Out[6]: 60000 In [7]: len(X_test) Out[7]: 10000 In [8]: X_train[0].shape
Out[8]: (28, 28) each element in the array is an 28x28 pixel image In [9]: X_train[0]
Out[9]: 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, 49, 238, 253, 253, 253, 253, 253, 253, 253, 253
[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,
190, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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, 0, 0, 0, 0, 0,
0, 0], [0, 0, 0, 0, 0, 0, 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, 253, 251, 78, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
[0, 0, 0, 0, 0, 0, 18, 171, 219, 253, 253, 253, 253, 253, 195, 195, 80, 9, 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
In [10]: plt.matshow(X_train[3]) Out[10]: <matplotlib.image.axesimage 0x1238dbf23b0="" at=""> 0 5 10 15 20 25</matplotlib.image.axesimage>
0 -
10 -
20 -
25 - In [11]: y_train[3]
Out[11]: 1 In [12]: y_train[:5] Out[12]: array([5, 0, 4, 1, 9], dtype=uint8)
so the X array contains matricial representation of the hand-written number and the Y array contains the tags of what number it is. I need to reshape the tridimensional array into an bidimensional one In [13]: X_train.shape Out[13]: (60000, 28, 28)
I need to normalize the data [0 - 1] In [14]: X_train = X_train /255 X_test = X_test /255
the first dimension is the number of examples it has, and then each individual image is 28x28 pixels long In [15]: X_train_flattened = X_train.reshape(len(X_train), 28*28)
Out[16]: array([[0., 0., 0.,, 0., 0., 0.],
[0., 0., 0.,, 0., 0., 0.]]) In [17]: print(X_train_flattened.shape) print(X_test_flattened.shape) (60000, 784)
(10000, 784) In [18]: X_train_flattened[0] Out[18]: array([0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
$egin{array}{cccccccccccccccccccccccccccccccccccc$
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$egin{array}{cccccccccccccccccccccccccccccccccccc$
$egin{array}{cccccccccccccccccccccccccccccccccccc$
0.
0. 66666667, 0.99215686, 0.992
0.99215686, 0.99215686, 0.99215686, 0.98431373, 0.36470588, 0.32156863, 0.32156863, 0.21960784, 0.15294118, 0. 0. , 0. , 0. , 0. , 0. , 0. 0. , 0. ,
0.96862745, 0.94509804, 0. , 0.
0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0.05490196, 0. 0.60392157, 0.60392157, 0.99215686, 0.35294118, 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. 0. , 0. , 0. , 0.
0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0.
0. , 0. , 0. , 0. 0. , 0.1372549 , 0.94509804, 0.88235294, 0.62745098, 0.42352941, 0.00392157, 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0.
0.31764706, 0.94117647, 0.99215686, 0.99215686, 0.4666667, 0.09803922, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0.72941176, 0.99215686, 0.99215686, 0.58823529, 0.10588235, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0.71764706, 0.99215686, 0.99215686, 0.81176471, 0.00784314, 0. , 0.
0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0.15294118, 0.58039216, 0.89803922, 0.99215686, 0.99215686, 0.99215686, 0.99215686, 0.99215686, 0.99215686, 0.99215686, 0.98039216, 0.71372549, 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. , 0. 0. , 0. , 0. , 0. , 0. , 0.
0. , 0. <
0.
0.31372549, 0.03529412, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0.
0.
$egin{array}{cccccccccccccccccccccccccccccccccccc$
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0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
<pre>keras.layers.Dense(10, input_shape=(784,), activation="sigmoid")]) model.compile(optimizer="adam", loss="sparse_categorical_crossentropy",</pre>
metrics=["accuracy"]) model.fit(X_train_flattened, y_train, epochs=5) Epoch 1/5 1875/1875 [====================================
