - loss: 0.1185  
Epoch 414/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.1178  
Epoch 415/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1172  
Epoch 416/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1165  
Epoch 417/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1158  
Epoch 418/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1152

Epoch 419/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1146  
Epoch 420/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1139  
Epoch 421/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1133  
Epoch 422/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1126  
Epoch 423/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1120  
Epoch 424/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1114  
Epoch 425/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1107  
Epoch 426/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1101  
Epoch 427/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1095  
Epoch 428/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1089  
Epoch 429/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1082  
Epoch 430/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1076  
Epoch 431/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1070  
Epoch 432/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1064  
Epoch 433/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1058  
Epoch 434/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1052  
Epoch 435/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1046  
Epoch 436/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1040  
Epoch 437/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1034  
Epoch 438/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1028  
Epoch 439/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1022  
Epoch 440/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.1016  
Epoch 441/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.1010  
Epoch 442/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.1004



Epoch 443/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0999  
Epoch 444/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0993  
Epoch 445/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0987  
Epoch 446/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0981  
Epoch 447/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0976  
Epoch 448/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0970  
Epoch 449/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0964  
Epoch 450/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0958  
Epoch 451/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0953  
Epoch 452/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0947  
Epoch 453/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0942  
Epoch 454/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0936  
Epoch 455/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0930  
Epoch 456/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0925  
Epoch 457/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0919  
Epoch 458/1000  
1/1 [=====] - 0s 23ms/step - loss: 0.0914  
Epoch 459/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.0909  
Epoch 460/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0903  
Epoch 461/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0898  
Epoch 462/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0893  
Epoch 463/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0887  
Epoch 464/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0882  
Epoch 465/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0877  
Epoch 466/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0872

Epoch 467/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0866  
Epoch 468/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0861  
Epoch 469/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0856  
Epoch 470/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0851  
Epoch 471/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0846  
Epoch 472/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0841  
Epoch 473/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0836  
Epoch 474/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0831  
Epoch 475/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0826  
Epoch 476/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0821  
Epoch 477/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0816  
Epoch 478/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0811  
Epoch 479/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0806  
Epoch 480/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0801  
Epoch 481/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0797  
Epoch 482/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0792  
Epoch 483/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0787  
Epoch 484/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0782  
Epoch 485/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0778  
Epoch 486/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0773  
Epoch 487/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0768  
Epoch 488/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0764  
Epoch 489/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0759  
Epoch 490/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0754

Epoch 491/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0750  
Epoch 492/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0745  
Epoch 493/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0741  
Epoch 494/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0736  
Epoch 495/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0732  
Epoch 496/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0727  
Epoch 497/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0723  
Epoch 498/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0718  
Epoch 499/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0714  
Epoch 500/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0710  
Epoch 501/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0705  
Epoch 502/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0701  
Epoch 503/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0697  
Epoch 504/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0693  
Epoch 505/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0688  
Epoch 506/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0684  
Epoch 507/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0680  
Epoch 508/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0676  
Epoch 509/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0672  
Epoch 510/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0668  
Epoch 511/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0663  
Epoch 512/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0659  
Epoch 513/1000  
1/1 [=====] - 0s 30ms/step - loss: 0.0655  
Epoch 514/1000  
1/1 [=====] - 0s 9ms/step - loss: 0.0651

Epoch 515/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0647  
Epoch 516/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0643  
Epoch 517/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0639  
Epoch 518/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0635  
Epoch 519/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0632  
Epoch 520/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0628  
Epoch 521/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0624  
Epoch 522/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0620  
Epoch 523/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0616  
Epoch 524/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0613  
Epoch 525/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0609  
Epoch 526/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0605  
Epoch 527/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0602  
Epoch 528/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0598  
Epoch 529/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0594  
Epoch 530/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0591  
Epoch 531/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0587  
Epoch 532/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0584  
Epoch 533/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0580  
Epoch 534/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0577  
Epoch 535/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0573  
Epoch 536/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0570  
Epoch 537/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0566  
Epoch 538/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0563

Epoch 539/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0559  
Epoch 540/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0556  
Epoch 541/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0553  
Epoch 542/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0549  
Epoch 543/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0546  
Epoch 544/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0543  
Epoch 545/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0540  
Epoch 546/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0536  
Epoch 547/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0533  
Epoch 548/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0530  
Epoch 549/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0527  
Epoch 550/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0523  
Epoch 551/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0520  
Epoch 552/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0517  
Epoch 553/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0514  
Epoch 554/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0511  
Epoch 555/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0508  
Epoch 556/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0505  
Epoch 557/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0502  
Epoch 558/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0499  
Epoch 559/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0496  
Epoch 560/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0493  
Epoch 561/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0490  
Epoch 562/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0487

Epoch 563/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0484  
Epoch 564/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0481  
Epoch 565/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0478  
Epoch 566/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0475  
Epoch 567/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0472  
Epoch 568/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0470  
Epoch 569/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0467  
Epoch 570/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0464  
Epoch 571/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0461  
Epoch 572/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0458  
Epoch 573/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0456  
Epoch 574/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0453  
Epoch 575/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0450  
Epoch 576/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0447  
Epoch 577/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0445  
Epoch 578/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0442  
Epoch 579/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0439  
Epoch 580/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0437  
Epoch 581/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0434  
Epoch 582/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0432  
Epoch 583/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0429  
Epoch 584/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0426  
Epoch 585/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0424  
Epoch 586/1000  
1/1 [=====] - 0s 21ms/step - loss: 0.0421

Epoch 587/1000  
1/1 [=====] - 0s 7ms/step - loss: 0.0419  
Epoch 588/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0416  
Epoch 589/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0414  
Epoch 590/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0411  
Epoch 591/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0409  
Epoch 592/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.0407  
Epoch 593/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0404  
Epoch 594/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0402  
Epoch 595/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0399  
Epoch 596/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0397  
Epoch 597/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0395  
Epoch 598/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0392  
Epoch 599/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0390  
Epoch 600/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0388  
Epoch 601/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0385  
Epoch 602/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0383  
Epoch 603/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0381  
Epoch 604/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0379  
Epoch 605/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0376  
Epoch 606/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0374  
Epoch 607/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0372  
Epoch 608/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0370  
Epoch 609/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0368  
Epoch 610/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0365

