Intento 6

En este intento volvemos al batch_size de 32 y añadimos una tercera capa de convolución de 64 filtros (junto con otra de Maxpooling 2x2). También probamos a reducir el índice de olvido al 20% para poder evaluar mejor la aportación de esta nueva capa al modelo.

0. Descarga del dataset

```
In [1]: # from google.colab import drive
# drive.mount('/content/drive')

train_ds_path ='../../deeplearning-az/datasets/Part 2 - Convolutional Neu
test_ds_path ='../../deeplearning-az/datasets/Part 2 - Convolutional Neu
cat_or_dog_path='../.deeplearning-az/datasets/Part 2 - Convolutional Neu
#train_ds_path ='C:/Users/Usuario/Documents/Master/Aprendizaje Profundo/Uc
#test_ds_path ='C:/Users/Usuario/Documents/Master/Aprendizaje Profundo/Uc
#cat_or_dog_path='C:/Users/Usuario/Documents/Master/Aprendizaje Profundo/Uc
#train_ds_path ='.\\data\\training_set'
#test_ds_path ='.\\data\\training_set'
#cat_or_dog_path='.\\data\\test_set'
#cat_or_dog_path='.\\data\\test_set'
#cat_or_dog_path='.\\data\\single_prediction\\cat_or_dog_1.jpg'
```

Primero, importar las librerías y paquetes

```
In [2]:
    from keras.models import Sequential
    from keras.layers import Conv2D
    from keras.layers import MaxPooling2D
    from keras.layers import Flatten
    from keras.layers import Dense
    from keras.layers import GlobalAveragePooling2D
    from keras.layers import Dropout
    # Nota, algunas capas no están importadas aquí y se importan directamente (
    import matplotlib.pyplot as plt
    import tensorflow as tf
    import os
    import numpy as np
    import random as rn
```

Fijamos seeds para poder reproducir resultados (aunque aun así a veces no lo conseguimos, probablementa haya inicializaciones que no dependan de estas seeds)

```
In [3]:
    os.environ['PYTHONHASHSEED'] = '0'
    np.random.seed(42)
    rn.seed(12345)
    tf.random.set_seed(1234)
```

1. Construcción del modelo CNN añadiendo un tamaño de imagen mayor

El tamaño de imagen que emplearemos será de 96x96, y el dropout rate es del 50%

```
In [4]:
         frame_size = (96, 96)
         esta dupla nos permitirá parametrizar la resolución
         de entrada de las imágenes
         def crear clasificador intento6():
             classifier = Sequential()
             classifier.add(Conv2D(filters = 32,kernel size = (3, 3),
                               input_shape = (*frame_size, 3), activation = "relu")
             classifier.add(MaxPooling2D(pool_size = (2,2)))
             classifier.add(Conv2D(filters = 32,kernel_size = (3, 3), activation =
             classifier.add(MaxPooling2D(pool_size = (2,2)))
             classifier.add(Conv2D(filters = 64,kernel_size = (3, 3), activation =
             classifier.add(MaxPooling2D(pool_size = (2,2)))
             classifier.add(Flatten())
             classifier.add(Dense(units = 128, activation = "relu"))
             classifier.add(Dropout(0.2))
             classifier.add(Dense(units = 1, activation = "sigmoid"))
             return classifier
```

2. Entrenamiento del intento 6

En primer lugar instanciamos nuestro modelo y compilamos usando:

- Un optimizador Adam. La learning rate que emplea por defecto es 0.001
- Binary cross entropy como función de coste a minimizar.

Model: "sequential"

Layer (type)	Output	Shape	Param #
conv2d (Conv2D)	(None,	94, 94, 32)	896
max_pooling2d (MaxPooling2D)	(None,	47, 47, 32)	0
conv2d_1 (Conv2D)	(None,	45, 45, 32)	9248
max_pooling2d_1 (MaxPooling2	(None,	22, 22, 32)	0
conv2d_2 (Conv2D)	(None,	20, 20, 64)	18496
max_pooling2d_2 (MaxPooling2	(None,	10, 10, 64)	0
flatten (Flatten)	(None,	6400)	0
dense (Dense)	(None,	128)	819328
dropout (Dropout)	(None,	128)	0
dense_1 (Dense)	(None,	1)	129

