

```
In [2]: import mnist_loader
import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

1

```
In [38]: training_data, validation_data, test_data = mnist_loader.load_data_wrapper()
training_data = list(training_data)
validation_data = list(validation_data)
test_data = list(test_data)

def plot_digit(digit):
    # A function to plot a vector of length 784 as a 28 x 28 image
    digit_image = digit.reshape(28,28)
    plt.imshow(digit_image, cmap = plt.get_cmap('gray'))
    plt.axis("off")
    plt.show()
```

a

```
In [39]: def sigmoid(z):
    return 1.0 / (1.0 + np.exp(-z))

def sigmoid_prime(z):
    return sigmoid(z) * (1 - sigmoid(z))

class Network(object):
    def __init__(self, sizes):
        self.num_layers = len(sizes)
        self.sizes = sizes
        self.biases = [np.random.randn(y, 1) for y in sizes[1:]]
        self.weights = [np.random.randn(y, x) for x, y in zip(sizes[:-1], sizes[1:])]

    def feedforward(self, a):
        for b, w in zip(self.biases, self.weights):
            a = sigmoid(np.dot(w, a) + b)
        return a

    def SGD(self, training_data, epochs, mini_batch_size, eta, test_data=None):
        training_data = list(training_data)
        n = len(training_data)
        if test_data:
            test_data = list(test_data)
            n_test = len(test_data)
        for j in range(epochs):
            random.shuffle(training_data)
            mini_batches = [training_data[k:k + mini_batch_size] for k in range(0, n, mini_batch_size)]
            for mini_batch in mini_batches:
                self.update_mini_batch(mini_batch, eta)
            if test_data:
                print("Epoch {} : {} / {}".format(j, self.evaluate(test_data), n_test))
            else:
                print("Epoch {} complete".format(j))

    def update_mini_batch(self, mini_batch, eta):
        nabla_b = [np.zeros(b.shape) for b in self.biases]
        nabla_w = [np.zeros(w.shape) for w in self.weights]
```

```

    for x, y in mini_batch:
        delta_nabla_b, delta_nabla_w = self.backprop(x, y)
        nabla_b = [nb + dnb for nb, dnb in zip(nabla_b, delta_nabla_b)]
        nabla_w = [nw + dnw for nw, dnw in zip(nabla_w, delta_nabla_w)]
        self.weights = [w - (eta / len(mini_batch)) * nw for w, nw in zip(self.weights, nabla_w)]
        self.biases = [b - (eta / len(mini_batch)) * nb for b, nb in zip(self.biases, nabla_b)]

    def backprop(self, x, y):
        nabla_b = [np.zeros(b.shape) for b in self.biases]
        nabla_w = [np.zeros(w.shape) for w in self.weights]
        activation = x
        activations = [x]
        zs = []
        for b, w in zip(self.biases, self.weights):
            z = np.dot(w, activation) + b
            zs.append(z)
            activation = sigmoid(z)
            activations.append(activation)
        delta = self.cost_derivative(activations[-1], y) * sigmoid_prime(zs[-1])
        nabla_b[-1] = delta
        nabla_w[-1] = np.dot(delta, activations[-2].transpose())
        for l in range(2, self.num_layers):
            z = zs[-l]
            sp = sigmoid_prime(z)
            delta = np.dot(self.weights[-l + 1].transpose(), delta) * sp
            nabla_b[-l] = delta
            nabla_w[-l] = np.dot(delta, activations[-l - 1].transpose())
        return (nabla_b, nabla_w)

    def evaluate(self, test_data):
        test_results = [(np.argmax(self.feedforward(x)), y) for (x, y) in test_data]
        return sum(int(x == y) for (x, y) in test_results)

    def cost_derivative(self, output_activations, y):
        return (output_activations - y)

```

```

In [40]: encoder=Network([784,10])
encoder.SGD(training_data,10,10,3.0,test_data=test_data)

```

```

Epoch 0 : 5799 / 10000
Epoch 1 : 6527 / 10000
Epoch 2 : 7389 / 10000
Epoch 3 : 7493 / 10000
Epoch 4 : 7494 / 10000
Epoch 5 : 7575 / 10000
Epoch 6 : 8369 / 10000
Epoch 7 : 8337 / 10000
Epoch 8 : 8344 / 10000
Epoch 9 : 8387 / 10000

```

b

```

In [42]: decoder=Network([10, 784])

latent_vectors=[encoder.feedforward(x) for x, _ in training_data]
targets =[x for x, _ in training_data]
training_data_decoder=list(zip(latent_vectors, targets))
decoder.SGD(training_data_decoder,10,10,3.0)

```

Epoch 0 complete
Epoch 1 complete
Epoch 2 complete
Epoch 3 complete
Epoch 4 complete
Epoch 5 complete
Epoch 6 complete
Epoch 7 complete
Epoch 8 complete
Epoch 9 complete

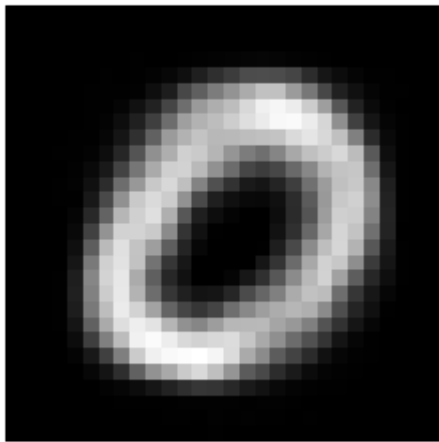
c

Each column of the decoder's weight matrix represents a basis vector in the original 784 dimensional space, capturing features or patterns like strokes or edges that are combined to reconstruct the input image from the latent vector.

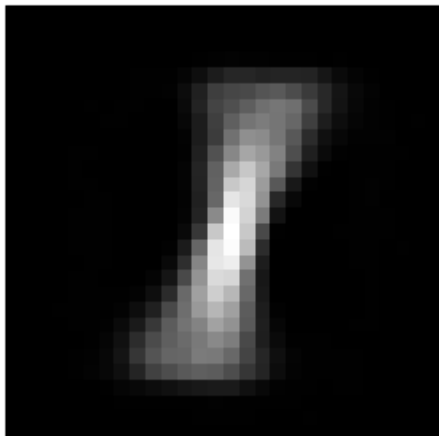
d

```
In [43]: perfect_vectors=[np.eye(10)[: ,k].reshape(10,1) for k in range(10)]  
  
reconstructed_images=[decoder.feedforward(vec) for vec in perfect_vectors]  
  