Epoch 611/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0363  
Epoch 612/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0361  
Epoch 613/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0359  
Epoch 614/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0357  
Epoch 615/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0355  
Epoch 616/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0353  
Epoch 617/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0351  
Epoch 618/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0349  
Epoch 619/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0347  
Epoch 620/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0345  
Epoch 621/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0343  
Epoch 622/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0341  
Epoch 623/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0339  
Epoch 624/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0337  
Epoch 625/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0335  
Epoch 626/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0333  
Epoch 627/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0331  
Epoch 628/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0329  
Epoch 629/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0327  
Epoch 630/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0325  
Epoch 631/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.0323  
Epoch 632/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0321  
Epoch 633/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0319  
Epoch 634/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0318



Epoch 635/1000  
1/1 [=====] - 0s 29ms/step - loss: 0.0316  
Epoch 636/1000  
1/1 [=====] - 0s 6ms/step - loss: 0.0314  
Epoch 637/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0312  
Epoch 638/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0310  
Epoch 639/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0309  
Epoch 640/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0307  
Epoch 641/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0305  
Epoch 642/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0303  
Epoch 643/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0302  
Epoch 644/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0300  
Epoch 645/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0298  
Epoch 646/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0296  
Epoch 647/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0295  
Epoch 648/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0293  
Epoch 649/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0291  
Epoch 650/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0290  
Epoch 651/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0288  
Epoch 652/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0287  
Epoch 653/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0285  
Epoch 654/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0283  
Epoch 655/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0282  
Epoch 656/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0280  
Epoch 657/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0279  
Epoch 658/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0277

Epoch 659/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0275  
Epoch 660/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0274  
Epoch 661/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0272  
Epoch 662/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0271  
Epoch 663/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0269  
Epoch 664/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0268  
Epoch 665/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0266  
Epoch 666/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0265  
Epoch 667/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0263  
Epoch 668/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0262  
Epoch 669/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0260  
Epoch 670/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0259  
Epoch 671/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0258  
Epoch 672/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0256  
Epoch 673/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0255  
Epoch 674/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0253  
Epoch 675/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0252  
Epoch 676/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0251  
Epoch 677/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0249  
Epoch 678/1000  
1/1 [=====] - 0s 18ms/step - loss: 0.0248  
Epoch 679/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0246  
Epoch 680/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0245  
Epoch 681/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0244  
Epoch 682/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0242

Epoch 683/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0241  
Epoch 684/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0240  
Epoch 685/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0239  
Epoch 686/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0237  
Epoch 687/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0236  
Epoch 688/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0235  
Epoch 689/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0234  
Epoch 690/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0232  
Epoch 691/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0231  
Epoch 692/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.0230  
Epoch 693/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0229  
Epoch 694/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0228  
Epoch 695/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0226  
Epoch 696/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0225  
Epoch 697/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0224  
Epoch 698/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0223  
Epoch 699/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0222  
Epoch 700/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0221  
Epoch 701/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0219  
Epoch 702/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0218  
Epoch 703/1000  
1/1 [=====] - 0s 986us/step - loss: 0.0217  
Epoch 704/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0216  
Epoch 705/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0215  
Epoch 706/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0214

Epoch 707/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0213  
Epoch 708/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0212  
Epoch 709/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0211  
Epoch 710/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0209  
Epoch 711/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0208  
Epoch 712/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0207  
Epoch 713/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0206  
Epoch 714/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0205  
Epoch 715/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0204  
Epoch 716/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0203  
Epoch 717/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0202  
Epoch 718/1000  
1/1 [=====] - 0s 28ms/step - loss: 0.0201  
Epoch 719/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.0200  
Epoch 720/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0199  
Epoch 721/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0198  
Epoch 722/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0197  
Epoch 723/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0196  
Epoch 724/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0195  
Epoch 725/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0194  
Epoch 726/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0193  
Epoch 727/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0192  
Epoch 728/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0191  
Epoch 729/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0190  
Epoch 730/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0189

Epoch 731/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0188  
Epoch 732/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0187  
Epoch 733/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0186  
Epoch 734/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0185  
Epoch 735/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0184  
Epoch 736/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0184  
Epoch 737/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0183  
Epoch 738/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0182  
Epoch 739/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0181  
Epoch 740/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0180  
Epoch 741/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0179  
Epoch 742/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0178  
Epoch 743/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0177  
Epoch 744/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0176  
Epoch 745/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0176  
Epoch 746/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0175  
Epoch 747/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0174  
Epoch 748/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0173  
Epoch 749/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0172  
Epoch 750/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0171  
Epoch 751/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0170  
Epoch 752/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0170  
Epoch 753/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0169  
Epoch 754/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0168

Epoch 755/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0167  
Epoch 756/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0166  
Epoch 757/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0165  
Epoch 758/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0165  
Epoch 759/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0164  
Epoch 760/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0163  
Epoch 761/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0162  
Epoch 762/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0161  
Epoch 763/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0161  
Epoch 764/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0160  
Epoch 765/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0159  
Epoch 766/1000  
1/1 [=====] - 0s 24ms/step - loss: 0.0158  
Epoch 767/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0157  
Epoch 768/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0157  
Epoch 769/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0156  
Epoch 770/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0155  
Epoch 771/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0154  
Epoch 772/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0154  
Epoch 773/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0153  
Epoch 774/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0152  
Epoch 775/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0151  
Epoch 776/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0151  
Epoch 777/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0150  
Epoch 778/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0149

Epoch 779/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0148  
Epoch 780/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0148  
Epoch 781/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0147  
Epoch 782/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0146  
Epoch 783/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0146  
Epoch 784/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0145  
Epoch 785/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0144  
Epoch 786/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0143  
Epoch 787/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0143  
Epoch 788/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0142  
Epoch 789/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0141  
Epoch 790/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0141  
Epoch 791/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0140  
Epoch 792/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0139  
Epoch 793/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0139  
Epoch 794/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0138  
Epoch 795/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0137  
Epoch 796/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0137  
Epoch 797/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0136  
Epoch 798/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0135  
Epoch 799/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0135  
Epoch 800/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0134  
Epoch 801/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0133  
Epoch 802/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0133

Epoch 803/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0132  
Epoch 804/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0131  
Epoch 805/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0131  
Epoch 806/1000  
1/1 [=====] - 0s 26ms/step - loss: 0.0130  
Epoch 807/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0130  
Epoch 808/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0129  
Epoch 809/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0128  
Epoch 810/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0128  
Epoch 811/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0127  
Epoch 812/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0126  
Epoch 813/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0126  
Epoch 814/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0125  
Epoch 815/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0125  
Epoch 816/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0124  
Epoch 817/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0123  
Epoch 818/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0123  
Epoch 819/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0122  
Epoch 820/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0122  
Epoch 821/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0121  
Epoch 822/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0121  
Epoch 823/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0120  
Epoch 824/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0119  
Epoch 825/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0119  
Epoch 826/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.0118