Total params: 848,097 Trainable params: 848,097 Non-trainable params: 0

En segundo lugar, generamos los datasets de entrenamiento y test. Emplearemos un tamaño de batch de 32

```
In [6]:
         from keras.preprocessing.image import ImageDataGenerator
         batch size=32
         train datagen = ImageDataGenerator(
                 rescale=1./255,
                 shear_range=0.2,
                 zoom range=0.2,
                 horizontal flip=True)
         test_datagen = ImageDataGenerator(rescale=1./255)
         training dataset = train datagen.flow from directory(train ds path,
                                                               target size=frame size
                                                               batch size=batch size
                                                               class mode='binary')
         testing dataset = test datagen.flow from directory(test ds path,
                                                             target size=frame size,
                                                             batch size=batch size,
                                                             class mode='binary')
```

Found 8000 images belonging to 2 classes. Found 2000 images belonging to 2 classes.

Definimos el callback y realizamos el entrenamiento con las condiciones descritas en la sección de introducción.

```
Epoch 6/100
accuracy: 0.7690 - val loss: 0.4564 - val accuracy: 0.7880
Epoch 7/100
accuracy: 0.7843 - val_loss: 0.4446 - val_accuracy: 0.7940
Epoch 8/100
accuracy: 0.7983 - val loss: 0.4250 - val accuracy: 0.7970
Epoch 9/100
accuracy: 0.8090 - val loss: 0.4376 - val accuracy: 0.7995
Epoch 10/100
accuracy: 0.8139 - val loss: 0.4393 - val accuracy: 0.7955
Epoch 11/100
accuracy: 0.8231 - val loss: 0.4128 - val accuracy: 0.8160
Epoch 12/100
accuracy: 0.8267 - val loss: 0.4154 - val accuracy: 0.8145
Epoch 13/100
accuracy: 0.8353 - val loss: 0.3837 - val accuracy: 0.8400
Epoch 14/100
accuracy: 0.8356 - val loss: 0.4149 - val accuracy: 0.8250
Epoch 15/100
accuracy: 0.8397 - val loss: 0.3835 - val accuracy: 0.8280
Epoch 16/100
accuracy: 0.8506 - val loss: 0.3798 - val accuracy: 0.8485
Epoch 17/100
accuracy: 0.8489 - val loss: 0.3912 - val accuracy: 0.8290
Epoch 18/100
accuracy: 0.8602 - val loss: 0.4399 - val accuracy: 0.8220
Epoch 19/100
accuracy: 0.8680 - val_loss: 0.3955 - val_accuracy: 0.8365
Epoch 20/100
accuracy: 0.8716 - val loss: 0.4297 - val accuracy: 0.8375
Epoch 21/100
accuracy: 0.8706 - val loss: 0.3784 - val accuracy: 0.8370
Epoch 22/100
accuracy: 0.8798 - val loss: 0.4103 - val accuracy: 0.8395
Epoch 23/100
accuracy: 0.8821 - val loss: 0.3818 - val accuracy: 0.8495
Epoch 24/100
accuracy: 0.8727 - val loss: 0.3671 - val accuracy: 0.8525
Epoch 25/100
accuracy: 0.8855 - val loss: 0.4001 - val accuracy: 0.8485
Epoch 26/100
accuracy: 0.8884 - val loss: 0.4052 - val accuracy: 0.8395
Epoch 27/100
```

```
accuracy: 0.8994 - val loss: 0.4071 - val accuracy: 0.8440
Epoch 28/100
accuracy: 0.9007 - val loss: 0.3818 - val accuracy: 0.8530
Epoch 29/100
accuracy: 0.8976 - val_loss: 0.4517 - val_accuracy: 0.8505
Epoch 30/100
accuracy: 0.8992 - val loss: 0.4283 - val accuracy: 0.8435
Epoch 31/100
accuracy: 0.9004 - val loss: 0.3870 - val accuracy: 0.8475
Epoch 32/100
accuracy: 0.9078 - val loss: 0.4980 - val accuracy: 0.8360
Epoch 33/100
accuracy: 0.9061 - val loss: 0.4475 - val accuracy: 0.8440
Epoch 34/100
accuracy: 0.9151 - val loss: 0.4367 - val accuracy: 0.8530
Epoch 35/100
accuracy: 0.9186 - val loss: 0.4722 - val accuracy: 0.8380
