```
1 # set tf 1.x for colab
2 %tensorflow_version 1.x
```

Fine-tuning InceptionV3 for flowers classification

In this task you will fine-tune InceptionV3 architecture for flowers classification task.

InceptionV3 architecture (https://research.googleblog.com/2016/03/train-your-own-image-classifier-with.html):

Flowers classification dataset (http://www.robots.ox.ac.uk/~vgg/data/flowers/102/index.html) consists of 102 flower categories commonly occurring in the United Kingdom. Each class contains between 40 and 258 images:

Running on Google Colab

Copy all files of intro-to-dl-master in root_path

```
1 ! shred -u setup_google_colab.py
2 ! wget https://raw.githubusercontent.com/hse-aml/intro-to-dl/master/setup_google_colab.

shred: setup_google_colab.py: failed to open for writing: No such file or directory
--2021-01-17 22:56:44-- https://raw.githubusercontent.com/hse-aml/intro-to-dl/master
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 151.101.0.133, 151
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|151.101.0.133|:44
HTTP request sent, awaiting response... 200 OK
Length: 3636 (3.6K) [text/plain]
Saving to: 'setup_google_colab.py'

setup_google_colab. 100%[==============]] 3.55K --.-KB/s in 0s
2021-01-17 22:56:45 (36.9 MB/s) - 'setup_google_colab.py' saved [3636/3636]
1 import setup_google_colab
```

Import stuff

```
1 root_path = '/content/gdrive/MyDrive/HSE_Introduction to Deep Learning'
 1 import sys
 2 sys.path.append(root path)
 3 import grading_utils
 4 import download_utils
 1 # !!! remember to clear session/graph if you rebuild your graph to avoid out-of-memory
 1 download_utils.link_all_keras_resources()
 1 import tensorflow as tf
 2 import keras
 3 from keras import backend as K
 4 import numpy as np
 5 %matplotlib inline
 6 import matplotlib.pyplot as plt
 7 print(tf. version )
 8 print(keras.__version__)
 9 import cv2 # for image processing
10 from sklearn.model selection import train test split
11 import scipy.io
12 import os
13 import tarfile
14 import keras utils
15 from keras_utils import reset_tf_session
16 import grading
    1.15.2
    2.3.1
```

Fill in your Coursera token and email

To successfully submit your answers to our grader, please fill in your Coursera submission token and email

Load dataset

Dataset was downloaded for you, it takes 12 min and 400mb. Relevant links (just in case):

- http://www.robots.ox.ac.uk/~vgg/data/flowers/102/index.html
- http://www.robots.ox.ac.uk/~vgg/data/flowers/102/102flowers.tgz
- http://www.robots.ox.ac.uk/~vgg/data/flowers/102/imagelabels.mat

```
1 # we downloaded them for you, just link them here
2 download_utils.link_week_3_resources()
```

Prepare images for model

```
1 # we will crop and resize input images to IMG_SIZE x IMG_SIZE
2 IMG_SIZE = 250

1 def decode_image_from_raw_bytes(raw_bytes):
2    img = cv2.imdecode(np.asarray(bytearray(raw_bytes), dtype=np.uint8), 1)
3    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
4    return img
```

We will take a center crop from each image like this:

```
1 def image_center_crop(img):
 2
 3
      Makes a square center crop of an img, which is a [h, w, 3] numpy array.
      Returns [min(h, w), min(h, w), 3] output with same width and height.
 4
 5
      For cropping use numpy slicing.
 6
 7
 8
      #cropped img = ### YOUR CODE HERE
 9
      w, h, c = img.shape
10
      if w > h:
11
12
         cropped_img = img[int((w-h)/2):int((w+h)/2), 0:h, 0:c]
13
       elif h > w:
         cropped img = img[0:w, int((h-w)/2):int((h+w)/2), 0:c]
14
15
      else:
16
         cropped_img = img[0:w, 0:h, 0:c]
17
18
       return cropped img
19
```

```
1 def prepare_raw_bytes_for_model(raw_bytes, normalize_for_model=True):
```

² img = decode image from raw bytes(raw bytes) # decode image raw bytes to matrix

(500, 591, 3) 100 200 300 400 0 100 200 300 400 500

```
1 img = prepare_raw_bytes_for_model(raw_bytes, normalize_for_model=False)
2 print(img.shape)
3 plt.imshow(img)
4 plt.show()
```

```
(250, 250, 3)
0
50
```

```
1 ## GRADED PART, DO NOT CHANGE!
2 # Test image preparation for model
3 prepared_img = prepare_raw_bytes_for_model(read_raw_from_tar("102flowers.tgz", "jpg/ima 4 grader.set_answer("qRsZ1", list(prepared_img.shape) + [np.mean(prepared_img), np.std(prepared_img))
```

1 # you can make submission with answers so far to check yourself at this stage
2 grader.submit(COURSERA_EMAIL, COURSERA_TOKEN)

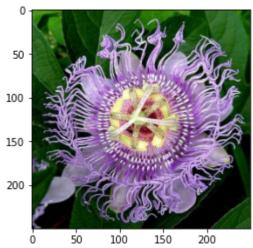
Submitted to Coursera platform. See results on assignment page!