for digit, image in enumerate(perfect_reconstructed_images):  
    print(f"Reconstructed Image for Perfect Example of Digit {digit}:")  
    plot_digit(image.reshape(28,28))
```

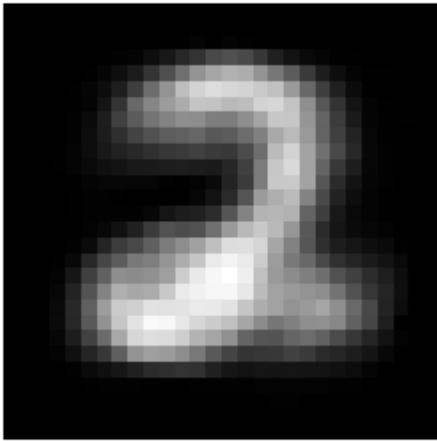
Reconstructed Image for Perfect Example of Digit 0:



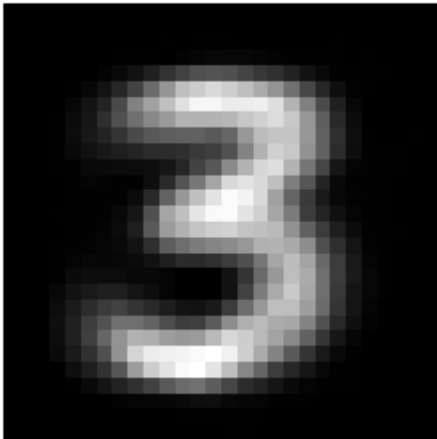
Reconstructed Image for Perfect Example of Digit 1:



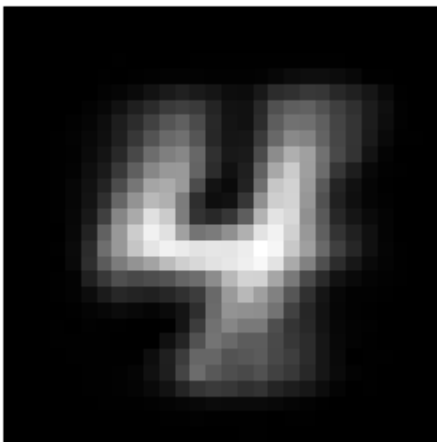
Reconstructed Image for Perfect Example of Digit 2:



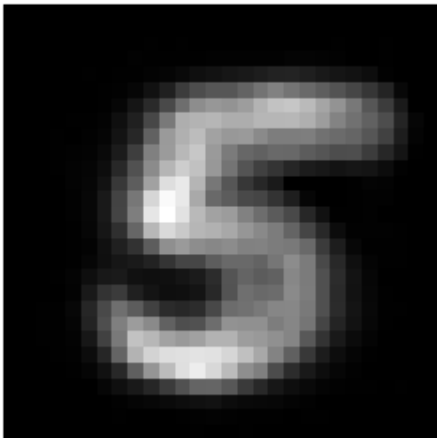
Reconstructed Image for Perfect Example of Digit 3:



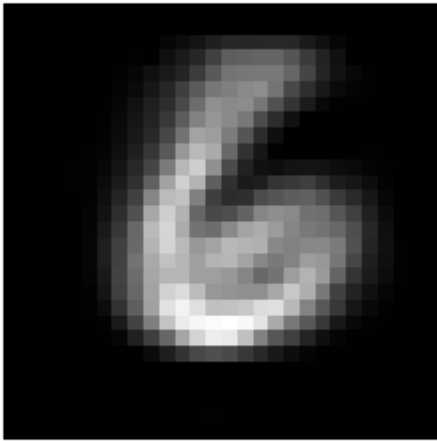
Reconstructed Image for Perfect Example of Digit 4:



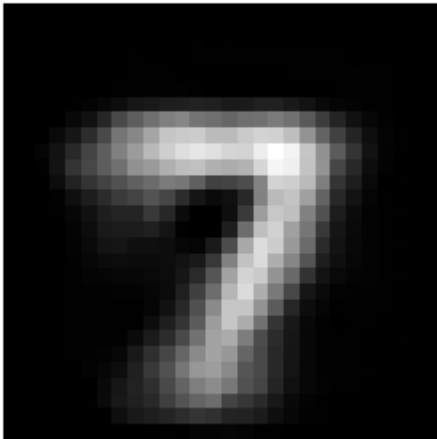
Reconstructed Image for Perfect Example of Digit 5:



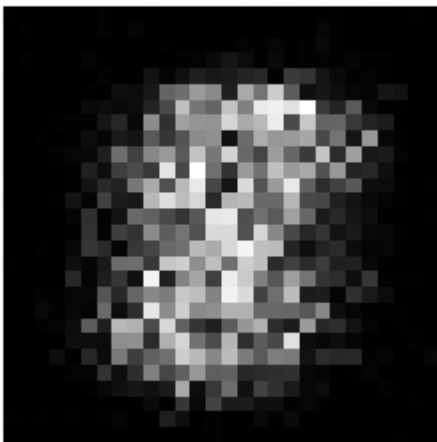
Reconstructed Image for Perfect Example of Digit 6:



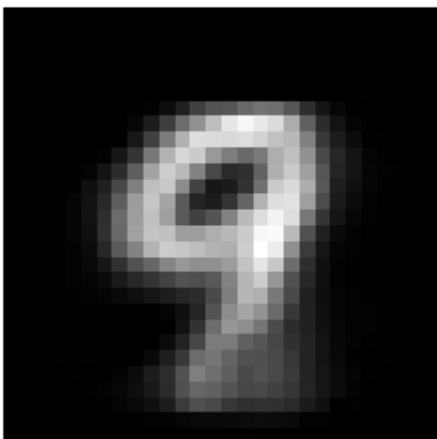
Reconstructed Image for Perfect Example of Digit 7:



Reconstructed Image for Perfect Example of Digit 8:



Reconstructed Image for Perfect Example of Digit 9:



e

```
In [46]: class Autoencoder:
    def __init__(self, encoder, decoder):
        self.encoder = encoder
        self.decoder = decoder

    def encode(self, input_data):
        return self.encoder.feedforward(input_data)

    def decode(self, latent_representation):
        return self.decoder.feedforward(latent_representation)

    def reconstruct(self, input_data):
        latent_representation = self.encode(input_data)
        reconstructed_output = self.decode(latent_representation)
        return reconstructed_output

    def train(self, training_data, epochs_encoder, epochs_decoder, mini_batch_size, eta, test_data):
        #Train encoder
        self.encoder.SGD(training_data, epochs_encoder, mini_batch_size, eta, test_data)

        #Latent vectors using trained encoder
        latent_vectors = [self.encoder.feedforward(x) for x, _ in training_data]
        targets = [x for x, _ in training_data]
        training_data_decoder = list(zip(latent_vectors, targets))

        #Train decoder
        self.decoder.SGD(training_data_decoder, epochs_decoder, mini_batch_size, eta)
```

f

```
In [104... encoder=Network([784,10])
decoder=Network([10,784])
autoencoder=Autoencoder(encoder,decoder)

autoencoder.train(training_data,10,10,10,3.0,test_data)
```

```
Epoch 0 : 8018 / 10000
Epoch 1 : 8215 / 10000
Epoch 2 : 8308 / 10000
Epoch 3 : 8310 / 10000
Epoch 4 : 8323 / 10000
Epoch 5 : 8356 / 10000
Epoch 6 : 8358 / 10000
Epoch 7 : 8367 / 10000
Epoch 8 : 8359 / 10000
Epoch 9 : 8384 / 10000
Epoch 0 complete
Epoch 1 complete
Epoch 2 complete
Epoch 3 complete
Epoch 4 complete
Epoch 5 complete
Epoch 6 complete
Epoch 7 complete
Epoch 8 complete
Epoch 9 complete
```

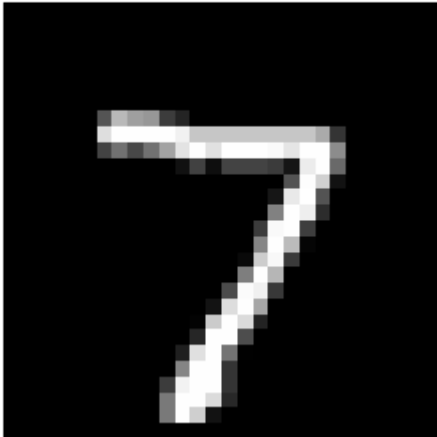
```
In [106... indices=[0,1,2,3,4]

for i in indices:
    x,y=test_data[i]

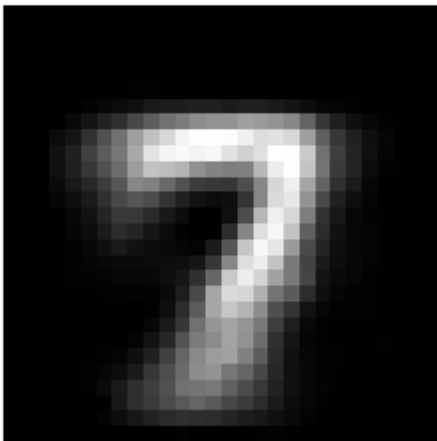
    reconstructed_image=autoencoder.reconstruct(x)
```

```
print(f"Original Image Labeled as {y}:")  
plot_digit(x.reshape(28,28))  
print("Reconstructed Image:")  
plot_digit(reconstructed_image.reshape(28,28))
```

Original Image Labeled as 7:



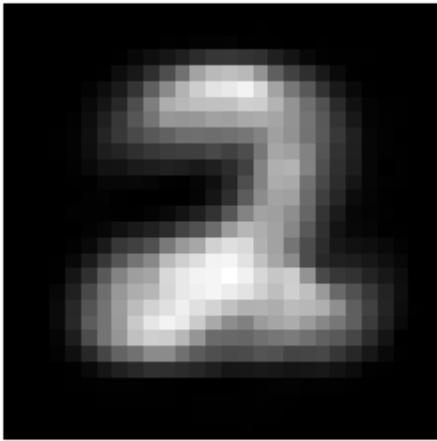
Reconstructed Image:



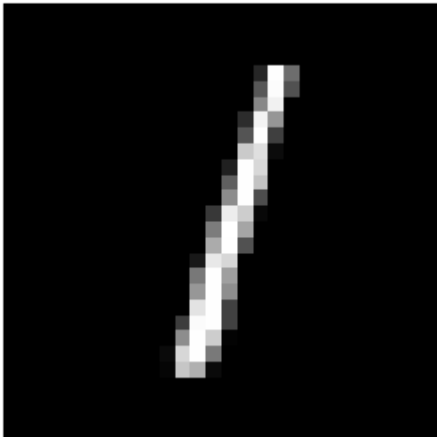
Original Image Labeled as 2:



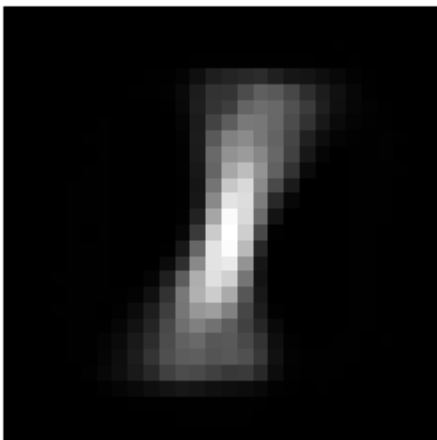
Reconstructed Image:



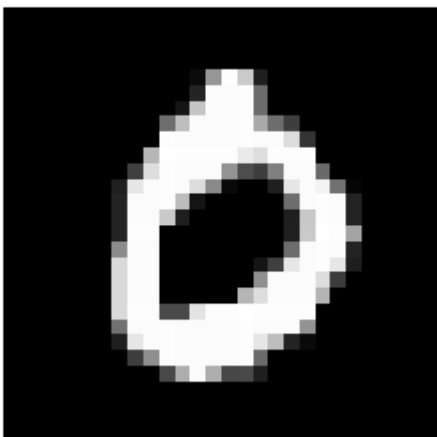
Original Image Labeled as 1:



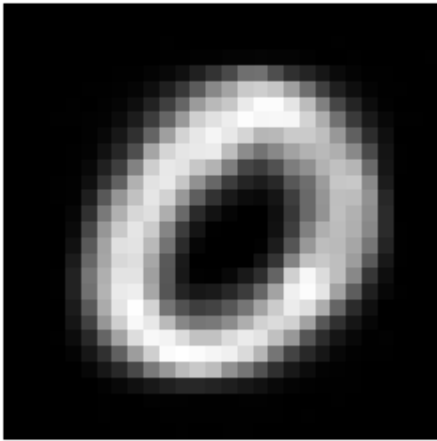
Reconstructed Image:



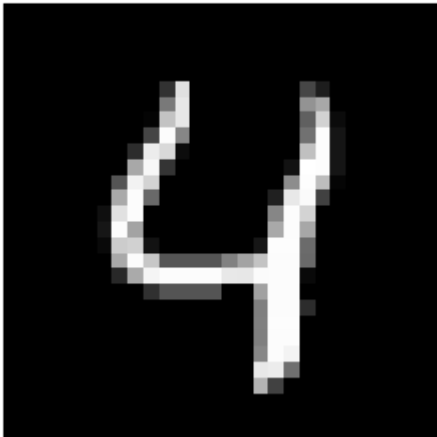
Original Image Labeled as 0:



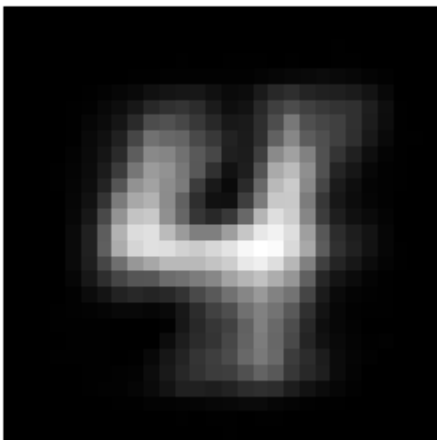
Reconstructed Image:



Original Image Labeled as 4:



Reconstructed Image:



In [107...

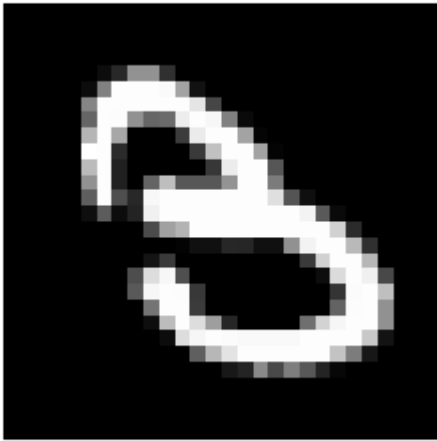
```
indices=[18,33,38,66,97]

