using-artificial-neural-network-1

March 3, 2024

Handwritten digits classification using neural network

In this notebook we will classify handwritten digits using a simple neural network which has only input and output layers. We will than add a hidden layer and see how the performance of the model improves

[47]:
```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np
```

[ ]:

[ ]:

[48]:
```
(X_train, y_train) , (X_test, y_test) = keras.datasets.mnist.load_data()
```

[ ]:

[49]:
```
len(X_train)
```

[49]: 60000

[50]:
```
len(X_test)
```

[50]: 10000

[51]:
```
X_train[9584].shape
```

[51]: (28, 28)

[52]:
```
X_train[0]
```

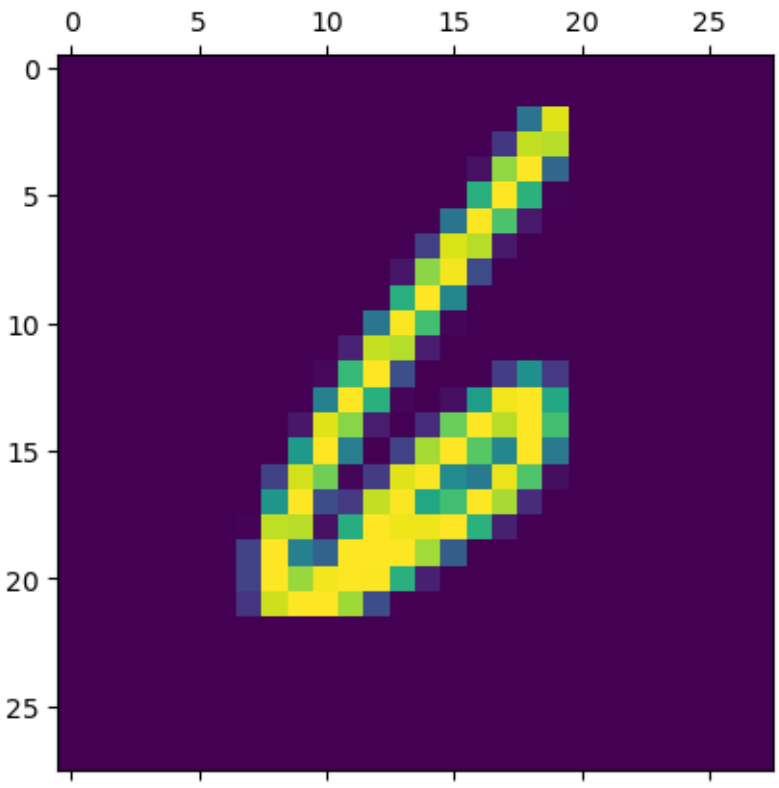
[52]:
```
array([[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
```

```
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   3,
  18,  18,  18, 126, 136, 175,  26, 166, 255, 247, 127,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,  30,  36,  94, 154, 170,
 253, 253, 253, 253, 253, 225, 172, 253, 242, 195,  64,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,  49, 238, 253, 253, 253, 253,
 253, 253, 253, 253, 251,  93,  82,  82,  56,  39,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,  18, 219, 253, 253, 253, 253,
 253, 198, 182, 247, 241,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,  80, 156, 107, 253, 253,
 205,  11,   0,  43, 154,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,  14,   1, 154, 253,
  90,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0, 139, 253,
 190,   2,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  11, 190,
 253,  70,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  35,
 241, 225, 160, 108,   1,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
  81, 240, 253, 253, 119,  25,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,  45, 186, 253, 253, 150,  27,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,  16,  93, 252, 253, 187,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
```

```
   0,   0,   0,   0, 249, 253, 249,  64,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,  46, 130, 183, 253, 253, 207,   2,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  39,
 148, 229, 253, 253, 253, 250, 182,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  24, 114, 221,
 253, 253, 253, 253, 201,  78,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,  23,  66, 213, 253, 253,
 253, 253, 198,  81,   2,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,  18, 171, 219, 253, 253, 253, 253,
 195,  80,   9,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,  55, 172, 226, 253, 253, 253, 253, 244, 133,
  11,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0, 136, 253, 253, 253, 212, 135, 132,  16,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0],
[  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
   0,   0]], dtype=uint8)
```