Epoch 827/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0118  
Epoch 828/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0117  
Epoch 829/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0117  
Epoch 830/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0116  
Epoch 831/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0115  
Epoch 832/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0115  
Epoch 833/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0114  
Epoch 834/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0114  
Epoch 835/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0113  
Epoch 836/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0113  
Epoch 837/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0112  
Epoch 838/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0112  
Epoch 839/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.0111  
Epoch 840/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0110  
Epoch 841/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0110  
Epoch 842/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0109  
Epoch 843/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0109  
Epoch 844/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0108  
Epoch 845/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0108  
Epoch 846/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0107  
Epoch 847/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0107  
Epoch 848/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0106  
Epoch 849/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0106  
Epoch 850/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0105

```

Epoch 851/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0105
Epoch 852/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0104
Epoch 853/1000
1/1 [=====] - 0s 3ms/step - loss: 0.0104
Epoch 854/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0103
Epoch 855/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0103
Epoch 856/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0102
Epoch 857/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0102
Epoch 858/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0101
Epoch 859/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0101
Epoch 860/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0100
Epoch 861/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0100
Epoch 862/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0099
Epoch 863/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0099
Epoch 864/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0099
Epoch 865/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0098
Epoch 866/1000
1/1 [=====] - 0s 925us/step - loss: 0.0098
Epoch 867/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0097
Epoch 868/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0097
Epoch 869/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0096
Epoch 870/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0096
Epoch 871/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0095
Epoch 872/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0095
Epoch 873/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0094
Epoch 874/1000
1/1 [=====] - 0s 2ms/step - loss: 0.0094

```

Epoch 875/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0094  
Epoch 876/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0093  
Epoch 877/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0093  
Epoch 878/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0092  
Epoch 879/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0092  
Epoch 880/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0091  
Epoch 881/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0091  
Epoch 882/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0090  
Epoch 883/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0090  
Epoch 884/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0090  
Epoch 885/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0089  
Epoch 886/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0089  
Epoch 887/1000  
1/1 [=====] - 0s 27ms/step - loss: 0.0088  
Epoch 888/1000  
1/1 [=====] - 0s 5ms/step - loss: 0.0088  
Epoch 889/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0087  
Epoch 890/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0087  
Epoch 891/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0087  
Epoch 892/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0086  
Epoch 893/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0086  
Epoch 894/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0085  
Epoch 895/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0085  
Epoch 896/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0085  
Epoch 897/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0084  
Epoch 898/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0084

Epoch 899/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0083  
Epoch 900/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0083  
Epoch 901/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0083  
Epoch 902/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0082  
Epoch 903/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0082  
Epoch 904/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0081  
Epoch 905/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0081  
Epoch 906/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0081  
Epoch 907/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0080  
Epoch 908/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0080  
Epoch 909/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0079  
Epoch 910/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0079  
Epoch 911/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0079  
Epoch 912/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0078  
Epoch 913/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0078  
Epoch 914/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0078  
Epoch 915/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0077  
Epoch 916/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0077  
Epoch 917/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0076  
Epoch 918/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0076  
Epoch 919/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0076  
Epoch 920/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0075  
Epoch 921/1000  
1/1 [=====] - 0s 8ms/step - loss: 0.0075  
Epoch 922/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0075

Epoch 923/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0074  
Epoch 924/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0074  
Epoch 925/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0074  
Epoch 926/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0073  
Epoch 927/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0073  
Epoch 928/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0073  
Epoch 929/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0072  
Epoch 930/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0072  
Epoch 931/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0072  
Epoch 932/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0071  
Epoch 933/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0071  
Epoch 934/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0071  
Epoch 935/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0070  
Epoch 936/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0070  
Epoch 937/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0070  
Epoch 938/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0069  
Epoch 939/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0069  
Epoch 940/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0069  
Epoch 941/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0068  
Epoch 942/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0068  
Epoch 943/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0068  
Epoch 944/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0067  
Epoch 945/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0067  
Epoch 946/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0067

Epoch 947/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0067  
Epoch 948/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0066  
Epoch 949/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0066  
Epoch 950/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0066  
Epoch 951/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0065  
Epoch 952/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0065  
Epoch 953/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0065  
Epoch 954/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0064  
Epoch 955/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0064  
Epoch 956/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0064  
Epoch 957/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0064  
Epoch 958/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0063  
Epoch 959/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0063  
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Epoch 961/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0062  
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1/1 [=====] - 0s 1ms/step - loss: 0.0062  
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1/1 [=====] - 0s 1ms/step - loss: 0.0062  
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1/1 [=====] - 0s 1ms/step - loss: 0.0062  
Epoch 965/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0061  
Epoch 966/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0061  
Epoch 967/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0061  
Epoch 968/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0061  
Epoch 969/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0060  
Epoch 970/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0060

Epoch 971/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0060  
Epoch 972/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0059  
Epoch 973/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0059  
Epoch 974/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0059  
Epoch 975/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0059  
Epoch 976/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0058  
Epoch 977/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0058  
Epoch 978/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0058  
Epoch 979/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0058  
Epoch 980/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0057  
Epoch 981/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0057  
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1/1 [=====] - 0s 1ms/step - loss: 0.0057  
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1/1 [=====] - 0s 2ms/step - loss: 0.0057  
Epoch 984/1000  
1/1 [=====] - 0s 2ms/step - loss: 0.0056  
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1/1 [=====] - 0s 3ms/step - loss: 0.0056  
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1/1 [=====] - 0s 1ms/step - loss: 0.0056  
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1/1 [=====] - 0s 1ms/step - loss: 0.0056  
Epoch 988/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0056  
Epoch 989/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0055  
Epoch 990/1000  
1/1 [=====] - 0s 1ms/step - loss: 0.0055  
Epoch 991/1000  
1/1 [=====] - 0s 16ms/step - loss: 0.0055  
Epoch 992/1000  
1/1 [=====] - 0s 10ms/step - loss: 0.0055  
Epoch 993/1000  
1/1 [=====] - 0s 3ms/step - loss: 0.0054  
Epoch 994/1000  
1/1 [=====] - 0s 4ms/step - loss: 0.0054

```
Epoch 995/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0054
Epoch 996/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0054
Epoch 997/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0053
Epoch 998/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0053
Epoch 999/1000
1/1 [=====] - 0s 968us/step - loss: 0.0053
Epoch 1000/1000
1/1 [=====] - 0s 1ms/step - loss: 0.0053
```