for i in indices:
    x,y=test_data[i]

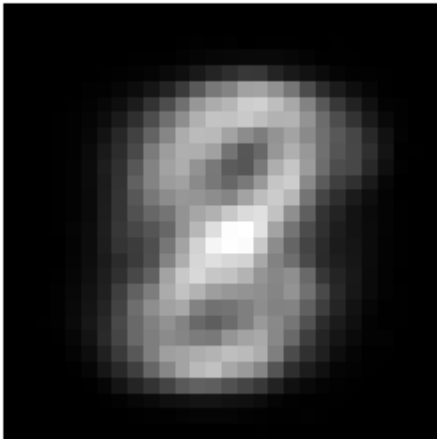
    reconstructed_image=autoencoder.reconstruct(x)

    print(f"Original Image Labeled as {y}:")
    plot_digit(x.reshape(28,28))
    print("Reconstructed Image:")
    plot_digit(reconstructed_image.reshape(28,28))
```

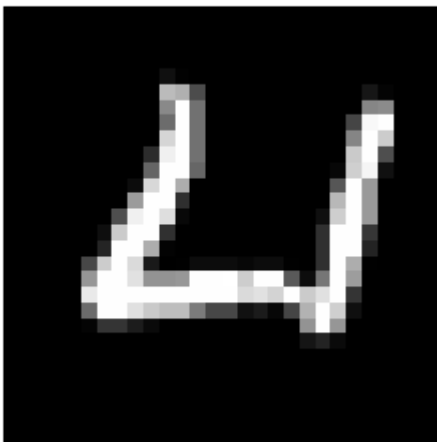
Original Image Labeled as 3:



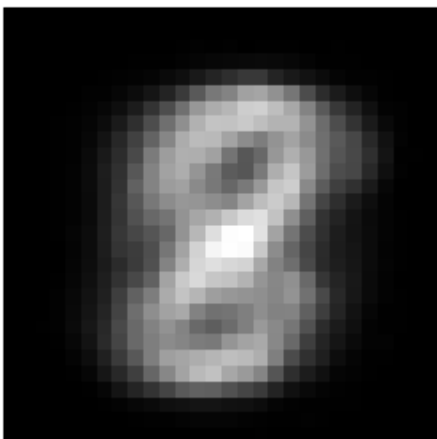
Reconstructed Image:



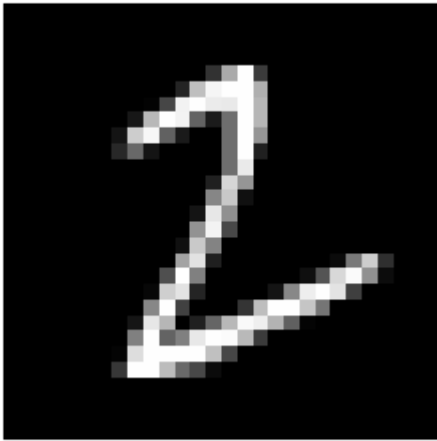
Original Image Labeled as 4:



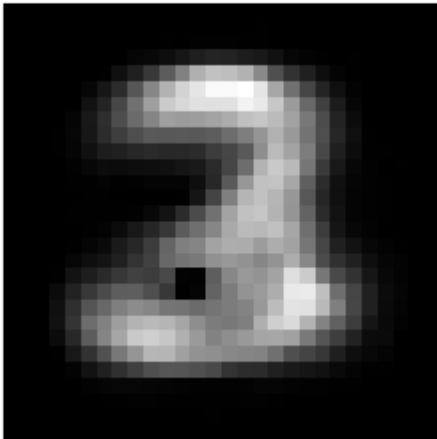
Reconstructed Image:



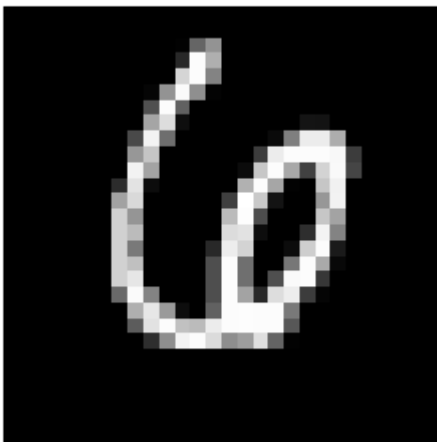
Original Image Labeled as 2:



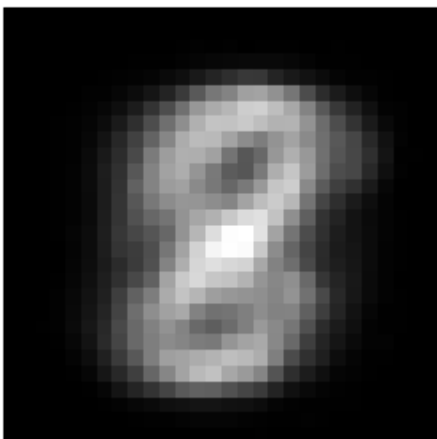
Reconstructed Image:



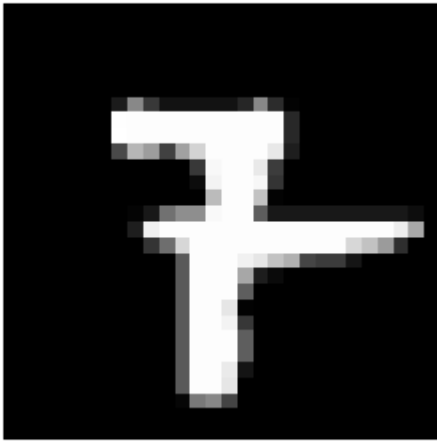
Original Image Labeled as 6:



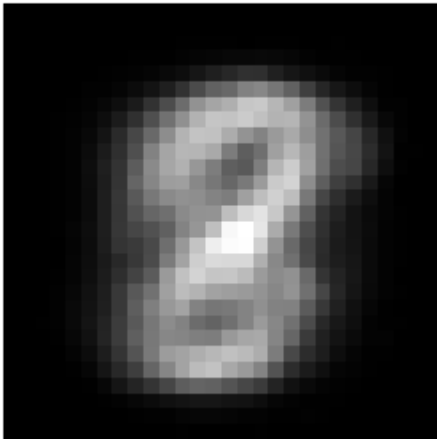
Reconstructed Image:



Original Image Labeled as 7:



Reconstructed Image:



g

a.1

```
In [108... encoder=Network([784,40,10])
encoder.SGD(training_data,10,10,3.0,test_data=test_data)
```