Epoch 36/100
accuracy: 0.9178 - val loss: 0.4657 - val accuracy: 0.8495
Epoch 37/100
accuracy: 0.9194 - val loss: 0.4857 - val accuracy: 0.8500
Epoch 38/100
accuracy: 0.9202 - val loss: 0.4880 - val accuracy: 0.8325
Epoch 39/100
accuracy: 0.9265 - val loss: 0.4757 - val accuracy: 0.8545
Epoch 40/100
accuracy: 0.9235 - val_loss: 0.4632 - val_accuracy: 0.8435
Epoch 41/100
accuracy: 0.9270 - val_loss: 0.4595 - val_accuracy: 0.8390
Epoch 42/100
accuracy: 0.9261 - val loss: 0.5226 - val accuracy: 0.8505
Epoch 43/100
accuracy: 0.9293 - val loss: 0.5695 - val accuracy: 0.8255
Epoch 44/100
accuracy: 0.9324 - val loss: 0.5274 - val accuracy: 0.8505
Epoch 45/100
accuracy: 0.9345 - val loss: 0.4886 - val accuracy: 0.8420
Epoch 46/100
accuracy: 0.9392 - val loss: 0.5189 - val accuracy: 0.8485
Epoch 47/100
accuracy: 0.9396 - val loss: 0.4718 - val accuracy: 0.8540
Epoch 48/100
```

```
accuracy: 0.9415 - val loss: 0.5719 - val accuracy: 0.8245
Epoch 49/100
accuracy: 0.9341 - val_loss: 0.5151 - val_accuracy: 0.8525
Epoch 50/100
accuracy: 0.9436 - val_loss: 0.4707 - val_accuracy: 0.8520
Epoch 51/100
accuracy: 0.9416 - val loss: 0.4788 - val accuracy: 0.8500
Epoch 52/100
accuracy: 0.9435 - val_loss: 0.5568 - val_accuracy: 0.8475
Epoch 53/100
accuracy: 0.9419 - val loss: 0.5339 - val accuracy: 0.8435
Epoch 54/100
accuracy: 0.9439 - val loss: 0.5265 - val accuracy: 0.8515
Epoch 55/100
accuracy: 0.9450 - val loss: 0.5515 - val accuracy: 0.8490
Epoch 56/100
accuracy: 0.9491 - val loss: 0.5198 - val accuracy: 0.8515
Epoch 57/100
accuracy: 0.9499 - val loss: 0.6195 - val accuracy: 0.8260
Epoch 58/100
accuracy: 0.9520 - val loss: 0.6331 - val accuracy: 0.8405
Epoch 59/100
accuracy: 0.9471 - val loss: 0.5211 - val accuracy: 0.8525
Epoch 60/100
accuracy: 0.9473 - val loss: 0.5735 - val accuracy: 0.8425
Epoch 61/100
accuracy: 0.9450 - val loss: 0.7643 - val accuracy: 0.8125
Epoch 62/100
accuracy: 0.9461 - val loss: 0.5254 - val accuracy: 0.8395
Epoch 63/100
accuracy: 0.9565 - val loss: 0.5917 - val accuracy: 0.8385
Epoch 64/100
accuracy: 0.9551 - val loss: 0.6431 - val accuracy: 0.8510
Epoch 65/100
accuracy: 0.9480 - val loss: 0.5674 - val accuracy: 0.8500
Epoch 66/100
accuracy: 0.9550 - val_loss: 0.5678 - val_accuracy: 0.8450
Epoch 67/100
accuracy: 0.9491 - val loss: 0.6206 - val accuracy: 0.8580
Epoch 68/100
accuracy: 0.9540 - val loss: 0.5905 - val accuracy: 0.8615
Epoch 69/100
accuracy: 0.9576 - val loss: 0.6223 - val accuracy: 0.8590
```

```
Epoch 70/100
accuracy: 0.9523 - val loss: 0.6188 - val accuracy: 0.8510
Epoch 71/100
accuracy: 0.9531 - val_loss: 0.5838 - val_accuracy: 0.8450
Epoch 72/100
accuracy: 0.9588 - val loss: 0.7065 - val_accuracy: 0.8585
Epoch 73/100
accuracy: 0.9580 - val loss: 0.7754 - val accuracy: 0.8545
Epoch 74/100
accuracy: 0.9561 - val loss: 0.6626 - val accuracy: 0.8455
Epoch 75/100
accuracy: 0.9604 - val loss: 0.6386 - val accuracy: 0.8570
Epoch 76/100
accuracy: 0.9591 - val loss: 0.6246 - val accuracy: 0.8565
Epoch 77/100
accuracy: 0.9565 - val loss: 0.5792 - val accuracy: 0.8620
Epoch 78/100
accuracy: 0.9585 - val loss: 0.6018 - val accuracy: 0.8610
Epoch 79/100
accuracy: 0.9609 - val loss: 0.6525 - val accuracy: 0.8490
Epoch 80/100
accuracy: 0.9621 - val loss: 0.6262 - val accuracy: 0.8580
Epoch 81/100
accuracy: 0.9616 - val loss: 0.5836 - val accuracy: 0.8505
Epoch 82/100
accuracy: 0.9628 - val loss: 0.6047 - val accuracy: 0.8545
Epoch 83/100
accuracy: 0.9628 - val loss: 0.7115 - val accuracy: 0.8325
Epoch 84/100