[28]: <keras.src.callbacks.History at 0x2838a5eb0>

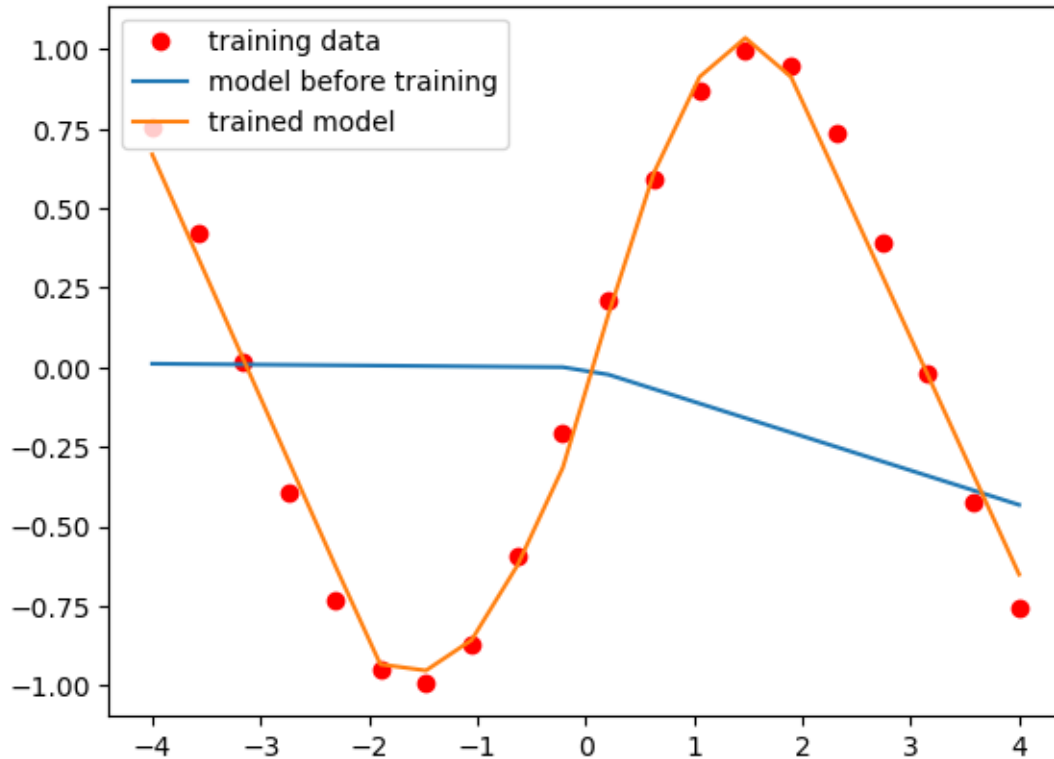
```
[29]: # Let's take a look at how the model looks like after training

y_pred = model(x)
plt.figure()
plt.plot(x,y,'ro',label = "training data")
plt.plot(x,y_pred_before_training,label = 'model before training')

plt.plot(x,y_pred,label = 'trained model')
plt.legend()
```

[29]: <matplotlib.legend.Legend at 0x28390af40>





### 3 3 NSL-KDD Example

#### 3.1 3.1. Data Ingestion and Preprocess with Spark

We are going to use the NSLKDD dataset, so we start with rerunning our old code to load and preprocess the data.

```
[30]: import pyspark
from pyspark.sql import SparkSession, SQLContext
from pyspark.ml import Pipeline, Transformer
from pyspark.ml.feature import Imputer, StandardScaler, StringIndexer, OneHotEncoder, VectorAssembler

from pyspark.sql.functions import *
from pyspark.sql.types import *
import numpy as np

col_names = ["duration", "protocol_type", "service", "flag", "src_bytes",
"dst_bytes", "land", "wrong_fragment", "urgent", "hot", "num_failed_logins",
"logged_in", "num_compromised", "root_shell", "su_attempted", "num_root",
"num_file_creations", "num_shells", "num_access_files", "num_outbound_cmds",
"is_host_login", "is_guest_login", "count", "srv_count", "serror_rate",
```

```

"srv_error_rate","error_rate","srv_error_rate","same_srv_rate",
"diff_srv_rate","srv_diff_host_rate","dst_host_count","dst_host_srv_count",
"dst_host_same_srv_rate","dst_host_diff_srv_rate","dst_host_same_src_port_rate",
"dst_host_srv_diff_host_rate","dst_host_error_rate","dst_host_srv_error_rate",
"dst_host_rerror_rate","dst_host_srv_rerror_rate","class","difficulty"]

nominal_cols = ['protocol_type','service','flag']
binary_cols = ['land', 'logged_in', 'root_shell', 'su_attempted',
    ↪ 'is_host_login',
    'is_guest_login']
continuous_cols = ['duration' , 'src_bytes', 'dst_bytes', 'wrong_fragment'
    ↪ , 'urgent', 'hot',
    'num_failed_logins', 'num_compromised', 'num_root' , 'num_file_creations',
    'num_shells', 'num_access_files', 'num_outbound_cmds', 'count' , 'srv_count',
    'error_rate', 'srv_error_rate' , 'error_rate' , 'srv_rerror_rate',
    'same_srv_rate', 'diff_srv_rate', 'srv_diff_host_rate' , 'dst_host_count',
    'dst_host_srv_count' , 'dst_host_same_srv_rate' , 'dst_host_diff_srv_rate',
    'dst_host_same_src_port_rate' , 'dst_host_srv_diff_host_rate',
    'dst_host_error_rate' , 'dst_host_srv_error_rate', 'dst_host_rerror_rate',
    'dst_host_srv_rerror_rate']

class OutcomeCreator(Transformer): # this defines a transformer that creates
    ↪ the outcome column

    def __init__(self):
        super().__init__()

    def _transform(self, dataset):
        label_to_binary = udf(lambda name: 0.0 if name == 'normal' else 1.0)
        output_df = dataset.withColumn('outcome',
    ↪ label_to_binary(col('class'))).drop("class")
        output_df = output_df.withColumn('outcome', col('outcome')).
    ↪ cast(DoubleType())
        output_df = output_df.drop('difficulty')
        return output_df

class FeatureTypeCaster(Transformer): # this transformer will cast the columns
    ↪ as appropriate types

    def __init__(self):
        super().__init__()

    def _transform(self, dataset):
        output_df = dataset
        for col_name in binary_cols + continuous_cols:
            output_df = output_df.withColumn(col_name,col(col_name)).
    ↪ cast(DoubleType())