Prepare for training

```
1 # read all filenames and labels for them
 3 # read filenames firectly from tar
 4 def get_all_filenames(tar_fn):
      with tarfile.open(tar fn) as f:
           return [m.name for m in f.getmembers() if m.isfile()]
 6
 7
 8 all files = sorted(get_all_filenames("102flowers.tgz")) # list all files in tar sorted
 9 all labels = scipy.io.loadmat('imagelabels.mat')['labels'][0] - 1 # read class labels
10 # all_files and all_labels are aligned now
11 N_CLASSES = len(np.unique(all_labels))
12 print(N_CLASSES)
     102
 1 # split into train/test
 2 tr files, te files, tr labels, te labels = \
      train_test_split(all_files, all_labels, test_size=0.2, random_state=42, stratify=al
 1 # will yield raw image bytes from tar with corresponding label
 2 def raw_generator_with_label_from_tar(tar_fn, files, labels):
 3
      label_by_fn = dict(zip(files, labels))
 4
      with tarfile.open(tar fn) as f:
          while True:
 5
               m = f.next()
 6
 7
               if m is None:
                   break
 8
 9
               if m.name in label by fn:
                   yield f.extractfile(m).read(), label_by_fn[m.name]
10
 1 # batch generator
 2 \text{ BATCH SIZE} = 32
```

```
1 # test training generator
2 for _ in train_generator(tr_files, tr_labels):
3    print(_[0].shape, _[1].shape)
4    plt.imshow(np.clip(_[0][0] / 2. + 0.5, 0, 1))
5    break
```

(32, 250, 250, 3) (32, 102)



Training

You cannot train such a huge architecture from scratch with such a small dataset.

But using fine-tuning of last layers of pre-trained network you can get a pretty good classifier very quickly.

```
1 def inception(use imagenet=True):
       # load pre-trained model graph, don't add final layer
 2
 3
       model = keras.applications.InceptionV3(include_top=False, input_shape=(IMG_SIZE, IM
 4
                                             weights='imagenet' if use imagenet else None)
 5
       # add global pooling just like in InceptionV3
 6
      new_output = keras.layers.GlobalAveragePooling2D()(model.output)
 7
       # add new dense layer for our labels
      new output = keras.layers.Dense(N CLASSES, activation='softmax')(new output)
 8
 9
       model = keras.engine.training.Model(model.inputs, new_output)
10
       return model
```

1 model = inception()

WARNING:tensorflow:From /tensorflow-1.15.2/python3.6/tensorflow_core/python/ops/resol Instructions for updating:

If using Keras pass *_constraint arguments to layers.

WARNING:tensorflow:From /tensorflow-1.15.2/python3.6/keras/backend/tensorflow_backend

WARNING:tensorflow:From /tensorflow-1.15.2/python3.6/keras/backend/tensorflow_backend

1 model.summary()

Datcii_IIOI IIIattZattOII_O/ (DatciiNO	(11011)	, ں	, ں	JU4/	1176	CO11V2U_0/[0][0]
batch_normalization_91 (BatchNo	(None,	6,	6,	384)	1152	conv2d_91[0][0]
activation_87 (Activation)	(None,	6,	6,	384)	0	batch_normalization
activation_91 (Activation)	(None,	6,	6,	384)	0	batch_normalizatio
conv2d_88 (Conv2D)	(None,	6,	6,	384)	442368	activation_87[0][
conv2d_89 (Conv2D)	(None,	6,	6,	384)	442368	activation_87[0][
conv2d_92 (Conv2D)	(None,	6,	6,	384)	442368	activation_91[0][0
conv2d_93 (Conv2D)	(None,	6,	6,	384)	442368	activation_91[0][0
average_pooling2d_9 (AveragePoo	(None,	6,	6,	2048)	0	mixed9[0][0]
conv2d_86 (Conv2D)	(None,	6,	6,	320)	655360	mixed9[0][0]
batch_normalization_88 (BatchNo	(None,	6,	6,	384)	1152	conv2d_88[0][0]
batch_normalization_89 (BatchNo	(None,	6,	6,	384)	1152	conv2d_89[0][0]
batch_normalization_92 (BatchNo	(None,	6,	6,	384)	1152	conv2d_92[0][0]
batch_normalization_93 (BatchNo	(None,	6,	6,	384)	1152	conv2d_93[0][0]
conv2d_94 (Conv2D)	(None,	6,	6,	192)	393216	average_pooling2d
batch_normalization_86 (BatchNo	(None,	6,	6,	320)	960	conv2d_86[0][0]
activation_88 (Activation)	(None,	6,	6,	384)	0	batch_normalization
activation_89 (Activation)	(None,	6,	6,	384)	0	batch_normalization
activation_92 (Activation)	(None,	6,	6,	384)	0	batch_normalization
activation_93 (Activation)	(None,	6,	6,	384)	0	batch_normalization
batch_normalization_94 (BatchNo	(None,	6,	6,	192)	576	conv2d_94[0][0]
activation_86 (Activation)	(None,	6,	6,	320)	0	batch_normalization
mixed9_1 (Concatenate)	(None,	6,	6,	768)	0	activation_88[0][(activation_89[0][(
	/N			760)		

