deeplearningfashion-a01250513

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Actividad: Actividad Deep Learning Fashion MNIST

Nombre: Luis Rodolfo Bojorquez Pineda

Matricula: A01250513

0.0.1 Importamos las librerías necesarias.

[41]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import datasets, layers, models
```

0.0.2 Cargamos la base de datos de Fashion MNIST.

[42]:
```
(train_images, train_labels), (test_images, test_labels) = datasets.
 ↪fashion_mnist.load_data()
```

0.0.3 Normalizamos los datos

[43]:
```
train_images, test_images = train_images/255.0, test_images/255.0
```

0.0.4 Graficamos las primeras 25 imagenes del dataset

[44]:
```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
                'Sandal',      'Shirt',   'Sneaker',  'Bag',   'Ankle boot']

plt.figure(figsize=(10,10))
for i in range(25):
  plt.subplot(5, 5, i+1)
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(train_images[i])
  plt.xlabel(class_names[train_labels[i]])
plt.show()
```

0.0.5 Capas de convolución

[45]:
```
model = models.Sequential()
model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)))
model.add(layers.MaxPooling2D((2,2)))
model.add(layers.Conv2D(64, (3,3), activation='relu'))
model.add(layers.MaxPooling2D((2,2)))
```

0.0.6 Arquitectura de la red

[46]:
```
model.summary()
```

```
Model: "sequential_6"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_14 (Conv2D)          (None, 26, 26, 32)        320

 max_pooling2d_12 (MaxPooli  (None, 13, 13, 32)        0
 ng2D)

 conv2d_15 (Conv2D)          (None, 11, 11, 64)        18496

 max_pooling2d_13 (MaxPooli  (None, 5, 5, 64)          0
 ng2D)

=================================================================
Total params: 18816 (73.50 KB)
Trainable params: 18816 (73.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

0.0.7 Generamos capas densas

[56]:
```
model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(128, activation='softmax'))
```

0.0.8 Volvemos a ver la arquitectura de la red

[48]:
```
model.summary()
```

```
Model: "sequential_6"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_14 (Conv2D)          (None, 26, 26, 32)        320

 max_pooling2d_12 (MaxPooli  (None, 13, 13, 32)        0
 ng2D)

 conv2d_15 (Conv2D)          (None, 11, 11, 64)        18496

 max_pooling2d_13 (MaxPooli  (None, 5, 5, 64)          0
 ng2D)
```

```
 flatten_3 (Flatten)         (None, 1600)              0

 dense_6 (Dense)             (None, 128)               204928

 dense_7 (Dense)             (None, 128)               16512

=================================================================
Total params: 240256 (938.50 KB)
Trainable params: 240256 (938.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

0.0.9 Compilamos el modelo

[57]:
```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(),
              metrics=['accuracy'])
```

0.0.10 Entrenamos el modelo

[58]:
```
history = model.fit(train_images, train_labels, epochs=10,
                    validation_data=(test_images, test_labels))
```

