Transfer_Learning

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1 Trabalho 1

1.1 OCR - Optical Character Recognizer

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Na primeira parte do trabalho, foi utilizada a técnica de Transfer Learning, para treinar uma rede neural capaz de reconhecer caracteres.

[0]:
```
from __future__ import absolute_import, division, print_function,␣
 ↪unicode_literals
import matplotlib.pylab as plt
import tensorflow as tf
import scipy.io as io
import tensorflow_hub as hub
from shutil import copyfile
from tensorflow.keras import layers
import pandas as pd
import PIL.Image as Image
import os
import numpy as np
import time
```

Primeiro, carregamos o dataset Chars74K, 75% é carregado como dataset de treinamento, 25% como validação

[7]:
```
IMAGE_SHAPE = (224, 224)
dataset_folder = './TrainSet'
image_generator = tf.keras.preprocessing.image.ImageDataGenerator(rescale=1/
 ↪255, validation_split=0.25)
image_data = image_generator.flow_from_directory(dataset_folder,␣
 ↪target_size=IMAGE_SHAPE, subset='training')
image_validation = image_generator.flow_from_directory(dataset_folder  ,␣
 ↪target_size=IMAGE_SHAPE, subset='validation')
```

```
Found 5806 images belonging to 62 classes.
Found 1899 images belonging to 62 classes.
```

A Rede que será utilizada para o Transfer Learning é a Inception V3 da Google.

Primeiramente, foi carregado o Inception V3 e executado sobre algumas imagens do dataset para vermos as predições antes de realizarmos a técnica do Transfer Learning

[8]:
```
classifier_url ="https://tfhub.dev/google/tf2-preview/inception_v3/
↪classification/4" #@param {type:"string"}
labels_path = tf.keras.utils.get_file('ImageNetLabels.txt','https://storage.
↪googleapis.com/download.tensorflow.org/data/ImageNetLabels.txt')
imagenet_labels = np.array(open(labels_path).read().splitlines())
```

```
Downloading data from
https://storage.googleapis.com/download.tensorflow.org/data/ImageNetLabels.txt
16384/10484 [==============================================] - 0s 0us/step
```

[9]:
```
classifier = tf.keras.Sequential([
    hub.KerasLayer(classifier_url, input_shape=IMAGE_SHAPE+(3,))
])

for image_batch, label_batch in image_data:
  print("Image batch shape: ", image_batch.shape)
  print("Label batch shape: ", label_batch.shape)
  break

result_batch = classifier.predict(image_batch)
print(result_batch.shape)

predicted_class_names = imagenet_labels[np.argmax(result_batch, axis=-1)]

plt.figure(figsize=(10,9))
plt.subplots_adjust(hspace=0.5)
for n in range(30):
  plt.subplot(6,5,n+1)
  plt.imshow(image_batch[n])
  plt.title(predicted_class_names[n])
  plt.axis('off')
_ = plt.suptitle("ImageNet predictions")

plt.show()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/ops/resource_variable_ops.py:1781: calling
BaseResourceVariable.__init__ (from tensorflow.python.ops.resource_variable_ops)
with constraint is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
```

```
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```

```
with constraint is deprecated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
```

```
Image batch shape:  (32, 224, 224, 3)
Label batch shape:  (32, 62)
(32, 1001)
```

1.1.1 Treinamento do classificador

Agora, carregamos uma versão do Inception V3 sem a camada final de predição, para podermos treinar no novo dataset e obtermos a classificação desejada

[10]:
```
feature_extractor_url = "https://tfhub.dev/google/tf2-preview/inception_v3/
↪feature_vector/4" #@param {type:"string"}
feature_extractor_layer = hub.KerasLayer(feature_extractor_url,
                                         input_shape=(224,224,3))
feature_batch = feature_extractor_layer(image_batch)
print(feature_batch.shape)
feature_extractor_layer.trainable = False
model = tf.keras.Sequential([
  feature_extractor_layer,
  layers.Dense(image_data.num_classes, activation='softmax')
])
model.summary()
```