```
Epoch 0 : 9099 / 10000
Epoch 1 : 9286 / 10000
Epoch 2 : 9303 / 10000
Epoch 3 : 9391 / 10000
Epoch 4 : 9403 / 10000
Epoch 5 : 9429 / 10000
Epoch 6 : 9412 / 10000
Epoch 7 : 9460 / 10000
Epoch 8 : 9464 / 10000
Epoch 9 : 9490 / 10000
```

b.1

```
In [109... decoder=Network([10,40, 784])

latent_vectors=[encoder.feedforward(x) for x, _ in training_data]
targets =[x for x, _ in training_data]
training_data_decoder=list(zip(latent_vectors, targets))
decoder.SGD(training_data_decoder,10,10,3.0)
```

Epoch 0 complete
Epoch 1 complete
Epoch 2 complete
Epoch 3 complete
Epoch 4 complete
Epoch 5 complete
Epoch 6 complete
Epoch 7 complete
Epoch 8 complete
Epoch 9 complete

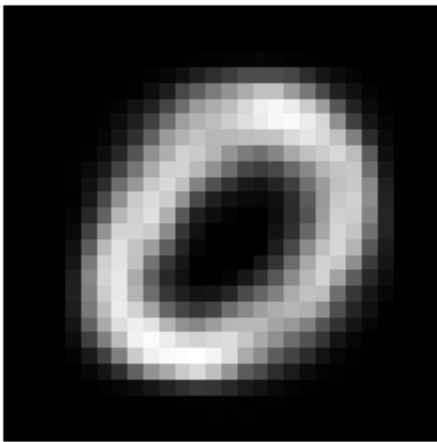
c.1

Each column of the decoder's weight matrices represents how the latent dimensions combine to form abstract features in the hidden layer, which are then mapped to reconstruct specific details of the original image.

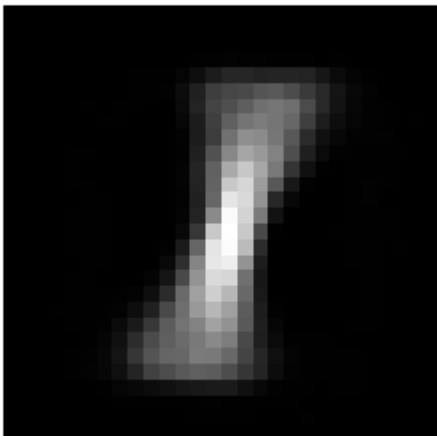
d.1

```
In [110... perfect_vectors=[np.eye(10)[: ,k].reshape(10,1) for k in range(10)]  
  
reconstructed_images=[decoder.feedforward(vec) for vec in perfect_vectors]  
  
for digit, image in enumerate(perfect_reconstructed_images):  
    print(f"Reconstructed Image for Perfect Example of Digit {digit}:")  
    plot_digit(image.reshape(28,28))
```

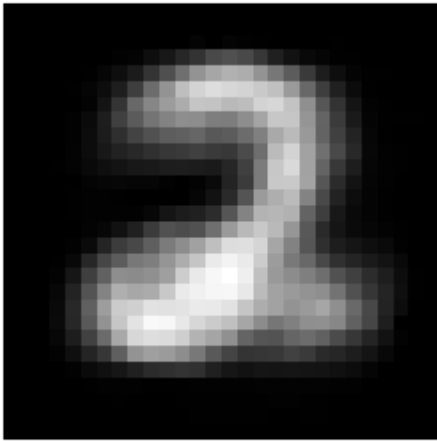
Reconstructed Image for Perfect Example of Digit 0:



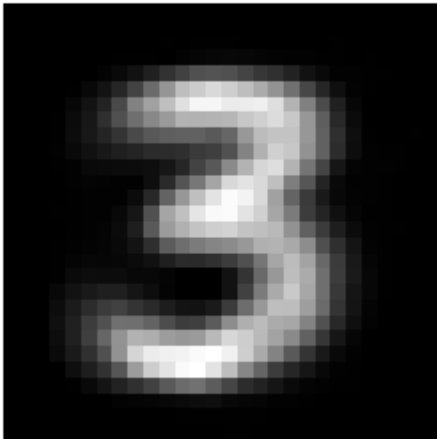
Reconstructed Image for Perfect Example of Digit 1:



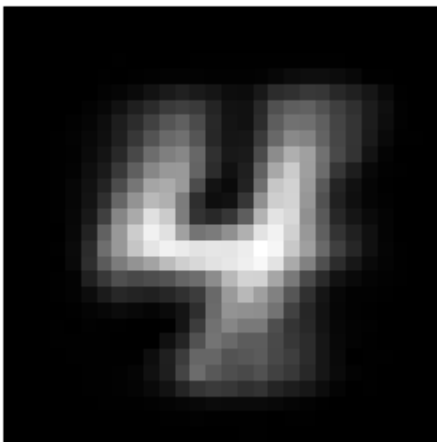
Reconstructed Image for Perfect Example of Digit 2:



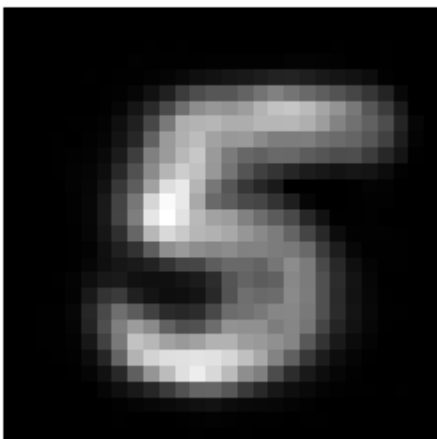
Reconstructed Image for Perfect Example of Digit 3:



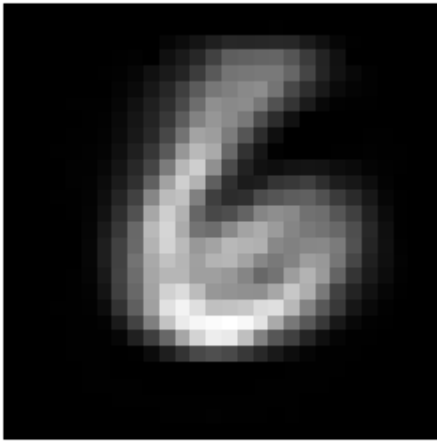
Reconstructed Image for Perfect Example of Digit 4:



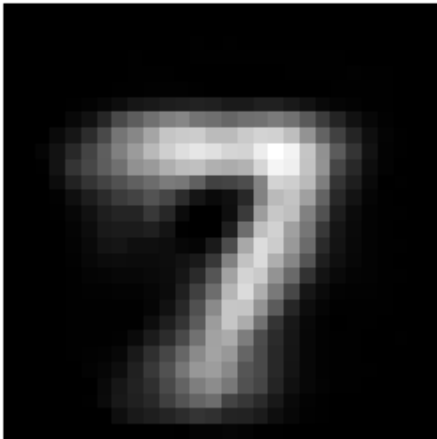
Reconstructed Image for Perfect Example of Digit 5:



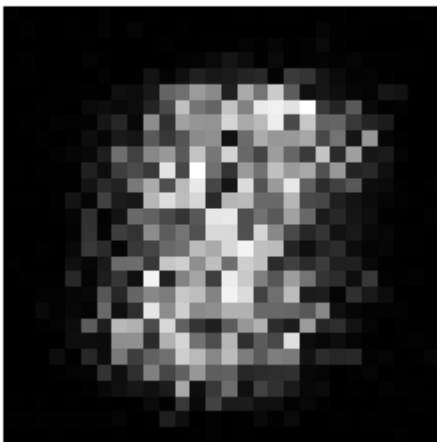
Reconstructed Image for Perfect Example of Digit 6:



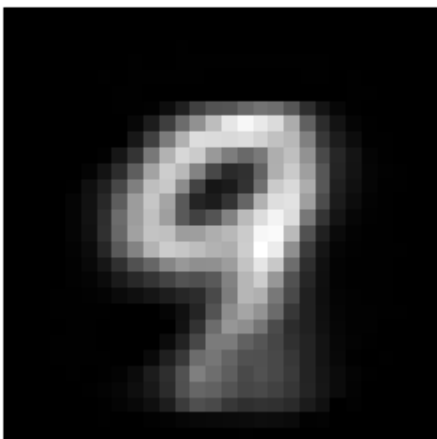
Reconstructed Image for Perfect Example of Digit 7:



Reconstructed Image for Perfect Example of Digit 8:



Reconstructed Image for Perfect Example of Digit 9:



e.1

Same as before

f.1

```
In [89]: encoder=Network([784,40, 10])
         decoder=Network([10, 40,784])
         autoencoder=Autoencoder(encoder,decoder)

         autoencoder.train(training_data,10,10,10,3.0,test_data)
```

```
Epoch 0 : 7336 / 10000
Epoch 1 : 8284 / 10000
Epoch 2 : 9287 / 10000
Epoch 3 : 9345 / 10000
Epoch 4 : 9360 / 10000
Epoch 5 : 9402 / 10000
Epoch 6 : 9445 / 10000
Epoch 7 : 9459 / 10000
Epoch 8 : 9445 / 10000
Epoch 9 : 9464 / 10000
Epoch 0 complete
Epoch 1 complete
Epoch 2 complete
Epoch 3 complete
Epoch 4 complete
Epoch 5 complete
Epoch 6 complete
Epoch 7 complete
Epoch 8 complete
Epoch 9 complete
```

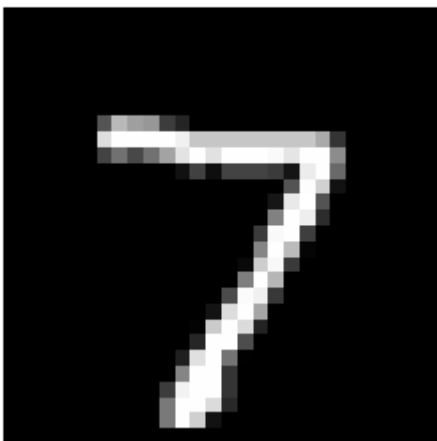
```
In [99]: indices=[0,1,2,3,4]

         for i in indices:
             x,y=test_data[i]