```

```

        return output_df
class ColumnDropper(Transformer): # this transformer drops unnecessary columns
    def __init__(self, columns_to_drop = None):
        super().__init__()
        self.columns_to_drop=columns_to_drop
    def _transform(self, dataset):
        output_df = dataset
        for col_name in self.columns_to_drop:
            output_df = output_df.drop(col_name)
        return output_df

def get_preprocess_pipeline():
    # Stage where columns are casted as appropriate types
    stage_typecaster = FeatureTypeCaster()

    # Stage where nominal columns are transformed to index columns using
    ↪StringIndexer
    nominal_id_cols = [x+"_index" for x in nominal_cols]
    nominal_onehot_cols = [x+"_encoded" for x in nominal_cols]
    stage_nominal_indexer = StringIndexer(inputCols = nominal_cols, outputCols=
    ↪nominal_id_cols )

    # Stage where the index columns are further transformed using OneHotEncoder
    stage_nominal_onehot_encoder = OneHotEncoder(inputCols=nominal_id_cols,
    ↪outputCols=nominal_onehot_cols)

    # Stage where all relevant features are assembled into a vector (and
    ↪dropping a few)
    feature_cols = continuous_cols+binary_cols+nominal_onehot_cols
    correlated_cols_to_remove =
    ↪["dst_host_serror_rate", "srv_serror_rate", "dst_host_srv_serror_rate",
    ↪
    ↪"srv_rerror_rate", "dst_host_rerror_rate", "dst_host_srv_rerror_rate"]
    for col_name in correlated_cols_to_remove:
        feature_cols.remove(col_name)
    stage_vector_assembler = VectorAssembler(inputCols=feature_cols,
    ↪outputCol="vectorized_features")

    # Stage where we scale the columns
    stage_scaler = StandardScaler(inputCol= 'vectorized_features', outputCol=
    ↪'features')

    # Stage for creating the outcome column representing whether there is
    ↪attack

```

```

stage_outcome = OutcomeCreator()

# Removing all unnecessary columns, only keeping the 'features' and
↳ 'outcome' columns
stage_column_dropper = ColumnDropper(columns_to_drop =
↳ nominal_cols+nominal_id_cols+
    nominal_onehot_cols+ binary_cols + continuous_cols +
↳ ['vectorized_features'])
# Connect the columns into a pipeline
pipeline =
↳ Pipeline(stages=[stage_typecaster,stage_nominal_indexer,stage_nominal_onehot_encoder,
    stage_vector_assembler,stage_scaler,stage_outcome,stage_column_dropper])
return pipeline

```

```

[31]: # if you installed Spark on windows,
# you may need findspark and need to initialize it prior to being able to use
↳ pyspark
# Also, you may need to initialize SparkContext yourself.
# Uncomment the following lines if you are using Windows!
#import findspark
#findspark.init()
#findspark.find()

spark = SparkSession.builder \
    .master("local[*]") \
    .appName("GenericAppName") \
    .getOrCreate()

nslkdd_raw = spark.read.csv('./NSL-KDD/KDDTrain+.txt',header=False).
↳ toDF(*col_names)
nslkdd_test_raw = spark.read.csv('./NSL-KDD/KDDTest+.txt',header=False).
↳ toDF(*col_names)

preprocess_pipeline = get_preprocess_pipeline()
preprocess_pipeline_model = preprocess_pipeline.fit(nslkdd_raw)

nslkdd_df = preprocess_pipeline_model.transform(nslkdd_raw)
nslkdd_df_test = preprocess_pipeline_model.transform(nslkdd_test_raw)

```

Setting default log level to "WARN".

To adjust logging level use `sc.setLogLevel(newLevel)`. For SparkR, use `setLogLevel(newLevel)`.

24/09/15 19:52:52 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable

24/09/15 19:53:05 WARN SparkStringUtils: Truncated the string representation of a plan since it was too large. This behavior can be adjusted by setting 'spark.sql.debug.maxToStringFields'.

In addition to the train and test dataset, let's also create a validation set.

Normally, the validation set should be a subset of the training set, but our training set is not challenging enough which makes the later tuning part not interesting. Therefore, for today's purpose, we are going to use 50% of the test set as the validation set, and the remaining 50% is left as the test set.

After splitting, we convert the three dataframes to pandas dataframes.

```
[32]: to_array = udf(lambda v: v.toArray().toList(), ArrayType(FloatType()))

nslkdd_df_train = nslkdd_df
nslkdd_df_validate, nslkdd_df_test = nslkdd_df_test.randomSplit([0.5, 0.5])

nslkdd_df_train_pandas = nslkdd_df_train.withColumn('features',
↳ to_array('features')).toPandas()
nslkdd_df_validate_pandas = nslkdd_df_validate.withColumn('features',
↳ to_array('features')).toPandas()
nslkdd_df_test_pandas = nslkdd_df_test.withColumn('features',
↳ to_array('features')).toPandas()
```

We further convert the pandas dataframes to nparrays, and then tensors. We will use these tensors for today's lecture.

```
[33]: import tensorflow as tf
from tensorflow import keras

# Converting the pandas DataFrame to tensors
# Note we are using 3 data sets train, validate, test

x_train = tf.constant(np.array(nslkdd_df_train_pandas['features'].values.
↳ tolist()))
y_train = tf.constant(np.array(nslkdd_df_train_pandas['outcome'].values.
↳ tolist()))

x_validate = tf.constant(np.array(nslkdd_df_validate_pandas['features'].values.
↳ tolist()))
y_validate = tf.constant(np.array(nslkdd_df_validate_pandas['outcome'].values.
↳ tolist()))

x_test = tf.constant(np.array(nslkdd_df_test_pandas['features'].values.
↳ tolist()))
y_test = tf.constant(np.array(nslkdd_df_test_pandas['outcome'].values.tolist()))
```

## 3.2 Building Neural Networks for NSL-KDD with tf.keras

Let's create a simple neural network.

```
[34]: model = keras.Sequential([keras.layers.Dense(10,activation='relu'),
                                keras.layers.Dense(10,activation='relu'),
                                keras.layers.Dense(10,activation='relu'),
                                keras.layers.Dense(10,activation='relu') ,
                                keras.layers.Dense(2)] )

y_pred = model(x_train)
model.summary()
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
dense_13 (Dense)	(125973, 10)	1140
dense_14 (Dense)	(125973, 10)	110
dense_15 (Dense)	(125973, 10)	110
dense_16 (Dense)	(125973, 10)	110
dense_17 (Dense)	(125973, 2)	22

=====  
Total params: 1492 (5.83 KB)  
Trainable params: 1492 (5.83 KB)  
Non-trainable params: 0 (0.00 Byte)  
=====

Let's now compile the model. You need to use the `SparseCategoricalCrossentropy` as the loss.

