camila-aula-21-ass195173ncrona-1

September 7, 2023

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1 Tópico I: Criando uma rede neural sem a Flatten:

1.1 Acompanhe o código abaixo:

[27]:
```
# Importando o tensorflow:
import tensorflow as tf

# Carregando o dataset:
mnist = tf.keras.datasets.mnist

# Carregando a base de dados já particionada:
(XX, y),(_, _) = mnist.load_data()
XX = XX.reshape(XX.shape[0], 28*28)

# Normalização:
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X = scaler.fit_transform(XX)

# Particionando o dado:
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
 ↪random_state = 42)

# Convertendo o problema em uma classificação binária
y_train_binary = (y_train >= 5).astype('int')  # Classes 0 para digitos de 0 a
 ↪4, Classes 1 para digitos de 5 a 9
y_test_binary = (y_test >= 5).astype('int')
```

[28]:
```
# Dimensão do Input Shape:
28 * 28
```

[28]: 784

[29]:
```
# Podemos seguir uma recomendação de número de neurônios para a primeira camada␣
 ↪intermediária.
# No entando, esta não é uma regra universal.

# Implementando a recomendação:
número_de_classes = 2
número_de_neuronios_camada_oculta = (784 + número_de_classes) / 2
número_de_neuronios_camada_oculta
```

[29]: 393.0

[30]:
```
# Entrada -> Oculta -> Oculta -> Saída
# 784 -> 393 -> 393 -> 1
network1 = tf.keras.models.Sequential()
network1.add(tf.keras.layers.Dense(input_shape = (784,), units = 393,␣
 ↪activation='relu'))
network1.add(tf.keras.layers.Dense(units = 393, activation='relu'))
network1.add(tf.keras.layers.Dense(units = 1, activation='sigmoid'))

network1.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_22 (Dense)            (None, 393)               308505

 dense_23 (Dense)            (None, 393)               154842

 dense_24 (Dense)            (None, 1)                 394

=================================================================
Total params: 463,741
Trainable params: 463,741
Non-trainable params: 0
_________________________________________________________________
```

[31]:
```
network1.compile(optimizer='Adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])
```

[32]:
```
historico = network1.fit(x_train, y_train_binary, epochs = 50)
```

```
Epoch 1/50
1500/1500 [==============================] - 6s 3ms/step - loss: 0.1144 -
accuracy: 0.9565
```

```
Epoch 2/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0538 -
accuracy: 0.9812
Epoch 3/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0390 -
accuracy: 0.9860
Epoch 4/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0296 -
accuracy: 0.9899
Epoch 5/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0231 -
accuracy: 0.9920
Epoch 6/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0179 -
accuracy: 0.9936
Epoch 7/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0153 -
accuracy: 0.9947
Epoch 8/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0136 -
accuracy: 0.9951
Epoch 9/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0123 -
accuracy: 0.9960
Epoch 10/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0100 -
accuracy: 0.9966
Epoch 11/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0096 -
accuracy: 0.9968
Epoch 12/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0092 -
accuracy: 0.9970
Epoch 13/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0075 -
accuracy: 0.9975
Epoch 14/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0070 -
accuracy: 0.9976
Epoch 15/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0058 -
accuracy: 0.9981
Epoch 16/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0060 -
accuracy: 0.9981
Epoch 17/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0077 -
accuracy: 0.9975
```

```
Epoch 18/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0051 -
accuracy: 0.9984
Epoch 19/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0039 -
accuracy: 0.9987
Epoch 20/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0050 -
accuracy: 0.9981
Epoch 21/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0039 -
accuracy: 0.9988
Epoch 22/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0048 -
accuracy: 0.9985
Epoch 23/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0042 -
accuracy: 0.9986
Epoch 24/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0033 -
accuracy: 0.9990
Epoch 25/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0040 -
accuracy: 0.9988
Epoch 26/50
1500/1500 [==============================] - 6s 4ms/step - loss: 0.0044 -
accuracy: 0.9988
Epoch 27/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0029 -
accuracy: 0.9991
Epoch 28/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0061 -
accuracy: 0.9981
Epoch 29/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0035 -
accuracy: 0.9991
Epoch 30/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0022 -
accuracy: 0.9994
Epoch 31/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0031 -
accuracy: 0.9991
Epoch 32/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0028 -
accuracy: 0.9993
Epoch 33/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0041 -
accuracy: 0.9988
```

```
Epoch 34/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0032 -
accuracy: 0.9991
Epoch 35/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0015 -
accuracy: 0.9996
Epoch 36/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0034 -
accuracy: 0.9991
Epoch 37/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0033 -
accuracy: 0.9990
Epoch 38/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0017 -
accuracy: 0.9994
Epoch 39/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0042 -
accuracy: 0.9989
Epoch 40/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0023 -
accuracy: 0.9993
Epoch 41/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0038 -
accuracy: 0.9991
Epoch 42/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0012 -
accuracy: 0.9996
Epoch 43/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0039 -
accuracy: 0.9991
Epoch 44/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0011 -
accuracy: 0.9996
Epoch 45/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0036 -
accuracy: 0.9989
Epoch 46/50
1500/1500 [==============================] - 5s 3ms/step - loss: 9.2891e-04 -
accuracy: 0.9998
Epoch 47/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0040 -
accuracy: 0.9989
Epoch 48/50
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0032 -
accuracy: 0.9991
Epoch 49/50
1500/1500 [==============================] - 4s 3ms/step - loss: 0.0025 -
accuracy: 0.9993
```