accuracy: 0.9575 - val loss: 0.5949 - val accuracy: 0.8520
Epoch 85/100
accuracy: 0.9632 - val loss: 0.7848 - val accuracy: 0.8175
Epoch 86/100
accuracy: 0.9620 - val loss: 0.5941 - val accuracy: 0.8510
Epoch 87/100
accuracy: 0.9617 - val loss: 0.6411 - val accuracy: 0.8535
Epoch 88/100
accuracy: 0.9678 - val loss: 0.6140 - val accuracy: 0.8570
Epoch 89/100
accuracy: 0.9647 - val loss: 0.5954 - val accuracy: 0.8585
Epoch 90/100
accuracy: 0.9639 - val loss: 0.5895 - val accuracy: 0.8625
Epoch 91/100
```

```
accuracy: 0.9672 - val loss: 0.6492 - val accuracy: 0.8555
     Epoch 92/100
     accuracy: 0.9649 - val loss: 0.5782 - val accuracy: 0.8445
     Epoch 93/100
     accuracy: 0.9626 - val_loss: 0.6141 - val_accuracy: 0.8530
     Epoch 94/100
     accuracy: 0.9620 - val loss: 0.6674 - val accuracy: 0.8515
     Epoch 95/100
     accuracy: 0.9659 - val loss: 0.7019 - val accuracy: 0.8525
     Epoch 96/100
     accuracy: 0.9630 - val loss: 0.8162 - val accuracy: 0.8230
     Epoch 97/100
     accuracy: 0.9663 - val loss: 0.6270 - val accuracy: 0.8565
     Epoch 98/100
     accuracy: 0.9685 - val loss: 0.6079 - val accuracy: 0.8580
     Epoch 99/100
     accuracy: 0.9663 - val loss: 0.6783 - val accuracy: 0.8530
     Epoch 100/100
     שבת / שבת ו
                                  E0c 22/mc/c+cn
     Ploteamos el resultado
In [8]:
      def plot resultados training(history):
        fig, axes = plt.subplots(1,2, figsize=(18,6))
        axes[0].plot(history.history['accuracy'], label='Train')
        axes[0].plot(history.history['val accuracy'], label='Validation')
        axes[0].legend()
        axes[0].set_title('Accuracy')
        axes[1].plot(history.history['loss'], label='Train')
        axes[1].plot(history.history['val loss'], label='Validation')
        axes[1].set title('Cross entropy')
      plot resultados training(history1)
        Train
Validation
                                0.8
                                     mm-Mm/M
                                0.7
     0.90
                                0.6
     0.85
     0.80
                                0.5
     0.75
                                0.4
     0.70
                                0.3
     0.65
                                0.2
                                0.1
                                                       100
In [9]:
      classifier.save('./models/clasificador6')
```

WARNING:tensorflow:From /home/llbernat/anaconda3/envs/musi-ap/lib/python3.7 /site-packages/tensorflow/python/training/tracking/tracking.py:111: Model.s tate updates (from tensorflow.python.keras.engine.training) is deprecated a

nd will be removed in a future version.

Instructions for updating:

This property should not be used in TensorFlow 2.0, as updates are applied automatically.

WARNING:tensorflow:From /home/llbernat/anaconda3/envs/musi-ap/lib/python3.7 /site-packages/tensorflow/python/training/tracking/tracking.py:111: Layer.u pdates (from tensorflow.python.keras.engine.base_layer) is deprecated and w ill be removed in a future version.

Instructions for updating:

This property should not be used in TensorFlow 2.0, as updates are applied automatically.

Comentario

En este intento hemos ampliado a tres capas de convolución con 32, 32 y 64 filtros de 3x3. El resultado ha sido esperanzador, pues hemos llegado a una precisón del 85.2% en validación.

Propuesta de mejora

Los mejora de resultados en cuanto hemos *complicado* la arquitectura de las capas convolucionales nos hace pensar que quizás ese sea el camino.