```
(32, 2048)
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
keras_layer_1 (KerasLayer)   (None, 2048)              21802784
_________________________________________________________________
dense (Dense)                (None, 62)                127038
=================================================================
Total params: 21,929,822
Trainable params: 127,038
Non-trainable params: 21,802,784
_________________________________________________________________
```

Agora, nós treinamos o modelo com o dataset Chars74K

[11]:
```
predictions = model(image_batch)
model.compile(
  optimizer=tf.keras.optimizers.Adam(),
  loss='categorical_crossentropy',
  metrics=['acc'])

class CollectBatchStats(tf.keras.callbacks.Callback):
  def __init__(self):
    self.batch_losses = []
    self.batch_acc = []

  def on_train_batch_end(self, batch, logs=None):
    self.batch_losses.append(logs['loss'])
    self.batch_acc.append(logs['acc'])
    self.model.reset_metrics()

steps_per_epoch = np.ceil(image_data.samples/image_data.batch_size)

batch_stats_callback = CollectBatchStats()
```

```
history = model.fit_generator(image_data, epochs=15,
                              steps_per_epoch=steps_per_epoch,
                              validation_data=image_validation,
                              callbacks = [batch_stats_callback])
```

```
Epoch 1/15
181/182 [============================>.] - ETA: 0s - loss: 2.5876 - acc:
0.6250Epoch 1/15
182/182 [==============================] - 49s 269ms/step - loss: 2.5887 - acc:
0.4375 - val_loss: 2.2215 - val_acc: 0.4413
Epoch 2/15
181/182 [============================>.] - ETA: 0s - loss: 1.3990 - acc:
0.7188Epoch 1/15
182/182 [==============================] - 41s 226ms/step - loss: 1.3976 - acc:
0.6875 - val_loss: 1.9872 - val_acc: 0.4882
Epoch 3/15
181/182 [============================>.] - ETA: 0s - loss: 0.9981 - acc:
0.6562Epoch 1/15
182/182 [==============================] - 41s 226ms/step - loss: 0.9974 - acc:
0.7812 - val_loss: 1.8751 - val_acc: 0.5134
Epoch 4/15
181/182 [============================>.] - ETA: 0s - loss: 0.7630 - acc:
0.6875Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.7631 - acc:
0.7812 - val_loss: 1.8670 - val_acc: 0.5108
Epoch 5/15
181/182 [============================>.] - ETA: 0s - loss: 0.6033 - acc:
0.9375Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.6027 - acc:
0.8438 - val_loss: 1.8338 - val_acc: 0.5182
Epoch 6/15
181/182 [============================>.] - ETA: 0s - loss: 0.4865 - acc:
0.9062Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.4876 - acc:
0.7812 - val_loss: 1.7936 - val_acc: 0.5340
Epoch 7/15
181/182 [============================>.] - ETA: 0s - loss: 0.4005 - acc:
0.9688Epoch 1/15
182/182 [==============================] - 41s 224ms/step - loss: 0.4015 - acc:
0.8125 - val_loss: 1.8447 - val_acc: 0.5313
Epoch 8/15
181/182 [============================>.] - ETA: 0s - loss: 0.3400 - acc:
0.9375Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.3402 - acc:
0.9375 - val_loss: 1.8602 - val_acc: 0.5361
Epoch 9/15
```