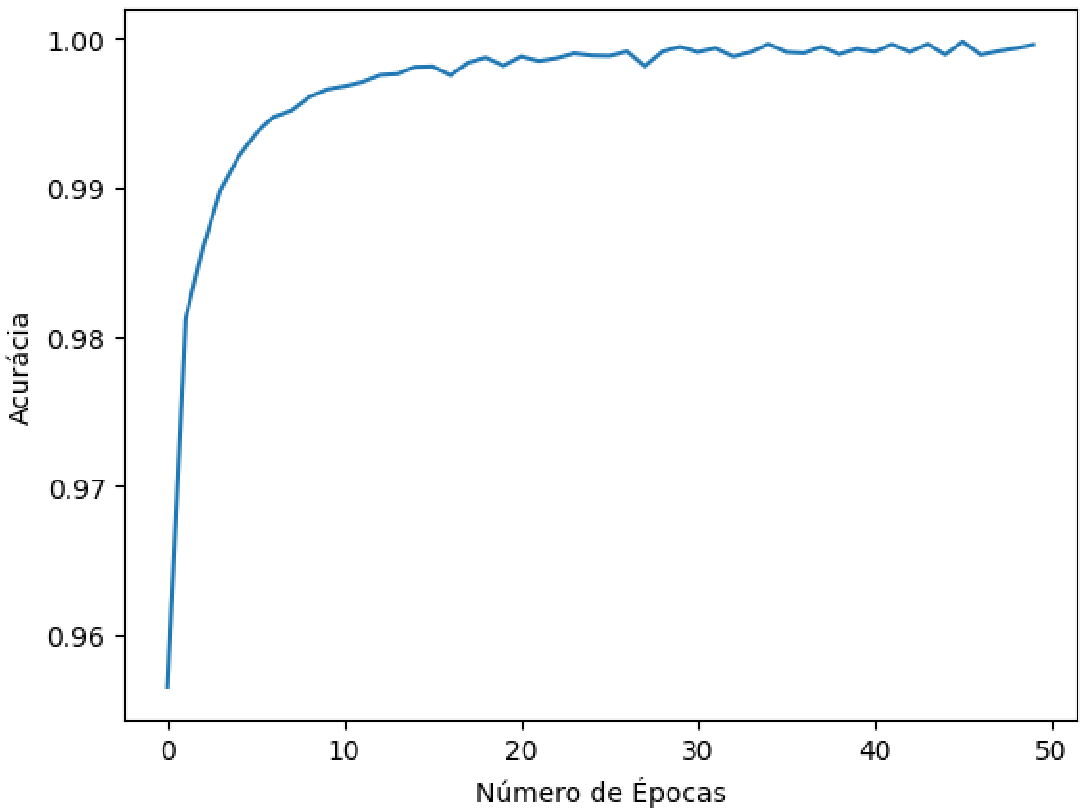
```
Epoch 50/50
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0015 -
accuracy: 0.9996
```

