dog_app

June 25, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

In this notebook, some template code has already been provided for you, and you will need to implement additional functionality to successfully complete this project. You will not need to modify the included code beyond what is requested. Sections that begin with **'(IMPLEMENTATION)'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section, and the specifics of the implementation are marked in the code block with a 'TODO' statement. Please be sure to read the instructions carefully!

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the Jupyter Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to **File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. Markdown cells can be edited by double-clicking the cell to enter edit mode.

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.

Step 0: Import Datasets

Make sure that you've downloaded the required human and dog datasets:

Note: if you are using the Udacity workspace, you *DO NOT* need to re-download these - they can be found in the `/data` folder as noted in the cell below.

- Download the dog dataset. Unzip the folder and place it in this project's home directory, at the location `/dog_images`.
- Download the human dataset. Unzip the folder and place it in the home directory, at location `/lfw`.

Note: If you are using a Windows machine, you are encouraged to use 7zip to extract the folder.

In the code cell below, we save the file paths for both the human (LFW) dataset and dog dataset in the numpy arrays `human_files` and `dog_files`.

```
In [1]: import numpy as np
        from glob import glob

        # load filenames for human and dog images
        human_files = np.array(glob("/data/lfw/*/*"))
        dog_files = np.array(glob("/data/dog_images/*/*/*"))

        # print number of images in each dataset
        print('There are %d total human images.' % len(human_files))
        print('There are %d total dog images.' % len(dog_files))
```

```
There are 13233 total human images.
There are 8351 total dog images.
```

Step 1: Detect Humans

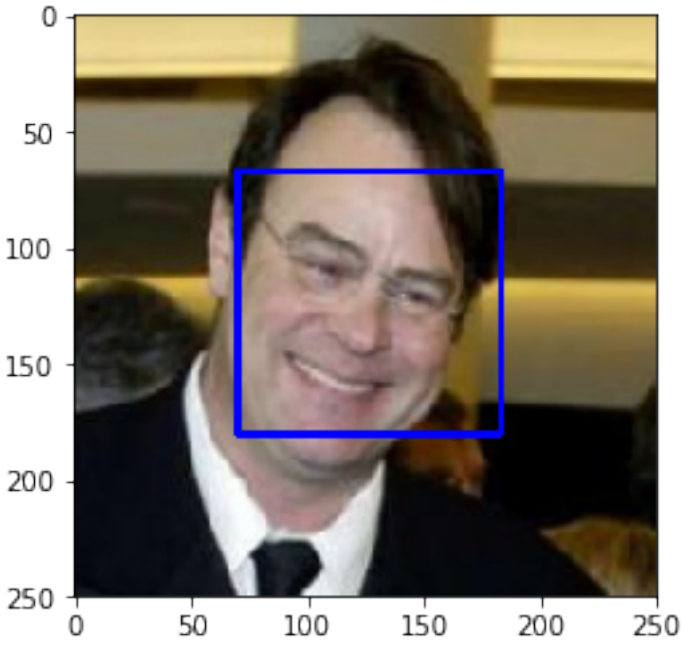
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

OpenCV provides many pre-trained face detectors, stored as XML files on github. We have downloaded one of these detectors and stored it in the `haarcascades` directory. In the next code cell, we demonstrate how to use this detector to find human faces in a sample image.

```
In [2]: import cv2
        import matplotlib.pyplot as plt
        %matplotlib inline

        # extract pre-trained face detector
        face_cascade = cv2.CascadeClassifier('haarcascades/haarcascade_frontalface_alt.xml')

        # load color (BGR) image
        img = cv2.imread(human_files[0])
        # convert BGR image to grayscale
        gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # find faces in image
        faces = face_cascade.detectMultiScale(gray)

        # print number of faces detected in the image
        print('Number of faces detected:', len(faces))
```

```
        # get bounding box for each detected face
        for (x,y,w,h) in faces:
            # add bounding box to color image
            cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)

        # convert BGR image to RGB for plotting
        cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

        # display the image, along with bounding box
        plt.imshow(cv_rgb)
        plt.show()
```

```
Number of faces detected: 1
```



Before using any of the face detectors, it is standard procedure to convert the images to grayscale. The `detectMultiScale` function executes the classifier stored in `face_cascade` and takes the grayscale image as a parameter.

In the above code, `faces` is a numpy array of detected faces, where each row corresponds to a detected face. Each detected face is a 1D array with four entries that specifies the bounding box of the detected face. The first two entries in the array (extracted in the above code as `x` and `y`) specify the horizontal and vertical positions of the top left corner of the bounding box. The last two entries in the array (extracted here as `w` and `h`) specify the width and height of the box.