```
[35]: # Compile the model
model.compile(optimizer = 'sgd',
              loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True))
```

Note that it is important to set `from_logits = True` in `keras.losses.SparseCategoricalCrossentropy`. This is because the output of the neural network is the score (in other words, “logits”), not the probability.

If you want to use `from_logits = False` (which is the default value), you need to convert the score to the probability via the softmax function. See experiment below.

```
[36]: loss_func_from_logit_true = keras.losses.
      ↪SparseCategoricalCrossentropy(from_logits=True)
```

```

loss_func_from_logit_false = keras.losses.
    ↪SparseCategoricalCrossentropy(from_logits=False)

loss_1 = loss_func_from_logit_true(y_train[:5],y_pred[:5])
    ↪          # This is correct as y_pred is score and from_logits = True in
    ↪loss_func_1
loss_2 = loss_func_from_logit_false(y_train[:5],y_pred[:5])
    ↪          # This is wrong as y_pred is score but from_logits = False in
    ↪loss_func_2
loss_3 = loss_func_from_logit_false(y_train[:5],
                                     tf.keras.activations.softmax(y_pred[:5])) # This is
    ↪correct as now we have converted the score to probability using the softmax

print("loss_1 = ", loss_1 )
print("loss_2 = ", loss_2 )
print("loss_3 = ", loss_3)

```

```

loss_1 = tf.Tensor(0.6546897, shape=(), dtype=float32)
loss_2 = tf.Tensor(0.6992447, shape=(), dtype=float32)
loss_3 = tf.Tensor(0.6546897, shape=(), dtype=float32)

```

Because of the equivalence between `loss_1` and `loss_3` above, another way to create the model is to add a softmax activation at the output layer, in which case you need to set `from_logits = False` when you compile.

```

[37]: model2 = keras.Sequential( [keras.layers.Dense(10,activation='relu'),
                                   keras.layers.Dense(10,activation='relu'),
                                   keras.layers.Dense(10,activation='relu'),
                                   keras.layers.Dense(10,activation='relu') ,
                                   keras.layers.Dense(2,activation='softmax')] )

model2.compile(optimizer = 'sgd',loss=keras.losses.
    ↪SparseCategoricalCrossentropy(from_logits=False))

```

Let's now fit the model. In addition to specify the training data `x_train,y_train`, here we can also specify `validation_data` as our validation data set. We can also provide a list of metrics, and we are using Accuracy.

After every epoch during the fitting process, the model will be evaluated using the validation dataset, and the metrics will be computed.

One thing to note is here we set `verbose = 2` to reduce the printing of the fit function to only print per epoch information.

```

[38]: model = keras.Sequential( [keras.layers.Dense(10,activation='relu'),
                                   keras.layers.Dense(10,activation='relu'),
                                   keras.layers.Dense(10,activation='relu'),
                                   keras.layers.Dense(10,activation='relu') ,
                                   keras.layers.Dense(2)] )

```

```

model.compile(optimizer = keras.optimizers.SGD(learning_rate=0.02),
              loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=[keras.metrics.SparseCategoricalAccuracy()])

model.fit(x_train,y_train, epochs = 5,batch_size = 64,
          validation_data=(x_validate,y_validate),verbose = 2)

```

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at `tf.keras.optimizers.legacy.SGD`.

WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e., `tf.keras.optimizers.legacy.SGD`.

```

Epoch 1/5
1969/1969 - 1s - loss: 0.1190 - sparse_categorical_accuracy: 0.9635 - val_loss:
0.8395 - val_sparse_categorical_accuracy: 0.7533 - 810ms/epoch - 411us/step
Epoch 2/5
1969/1969 - 1s - loss: 0.0563 - sparse_categorical_accuracy: 0.9799 - val_loss:
0.8437 - val_sparse_categorical_accuracy: 0.7711 - 534ms/epoch - 271us/step
Epoch 3/5
1969/1969 - 1s - loss: 0.0360 - sparse_categorical_accuracy: 0.9879 - val_loss:
0.9250 - val_sparse_categorical_accuracy: 0.8025 - 542ms/epoch - 275us/step
Epoch 4/5
1969/1969 - 1s - loss: 0.0299 - sparse_categorical_accuracy: 0.9904 - val_loss:
1.0321 - val_sparse_categorical_accuracy: 0.8032 - 549ms/epoch - 279us/step
Epoch 5/5
1969/1969 - 1s - loss: 0.0276 - sparse_categorical_accuracy: 0.9913 - val_loss:
1.2070 - val_sparse_categorical_accuracy: 0.7859 - 548ms/epoch - 278us/step

```

[38]: <keras.src.callbacks.History at 0x2d55cb940>

Finally, let's evaluate on Test Data

```
[39]: model.evaluate(x_test,y_test, verbose = 2)
```

```

350/350 - 0s - loss: 1.2451 - sparse_categorical_accuracy: 0.7797 - 89ms/epoch -
255us/step

```

[39]: [1.245111346244812, 0.7797065377235413]



## 4 4. TensorBoard

### 4.1 4.1 Displaying the results in TensorBoard

TensorBoard is a very powerful visualization tool. One simple usage of TensorBoard is to visualize the fitting process.

To that end, we need to create a `tf.keras.callbacks.TensorBoard` callback object that points to a log directory - you can pick any directory you want. Then, when calling `Model.fit()`, you need to pass the callback object to `Model.fit()`.