[33]:
```
historico.history.keys()

import matplotlib.pyplot as plt
plt.plot(historico.history['accuracy']);

plt.xlabel("Número de Épocas")
plt.ylabel("Acurácia")

plt.show()
```



[34]:
```
pred = network1.predict(x_test)
pred = (pred > 0.5)

from sklearn.metrics import accuracy_score
acc = accuracy_score(y_test_binary, pred)

print('Acurácia Obtida: ',acc*100)
```

```
375/375 [==============================] - 1s 2ms/step
Acurácia Obtida:  98.79166666666667
```

1.2 Tópico II: Agora é a sua vez:

- Proponha uma arquitetura que supere o resultado anterior.

[45]:
```
# Carregando o dataset MNIST
mnist = tf.keras.datasets.mnist
(XX, y), (_, _) = mnist.load_data()
XX = XX.reshape(XX.shape[0], 28, 28, 1)  # Adicionando uma dimensão para canais␣
↪(1 para imagens em escala de cinza)

# Normalização
scaler = MinMaxScaler()
X = scaler.fit_transform(XX.reshape(-1, 28*28))  # Aplique a normalização

# Particionando o dado
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Convertendo o problema em uma classificação binária
y_train_binary = (y_train >= 5).astype('int')
y_test_binary = (y_test >= 5).astype('int')
```

[46]:
```
# Criando a CNN
model = tf.keras.models.Sequential()

# Camadas de convolução e max-pooling
model.add(tf.keras.layers.Conv2D(32, (3, 3), activation='relu',␣
↪input_shape=(28, 28, 1)))
model.add(tf.keras.layers.MaxPooling2D((2, 2)))
model.add(tf.keras.layers.Conv2D(64, (3, 3), activation='relu'))
model.add(tf.keras.layers.MaxPooling2D((2, 2)))

# Flatten
model.add(tf.keras.layers.Flatten())

# Camadas totalmente conectadas
model.add(tf.keras.layers.Dense(64, activation='relu'))
model.add(tf.keras.layers.Dense(1, activation='sigmoid'))

model.summary()
```

```
Model: "sequential_14"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 conv2d_16 (Conv2D)          (None, 26, 26, 32)        320

 max_pooling2d_16 (MaxPoolin  (None, 13, 13, 32)       0
 g2D)

 conv2d_17 (Conv2D)          (None, 11, 11, 64)        18496

 max_pooling2d_17 (MaxPoolin  (None, 5, 5, 64)         0
 g2D)

 flatten_7 (Flatten)         (None, 1600)              0

 dense_35 (Dense)            (None, 64)                102464

 dense_36 (Dense)            (None, 1)                 65

=================================================================
Total params: 121,345
Trainable params: 121,345
Non-trainable params: 0
_________________________________________________________________
```