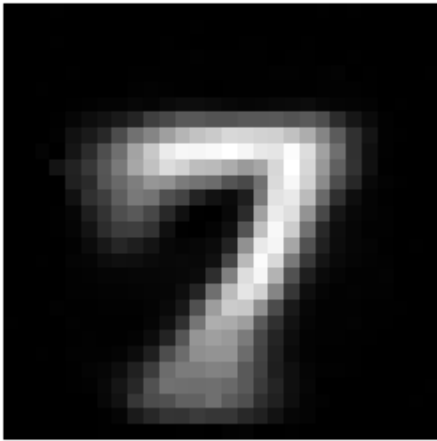
             reconstructed_image=autoencoder.reconstruct(x)

             print(f"Original Image Labeled as {y}:")
             plot_digit(x.reshape(28,28))
             print("Reconstructed Image:")
             plot_digit(reconstructed_image.reshape(28,28))
```

Original Image Labeled as 7:



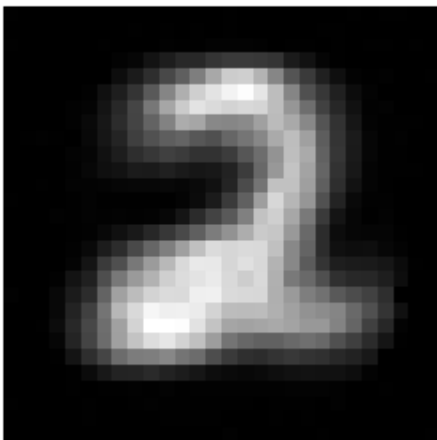
Reconstructed Image:



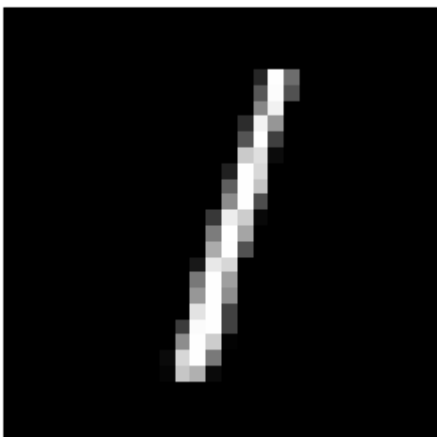
Original Image Labeled as 2:



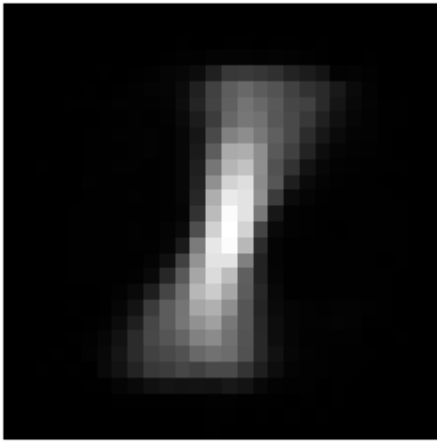
Reconstructed Image:



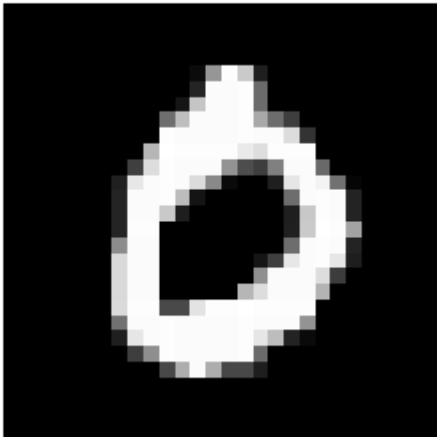
Original Image Labeled as 1:



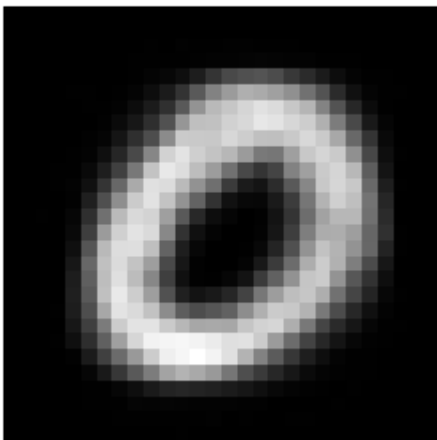
Reconstructed Image:



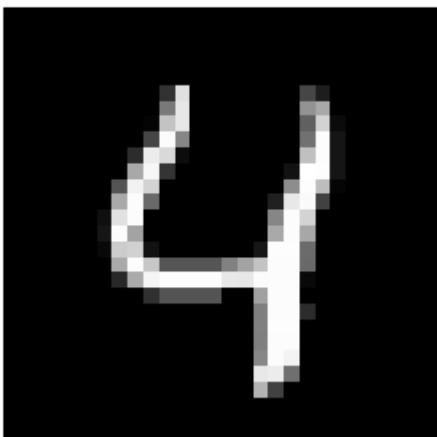
Original Image Labeled as 0:



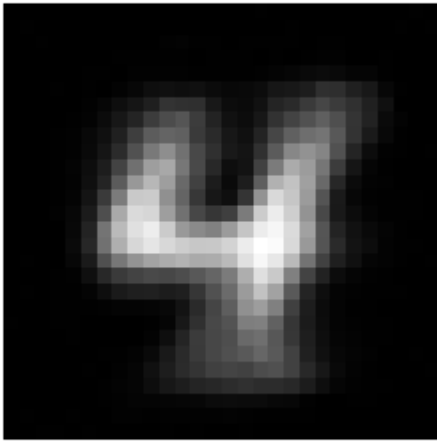
Reconstructed Image:



Original Image Labeled as 4:



Reconstructed Image:



In [100...

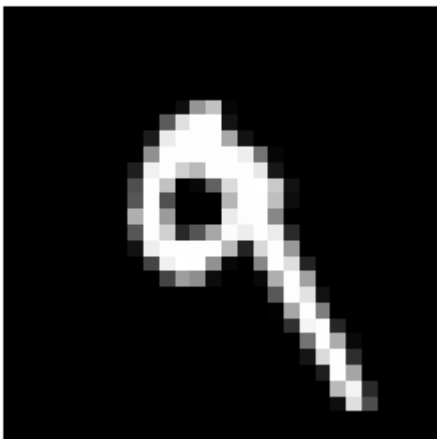
```
indices=[7,24,61,149,151]

for i in indices:
    x,y=test_data[i]

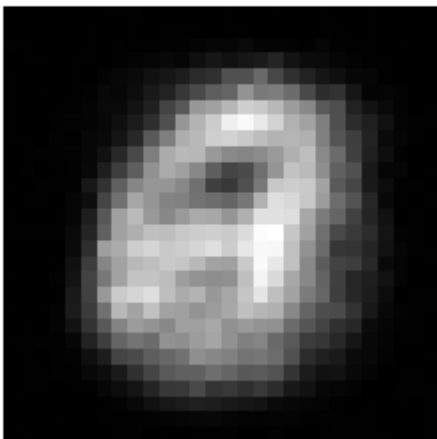
    reconstructed_image=autoencoder.reconstruct(x)