[53]:
```
plt.matshow(X_train[955])
```

[53]:
```
<matplotlib.image.AxesImage at 0x1b3a7d16990>
```



[54]:
```
y_train[955]
```

[54]: 6

[ ]:

[55]:
```
X_train = X_train / 255
X_test = X_test / 255
```

[56]:
```
X_train_flattened = X_train.reshape(len(X_train), 28*28)
X_test_flattened = X_test.reshape(len(X_test), 28*28)
```

[57]:
```
X_train_flattened.shape
```

[57]: (60000, 784)

[58]:
```
X_train_flattened[955]
```

[58]:
```
array([0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
```

```
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.38039216,
0.94901961, 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.16078431, 0.90588235, 0.89019608, 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.04313725, 0.83529412,
0.99607843, 0.32941176, 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.62745098, 0.99607843, 0.63921569, 0.00784314,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.38823529, 0.99215686,
0.71764706, 0.06666667, 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.18823529, 0.94117647, 0.89019608, 0.06666667, 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.05490196, 0.82352941, 0.98039216,
0.22745098, 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
```

```
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.62745098, 0.99607843, 0.4627451 , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.39215686, 0.98823529, 0.69411765,
0.01568627, 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.09019608,
0.90980392, 0.88627451, 0.0745098 , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.01960784, 0.66666667, 0.99607843, 0.24313725,
0.        , 0.        , 0.        , 0.18039216, 0.49803922,
0.16470588, 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.43921569,
0.99607843, 0.63137255, 0.01568627, 0.        , 0.03921569,
0.55294118, 0.97647059, 0.99607843, 0.59607843, 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.0627451 , 0.94901961, 0.81960784, 0.07843137,
0.        , 0.12941176, 0.76862745, 0.99607843, 0.89019608,
0.99607843, 0.69411765, 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.5372549 ,
0.99607843, 0.42745098, 0.        , 0.2       , 0.8627451 ,
0.99607843, 0.7372549 , 0.4627451 , 0.99607843, 0.4       ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.19215686, 0.92941176, 0.78039216, 0.01568627,
0.17647059, 0.94901961, 0.99215686, 0.48235294, 0.41568627,
0.96862745, 0.72156863, 0.03529412, 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.51764706,
0.99607843, 0.23529412, 0.16470588, 0.90588235, 0.99215686,
```

```
0.59215686, 0.69411765, 0.99607843, 0.86666667, 0.1254902 ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.00784314, 0.90196078, 0.89019608, 0.04313725,
0.61960784, 0.99607843, 0.97254902, 0.97254902, 0.99607843,
0.63529412, 0.08627451, 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.20392157,
0.99607843, 0.43529412, 0.31372549, 0.99607843, 0.99607843,
0.99607843, 0.85882353, 0.29411765, 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.20392157, 0.99607843, 0.84313725,
0.98039216, 0.99607843, 0.99215686, 0.63137255, 0.08627451,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.15294118, 0.92156863, 0.99607843, 0.99607843, 0.85490196,
0.23529412, 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
0.        , 0.        , 0.        , 0.        , 0.        ,
```

```
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        ])
```

Very simple neural network with no hidden layers

[59]:
```
model = keras.Sequential([
    keras.layers.Dense(10, input_shape=(784,), activation='sigmoid')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(X_train_flattened, y_train, epochs=5)
```

```
Epoch 1/5
1875/1875 [==============================] - 3s 1ms/step - loss: 0.4690 -
accuracy: 0.8783
Epoch 2/5
1875/1875 [==============================] - 2s 1ms/step - loss: 0.3036 -
accuracy: 0.9152
Epoch 3/5
1875/1875 [==============================] - 2s 1ms/step - loss: 0.2837 -
accuracy: 0.9210
Epoch 4/5
1875/1875 [==============================] - 2s 1ms/step - loss: 0.2734 -
accuracy: 0.9236
Epoch 5/5
1875/1875 [==============================] - 2s 1ms/step - loss: 0.2665 -
accuracy: 0.9252
```

[59]:
```
<keras.src.callbacks.History at 0x1b3a7d16590>
```

[60]:
```
model.evaluate(X_test_flattened, y_test)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.2665 -
accuracy: 0.9265
```

[60]: [0.2664899528026581, 0.9265000224113464]