```
[40]: import datetime

model = keras.Sequential( [keras.layers.Dense(10,activation='relu'),
    keras.layers.Dense(10,activation='relu'),
    keras.layers.Dense(10,activation='relu') ,
    keras.layers.Dense(2)] )
model.compile(loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
    metrics=[keras.metrics.SparseCategoricalAccuracy(name='Accuracy')])
log_dir = "logs14763/myfirstlog/" + datetime.datetime.now().
    ↪strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,
    ↪histogram_freq=1)
model.fit(x=x_train, y=y_train,
    epochs=20, verbose = 2,
    validation_data=(x_validate, y_validate),
    callbacks=[tensorboard_callback])
```

Epoch 1/20

3937/3937 - 2s - loss: 0.0713 - Accuracy: 0.9781 - val\_loss: 1.0103 -  
val\_Accuracy: 0.7814 - 2s/epoch - 391us/step

Epoch 2/20

3937/3937 - 2s - loss: 0.0403 - Accuracy: 0.9899 - val\_loss: 1.3445 -  
val\_Accuracy: 0.7787 - 2s/epoch - 548us/step

Epoch 3/20

3937/3937 - 1s - loss: 0.0367 - Accuracy: 0.9913 - val\_loss: 1.3546 -  
val\_Accuracy: 0.7855 - 1s/epoch - 329us/step

Epoch 4/20

3937/3937 - 1s - loss: 0.0365 - Accuracy: 0.9918 - val\_loss: 1.5001 -  
val\_Accuracy: 0.7838 - 1s/epoch - 314us/step

Epoch 5/20

3937/3937 - 1s - loss: 0.0359 - Accuracy: 0.9922 - val\_loss: 2.1015 -  
val\_Accuracy: 0.7803 - 1s/epoch - 321us/step

Epoch 6/20

3937/3937 - 2s - loss: 0.0422 - Accuracy: 0.9922 - val\_loss: 2.2532 -  
val\_Accuracy: 0.7783 - 2s/epoch - 384us/step

Epoch 7/20

3937/3937 - 1s - loss: 0.0415 - Accuracy: 0.9924 - val\_loss: 2.0472 -

```

val_Accuracy: 0.7765 - 1s/epoch - 290us/step
Epoch 8/20
3937/3937 - 1s - loss: 0.0431 - Accuracy: 0.9923 - val_loss: 1.8469 -
val_Accuracy: 0.7898 - 1s/epoch - 294us/step
Epoch 9/20
3937/3937 - 1s - loss: 0.0410 - Accuracy: 0.9920 - val_loss: 1.9142 -
val_Accuracy: 0.7978 - 1s/epoch - 287us/step
Epoch 10/20
3937/3937 - 1s - loss: 0.0400 - Accuracy: 0.9918 - val_loss: 2.6968 -
val_Accuracy: 0.7828 - 1s/epoch - 294us/step
Epoch 11/20
3937/3937 - 1s - loss: 0.0393 - Accuracy: 0.9916 - val_loss: 3.0248 -
val_Accuracy: 0.7851 - 1s/epoch - 288us/step
Epoch 12/20
3937/3937 - 1s - loss: 0.0364 - Accuracy: 0.9915 - val_loss: 4.0466 -
val_Accuracy: 0.7870 - 1s/epoch - 285us/step
Epoch 13/20
3937/3937 - 1s - loss: 0.0385 - Accuracy: 0.9919 - val_loss: 4.3652 -
val_Accuracy: 0.7941 - 1s/epoch - 287us/step
Epoch 14/20
3937/3937 - 1s - loss: 0.0399 - Accuracy: 0.9918 - val_loss: 3.9634 -
val_Accuracy: 0.8111 - 1s/epoch - 285us/step
Epoch 15/20
3937/3937 - 1s - loss: 0.0376 - Accuracy: 0.9923 - val_loss: 4.3366 -
val_Accuracy: 0.8041 - 1s/epoch - 291us/step
Epoch 16/20
3937/3937 - 2s - loss: 0.0411 - Accuracy: 0.9918 - val_loss: 3.9977 -
val_Accuracy: 0.8330 - 2s/epoch - 457us/step
Epoch 17/20
3937/3937 - 1s - loss: 0.0493 - Accuracy: 0.9918 - val_loss: 5.2738 -
val_Accuracy: 0.8264 - 1s/epoch - 292us/step
Epoch 18/20
3937/3937 - 1s - loss: 0.0484 - Accuracy: 0.9918 - val_loss: 5.3899 -
val_Accuracy: 0.8402 - 1s/epoch - 299us/step
Epoch 19/20
3937/3937 - 1s - loss: 0.0516 - Accuracy: 0.9916 - val_loss: 4.8307 -
val_Accuracy: 0.8226 - 1s/epoch - 288us/step
Epoch 20/20
3937/3937 - 1s - loss: 0.0559 - Accuracy: 0.9917 - val_loss: 4.2636 -
val_Accuracy: 0.8103 - 1s/epoch - 289us/step

```

[40]: <keras.src.callbacks.History at 0x283b4bbb0>

To launch tensorboard in notebook, you can run the code below.

You can also run `tensorboard --logdir logs14763/myfirstlog/` in the terminal, which will show a URL, and you can open it in the browser.

No matter which way you use, it is important to specify the correct log directory - it should be the

same as the directory when you created the callback.

```
[ ]: %load_ext tensorboard
      %tensorboard --logdir logs14763/myfirstlog/
```

## 4.2 4.2 Hyper-Parameter Tuning with Tensor Board

TensorBoard also provides a powerful tool for visualizing hyper parameter tuning.

The first step is to specify what hyper parameters to tune and set up the configuration.

```
[42]: from tensorboard.plugins.hparams import api as hp

HP_WIDTH = hp.HParam('NN_width', hp.Discrete([20,30]))
HP_DEPTH = hp.HParam('NN_depth', hp.Discrete([4,6]))

with tf.summary.create_file_writer('logs14763/hparam_tuning').as_default():
    hp.hparams_config(
        hparams=[HP_WIDTH, HP_DEPTH],
        metrics=[hp.Metric('Accuracy')],
    )
```

Next, we write a training function, which takes the hyper parameters as the input and train a model using the hyper parameters. This function will return the metrics corresponding to the hyper parameters.

```
[43]: def train_test_model(hparams, logdir):
        model = keras.Sequential()
        for _ in range(hparams[HP_DEPTH]):
            model.add(keras.layers.Dense(hparams[HP_WIDTH], activation='relu'))
        model.add(keras.layers.Dense(2))
        model.compile(
            optimizer=keras.optimizers.SGD(),
            loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True),
            metrics=[keras.metrics.SparseCategoricalAccuracy(name="Accuracy_epochs")]

        history = model.fit(x_train, y_train, epochs=5, verbose = 2,
            callbacks=[tf.keras.callbacks.TensorBoard(log_dir=logdir, histogram_freq=1)],
            validation_data = (x_validate, y_validate))

        accuracy = np.max(history.history["val_Accuracy_epochs"])
        return accuracy
```

Finally, we go through all combinations of hyper parameters and run the `train_test_model` above. After each run, we will record the hyper parameters we used in this run, and the corresponding metrics.