1.1.1 Write a Human Face Detector

We can use this procedure to write a function that returns `True` if a human face is detected in an image and `False` otherwise. This function, aptly named `face_detector`, takes a string-valued file path to an image as input and appears in the code block below.

```
In [3]: # returns "True" if face is detected in image stored at img_path
        def face_detector(img_path):
            img = cv2.imread(img_path)
            gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
            faces = face_cascade.detectMultiScale(gray)
            return len(faces) > 0
```

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

Question 1: Use the code cell below to test the performance of the `face_detector` function.
- What percentage of the first 100 images in `human_files` have a detected human face?
- What percentage of the first 100 images in `dog_files` have a detected human face?

Ideally, we would like 100% of human images with a detected face and 0% of dog images with a detected face. You will see that our algorithm falls short of this goal, but still gives acceptable performance. We extract the file paths for the first 100 images from each of the datasets and store them in the numpy arrays `human_files_short` and `dog_files_short`.

Answer: (You can print out your results and/or write your percentages in this cell)

```
In [4]: from tqdm import tqdm

        human_files_short = human_files[:100]
        dog_files_short = dog_files[:100]

        #-#-# Do NOT modify the code above this line. #-#-#

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.

        face_dec_vector = np.vectorize(face_detector)

        human_face_detected = face_dec_vector(human_files_short)
        dog_detected = face_dec_vector(dog_files_short)

        print("Human face detected with {:.1f}% accuracy".format(sum(human_face_detected)))
        print("Dog detected with  {:.1f}% error".format(sum(dog_detected)))
```

```
Human face detected with 98.0% accuracy
Dog detected with  17.0% error
```

We suggest the face detector from OpenCV as a potential way to detect human images in your algorithm, but you are free to explore other approaches, especially approaches that make use of deep learning :). Please use the code cell below to design and test your own face detection

algorithm. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [5]: ### (Optional)
        ### TODO: Test performance of anotherface detection algorithm.
        ### Feel free to use as many code cells as needed.
```

Step 2: Detect Dogs

In this section, we use a pre-trained model to detect dogs in images.

1.1.3 Obtain Pre-trained VGG-16 Model

The code cell below downloads the VGG-16 model, along with weights that have been trained on ImageNet, a very large, very popular dataset used for image classification and other vision tasks. ImageNet contains over 10 million URLs, each linking to an image containing an object from one of 1000 categories.

```
In [6]: import torch
        import torchvision.models as models

        # define VGG16 model
        VGG16 = models.vgg16(pretrained=True)

        # check if CUDA is available
        use_cuda = torch.cuda.is_available()

        # move model to GPU if CUDA is available
        if use_cuda:
            VGG16 = VGG16.cuda()
```

Given an image, this pre-trained VGG-16 model returns a prediction (derived from the 1000 possible categories in ImageNet) for the object that is contained in the image.

1.1.4 (IMPLEMENTATION) Making Predictions with a Pre-trained Model

In the next code cell, you will write a function that accepts a path to an image (such as `'dogImages/train/001.Affenpinscher/Affenpinscher_00001.jpg'`) as input and returns the index corresponding to the ImageNet class that is predicted by the pre-trained VGG-16 model. The output should always be an integer between 0 and 999, inclusive.

Before writing the function, make sure that you take the time to learn how to appropriately pre-process tensors for pre-trained models in the PyTorch documentation.

```
In [7]: from PIL import Image
        import torchvision.transforms as transforms

        # Set PIL to be tolerant of image files that are truncated.
        from PIL import ImageFile
```

```
ImageFile.LOAD_TRUNCATED_IMAGES = True

def transform_image(img_path):
    transform_img = transforms.Compose([
        transforms.Resize(size=(224,224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406],
                             std=[0.229, 0.224, 0.225])

    ])
    img = Image.open(img_path)
    img = transform_img(img)

    # PyTorch pretrained models expect the Tensor dims to be (num input imgs, num color
    # Currently however, we have (num color channels, height, width); let's fix this by
    img = img.unsqueeze(0)  # Insert the new axis at index 0 i.e. in front of the other
    return img

def VGG16_predict(img_path):
    '''
    Use pre-trained VGG-16 model to obtain index corresponding to
    predicted ImageNet class for image at specified path

    Args:
        img_path: path to an image

    Returns:
        Index corresponding to VGG-16 model's prediction
    '''

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image

    img = transform_image(img_path)
    if use_cuda:
        img = img.cuda()
    ret = VGG16(img)
    return torch.max(ret,1)[1].item() # predicted class index
```

In [8]:
```
# predict dog using ImageNet class
VGG16_predict(dog_files_short[0])
```

Out[8]: 243

1.1.5 (IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary, you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all

categories from 'Chihuahua' to 'