deeplearningcifar-a01250513

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Actividad: Actividad Deep Learning CIFAR-10

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0.0.1 Importamos las librerías necesarias.

[46]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import datasets, layers, models
```

0.0.2 Cargamos la base de datos CIFAR-10

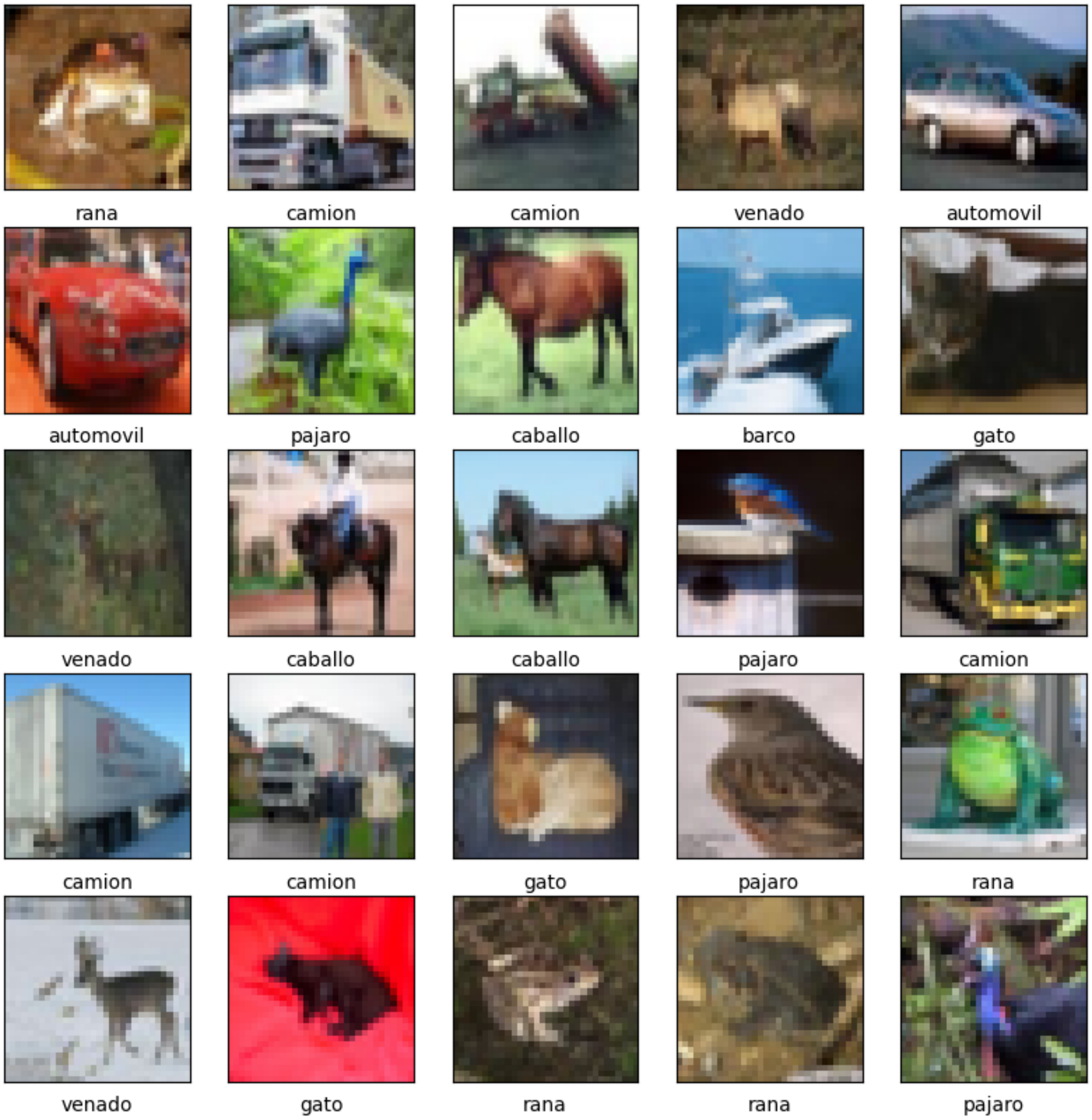
[47]:
```
(train_images, train_labels), (test_images, test_labels) = datasets.cifar10.
↪load_data()
```

0.0.3 Normalizamos los datos

[48]:
```
train_images, test_images = train_images/255.0, test_images/255.0
```

0.0.4 Graficamos las primeras 25 imagenes del dataset

[49]:
```
class_names = ['avion', 'automovil', 'pajaro', 'gato', 'venado', 'perro',␣
↪'rana', 'caballo', 'barco', 'camion']
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.imshow(train_images[i])
    plt.xlabel(class_names[train_labels[i][0]])
    plt.xticks([])
    plt.yticks([])
plt.show()
```



0.0.5 Capas de convolución

[50]:
```
model = models.Sequential()
model.add(layers.Conv2D(64, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(256, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(267, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2,2)))
```

0.0.6 Arquitectura de la red

[51]:
```
model.summary()
```

```
Model: "sequential_5"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_9 (Conv2D)           (None, 30, 30, 64)        1792

 max_pooling2d_6 (MaxPoolin  (None, 15, 15, 64)        0
 g2D)

 conv2d_10 (Conv2D)          (None, 13, 13, 256)       147712

 max_pooling2d_7 (MaxPoolin  (None, 6, 6, 256)         0
 g2D)

 conv2d_11 (Conv2D)          (None, 4, 4, 267)         615435

 max_pooling2d_8 (MaxPoolin  (None, 2, 2, 267)         0
 g2D)

=================================================================
Total params: 764939 (2.92 MB)
Trainable params: 764939 (2.92 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

0.0.7 Generamos capas densas

[52]:
```
model.add(layers.Flatten())
model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(128, activation='sigmoid'))
```

0.0.8 Volvemos a ver la arquitectura de la red

[53]:
```
model.summary()
```

```
Model: "sequential_5"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_9 (Conv2D)           (None, 30, 30, 64)        1792

 max_pooling2d_6 (MaxPoolin  (None, 15, 15, 64)        0
 g2D)
```

```
 conv2d_10 (Conv2D)          (None, 13, 13, 256)       147712

 max_pooling2d_7 (MaxPoolin  (None, 6, 6, 256)         0
 g2D)

 conv2d_11 (Conv2D)          (None, 4, 4, 267)         615435

 max_pooling2d_8 (MaxPoolin  (None, 2, 2, 267)         0
 g2D)

 flatten_5 (Flatten)         (None, 1068)              0

 dense_10 (Dense)            (None, 128)               136832

 dense_11 (Dense)            (None, 128)               16512

=================================================================
Total params: 918283 (3.50 MB)
Trainable params: 918283 (3.50 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

0.0.9 Compilamos el modelo

[54]:
```
model.compile(optimizer='adam',
              loss=tf.keras.losses.
 ↪SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

0.0.10 Entrenamos el modelo

[55]:
```
history = model.fit(train_images, train_labels, epochs=10,
                    validation_data=(test_images, test_labels))
```