Epoch 2/5 1875/1875 [====================================
Epoch 5/5 1875/1875 [====================================
model is where we define out neural network. then we compile it fit is where the training actually happens
0.99 means high accuracy now we are going to evaluate the accuracy in a test dataset. In [20]: model.evaluate(X_test_flattened, y_test)
313/313 [===================================
In [21]: plt.matshow(X_test[0]) Out[21]: <matplotlib.image.axesimage 0x1239099ac80="" at=""> 0 5 10 15 20 25 0 -</matplotlib.image.axesimage>
5-
15 -
20 -
<pre>In [22]: y_predicted = model.predict(X_test_flattened) y_predicted[0] 313/313 [===================================</pre>
Out[22]: array([2.7076501e-02, 3.8983100e-07, 4.7113474e-02, 9.5962936e-01, 2.2483135e-03, 7.9534128e-02, 1.2163443e-06, 9.9977410e-01, 9.7365603e-02, 6.0674453e-01], dtype=float32) it tells me the output of the 10 outcome options it has. The probabilities for every output
In [23]: np.argmax(y_predicted[0]) Out[23]: 7 The prediction looks to work very well, we are going to use a confusion matrix to check the overall performance
<pre>In [24]: y_predicted_labels = [np.argmax(i) for i in y_predicted] y_predicted_labels[:5] Out[24]: [7, 2, 1, 0, 4] In [25]: cm = tf.math.confusion_matrix(labels = y_test, predicted_labels)</pre>
<pre>cm Out[25]: <tf.tensor: 10),="" dtype="int32," numpy="</th" shape="(10,"></tf.tensor:></pre>
[8, 9, 926, 16, 8, 2, 12, 9, 39, 3], [4, 0, 20, 923, 1, 20, 2, 9, 24, 7], [1, 1, 4, 1, 920, 0, 10, 3, 10, 32], [11, 3, 5, 38, 11, 755, 14, 6, 42, 7], [14, 3, 6, 1, 7, 10, 912, 2, 3, 0], [1, 5, 26, 6, 10, 0, 0, 942, 3, 35], [7, 7, 6, 16, 9, 18, 9, 10, 886, 6],
[11, 7, 1, 11, 32, 5, 0, 12, 10, 920]])> In [28]: import seaborn as sn plt.figure(figsize=(10, 7)) sn.heatmap(cm, annot=True, fmt='d')
<pre>plt.xlabel("Predicted") plt.ylabel("Truth") Out[28]: Text(95.722222222221, 0.5, 'Truth') 0 - 964</pre>
- 1000 N -
M - 800
به - المراجعة
ν - ω -
o -
gonna add a hidden layer into this. model = keras.Sequential([keras.layers.Dense(100, input_shape=(784,), activation="relu"), #100 neurons in the hidden layer input: 784 - output: 100 keras.layers.Dense(10, activation="sigmoid") #input: 100 - output: 10]) model.compile(optimizer="adam", loss="sparse_categorical_crossentropy", metrics=["accuracy"]) model.fit(X_train_flattened, y_train, epochs=5) In [31]: model.evaluate(X_test_flattened, y_test)
313/313 [===========] - 1s 2ms/step - loss: 0.0813 - accuracy: 0.9768 Out[31]: [0.08128076791763306, 0.9768000245094299] the accuracy improved in the new model with a hidden layer (92 -> 97)
<pre>In [32]: y_predicted = model.predict(X_test_flattened)</pre>
plt.ylabel("Truth") 313/313 [===========] - 1s 1ms/step Out[32]: Text(95.722222222221, 0.5, 'Truth')
0 - 970
N - 800
- 400 4 -
υ - - 400 - 200
φ - σ -
O 1 2 3 4 5 6 7 8 9 Predicted there is a way of skipping the flattening part though
<pre>In [35]: model = keras.Sequential([</pre>
<pre>model.compile(optimizer="adam", loss="sparse_categorical_crossentropy", metrics=["accuracy"]) model.fit(X train, y train, epochs=5)</pre>
model.fit(X_train, y_train, epochs=5) Epoch 1/5 1875/1875 [=============] - 6s 3ms/step - loss: 0.2713 - accuracy: 0.9229 Epoch 2/5 1875/1875 [==================] - 5s 3ms/step - loss: 0.1268 - accuracy: 0.9621 Epoch 3/5
<pre>In [36]: y_predicted = model.predict(X_test) 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))</pre>
<pre>plt.figure(figsize=(10, 7)) sn.heatmap(cm, annot=True, fmt='d') plt.xlabel("Predicted") plt.ylabel("Truth")</pre>

import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import pandas as pd

In [6]: len(X_train)

In [5]: (X_train, y_train), (X_test, y_test) = keras.datasets.mnist.load_data()