[47]:

```python
# Compilando o modelo
model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

# Treinamento
hist = model.fit(x_train.reshape(-1, 28, 28, 1), y_train_binary, epochs=50,␣
 ↪batch_size=64)
```

```
Epoch 1/50
750/750 [==============================] - 4s 4ms/step - loss: 0.1212 -
accuracy: 0.9525
Epoch 2/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0425 -
accuracy: 0.9852
Epoch 3/50
750/750 [==============================] - 4s 5ms/step - loss: 0.0298 -
accuracy: 0.9901
Epoch 4/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0225 -
accuracy: 0.9924
Epoch 5/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0173 -
accuracy: 0.9943
Epoch 6/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0134 -
accuracy: 0.9955
```

```
Epoch 7/50
750/750 [==============================] - 3s 5ms/step - loss: 0.0111 -
accuracy: 0.9964
Epoch 8/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0099 -
accuracy: 0.9967
Epoch 9/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0075 -
accuracy: 0.9975
Epoch 10/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0058 -
accuracy: 0.9982
Epoch 11/50
750/750 [==============================] - 3s 5ms/step - loss: 0.0047 -
accuracy: 0.9982
Epoch 12/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0045 -
accuracy: 0.9984
Epoch 13/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0036 -
accuracy: 0.9987
Epoch 14/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0030 -
accuracy: 0.9991
Epoch 15/50
750/750 [==============================] - 4s 5ms/step - loss: 0.0028 -
accuracy: 0.9990
Epoch 16/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0030 -
accuracy: 0.9990
Epoch 17/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0030 -
accuracy: 0.9989
Epoch 18/50
750/750 [==============================] - 3s 4ms/step - loss: 9.4783e-04 -
accuracy: 0.9997
Epoch 19/50
750/750 [==============================] - 3s 5ms/step - loss: 0.0028 -
accuracy: 0.9991
Epoch 20/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0025 -
accuracy: 0.9991
Epoch 21/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0017 -
accuracy: 0.9993
Epoch 22/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0027 -
accuracy: 0.9990
```

```
Epoch 23/50
750/750 [==============================] - 3s 5ms/step - loss: 0.0014 -
accuracy: 0.9995
Epoch 24/50
750/750 [==============================] - 4s 5ms/step - loss: 0.0022 -
accuracy: 0.9991
Epoch 25/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0017 -
accuracy: 0.9995
Epoch 26/50
750/750 [==============================] - 3s 4ms/step - loss: 5.0443e-04 -
accuracy: 0.9998
Epoch 27/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0023 -
accuracy: 0.9992
Epoch 28/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0024 -
accuracy: 0.9992
Epoch 29/50
750/750 [==============================] - 3s 4ms/step - loss: 0.0013 -
accuracy: 0.9996
Epoch 30/50
750/750 [==============================] - 3s 4ms/step - loss: 4.5760e-04 -
accuracy: 0.9999
Epoch 31/50
750/750 [==============================] - 4s 5ms/step - loss: 0.0023 -
accuracy: 0.9992
Epoch 32/50
750/750 [==============================] - 4s 6ms/step - loss: 5.2058e-04 -
accuracy: 0.9999
Epoch 33/50
750/750 [==============================] - 3s 4ms/step - loss: 9.4560e-05 -
accuracy: 1.0000
Epoch 34/50
750/750 [==============================] - 3s 4ms/step - loss: 2.8390e-05 -
accuracy: 1.0000
Epoch 35/50
750/750 [==============================] - 3s 4ms/step - loss: 8.4207e-06 -
accuracy: 1.0000
Epoch 36/50
750/750 [==============================] - 3s 4ms/step - loss: 4.1303e-06 -
accuracy: 1.0000
Epoch 37/50
750/750 [==============================] - 3s 4ms/step - loss: 2.9191e-06 -
accuracy: 1.0000
Epoch 38/50
750/750 [==============================] - 3s 4ms/step - loss: 2.1279e-06 -
accuracy: 1.0000
```