```
181/182 [============================>.] - ETA: 0s - loss: 0.2801 - acc:
0.9375Epoch 1/15
182/182 [==============================] - 41s 224ms/step - loss: 0.2801 - acc:
0.9062 - val_loss: 1.8797 - val_acc: 0.5355
Epoch 10/15
181/182 [============================>.] - ETA: 0s - loss: 0.2393 - acc:
0.9688Epoch 1/15
182/182 [==============================] - 41s 226ms/step - loss: 0.2392 - acc:
0.9688 - val_loss: 1.8614 - val_acc: 0.5377
Epoch 11/15
181/182 [============================>.] - ETA: 0s - loss: 0.2051 - acc:
0.9688Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.2057 - acc:
0.9375 - val_loss: 1.8617 - val_acc: 0.5503
Epoch 12/15
181/182 [============================>.] - ETA: 0s - loss: 0.1761 - acc:
1.0000Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.1761 - acc:
1.0000 - val_loss: 1.9790 - val_acc: 0.5255
Epoch 13/15
181/182 [============================>.] - ETA: 0s - loss: 0.1495 - acc:
0.9688Epoch 1/15
182/182 [==============================] - 41s 225ms/step - loss: 0.1500 - acc:
0.9375 - val_loss: 1.9131 - val_acc: 0.5466
Epoch 14/15
181/182 [============================>.] - ETA: 0s - loss: 0.1331 - acc:
0.9688Epoch 1/15
182/182 [==============================] - 41s 226ms/step - loss: 0.1329 - acc:
1.0000 - val_loss: 1.9098 - val_acc: 0.5382
Epoch 15/15
181/182 [============================>.] - ETA: 0s - loss: 0.1181 - acc:
1.0000Epoch 1/15
182/182 [==============================] - 41s 226ms/step - loss: 0.1183 - acc:
1.0000 - val_loss: 1.9586 - val_acc: 0.5503
```

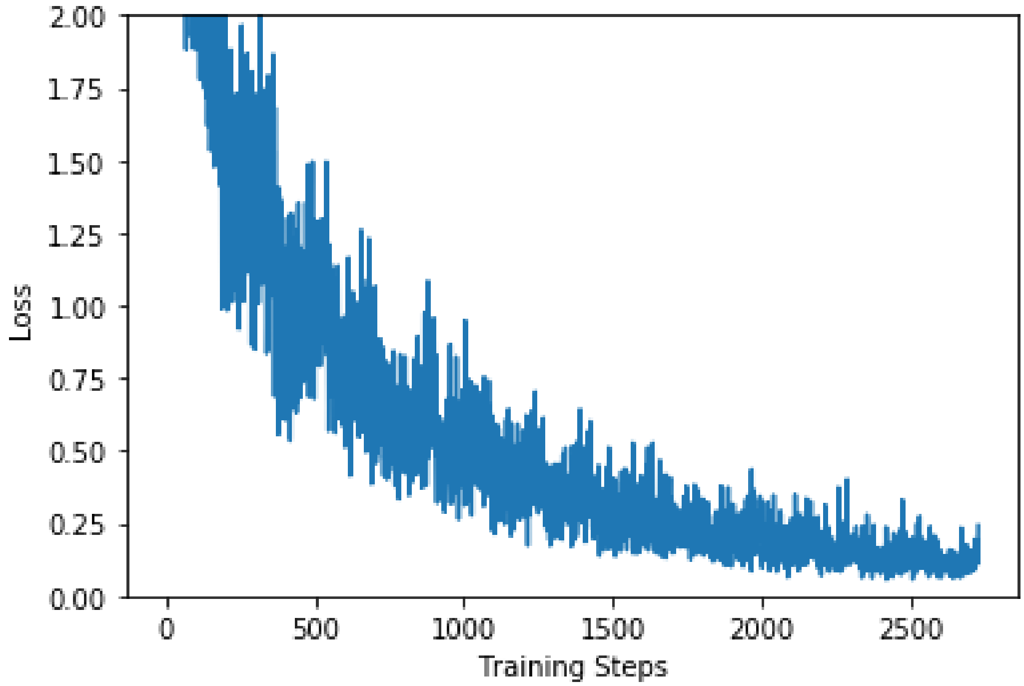
Com o modelo treinado, podemos visualizar os gráficos de como as medidas de Loss e Accuracy se modificaram com os passos do treinamento

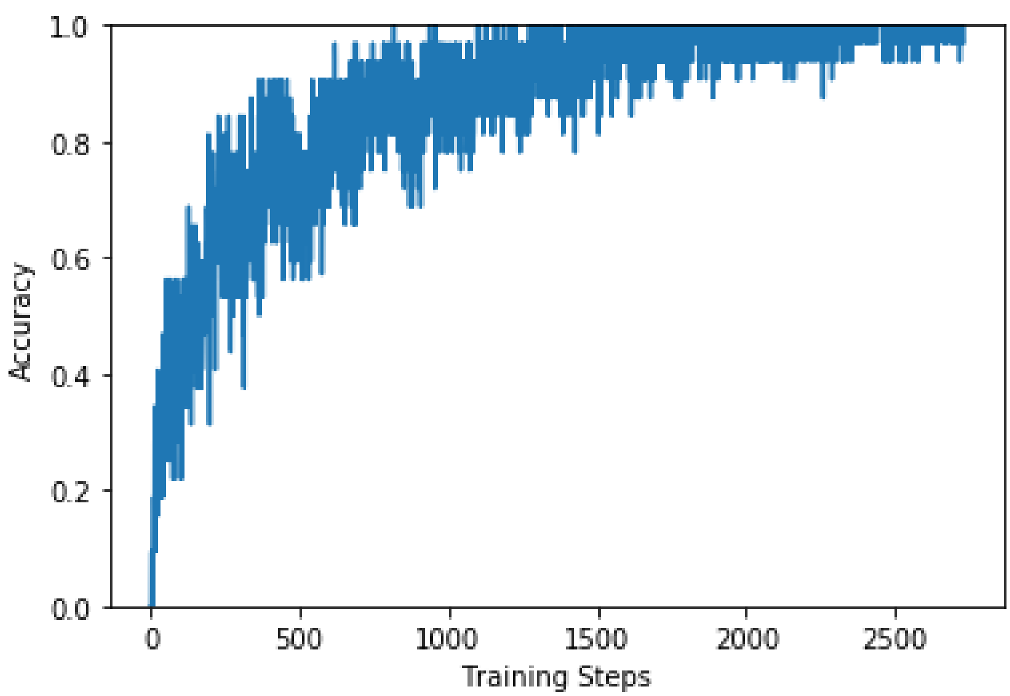
[12]:
```python
plt.figure()
plt.ylabel("Loss")
plt.xlabel("Training Steps")
plt.ylim([0,2])
plt.plot(batch_stats_callback.batch_losses)