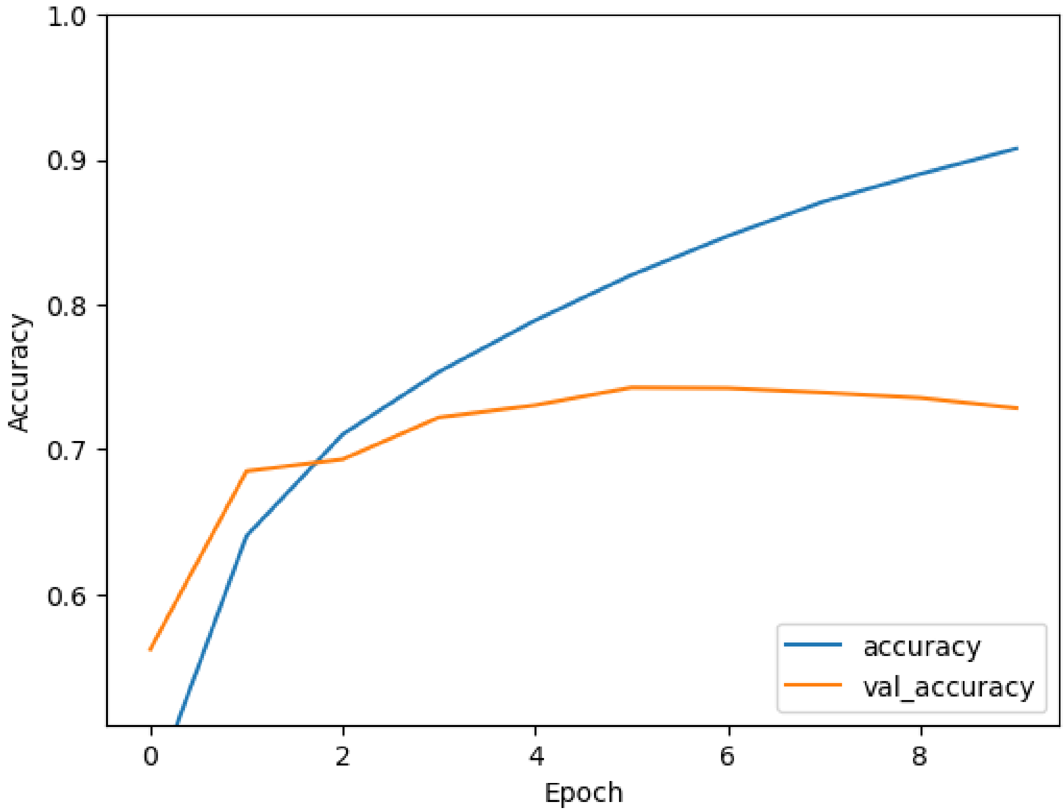
```
Epoch 1/10
1563/1563 [==============================] - 65s 41ms/step - loss: 1.4941 -
accuracy: 0.4600 - val_loss: 1.1979 - val_accuracy: 0.5619
Epoch 2/10
1563/1563 [==============================] - 63s 40ms/step - loss: 1.0315 -
accuracy: 0.6402 - val_loss: 0.9111 - val_accuracy: 0.6849
Epoch 3/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.8360 -
accuracy: 0.7103 - val_loss: 0.8808 - val_accuracy: 0.6931
Epoch 4/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.7087 -
accuracy: 0.7534 - val_loss: 0.8030 - val_accuracy: 0.7220
Epoch 5/10
```

```
1563/1563 [==============================] - 64s 41ms/step - loss: 0.6046 -
accuracy: 0.7889 - val_loss: 0.8007 - val_accuracy: 0.7304
Epoch 6/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.5152 -
accuracy: 0.8203 - val_loss: 0.8000 - val_accuracy: 0.7426
Epoch 7/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.4367 -
accuracy: 0.8471 - val_loss: 0.8240 - val_accuracy: 0.7422
Epoch 8/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.3678 -
accuracy: 0.8710 - val_loss: 0.8653 - val_accuracy: 0.7391
Epoch 9/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.3062 -
accuracy: 0.8899 - val_loss: 0.9341 - val_accuracy: 0.7355
Epoch 10/10
1563/1563 [==============================] - 64s 41ms/step - loss: 0.2630 -
accuracy: 0.9075 - val_loss: 1.0485 - val_accuracy: 0.7284
```

0.0.11 Evaluamos el modelo

[56]:
```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.510,1])
plt.legend(loc='lower right')
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
```

```
313/313 - 3s - loss: 1.0485 - accuracy: 0.7284 - 3s/epoch - 11ms/step
```