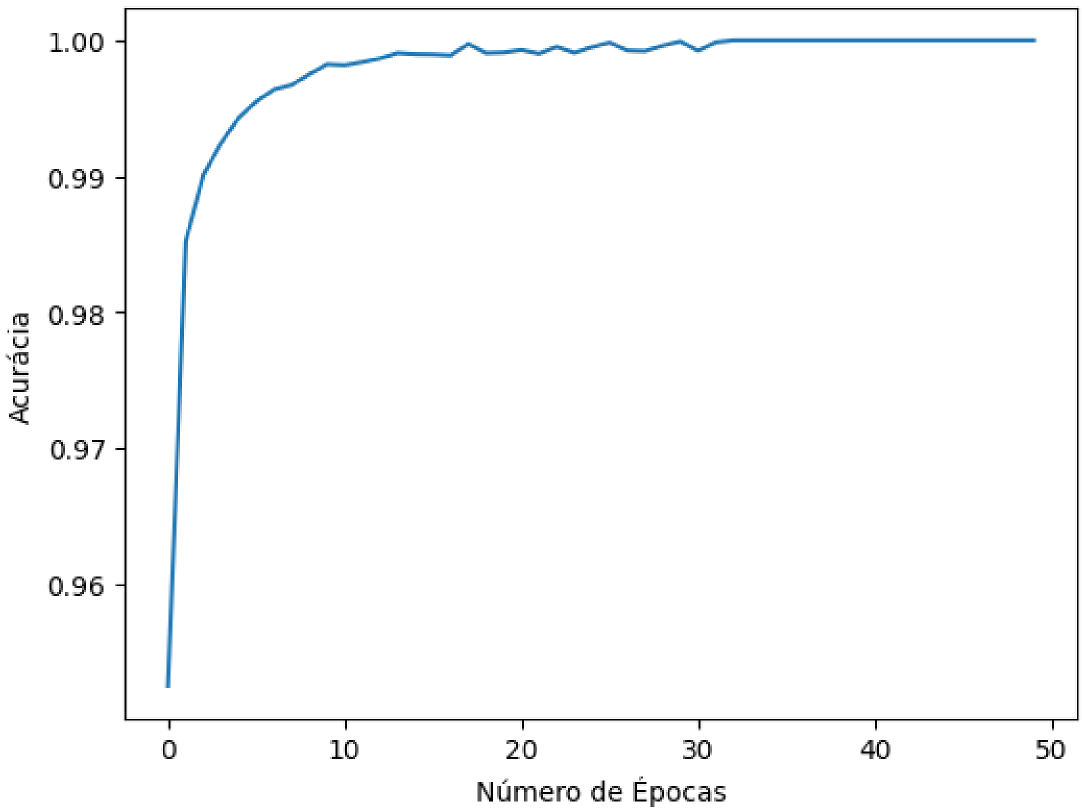
```
Epoch 39/50
750/750 [==============================] - 3s 4ms/step - loss: 1.5399e-06 -
accuracy: 1.0000
Epoch 40/50
750/750 [==============================] - 4s 5ms/step - loss: 1.1131e-06 -
accuracy: 1.0000
Epoch 41/50
750/750 [==============================] - 3s 4ms/step - loss: 7.9119e-07 -
accuracy: 1.0000
Epoch 42/50
750/750 [==============================] - 3s 4ms/step - loss: 5.6037e-07 -
accuracy: 1.0000
Epoch 43/50
750/750 [==============================] - 3s 4ms/step - loss: 3.9530e-07 -
accuracy: 1.0000
Epoch 44/50
750/750 [==============================] - 3s 4ms/step - loss: 2.7995e-07 -
accuracy: 1.0000
Epoch 45/50
750/750 [==============================] - 3s 4ms/step - loss: 1.8993e-07 -
accuracy: 1.0000
Epoch 46/50
750/750 [==============================] - 3s 4ms/step - loss: 1.3188e-07 -
accuracy: 1.0000
Epoch 47/50
750/750 [==============================] - 3s 4ms/step - loss: 9.0580e-08 -
accuracy: 1.0000
Epoch 48/50
750/750 [==============================] - 3s 5ms/step - loss: 6.6461e-08 -
accuracy: 1.0000
Epoch 49/50
750/750 [==============================] - 3s 4ms/step - loss: 4.4940e-08 -
accuracy: 1.0000
Epoch 50/50
750/750 [==============================] - 3s 4ms/step - loss: 3.0544e-08 -
accuracy: 1.0000
```

[48]:
```python
hist.history.keys()

import matplotlib.pyplot as plt
plt.plot(hist.history['accuracy']);

plt.xlabel("Número de Épocas")
plt.ylabel("Acurácia")

plt.show()
```



[49]:
```
# Avaliação da acurácia no conjunto de teste
y_pred = model.predict(x_test.reshape(-1, 28, 28, 1))
y_pred_binary = (y_pred > 0.5).astype('int')
acc = accuracy_score(y_test_binary, y_pred_binary)
print('Acurácia Obtida: ', acc * 100)
```

```
375/375 [==============================] - 1s 2ms/step
Acurácia Obtida:  99.45
```