plt.figure()
plt.ylabel("Accuracy")
plt.xlabel("Training Steps")
plt.ylim([0,1])
```

```
plt.plot(batch_stats_callback.batch_acc)
```

[12]: [<matplotlib.lines.Line2D at 0x7f79610d7668>]





1.1.2 Testando o classificador

Após todos os passos completos, podemos executar a predição sobre as mesmas imagens que foram classificadas pelo ImageNet anteriormente e vermos os resultados:

[13]:
```
class_names = sorted(image_data.class_indices.items(), key=lambda pair:pair[1])
class_names = np.array([key.title() for key, value in class_names])
class_names
predicted_batch = model.predict(image_batch)
predicted_id = np.argmax(predicted_batch, axis=-1)
predicted_label_batch = class_names[predicted_id]
label_id = np.argmax(label_batch, axis=-1)

plt.figure(figsize=(10,9))
plt.subplots_adjust(hspace=0.5)
for n in range(30):
  plt.subplot(6,5,n+1)
  plt.imshow(image_batch[n])
  color = "green" if predicted_id[n] == label_id[n] else "red"
  plt.title(predicted_label_batch[n].title(), color=color)
  plt.axis('off')
_ = plt.suptitle("Model predictions (green: correct, red: incorrect)")
```

Também, podemos executar a predição em imagens do dataset de validação:

[14]:
```
for validation_batch, label_batch in image_validation:
  print("Validation batch shape: ", validation_batch.shape)
  print("Label batch shape: ", label_batch.shape)
  break

predicted_batch = model.predict(validation_batch)
predicted_id = np.argmax(predicted_batch, axis=-1)
predicted_label_batch = class_names[predicted_id]
label_id = np.argmax(label_batch, axis=-1)
```

```python
plt.figure(figsize=(10,9))
plt.subplots_adjust(hspace=0.5)
for n in range(30):
  plt.subplot(6,5,n+1)
  plt.imshow(validation_batch[n])
  color = "green" if predicted_id[n] == label_id[n] else "red"
  plt.title(predicted_label_batch[n].title(), color=color)
  plt.axis('off')
_ = plt.suptitle("Model predictions - validation set (green: correct, red: incorrect)")
```

```
Validation batch shape:  (32, 224, 224, 3)
Label batch shape:  (32, 62)
```

1.1.3 Exportando o modelo

Por ultimo, precisamos exportar o modelo para podermos utilizarmos posteriormente

[0]:
```
t = time.time()

export_path = "./saved_models/{}".format(int(t))
tf.keras.experimental.export_saved_model(model, export_path)

export_path
```