Transfer learning - Cats vs. Dogs

Nuova sezione

```
Unzip data
# !unzip train.zip -d train/
# !unzip test.zip -d test/
 Code to initiliaze Tensorflow 2.0 in Colab
from __future__ import absolute_import, division, print_function, unicode_literals
%tensorflow_version 2.x
import tensorflow as tf
%load_ext tensorboard
import datetime
import numpy as no
%matplotlib inline
import matplotlib.pyplot as plt
       Colab only includes TensorFlow 2.x; %tensorflow version has no effect.
         The tensorboard extension is already loaded. To reload it, use:
            %reload_ext tensorboard
[TODO] Create a data loader function that returns a tuple with a tf.float32 tensor for the image and a label. Images must be resized to
 128x128. N.B.: filenames are formatted as class.number.jpg
def load_and_preprocess_image(filename): # load images
       image = tf.io.read_file(filename) # read the raw data from the file as a string
       image = tf.image.decode_jpeg(image, channels=3) # decode the jpeg image to a tensor
       image = tf.image.resize(image, [128, 128]) # resize the image to 128x128
       image = tf.cast(image, tf.float32) / 255.0 # transform the image to a tf.float32 type and normalize it to [0, 1]
       return image
def parse_filename(filename): # load labels
       label = tf.strings.split(filename, sep='/') # split the filename by '/' (label[0]: 'train', label[1]: 'class.number.jpg')
       label = tf.strings.split(label[-1], sep='.') # split the last element of the filename by '.' (label[0]: 'class', label[1]: 'number', label[2]: 'jpg')
       label = tf.strings.to_number(label[0], out_type=tf.int32) # convert the label[0] to a tf.int32 type
       return label
[TODO] Create a tf.Dataset, map the loader function and prepare a batch object for training
trainDataSet = tf.data.Dataset.list_files('train/*')  # create a dataset from the filenames (filename: train/class.number.jpg)
testDataSet = tf.data.Dataset.list files('test/*') # create a dataset from the filenames (filename: test/class.number.jpg)
trainDataSet = trainDataSet.map(lambda \ x: (load\_and\_preprocess\_image(x), parse\_filename(x))) \\ \qquad \# \ for \ each \ filename, \ load \ the \ image \ and \ the \ label
testDataSet = testDataSet.map(lambda \ x: (load\_and\_preprocess\_image(x), parse\_filename(x))) \ \# \ for \ each \ filename, \ load \ the \ image \ and \ the \ label
 Prepare Keras callback for Tensorboard
# logdir = "logs/scalars/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
# %tensorboard --logdir logs
# tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir, update_freq='batch')
[TODO] Import the MobileNetV2 model trained on ImageNet without the final layer
# because build a deep learning model can be too complex, we can consider to use a pre-trained model for performing feature extraction, and then add the final layer to performing feature extraction, and then add the final layer to perform the final layer the final layer to perform the final layer to perform the final layer to perform the final layer the final layer to perform the final layer to perform the final layer the fina
# classification as we want
# import the MobileNetV2 model, input_shape is the shape of the images. They have 3 channels cause they are RGB images
# include top=False means that we exclude the last fully connected layer of the model
\hbox{\# weights='imagenet' means that we initialize the model with pre-trained weights on } ImageNet
base_model = tf.keras.applications.MobileNetV2(input_shape=(128, 128, 3), include_top=False, weights='imagenet')
                                                                                                                                                                                                              # load the MobileNetV2 model7
base model.trainable = False
 Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobilenet_v2/mobi
        9406464/9406464
                                                                        - 2s Ous/step
[TODO] Add a final classification layer for 2 classes and create the final Keras model
# We know that the final layer, the one that performs the classification through the softmax function, need that the input is a vector. This is why, as seen in the previous
# have performed a flattening operation on the input. The problem of flattening is that than the classification layer depends on the size of the input (HxW), so if the model
# with different shapes then the classification will not work. This is why in this case we use the GlobalAveragePooling2D layer, cause we want that our model could work with
# different shapes. What GlobalAvaragePooling2D does is to evaluate the mean value of each image feature map and build a F dimensional vector where each value rappresent the
# the image on that channel.
x = base\_model.output # get the output of the model, on it we will add the final layers
x = tf.keras.layers.GlobalAveragePooling2D()(x) # evaluate the mean value of each image feature map. So we receive an input of shape (HxWxF) and we return an output of shape
y = tf.keras.layers.Dense(2, activation='softmax')(x) # build a pdf with the two possible classes, dog and cat
model = tf.keras.Model(inputs=base_model.input, outputs=y) # create the final model
[TODO] Compile the Keras model: specify the optimization algorithm, the loss function and the test metric
lr = 0.01 # learning rate
model.compile(optimizer = tf.keras.optimizers.Adam(lr), loss = 'sparse_categorical_crossentropy', metrics=['accuracy'])
[TODO] Train the Keras model
model.fit(trainDataSet.batch(32), epochs=5)  # train the model
 → Epoch 1/5
                                                     - 15s 78ms/step - accuracy: 0.8386 - loss: 0.6377
        63/63 -
        Epoch 2/5
        63/63 -
                                                      - 3s 46ms/step - accuracy: 0.9694 - loss: 0.0894
```

Epoch 3/5

```
21/01/25, 16:42
        63/63
                                  - 3s 49ms/step - accuracy: 0.9721 - loss: 0.0838
        Epoch 4/5
        63/63 -
                                   2s 33ms/step - accuracy: 0.9756 - loss: 0.0627
        Epoch 5/5
                                   3s 33ms/step - accuracy: 0.9947 - loss: 0.0183
        <keras.src.callbacks.history.History at 0x7f87b49d1bd0>
```

[TODO] Print model summary

model.summary()

[TODO] Test the Keras model by computing the accuracy the whole test set

```
model.evaluate(trainDataSet.batch(32))
                                         # evaluate the model on the training set
                              - 9s 83ms/step - accuracy: 0.9837 - loss: 0.0314
    [0.03328186646103859, 0.984499990940094]
```

[TODO] Load Test image 'test/0.1047.jpg', visualize it and check the network prediction

```
# plt.imshow(x_test[47].reshape(28, 28), cmap='gray')
# plt.title(f'Label: {y_test[47]}')
# plt.show()
# y_pred = model.predict(x_test[47][np.newaxis, :, :, :])
# print(f'Predicted label: {np.argmax(y_pred)}')
show Image = tf.io.read\_file('test/0.1047.jpg') \\ \textit{\# read the raw data from the file as a string}
showImage = tf.image.decode_jpeg(showImage) # decode the jpeg image to a tensor
plt.imshow(showImage) # show the image
plt.show()
# prepare the image for the model
showImage = tf.image.resize(showImage, [128, 128]) \  \  \# \  resize \  the \  image \  to \  128x128
showImage = tf.cast(showImage, tf.float32) / 255.0 # transform the image to a tf.float32 type and normalize it to [0, 1]
showImage = showImage[tf.newaxis, :, :, :] # add a batch dimension
predict = model.predict(showImage) # predict the label of the image
print(f'Predicted label: {np.argmax(predict)}')  # print the predicted label
```