    print(f"Original Image Labeled as {y}:")
    plot_digit(x.reshape(28,28))
    print("Reconstructed Image:")
    plot_digit(reconstructed_image.reshape(28,28))
```

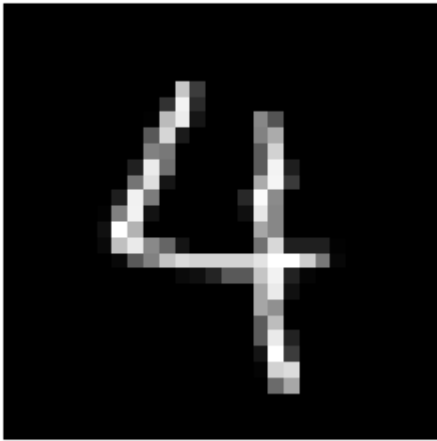
Original Image Labeled as 9:



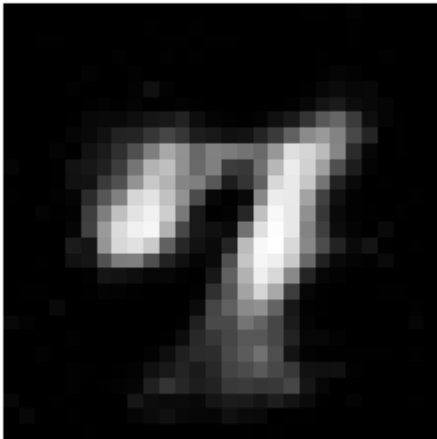
Reconstructed Image:



Original Image Labeled as 4:



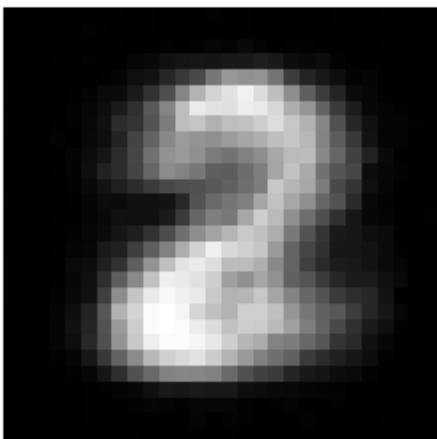
Reconstructed Image:



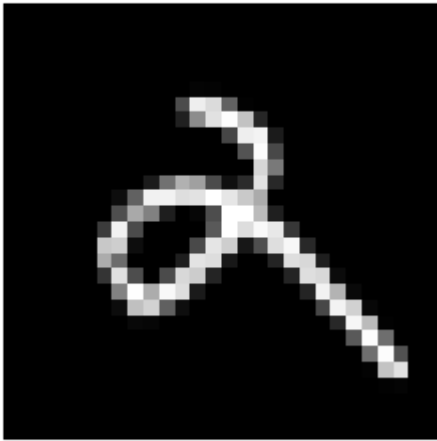
Original Image Labeled as 8:



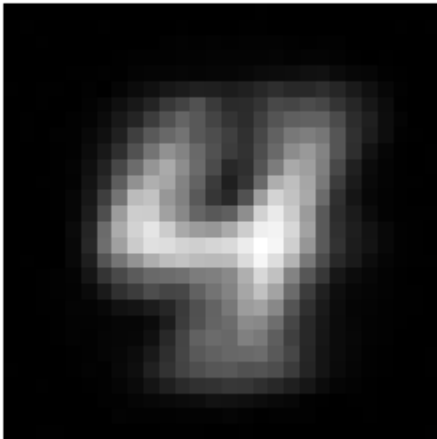
Reconstructed Image:



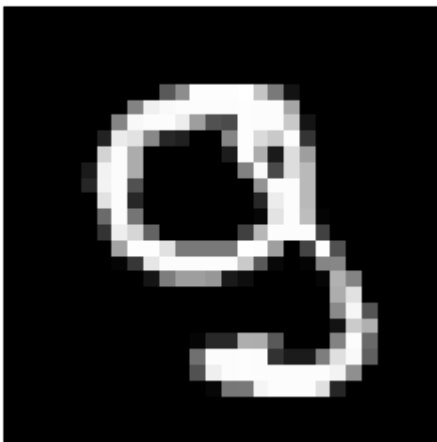
Original Image Labeled as 2:



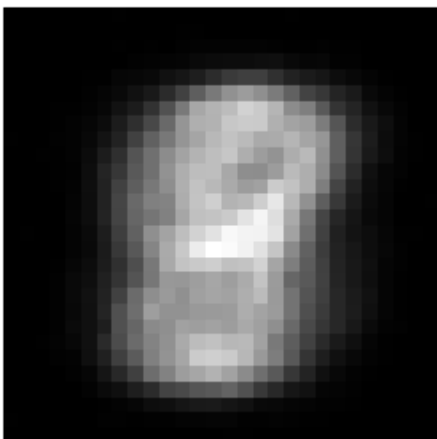
Reconstructed Image:



Original Image Labeled as 9:



Reconstructed Image:



a

```
In [8]: x_vals=np.linspace(0,2*np.pi,10000)

f_vals=np.sin(x_vals)
g_vals=(1+np.sin(x_vals))/2

f_training_data=list(zip(x_vals,f_vals))
g_training_data=list(zip(x_vals,g_vals))
```

b

```
In [9]: def create_model():
        model=Sequential([
            Dense(3,activation='sigmoid',input_shape=(1,)),
            Dense(1,activation='sigmoid')
        ])
        model.compile(optimizer='adam',loss='mse')
        return model

f_model=create_model()
g_model=create_model()

g_model.summary()
```

C:\Users\antho\anaconda3\lib\site-packages\keras\src\layers\core\dense.py:88: User Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Model: "sequential_3"

Layer (type)	Output Shape	
dense_6 (Dense)	(None, 3)	
dense_7 (Dense)	(None, 1)	

Total params: 10 (40.00 B)


Trainable params: 10 (40.00 B)


Non-trainable params: 0 (0.00 B)


c


```
In [10]: #input shape of (1,) for Keras
x_vals=x_vals.reshape(-1,1)
f_vals=f_vals.reshape(-1,1)
g_vals=g_vals.reshape(-1,1)


