## Intento 5

La diferencia entre este intento y el anterior es que hemos reducido el batch\_size de 32 a 20 imágenes por lote.

## 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/Ud
  #test_ds_path ='C:/Users/Usuario/Documents/Master/Aprendizaje Profundo/Ud
  #cat_or_dog_path='C:/Users/Usuario/Documents/Master/Aprendizaje Profundo/Ud
  #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

```
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 d
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 intento5():
             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(Flatten())
             classifier.add(Dense(units = 128, activation = "relu"))
             classifier.add(Dropout(0.5))
             classifier.add(Dense(units = 1, activation = "sigmoid"))
             return classifier
```

#### 2. Entrenamiento del intento 5

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"

Non-trainable params: 0

Layer (type)	0utput	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
flatten (Flatten)	(None,	15488)	0
dense (Dense)	(None,	128)	1982592
dropout (Dropout)	(None,	128)	0
dense_1 (Dense)	(None,	1)	129

1----- de beteb de 00

```
In [6]:
         from keras.preprocessing.image import ImageDataGenerator
         batch size=20
         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 1/100
accuracy: 0.5504 - val loss: 0.6769 - val accuracy: 0.5725
Epoch 2/100
accuracy: 0.6101 - val loss: 0.6686 - val accuracy: 0.6155
Epoch 3/100
accuracy: 0.6530 - val_loss: 0.6107 - val_accuracy: 0.6815
Epoch 4/100
accuracy: 0.6865 - val loss: 0.5768 - val accuracy: 0.7135
Epoch 5/100
accuracy: 0.7014 - val loss: 0.5922 - val accuracy: 0.6945
Epoch 6/100
accuracy: 0.7147 - val loss: 0.5656 - val accuracy: 0.7270
Epoch 7/100
accuracy: 0.7361 - val loss: 0.5642 - val accuracy: 0.7240
```

```
Epoch 8/100
accuracy: 0.7475 - val loss: 0.5380 - val accuracy: 0.7330
Epoch 9/100
accuracy: 0.7602 - val_loss: 0.4951 - val_accuracy: 0.7625
Epoch 10/100
accuracy: 0.7661 - val loss: 0.5526 - val accuracy: 0.7370
Epoch 11/100
accuracy: 0.7684 - val loss: 0.5245 - val accuracy: 0.7415
Epoch 12/100
accuracy: 0.7747 - val loss: 0.5040 - val accuracy: 0.7620
Epoch 13/100
accuracy: 0.7864 - val loss: 0.4805 - val accuracy: 0.7840
Epoch 14/100
accuracy: 0.7894 - val loss: 0.4879 - val accuracy: 0.7770
Epoch 15/100
accuracy: 0.7956 - val loss: 0.4864 - val accuracy: 0.7785
Epoch 16/100
accuracy: 0.7946 - val loss: 0.4869 - val accuracy: 0.7810
Epoch 17/100
accuracy: 0.8050 - val loss: 0.4827 - val accuracy: 0.7745
Epoch 18/100
accuracy: 0.8046 - val loss: 0.4856 - val accuracy: 0.7800
Epoch 19/100
accuracy: 0.8124 - val loss: 0.4728 - val accuracy: 0.7655
Epoch 20/100
accuracy: 0.8138 - val loss: 0.4641 - val accuracy: 0.7785
Epoch 21/100
accuracy: 0.8263 - val_loss: 0.4703 - val_accuracy: 0.7870
Epoch 22/100
accuracy: 0.8259 - val loss: 0.4679 - val accuracy: 0.7840
Epoch 23/100
accuracy: 0.8319 - val loss: 0.4627 - val accuracy: 0.7895
Epoch 24/100
accuracy: 0.8311 - val loss: 0.4907 - val accuracy: 0.7965
Epoch 25/100
accuracy: 0.8396 - val loss: 0.4536 - val accuracy: 0.8075
Epoch 26/100
accuracy: 0.8384 - val loss: 0.4898 - val accuracy: 0.7895
Epoch 27/100
accuracy: 0.8516 - val loss: 0.5183 - val accuracy: 0.7835
Epoch 28/100
accuracy: 0.8435 - val loss: 0.4958 - val accuracy: 0.7805
Epoch 29/100
```

```
accuracy: 0.8504 - val loss: 0.5429 - val accuracy: 0.7720
Epoch 30/100
accuracy: 0.8520 - val loss: 0.5438 - val accuracy: 0.7790
Epoch 31/100
accuracy: 0.8518 - val_loss: 0.4823 - val_accuracy: 0.7935
Epoch 32/100
400/400 [============= ] - 63s 157ms/step - loss: 0.3159 -
accuracy: 0.8634 - val loss: 0.5004 - val accuracy: 0.7855
Epoch 33/100
accuracy: 0.8586 - val_loss: 0.4856 - val_accuracy: 0.7905
Epoch 34/100
accuracy: 0.8669 - val loss: 0.4897 - val accuracy: 0.7940
Epoch 35/100
accuracy: 0.8660 - val loss: 0.5026 - val accuracy: 0.7945
Epoch 36/100
accuracy: 0.8677 - val loss: 0.5205 - val accuracy: 0.7865
Epoch 37/100
accuracy: 0.8736 - val loss: 0.4962 - val accuracy: 0.7980
Epoch 38/100
accuracy: 0.8690 - val loss: 0.5053 - val accuracy: 0.7900
Epoch 39/100
accuracy: 0.8726 - val loss: 0.5193 - val accuracy: 0.8000
Epoch 40/100
accuracy: 0.8755 - val loss: 0.5133 - val accuracy: 0.8030
Epoch 41/100
accuracy: 0.8783 - val loss: 0.5399 - val accuracy: 0.7975
Epoch 42/100
accuracy: 0.8850 - val loss: 0.5444 - val accuracy: 0.7925
Epoch 43/100
accuracy: 0.8802 - val_loss: 0.5327 - val_accuracy: 0.7995
Epoch 44/100
accuracy: 0.8839 - val loss: 0.5396 - val accuracy: 0.7890
Epoch 45/100
accuracy: 0.8831 - val loss: 0.5437 - val accuracy: 0.8030
Epoch 46/100
accuracy: 0.8901 - val loss: 0.5166 - val accuracy: 0.8040
Epoch 47/100
accuracy: 0.8969 - val loss: 0.5111 - val accuracy: 0.7975
Epoch 48/100
accuracy: 0.8934 - val loss: 0.5454 - val accuracy: 0.7945
Epoch 49/100
accuracy: 0.8916 - val loss: 0.5445 - val accuracy: 0.7975
Epoch 50/100
```