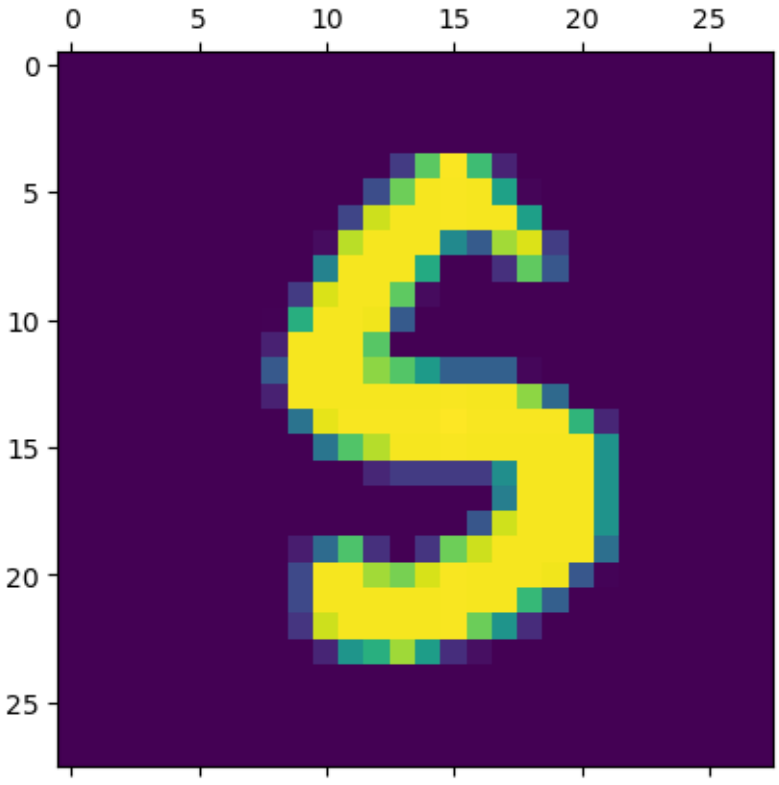
[61]:
```
y_predicted = model.predict(X_test_flattened)
y_predicted[955]
```

```
313/313 [==============================] - 0s 913us/step
```

[61]:
```
array([1.64743501e-03, 1.04167511e-05, 2.29423065e-02, 4.47202355e-01,
       1.01424586e-02, 9.60669518e-01, 6.24117017e-01, 6.82955579e-06,
       4.10067946e-01, 1.50518445e-02], dtype=float32)
```