/None

concetenate 2 /Concetenate)

--+: ... 02[0][

```
concatenate z (concatenate)
                                                                    activation 92|0||0
                                 (NONE, b, b, /bb)
                                                                    activation_93[0][(
activation 94 (Activation)
                                 (None, 6, 6, 192)
                                                                    batch_normalization
                                                       0
mixed10 (Concatenate)
                                 (None, 6, 6, 2048)
                                                       0
                                                                    activation_86[0][
                                                                    mixed9_1[0][0]
                                                                    concatenate_2[0][(
                                                                    activation_94[0][
global_average_pooling2d_1 (Glo (None, 2048)
                                                       0
                                                                    mixed10[0][0]
```

```
1 # how many layers our model has
 2 print(len(model.layers))
     313
 1 # set all layers trainable by default
 2 for layer in model.layers:
      layer.trainable = True
       if isinstance(layer, keras.layers.BatchNormalization):
 4
 5
           # we do aggressive exponential smoothing of batch norm
 6
           # parameters to faster adjust to our new dataset
 7
          layer.momentum = 0.9
 8
 9 # fix deep layers (fine-tuning only last 50)
10 for layer in model.layers[:-50]:
      # fix all but batch norm layers, because we neeed to update moving averages for a n
11
       if not isinstance(layer, keras.layers.BatchNormalization):
12
13
           layer.trainable = False
 1 # compile new model
 2 model.compile(
 3
      loss='categorical crossentropy', # we train 102-way classification
       optimizer=keras.optimizers.adamax(lr=1e-2), # we can take big lr here because we f
 4
       metrics=['accuracy'] # report accuracy during training
 5
 6)
 1 # we will save model checkpoints to continue training in case of kernel death
 2 model filename = 'flowers.{0:03d}.hdf5'
 3 last finished epoch = None
 4
 5 #### uncomment below to continue training from model checkpoint
 6 #### fill `last finished epoch` with your latest finished epoch
 7 # from keras.models import load model
 8 # s = reset_tf_session()
 9 # last finished epoch = 10
10 # model = load_model(model_filename.format(last_finished_epoch))
```

Training takes **2 hours**. You're aiming for ~0.93 validation accuracy.

```
1 # fine tune for 2 epochs (full passes through all training data)
2 # we make 2*8 epochs, where epoch is 1/8 of our training data to see progress more ofte
3 model.fit generator(
      train_generator(tr_files, tr_labels),
4
5
      steps_per_epoch=len(tr_files) // BATCH_SIZE // 8,
6
      epochs= 10,
7
      validation_data=train_generator(te_files, te_labels),
      validation steps=len(te files) // BATCH SIZE // 4,
8
      callbacks=[keras_utils.TqdmProgressCallback(),
9
10
                keras_utils.ModelSaveCallback(model_filename)],
11
      verbose=0,
12
      initial epoch=last finished epoch or 0
13)
    WARNING:tensorflow:From /tensorflow-1.15.2/python3.6/keras/backend/tensorflow backend
    Epoch 1/10
    *********
    loss: 4.4671; accuracy: 0.1904; val_loss: 21.5944; val_accuracy: 0.1432
    Model saved in flowers.000.hdf5
    Epoch 2/10
    **********
    loss: 2.5581; accuracy: 0.4232; val_loss: 6.8255; val_accuracy: 0.3698
    Model saved in flowers.001.hdf5
    Epoch 3/10
    *********
    loss: 1.5520; accuracy: 0.6190; val_loss: 3.0175; val_accuracy: 0.5339
    Model saved in flowers.002.hdf5
    Epoch 4/10
    **********
    loss: 1.0951; accuracy: 0.7233; val_loss: 0.5756; val_accuracy: 0.7292
    Model saved in flowers.003.hdf5
    Epoch 5/10
    **********
    loss: 0.7477; accuracy: 0.8038; val_loss: 1.2126; val_accuracy: 0.8128
    Model saved in flowers.004.hdf5
    Epoch 6/10
    ************
    loss: 0.6746; accuracy: 0.8394; val loss: 1.0167; val accuracy: 0.8802
    Model saved in flowers.005.hdf5
    Epoch 7/10
    *********
    loss: 0.5160; accuracy: 0.8741; val loss: 0.1965; val accuracy: 0.9167
    Model saved in flowers.006.hdf5
    Epoch 8/10
    loss: 0.4151; accuracy: 0.8800; val_loss: 0.2613; val_accuracy: 0.8828
    Model saved in flowers.007.hdf5
    Epoch 9/10
    *********
```

That's it! Congratulations!

What you've done:

- prepared images for the model
- implemented your own batch generator
- fine-tuned the pre-trained model