Actividad Redes Neuronales Profundas - Problema 1

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Llamado a librerías

```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import datasets, layers, models
```

Carga de datos

```
(train_images, train_labels),(test_images, test_labels) = datasets.fashion_mnist.load_data()
```

Proceso de normalización de las imágenes

```
train_images, test_images = train_images/255.0, test_images/255.0
```

```
# Validación de respuestas "Labels"
print(train_labels)
```

```
[9 0 0 ... 3 0 5]
```

Mostramos un grid con el ejemplo de las imágenes

```
class_names=['camiseta/top', 'pantalón', 'sudadera','vestido','coat','sandalia','camisa','sneaker','bolsa','botín']

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()
```

Capas de convolución

```
# Agrego las primeras 3 capas de convolución
model = models.Sequential()
# En la primer capa es necesario definir el tamaño de las imágenes de entrada.
model.add(layers.Conv2D(64, (3,3), activation='relu', input_shape=(28,28,1)))
model.add(layers.MaxPooling2D((2,2)))
model.add(layers.Conv2D(128, (3,3), activation='relu'))
model.add(layers.MaxPooling2D((2,2)))
model.add(layers.Conv2D(128, (3,3), activation='relu'))
```

Arquitectura

```
'''
Mostramos la arquitectura de la red neuronal y se observa el cambio que
tienen las imágenes al pasar por cada una de las capas de convolución.
'''

model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 26, 26, 64)        640

 max_pooling2d_4 (MaxPoolin  (None, 13, 13, 64)        0
 g2D)

 conv2d_7 (Conv2D)           (None, 11, 11, 128)       73856

 max_pooling2d_5 (MaxPoolin  (None, 5, 5, 128)         0
 g2D)

 conv2d_8 (Conv2D)           (None, 3, 3, 128)         147584

=================================================================
Total params: 222080 (867.50 KB)
Trainable params: 222080 (867.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Capas densas

```
# Se agregan las capas densas a la red
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='sigmoid'))
```

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 26, 26, 64)        640

 max_pooling2d_4 (MaxPoolin  (None, 13, 13, 64)        0
 g2D)

 conv2d_7 (Conv2D)           (None, 11, 11, 128)       73856

 max_pooling2d_5 (MaxPoolin  (None, 5, 5, 128)         0
 g2D)

 conv2d_8 (Conv2D)           (None, 3, 3, 128)         147584

 flatten_2 (Flatten)         (None, 1152)              0

 dense_4 (Dense)             (None, 64)                73792

 dense_5 (Dense)             (None, 10)                650

=================================================================
Total params: 296522 (1.13 MB)
Trainable params: 296522 (1.13 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

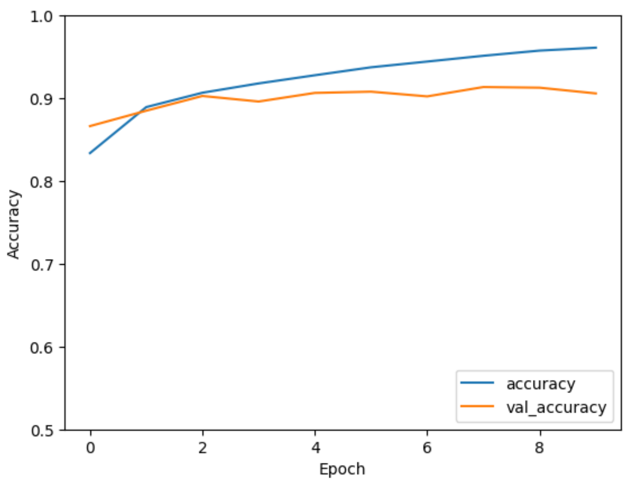
```
'''
Se procede a hacer el entrenaiento de la red y se definen la función de
optimización, la función de pérdida y las épocas de entrenamiento.
'''
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
history = model.fit(train_images, train_labels, epochs=10, validation_data=(test_images,test_labels))
```

```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/backend.py:5714: UserWarning: "`sparse_categorical_crossentropy` received `from_logits=True`, but the `output` ar
  output, from_logits = _get_logits(
1875/1875 [==============================] - 104s 55ms/step - loss: 0.4586 - accuracy: 0.8337 - val_loss: 0.3670 - val_accuracy: 0.8663
Epoch 2/10
```

```
1875/1875 [==============================] - 101s 54ms/step - loss: 0.2991 - accuracy: 0.8892 - val_loss: 0.3153 - val_accuracy: 0.8849
Epoch 3/10
1875/1875 [==============================] - 102s 54ms/step - loss: 0.2546 - accuracy: 0.9066 - val_loss: 0.2641 - val_accuracy: 0.9027
Epoch 4/10
1875/1875 [==============================] - 101s 54ms/step - loss: 0.2209 - accuracy: 0.9179 - val_loss: 0.2846 - val_accuracy: 0.8960
Epoch 5/10
1875/1875 [==============================] - 102s 55ms/step - loss: 0.1918 - accuracy: 0.9277 - val_loss: 0.2553 - val_accuracy: 0.9064
Epoch 6/10
1875/1875 [==============================] - 101s 54ms/step - loss: 0.1693 - accuracy: 0.9373 - val_loss: 0.2573 - val_accuracy: 0.9079
Epoch 7/10
1875/1875 [==============================] - 100s 54ms/step - loss: 0.1484 - accuracy: 0.9443 - val_loss: 0.2887 - val_accuracy: 0.9022
Epoch 8/10
1875/1875 [==============================] - 103s 55ms/step - loss: 0.1312 - accuracy: 0.9513 - val_loss: 0.2855 - val_accuracy: 0.9135
Epoch 9/10
1875/1875 [==============================] - 100s 53ms/step - loss: 0.1150 - accuracy: 0.9575 - val_loss: 0.2827 - val_accuracy: 0.9127
Epoch 10/10
1875/1875 [==============================] - 101s 54ms/step - loss: 0.1019 - accuracy: 0.9610 - val_loss: 0.3193 - val_accuracy: 0.9058
```

```python
# Gráfica para mostrar el accuracy de la red en cada época
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.5,1])
plt.legend(loc='lower right')
```

```
<matplotlib.legend.Legend at 0x7a60f0f351b0>
```

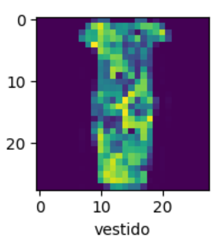


Predicción

Pruba con un dato random del conjunto de imágenes para validar si la red lo clasifica correctamente

```python
n = 100 # Número de imagen

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




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

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

```
313/313 [==============================] - 4s 12ms/step
[2.7665254e-01 8.1508613e-01 2.9295231e-03 9.9993777e-01 2.4824776e-01
 2.9144303e-05 7.5484276e-01 6.3609215e-04 7.7716359e-03 8.7610388e-06]
La imagen pertenece al grupo vestido con una probalidad de 99.99%
```