f_model.fit(x_vals,f_vals,epochs=200,batch_size=20,verbose=1)
g_model.fit(x_vals,g_vals,epochs=200,batch_size=20,verbose=1)
```


Epoch 1/200
500/500  1s 1ms/step - loss: 0.6970


Epoch 2/200
500/500  1s 1ms/step - loss: 0.5199


Epoch 3/200
500/500  1s 1ms/step - loss: 0.4791


Epoch 4/200
500/500  1s 1ms/step - loss: 0.4693


Epoch 5/200
500/500  1s 1ms/step - loss: 0.4422


Epoch 6/200
500/500  1s 1ms/step - loss: 0.4231


Epoch 7/200
500/500  1s 1ms/step - loss: 0.3957


Epoch 8/200
500/500  1s 1ms/step - loss: 0.3691


Epoch 9/200
500/500  1s 1ms/step - loss: 0.3438


Epoch 10/200
500/500  1s 1ms/step - loss: 0.3383


Epoch 11/200
500/500  1s 1ms/step - loss: 0.3245


Epoch 12/200
500/500  1s 993us/step - loss: 0.3126


Epoch 13/200
500/500  1s 1ms/step - loss: 0.3090


Epoch 14/200
500/500  1s 1ms/step - loss: 0.3065


Epoch 15/200
500/500  1s 1ms/step - loss: 0.3031


Epoch 16/200
500/500  1s 1ms/step - loss: 0.2994


Epoch 17/200
500/500  1s 1ms/step - loss: 0.3007


Epoch 18/200
500/500  1s 1ms/step - loss: 0.2976


Epoch 19/200
500/500  1s 1ms/step - loss: 0.2950


Epoch 20/200
500/500  1s 1ms/step - loss: 0.2940


Epoch 21/200
500/500  1s 1ms/step - loss: 0.2937


Epoch 22/200
500/500  1s 1ms/step - loss: 0.2979


Epoch 23/200
500/500  1s 1ms/step - loss: 0.2951


Epoch 24/200
500/500  1s 1ms/step - loss: 0.2910


Epoch 25/200
500/500  1s 1ms/step - loss: 0.2892


Epoch 26/200
500/500  1s 1ms/step - loss: 0.2847


Epoch 27/200
500/500  1s 1ms/step - loss: 0.2900


Epoch 28/200
500/500  1s 1ms/step - loss: 0.2826


Epoch 29/200
500/500  1s 1ms/step - loss: 0.2850


Epoch 30/200
500/500  1s 1ms/step - loss: 0.2873


Epoch 31/200
500/500  1s 1ms/step - loss: 0.2874


Epoch 32/200
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Epoch 33/200
500/500  1s 1ms/step - loss: 0.2875


Epoch 34/200
500/500  1s 1ms/step - loss: 0.2824


Epoch 35/200
500/500  1s 1ms/step - loss: 0.2825


Epoch 36/200
500/500  1s 1ms/step - loss: 0.2840


Epoch 37/200
500/500  1s 1ms/step - loss: 0.2871


Epoch 38/200
500/500  1s 1ms/step - loss: 0.2782


Epoch 39/200
500/500  1s 1ms/step - loss: 0.2861


Epoch 40/200
500/500  1s 1ms/step - loss: 0.2821


Epoch 41/200
500/500  1s 1ms/step - loss: 0.2858


Epoch 42/200
500/500  1s 1ms/step - loss: 0.2792


Epoch 43/200
500/500  1s 1ms/step - loss: 0.2830


Epoch 44/200
500/500  1s 1ms/step - loss: 0.2801


Epoch 45/200
500/500  1s 1ms/step - loss: 0.2870


Epoch 46/200
500/500  1s 1ms/step - loss: 0.2847


Epoch 47/200
500/500  1s 1ms/step - loss: 0.2793


Epoch 48/200
500/500  1s 1ms/step - loss: 0.2776


Epoch 49/200
500/500  1s 2ms/step - loss: 0.2899


Epoch 50/200
500/500  1s 1ms/step - loss: 0.2792


Epoch 51/200
500/500  1s 2ms/step - loss: 0.2853


Epoch 52/200
500/500  1s 1ms/step - loss: 0.2851


Epoch 53/200
500/500  1s 1ms/step - loss: 0.2802


Epoch 54/200
500/500  1s 1ms/step - loss: 0.2817


Epoch 55/200
500/500  1s 1ms/step - loss: 0.2768


Epoch 56/200
500/500  1s 1ms/step - loss: 0.2822


Epoch 57/200
500/500  1s 1ms/step - loss: 0.2811


Epoch 58/200
500/500  1s 1ms/step - loss: 0.2861


Epoch 59/200
500/500  1s 1ms/step - loss: 0.2820


Epoch 60/200
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Epoch 61/200
500/500  1s 1ms/step - loss: 0.2832


Epoch 62/200
500/500  1s 2ms/step - loss: 0.2744


Epoch 63/200
500/500  2s 2ms/step - loss: 0.2678


Epoch 64/200
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Epoch 65/200
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Epoch 66/200
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Epoch 67/200
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Epoch 68/200
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Epoch 69/200
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Epoch 70/200
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Epoch 71/200
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Epoch 72/200
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Epoch 73/200
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Epoch 74/200
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Epoch 75/200
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Epoch 76/200
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Epoch 77/200
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Epoch 78/200
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Epoch 79/200
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Epoch 80/200
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Epoch 81/200
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Epoch 82/200
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Epoch 83/200
500/500  1s 3ms/step - loss: 0.2510


Epoch 84/200
500/500  1s 3ms/step - loss: 0.2485


Epoch 85/200
500/500  1s 3ms/step - loss: 0.2517


Epoch 86/200
500/500  2s 3ms/step - loss: 0.2492


Epoch 87/200
500/500  1s 3ms/step - loss: 0.2508


Epoch 88/200
500/500  1s 3ms/step - loss: 0.2542


Epoch 89/200
500/500  1s 2ms/step - loss: 0.2534


Epoch 90/200
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Epoch 91/200
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Epoch 92/200
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Epoch 93/200
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Epoch 94/200
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Epoch 95/200
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Epoch 96/200
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Epoch 97/200
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Epoch 100/200
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Epoch 101/200
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Epoch 102/200
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Epoch 103/200
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Epoch 104/200
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Epoch 107/200
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Epoch 110/200
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Epoch 126/200
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Epoch 127/200
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Epoch 128/200
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Epoch 129/200
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Epoch 130/200
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Epoch 131/200
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Epoch 132/200
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Epoch 133/200
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Epoch 134/200
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Epoch 135/200
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Epoch 136/200
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Epoch 137/200
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Epoch 138/200
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Epoch 139/200
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Epoch 140/200
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Epoch 141/200
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Epoch 142/200
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Epoch 143/200
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Epoch 144/200
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Epoch 145/200
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Epoch 146/200
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Epoch 147/200
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Epoch 148/200
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Epoch 149/200
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Epoch 150/200
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Epoch 151/200
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Epoch 152/200
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Epoch 153/200
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Epoch 154/200
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Epoch 155/200
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Epoch 156/200
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Epoch 157/200
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Epoch 158/200
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Epoch 159/200
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Epoch 160/200
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Epoch 161/200
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Epoch 162/200
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Epoch 163/200
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Epoch 164/200
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Epoch 165/200
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Epoch 166/200
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Epoch 167/200
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Epoch 168/200
500/500  1s 1ms/step - loss: 0.2504


Epoch 169/200
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Epoch 170/200
500/500  1s 1ms/step - loss: 0.2446


Epoch 171/200
500/500  1s 1ms/step - loss: 0.2456


Epoch 172/200
500/500  1s 1ms/step - loss: 0.2481


Epoch 173/200
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Epoch 174/200
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Epoch 175/200
500/500  1s 1ms/step - loss: 0.2468


Epoch 176/200
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Epoch 177/200
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Epoch 178/200
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Epoch 179/200
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Epoch 180/200
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Epoch 181/200
500/500  1s 1ms/step - loss: 0.2569


Epoch 182/200
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Epoch 183/200
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Epoch 184/200
500/500  1s 1ms/step - loss: 0.2471


Epoch 185/200
500/500  1s 1ms/step - loss: 0.2478


Epoch 186/200
500/500  1s 1ms/step - loss: 0.2524


Epoch 187/200
500/500  1s 1ms/step - loss: 0.2512


Epoch 188/200
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Epoch 189/200
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Epoch 190/200
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Epoch 191/200
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Epoch 192/200
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Epoch 193/200
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Epoch 194/200
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Epoch 195/200
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Epoch 196/200
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Epoch 197/200
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Epoch 198/200
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Epoch 199/200
500/500  1s 1ms/step - loss: 0.2448


Epoch 200/200
500/500  1s 1ms/step - loss: 0.2484


Epoch 1/200
500/500  1s 1ms/step - loss: 0.1136


Epoch 2/200
500/500  1s 1ms/step - loss: 0.0869


Epoch 3/200
500/500  1s 1ms/step - loss: 0.0674


Epoch 4/200
500/500  1s 1ms/step - loss: 0.0530


Epoch 5/200
500/500  1s 1ms/step - loss: 0.0431


Epoch 6/200
500/500  1s 1ms/step - loss: 0.0359


Epoch 7/200
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Epoch 8/200
500/500  1s 1ms/step - loss: 0.0277


Epoch 9/200
500/500  1s 1ms/step - loss: 0.0250


Epoch 10/200
500/500  1s 1ms/step - loss: 0.0229


Epoch 11/200
500/500  1s 1ms/step - loss: 0.0199


Epoch 12/200
500/500  1s 1ms/step - loss: 0.0173


Epoch 13/200
500/500  1s 1ms/step - loss: 0.0139


Epoch 14/200
500/500  1s 2ms/step - loss: 0.0127


Epoch 15/200
500/500  1s 2ms/step - loss: 0.0113


Epoch 16/200
500/500  1s 1ms/step - loss: 0.0106


Epoch 17/200
500/500  1s 1ms/step - loss: 0.0102


Epoch 18/200
500/500  1s 2ms/step - loss: 0.0094


Epoch 19/200
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Epoch 20/200
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Epoch 21/200
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Epoch 22/200
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Epoch 23/200
500/500  1s 1ms/step - loss: 0.0091


Epoch 24/200
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Epoch 25/200
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Epoch 26/200
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Epoch 27/200
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Epoch 28/200
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Epoch 29/200
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Epoch 30/200
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Epoch 31/200
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Epoch 32/200
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Epoch 33/200
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Epoch 34/200
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Epoch 35/200
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Epoch 36/200
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Epoch 37/200
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Epoch 38/200
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Epoch 39/200
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Epoch 40/200
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Epoch 41/200
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Epoch 42/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 43/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 44/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 45/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 46/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 47/200
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Epoch 48/200
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Epoch 49/200
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Epoch 50/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 51/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 52/200
500/500  1s 1ms/step - loss: 0.0093


Epoch 53/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 54/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 55/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 56/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 57/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 58/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 59/200
500/500  1s 1ms/step - loss: 0.0091


Epoch 60/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 61/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 62/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 63/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 64/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 65/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 66/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 67/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 68/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 69/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 70/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 71/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 72/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 73/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 74/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 75/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 76/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 77/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 78/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 79/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 80/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 81/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 82/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 83/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 84/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 85/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 86/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 87/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 88/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 89/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 90/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 91/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 92/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 93/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 94/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 95/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 96/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 97/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 98/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 99/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 100/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 101/200
500/500  1s 1ms/step - loss: 0.0089


Epoch 102/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 103/200
500/500  1s 1ms/step - loss: 0.0088


Epoch 104/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 105/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 106/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 107/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 108/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 109/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 110/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 111/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 112/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 113/200
500/500  1s 1ms/step - loss: 0.0090


Epoch 114/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 115/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 116/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 117/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 118/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 119/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 120/200
500/500  1s 2ms/step - loss: 0.0083


Epoch 121/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 122/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 123/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 124/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 125/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 126/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 127/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 128/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 129/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 130/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 131/200
500/500  1s 1ms/step - loss: 0.0087


Epoch 132/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 133/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 134/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 135/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 136/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 137/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 138/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 139/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 140/200
500/500  1s 1ms/step - loss: 0.0080


Epoch 141/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 142/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 143/200
500/500  1s 1ms/step - loss: 0.0086


Epoch 144/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 145/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 146/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 147/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 148/200
500/500  1s 1ms/step - loss: 0.0080


Epoch 149/200
500/500  1s 1ms/step - loss: 0.0080


Epoch 150/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 151/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 152/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 153/200
500/500  1s 1ms/step - loss: 0.0080


Epoch 154/200
500/500  1s 1ms/step - loss: 0.0085


Epoch 155/200
500/500  1s 1ms/step - loss: 0.0080


Epoch 156/200
500/500  1s 1ms/step - loss: 0.0079


Epoch 157/200
500/500  1s 1ms/step - loss: 0.0079


Epoch 158/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 159/200
500/500  1s 2ms/step - loss: 0.0081


Epoch 160/200
500/500  1s 2ms/step - loss: 0.0081


Epoch 161/200
500/500  1s 2ms/step - loss: 0.0081


Epoch 162/200
500/500  1s 1ms/step - loss: 0.0077


Epoch 163/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 164/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 165/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 166/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 167/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 168/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 169/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 170/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 171/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 172/200
500/500  1s 1ms/step - loss: 0.0083


Epoch 173/200
500/500  1s 1ms/step - loss: 0.0084


Epoch 174/200
500/500  1s 1ms/step - loss: 0.0082


Epoch 175/200
500/500  1s 1ms/step - loss: 0.0081


Epoch 176/200
500/500  1s 2ms/step - loss: 0.0083


Epoch 177/200
500/500  1s 2ms/step - loss: 0.0079


Epoch 178/200
500/500  1s 1ms/step - loss: 0.0080

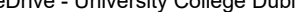
Epoch 179/200
500/500  1s 1ms/step - loss: 0.0083

Epoch 180/200
500/500  1s 1ms/step - loss: 0.0082

Epoch 181/200
500/500  1s 1ms/step - loss: 0.0079

Epoch 182/200
500/500  1s 1ms/step - loss: 0.0082

Epoch 183/200
500/500  1s 1ms/step - loss: 0.0081

Epoch 184/200
500/500  1s 1ms/step - loss: 0.0080