```
[44]: for hp_width in HP_WIDTH.domain.values:
      for hp_depth in (HP_DEPTH.domain.values):
          hparams = {
              HP_WIDTH: hp_width,
              HP_DEPTH: hp_depth,
          }
          run_name = f"run-WIDTH{int(hparams[HP_WIDTH])}-DEPTH{hparams[HP_DEPTH]}"
          print('--- Starting trial: %s' % run_name)
          print({h.name: hparams[h] for h in hparams})

          run_dir = 'logs14763/hparam_tuning/' + run_name
          accuracy = train_test_model(hparams, run_dir)

          with tf.summary.create_file_writer(run_dir).as_default():
              hp.hparams(hparams) # record the values used in this trial
              tf.summary.scalar("Accuracy", accuracy, step=1)
```

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at `tf.keras.optimizers.legacy.SGD`.

WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e., `tf.keras.optimizers.legacy.SGD`.

--- Starting trial: run-WIDTH20-DEPTH4

{'NN\_width': 20, 'NN\_depth': 4}

Epoch 1/5

3937/3937 - 2s - loss: 0.0992 - Accuracy\_epochs: 0.9702 - val\_loss: 1.3471 - val\_Accuracy\_epochs: 0.7597 - 2s/epoch - 396us/step

Epoch 2/5

3937/3937 - 2s - loss: 0.0397 - Accuracy\_epochs: 0.9866 - val\_loss: 1.3635 - val\_Accuracy\_epochs: 0.7792 - 2s/epoch - 416us/step

Epoch 3/5

3937/3937 - 1s - loss: 0.0274 - Accuracy\_epochs: 0.9912 - val\_loss: 1.6254 - val\_Accuracy\_epochs: 0.7856 - 1s/epoch - 258us/step

Epoch 4/5

3937/3937 - 1s - loss: 0.0234 - Accuracy\_epochs: 0.9922 - val\_loss: 1.5332 - val\_Accuracy\_epochs: 0.7856 - 1s/epoch - 263us/step

Epoch 5/5

3937/3937 - 1s - loss: 0.0216 - Accuracy\_epochs: 0.9928 - val\_loss: 1.5466 - val\_Accuracy\_epochs: 0.7853 - 1s/epoch - 259us/step

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at `tf.keras.optimizers.legacy.SGD`.

WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on

```

M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e.,
`tf.keras.optimizers.legacy.SGD`.

--- Starting trial: run-WIDTH20-DEPTH6
{'NN_width': 20, 'NN_depth': 6}
Epoch 1/5
3937/3937 - 2s - loss: 0.1021 - Accuracy_epochs: 0.9714 - val_loss: 0.7667 -
val_Accuracy_epochs: 0.8026 - 2s/epoch - 401us/step
Epoch 2/5
3937/3937 - 1s - loss: 0.0325 - Accuracy_epochs: 0.9892 - val_loss: 0.8954 -
val_Accuracy_epochs: 0.7991 - 1s/epoch - 341us/step
Epoch 3/5
3937/3937 - 1s - loss: 0.0267 - Accuracy_epochs: 0.9905 - val_loss: 1.1704 -
val_Accuracy_epochs: 0.7897 - 1s/epoch - 273us/step
Epoch 4/5
3937/3937 - 1s - loss: 0.0240 - Accuracy_epochs: 0.9915 - val_loss: 1.2842 -
val_Accuracy_epochs: 0.7858 - 1s/epoch - 271us/step
Epoch 5/5
3937/3937 - 1s - loss: 0.0219 - Accuracy_epochs: 0.9928 - val_loss: 1.2027 -
val_Accuracy_epochs: 0.7931 - 1s/epoch - 288us/step

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.SGD`.
WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on
M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e.,
`tf.keras.optimizers.legacy.SGD`.

--- Starting trial: run-WIDTH30-DEPTH4
{'NN_width': 30, 'NN_depth': 4}
Epoch 1/5
3937/3937 - 2s - loss: 0.0989 - Accuracy_epochs: 0.9696 - val_loss: 1.2051 -
val_Accuracy_epochs: 0.7461 - 2s/epoch - 424us/step
Epoch 2/5
3937/3937 - 1s - loss: 0.0429 - Accuracy_epochs: 0.9843 - val_loss: 1.2038 -
val_Accuracy_epochs: 0.7727 - 1s/epoch - 275us/step
Epoch 3/5
3937/3937 - 1s - loss: 0.0301 - Accuracy_epochs: 0.9902 - val_loss: 1.4188 -
val_Accuracy_epochs: 0.7753 - 1s/epoch - 267us/step
Epoch 4/5
3937/3937 - 1s - loss: 0.0252 - Accuracy_epochs: 0.9914 - val_loss: 1.3904 -
val_Accuracy_epochs: 0.7827 - 1s/epoch - 271us/step
Epoch 5/5
3937/3937 - 1s - loss: 0.0229 - Accuracy_epochs: 0.9918 - val_loss: 1.3934 -
val_Accuracy_epochs: 0.7810 - 1s/epoch - 265us/step

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.SGD` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.SGD`.
WARNING:absl:There is a known slowdown when using v2.11+ Keras optimizers on

```

M1/M2 Macs. Falling back to the legacy Keras optimizer, i.e.,  
`tf.keras.optimizers.legacy.SGD`.

--- Starting trial: run-WIDTH30-DEPTH6

{'NN\_width': 30, 'NN\_depth': 6}

Epoch 1/5

3937/3937 - 1s - loss: 0.0932 - Accuracy\_epochs: 0.9735 - val\_loss: 1.2155 -  
val\_Accuracy\_epochs: 0.7480 - 1s/epoch - 347us/step

Epoch 2/5

3937/3937 - 2s - loss: 0.0323 - Accuracy\_epochs: 0.9894 - val\_loss: 1.1343 -  
val\_Accuracy\_epochs: 0.7845 - 2s/epoch - 408us/step

Epoch 3/5

3937/3937 - 1s - loss: 0.0250 - Accuracy\_epochs: 0.9914 - val\_loss: 1.1070 -  
val\_Accuracy\_epochs: 0.7817 - 1s/epoch - 350us/step

Epoch 4/5

3937/3937 - 1s - loss: 0.0220 - Accuracy\_epochs: 0.9923 - val\_loss: 1.2443 -  
val\_Accuracy\_epochs: 0.7799 - 1s/epoch - 290us/step

Epoch 5/5

3937/3937 - 1s - loss: 0.0202 - Accuracy\_epochs: 0.9930 - val\_loss: 1.1642 -  
val\_Accuracy\_epochs: 0.7814 - 1s/epoch - 288us/step