0.0.12 Imprimimos la precisión del modelo

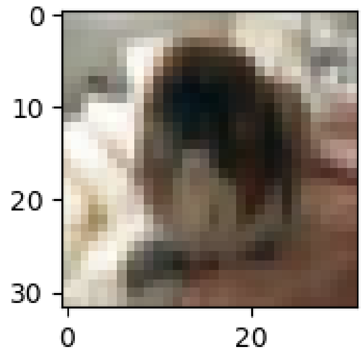
[57]:
```
print(test_acc)
```

```
0.7283999919891357
```

0.0.13 Predecimos las etiquetas de las imágenes de prueba

[58]:
```
n = 200

plt.figure(figsize=(2,2))
plt.imshow(test_images[n])
plt.xlabel(class_names[test_labels[n][0]])
plt.show()
```



[59]:
```
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 [==============================] - 4s 11ms/step
[5.49184484e-03 4.52411138e-02 9.26821887e-01 9.99869168e-01
 9.64995086e-01 9.99965131e-01 7.46347189e-01 8.27987254e-01
 1.69164687e-03 5.19784749e-01 1.83169868e-11 2.78707352e-11
 4.18961255e-10 1.59620737e-11 1.42381357e-10 1.90483618e-11
 1.93198981e-11 1.76825415e-10 6.82865361e-11 4.65609495e-12
 9.45415100e-12 6.46065956e-09 4.97058089e-11 7.38178442e-12
 8.38192640e-11 4.01974461e-11 1.44226916e-13 5.29538349e-12
 1.44472585e-12 5.73891195e-13 4.40043878e-12 2.28159241e-10
 2.34332154e-09 6.97348321e-13 3.95283195e-10 2.03335948e-09
 9.33160558e-13 7.09007549e-12 4.85828868e-12 9.83115499e-12
 5.76880991e-12 9.71917100e-13 3.03139874e-11 4.71437958e-11
 4.32055650e-12 1.71211812e-11 4.19262194e-12 2.32284920e-11
 1.33520153e-10 3.85418216e-12 6.42484788e-10 2.33766867e-10
 8.26038109e-12 1.93719151e-12 1.92084434e-12 4.53096241e-12
 8.50173144e-12 9.03396823e-13 3.04362763e-12 1.05360848e-12
 1.09143788e-11 1.58222865e-10 1.61169342e-11 6.07451450e-11
 6.13809351e-11 1.84179016e-09 8.98801433e-12 4.94261403e-12
 6.69722680e-11 4.00544042e-11 9.76207934e-11 1.92417797e-08
 3.62242562e-11 4.16772450e-11 2.78215145e-10 1.16764107e-11
 4.41129043e-11 7.87809748e-12 2.43402694e-12 2.53101641e-12
 6.64693370e-11 3.20774115e-12 3.71691653e-12 4.95311986e-11
 4.58491682e-11 1.07634686e-10 2.30313355e-11 9.46671422e-11
 2.91112238e-11 2.08624933e-13 8.65832406e-12 5.04290620e-12
```

```
 1.84626468e-12 1.66496639e-09 1.68980639e-12 2.56104664e-12
 7.69050676e-13 1.47736814e-12 3.35782790e-11 1.51985577e-11
 1.06540776e-09 4.67412463e-11 3.21504386e-11 1.95049914e-11
 2.85257256e-12 1.06349001e-11 1.78067422e-11 1.51877122e-12
 2.34353925e-10 1.40883095e-11 6.33895323e-12 2.99959259e-11
 1.57214200e-10 1.80867196e-10 9.85270546e-12 3.67524478e-09
 1.24184083e-11 8.78140727e-10 1.58321015e-13 2.62731781e-11
 1.66729720e-11 9.38114741e-09 7.11128097e-13 1.09746231e-11
 2.14791032e-12 3.04631483e-13 3.33154476e-11 1.22498279e-11]
La imagen pertenece al grupo perro con una probabilidad de 99.996513 %
```

```
[ ]:
```