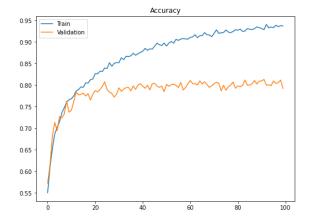
```
accuracy: 0.8974 - val loss: 0.5336 - val accuracy: 0.7845
Epoch 51/100
accuracy: 0.8904 - val_loss: 0.5987 - val_accuracy: 0.8015
Epoch 52/100
accuracy: 0.8972 - val_loss: 0.5794 - val_accuracy: 0.7970
Epoch 53/100
accuracy: 0.9010 - val loss: 0.5582 - val accuracy: 0.8010
Epoch 54/100
400/400 [============== ] - 71s 177ms/step - loss: 0.2451 -
accuracy: 0.8970 - val loss: 0.5773 - val accuracy: 0.8020
Epoch 55/100
accuracy: 0.9060 - val loss: 0.5629 - val accuracy: 0.7995
Epoch 56/100
accuracy: 0.9034 - val loss: 0.5397 - val accuracy: 0.7940
Epoch 57/100
accuracy: 0.9065 - val loss: 0.5475 - val accuracy: 0.8060
Epoch 58/100
accuracy: 0.9076 - val loss: 0.5976 - val accuracy: 0.7885
Epoch 59/100
accuracy: 0.9069 - val loss: 0.5555 - val accuracy: 0.7940
Epoch 60/100
accuracy: 0.9064 - val loss: 0.5553 - val accuracy: 0.8035
Epoch 61/100
accuracy: 0.9104 - val loss: 0.5952 - val accuracy: 0.8105
Epoch 62/100
accuracy: 0.9115 - val loss: 0.5896 - val accuracy: 0.8030
Epoch 63/100
accuracy: 0.9166 - val loss: 0.6615 - val accuracy: 0.8030
Epoch 64/100
accuracy: 0.9097 - val loss: 0.6891 - val accuracy: 0.8000
Epoch 65/100
accuracy: 0.9143 - val loss: 0.5849 - val accuracy: 0.8095
Epoch 66/100
accuracy: 0.9143 - val loss: 0.6366 - val accuracy: 0.8025
Epoch 67/100
accuracy: 0.9215 - val loss: 0.5902 - val accuracy: 0.8075
Epoch 68/100
accuracy: 0.9168 - val_loss: 0.6109 - val_accuracy: 0.8015
Epoch 69/100
accuracy: 0.9159 - val loss: 0.6387 - val accuracy: 0.7945
Epoch 70/100
accuracy: 0.9120 - val loss: 0.6369 - val accuracy: 0.7985
Epoch 71/100
accuracy: 0.9197 - val loss: 0.6448 - val accuracy: 0.8030
```