```
Epoch 1/10
1875/1875 [==============================] - 17s 9ms/step - loss: 0.4942 -
accuracy: 0.8219 - val_loss: 0.3819 - val_accuracy: 0.8643
Epoch 2/10
1875/1875 [==============================] - 18s 10ms/step - loss: 0.3170 -
accuracy: 0.8841 - val_loss: 0.3002 - val_accuracy: 0.8930
Epoch 3/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.2701 -
accuracy: 0.9002 - val_loss: 0.2950 - val_accuracy: 0.8931
Epoch 4/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.2438 -
accuracy: 0.9097 - val_loss: 0.2922 - val_accuracy: 0.8910
Epoch 5/10
1875/1875 [==============================] - 17s 9ms/step - loss: 0.2217 -
accuracy: 0.9178 - val_loss: 0.2776 - val_accuracy: 0.9014
Epoch 6/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.1997 -
accuracy: 0.9252 - val_loss: 0.2934 - val_accuracy: 0.8967
Epoch 7/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.1861 -
accuracy: 0.9299 - val_loss: 0.2773 - val_accuracy: 0.9009
Epoch 8/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.1699 -
accuracy: 0.9359 - val_loss: 0.2648 - val_accuracy: 0.9060
```

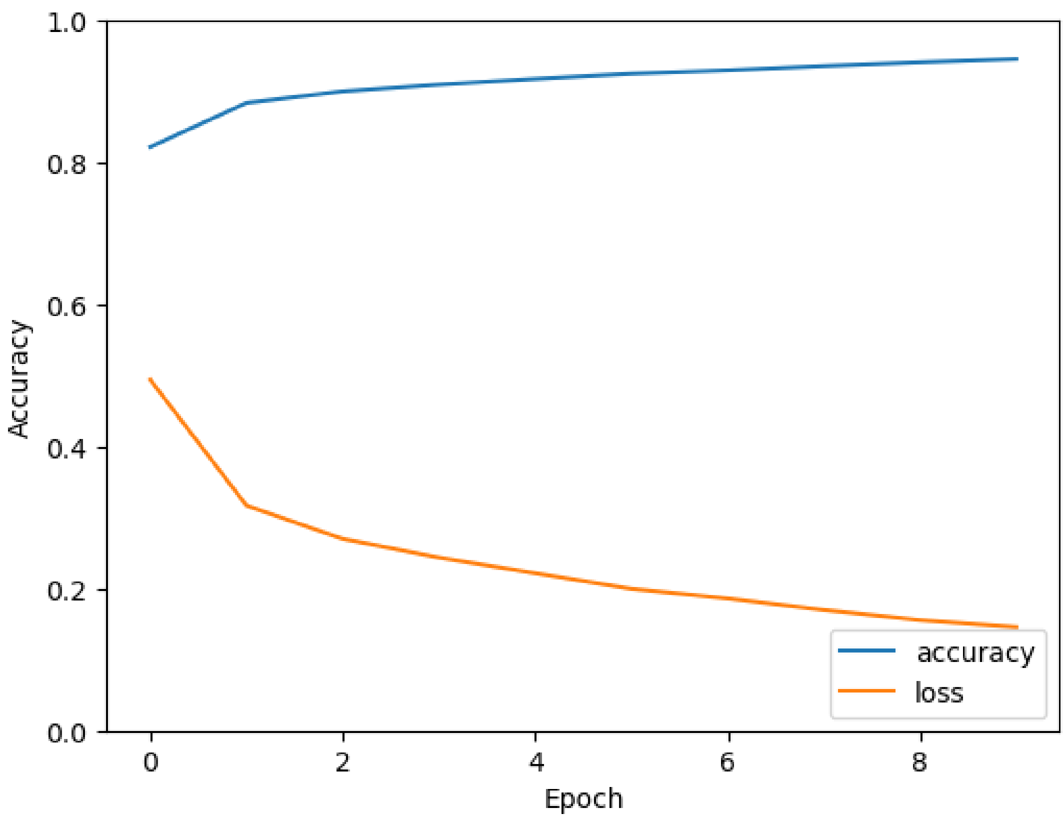
```
Epoch 9/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.1556 -
accuracy: 0.9411 - val_loss: 0.2834 - val_accuracy: 0.9131
Epoch 10/10
1875/1875 [==============================] - 18s 9ms/step - loss: 0.1459 -
accuracy: 0.9458 - val_loss: 0.2889 - val_accuracy: 0.9138
```

0.0.11 Evaluamos el modelo

[59]:
```python
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
print(test_acc)

plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['loss'], label='loss')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0, 1])
plt.legend(loc='lower right')
plt.show()
```

```
313/313 - 1s - loss: 0.2889 - accuracy: 0.9138 - 1s/epoch - 3ms/step
0.9138000011444092
```



0.0.12 Imprimimos la precisión del modelo

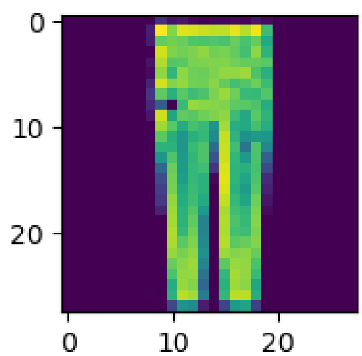
[60]:
```
print(test_acc)
```

```
0.9138000011444092
```

0.0.13 Predecimos las etiquetas de las imágenes de prueba

[63]:
```
n = 200

plt.figure(figsize=(2,2))
plt.imshow(test_images[n])
plt.show()
```



[62]:
```
predictions = model.predict(test_images)
print(predictions[n])

import numpy as np

print('La imagen pertenece al grupo {} con una probabilidad de {:2f} %'
      .format(class_names[np.argmax(predictions[n])], 100 * np.
 ↪max(predictions[n])))
```

```
313/313 [==============================] - 1s 3ms/step
[1.08256249e-14 1.00000000e+00 4.61348963e-14 2.89043258e-13
 4.67073320e-13 3.87871270e-22 8.92447466e-14 1.04846815e-20
 1.11620246e-22 3.74975092e-23 0.00000000e+00 0.00000000e+00
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```

```
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 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00]
La imagen pertenece al grupo Trouser con una probabilidad de 100.000000 %
```

```
[ ]:
```