[62]:
```
plt.matshow(X_test[955])
```

[62]:
```
<matplotlib.image.AxesImage at 0x1b3a7d31a10>
```



np.argmax finds a maximum element from an array and returns the index of it

[63]:
```
np.argmax(y_predicted[955])
```

[63]:
```
5
```

[64]:
```
y_test[95]
```

[64]:
```
4
```

[65]:
```
y_predicted_labels = [np.argmax(i) for i in y_predicted]
```

[66]:
```
y_predicted_labels[:5]
```

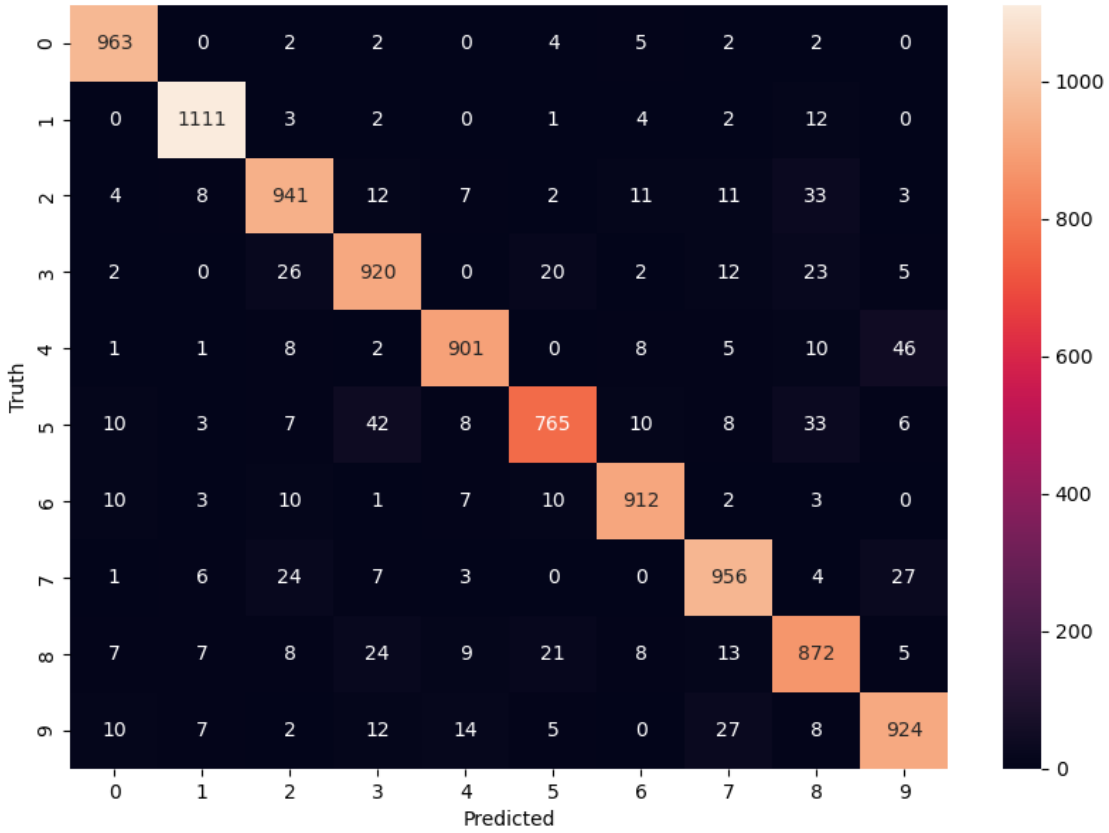
[66]:
```
[7, 2, 1, 0, 4]
```

[67]:
```
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_predicted_labels)
cm
```

[67]:
```
<tf.Tensor: shape=(10, 10), dtype=int32, numpy=
array([[ 963,    0,    2,    2,    0,    4,    5,    2,    2,    0],
       [   0, 1111,    3,    2,    0,    1,    4,    2,   12,    0],
       [   4,    8,  941,   12,    7,    2,   11,   11,   33,    3],
       [   2,    0,   26,  920,    0,   20,    2,   12,   23,    5],
       [   1,    1,    8,    2,  901,    0,    8,    5,   10,   46],
       [  10,    3,    7,   42,    8,  765,   10,    8,   33,    6],
       [  10,    3,   10,    1,    7,   10,  912,    2,    3,    0],
       [   1,    6,   24,    7,    3,    0,    0,  956,    4,   27],
       [   7,    7,    8,   24,    9,   21,    8,   13,  872,    5],
       [  10,    7,    2,   12,   14,    5,    0,   27,    8,  924]])>
```

[68]:
```
import seaborn as sn
plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

[68]:
```
Text(95.72222222222221, 0.5, 'Truth')
```



Using hidden layer

[69]:
```
model = keras.Sequential([
    keras.layers.Dense(100, input_shape=(784,), activation='relu'),
    keras.layers.Dense(10, activation='sigmoid')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(X_train_flattened, y_train, epochs=5)
```

```
Epoch 1/5
1875/1875 [==============================] - 5s 2ms/step - loss: 0.2660 -
accuracy: 0.9241
Epoch 2/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1205 -
accuracy: 0.9652
Epoch 3/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0842 -
```

```
accuracy: 0.9746
Epoch 4/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0643 -
accuracy: 0.9801
Epoch 5/5
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0496 -
accuracy: 0.9849
```

[69]:
```
<keras.src.callbacks.History at 0x1b3a902ab50>
```

[70]:
```
model.evaluate(X_test_flattened,y_test)
```