```

Epoch 185/200
500/500 ————— 1s 1ms/step - loss: 0.0079
Epoch 186/200
500/500 ————— 1s 1ms/step - loss: 0.0080
Epoch 187/200
500/500 ————— 1s 1ms/step - loss: 0.0077
Epoch 188/200
500/500 ————— 1s 1ms/step - loss: 0.0080
Epoch 189/200
500/500 ————— 1s 1ms/step - loss: 0.0080
Epoch 190/200
500/500 ————— 1s 1ms/step - loss: 0.0079
Epoch 191/200
500/500 ————— 1s 1ms/step - loss: 0.0080
Epoch 192/200
500/500 ————— 1s 1ms/step - loss: 0.0081
Epoch 193/200
500/500 ————— 1s 1ms/step - loss: 0.0082
Epoch 194/200
500/500 ————— 1s 1ms/step - loss: 0.0080
Epoch 195/200
500/500 ————— 1s 1ms/step - loss: 0.0081
Epoch 196/200
500/500 ————— 1s 1ms/step - loss: 0.0083
Epoch 197/200
500/500 ————— 1s 2ms/step - loss: 0.0080
Epoch 198/200
500/500 ————— 1s 2ms/step - loss: 0.0077
Epoch 199/200
500/500 ————— 1s 1ms/step - loss: 0.0080
Epoch 200/200
500/500 ————— 1s 1ms/step - loss: 0.0082
<keras.src.callbacks.history.History at 0x286fc88eb50>

```

Out[10]:

d

```

In [11]: x_test=x_vals.reshape(-1,1)
          f_true=np.sin(x_test)
          g_true=(1+np.sin(x_test))/2

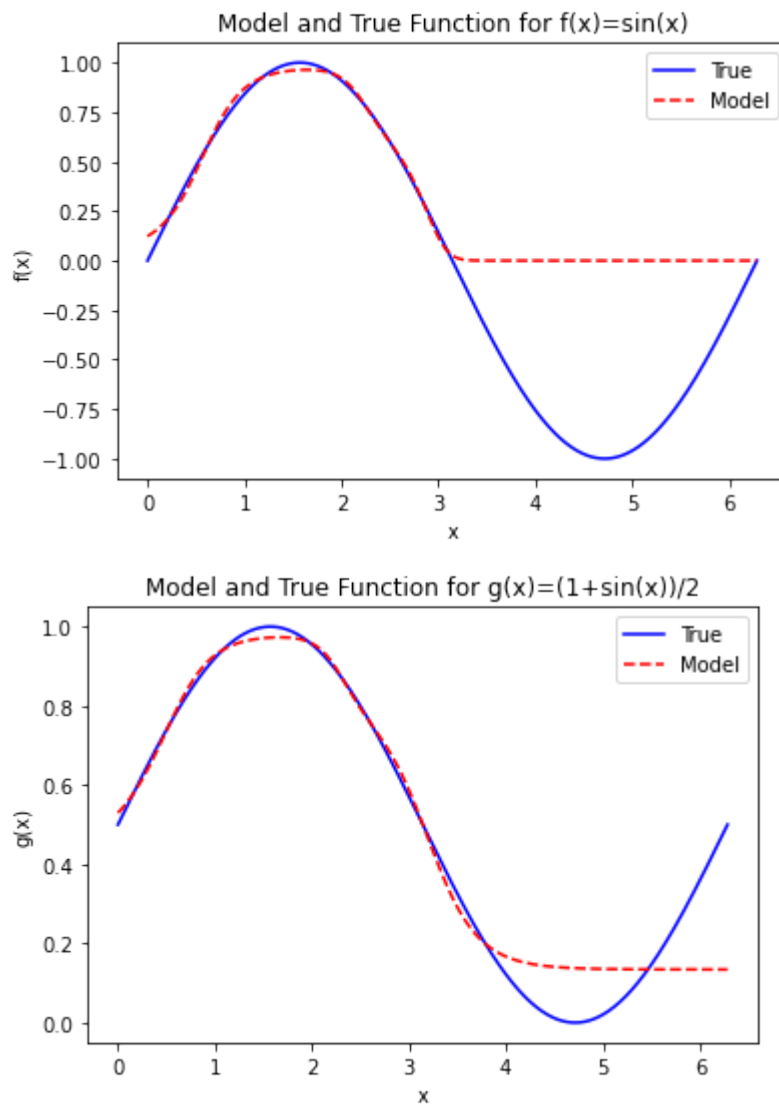
          f_pred=f_model.predict(x_test)
          g_pred=g_model.predict(x_test)

          plt.plot(x_test,f_true,label="True",color='blue')
          plt.plot(x_test,f_pred,label="Model",color='red',linestyle='dashed')
          plt.xlabel("x")
          plt.ylabel("f(x)")
          plt.title("Model and True Function for f(x)=sin(x)")
          plt.legend()
          plt.show()

          plt.plot(x_test,g_true,label="True",color='blue')
          plt.plot(x_test,g_pred,label="Model",color='red',linestyle='dashed')
          plt.xlabel("x")
          plt.ylabel("g(x)")
          plt.title("Model and True Function for g(x)=(1+sin(x))/2")
          plt.legend()
          plt.show()

313/313 ————— 0s 1ms/step
313/313 ————— 0s 1ms/step

```



The model for $g(x) = \frac{1+\sin(x)}{2}$ performs better than $f(x) = \sin(x)$ because $g(x)$ exactly aligns with the sigmoid activation's output range ($[0, 1]$), while $f(x)$, ranging from $[-1, 1]$, is harder for the sigmoid to approximate. Scaling or using tanh activations could improve $f(x)$'s performance.

e

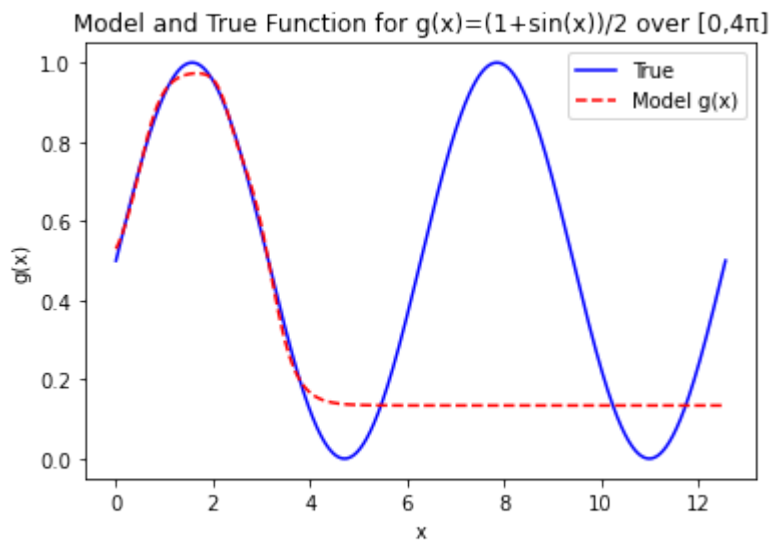
```
In [12]: x_test_ext=np.linspace(0,4*np.pi,1000).reshape(-1,1)

g_true_ext=(1 + np.sin(x_test_ext)) / 2

g_pred_ext=g_model.predict(x_test_ext)

plt.plot(x_test_ext,g_true_ext,label="True",color='blue')
plt.plot(x_test_ext,g_pred_ext,label="Model g(x)",color='red',linestyle='dashed')
plt.xlabel("x")
plt.ylabel("g(x)")
plt.title("Model and True Function for  $g(x)=(1+\sin(x))/2$  over  $[0,4\pi]$ ")
plt.legend()
plt.show()
```

32/32 ————— 0s 2ms/step



The model's performance declines significantly outside the training range $x \in [0, 2\pi]$.

Explanations:

1. Training Data Used:

The model was trained only on $x \in [0, 2\pi]$, so it has no knowledge of the function's behavior beyond this interval. Neural networks can learn well within the training range but can struggle to find periodic patterns accurately.

2. Expressivity of the Network:

The network isn't able to fully capture the periodic nature of $g(x)$ over extended intervals with only three hidden neurons, since each neuron in the hidden layer can represent a simple, smooth feature, but periodic functions require multiple features to approximate the oscillations. Additionally, smooth and bounded sigmoid activations, further limit the ability to represent high frequency oscillations.

The model's performance declines significantly outside the training range $x \in [0, 2\pi]$.

Explanations:

1. Training Data Used:

The model was only trained on $x \in [0, 2\pi]$, so it has no knowledge of the function's behavior beyond this interval. Neural networks can learn periodic patterns well if given sufficient training data, but here the limited range of training data prevents the network from modelling the periodicity of $g(x)$.

2. Expressivity of the Network:

The network isn't able to fully capture the periodic nature of $g(x)$ over extended intervals with only three hidden neurons. Each neuron in the hidden layer represents a simple, smooth feature, but periodic functions require the network to combine multiple features to approximate oscillations. Additionally, smooth and bounded sigmoid activations further limit the ability to represent high frequency oscillations effectively.