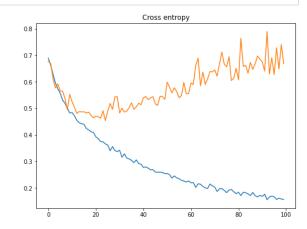
```
Epoch 72/100
accuracy: 0.9279 - val loss: 0.6212 - val accuracy: 0.8065
Epoch 73/100
accuracy: 0.9195 - val_loss: 0.6680 - val_accuracy: 0.8040
Epoch 74/100
accuracy: 0.9212 - val loss: 0.7121 - val accuracy: 0.7865
Epoch 75/100
accuracy: 0.9218 - val loss: 0.6666 - val accuracy: 0.7995
Epoch 76/100
accuracy: 0.9276 - val loss: 0.6559 - val accuracy: 0.7880
Epoch 77/100
accuracy: 0.9226 - val loss: 0.6945 - val accuracy: 0.7960
Epoch 78/100
accuracy: 0.9214 - val loss: 0.6047 - val accuracy: 0.8000
Epoch 79/100
accuracy: 0.9241 - val loss: 0.6136 - val accuracy: 0.8070
Epoch 80/100
accuracy: 0.9281 - val_loss: 0.6507 - val_accuracy: 0.7925
Epoch 81/100
accuracy: 0.9270 - val loss: 0.6070 - val accuracy: 0.7980
Epoch 82/100
accuracy: 0.9296 - val loss: 0.7638 - val accuracy: 0.7960
Epoch 83/100
accuracy: 0.9244 - val loss: 0.6577 - val accuracy: 0.7990
Epoch 84/100
accuracy: 0.9250 - val loss: 0.6616 - val accuracy: 0.8115
Epoch 85/100
accuracy: 0.9309 - val_loss: 0.6322 - val_accuracy: 0.7995
Epoch 86/100
accuracy: 0.9293 - val loss: 0.6730 - val accuracy: 0.8000
Epoch 87/100
accuracy: 0.9285 - val loss: 0.6465 - val accuracy: 0.8030
Epoch 88/100
accuracy: 0.9306 - val loss: 0.6676 - val accuracy: 0.8105
Epoch 89/100
accuracy: 0.9349 - val loss: 0.6971 - val accuracy: 0.8020
Epoch 90/100
accuracy: 0.9326 - val loss: 0.6851 - val accuracy: 0.8090
Epoch 91/100
accuracy: 0.9312 - val loss: 0.6744 - val accuracy: 0.8095
Epoch 92/100
accuracy: 0.9281 - val loss: 0.6401 - val accuracy: 0.8130
Epoch 93/100
```

```
accuracy: 0.9404 - val loss: 0.7896 - val accuracy: 0.7995
Epoch 94/100
accuracy: 0.9325 - val loss: 0.6293 - val accuracy: 0.8005
Epoch 95/100
accuracy: 0.9346 - val_loss: 0.6907 - val_accuracy: 0.7985
Epoch 96/100
accuracy: 0.9330 - val loss: 0.6273 - val accuracy: 0.8095
Epoch 97/100
accuracy: 0.9386 - val loss: 0.7284 - val accuracy: 0.8035
Epoch 98/100
accuracy: 0.9351 - val loss: 0.6480 - val accuracy: 0.8055
Epoch 99/100
accuracy: 0.9377 - val loss: 0.7406 - val accuracy: 0.8115
Epoch 100/100
```

#### Ploteamos el resultado

```
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')
```





In [9]: classifier.save('./models/clasificador5')

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

La reducción del número de imágenes por lote no ha dado el resultado esperado. De hecho en esta ejecución ha arrojado precisiones un poco peores que en el anterior y se sigue produciendo sobre-entrenamiento, que despunta a partir de la epoch 20.

## Propuesta de mejora

Un número más rico de *features* a la salida de la convolución también puede favorecer que la red neuronal valore otros patrones de las imagenes que ayuden a evitar el sobre-entrenamiento.

Porponemos la creacion de una tercera capa de convolucion mas rica en filtros (actualmente trabajamos con 2) y volver al tamaño de lote por defecto en keras (32).