```
313/313 [==============================] - 1s 1ms/step - loss: 0.0796 -
accuracy: 0.9754
```

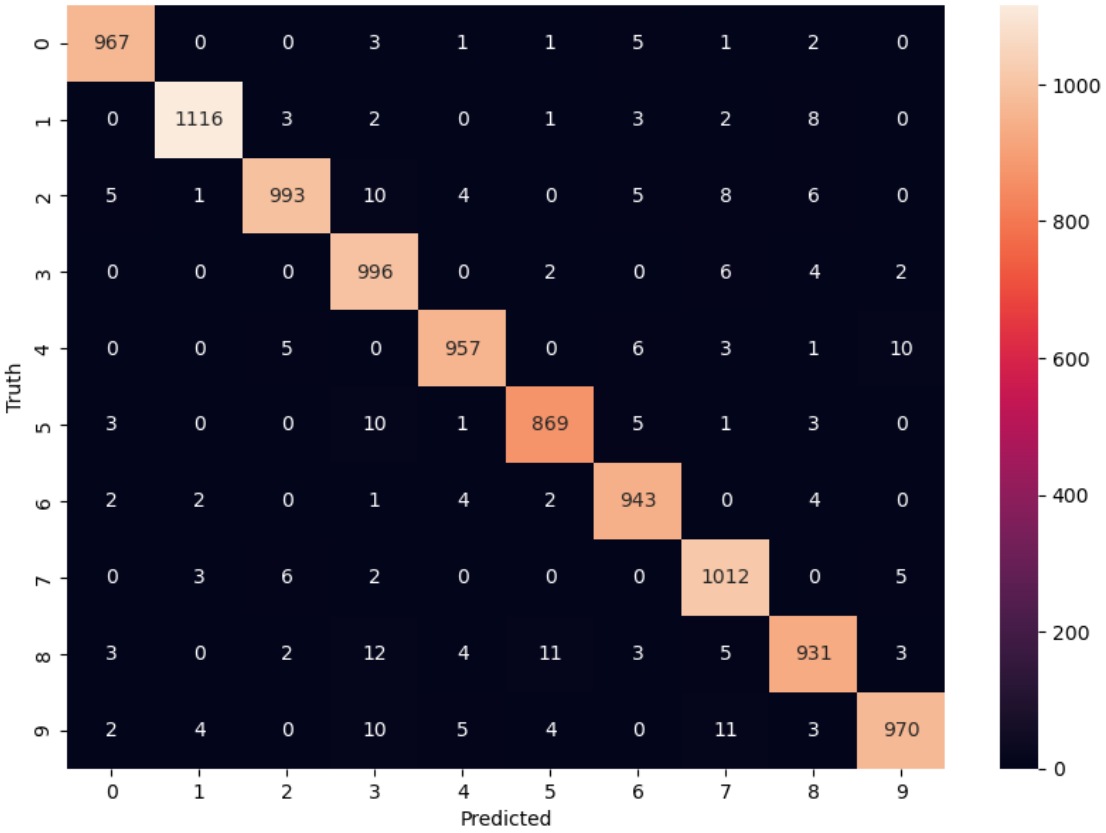
[70]:
```
[0.07959622889757156, 0.9753999710083008]
```

[71]:
```
y_predicted = model.predict(X_test_flattened)
y_predicted_labels = [np.argmax(i) for i in y_predicted]
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_predicted_labels)

plt.figure(figsize = (10,7))
sn.heatmap(cm, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
313/313 [==============================] - 0s 1ms/step
```

[71]:
```
Text(95.72222222222221, 0.5, 'Truth')
```



Using Flatten layer so that we don't have to call .reshape on input dataset

[72]:
```
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(100, activation='relu'),
    keras.layers.Dense(10, activation='sigmoid')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2798 -
accuracy: 0.9201
Epoch 2/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1269 -
accuracy: 0.9618
Epoch 3/10
```

```
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0877 -
accuracy: 0.9734
Epoch 4/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0656 -
accuracy: 0.9802
Epoch 5/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0518 -
accuracy: 0.9843
Epoch 6/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0416 -
accuracy: 0.9866
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0344 -
accuracy: 0.9893
Epoch 8/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0278 -
accuracy: 0.9914
Epoch 9/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.0228 -
accuracy: 0.9929
Epoch 10/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0198 -
accuracy: 0.9940
```

[72]:
```
<keras.src.callbacks.History at 0x1b39afae850>
```

[73]:
```
model.evaluate(X_test,y_test)
```

```
313/313 [==============================] - 1s 1ms/step - loss: 0.0834 -
accuracy: 0.9777
```

[73]:
```
[0.08341177552938461, 0.9776999950408936]
```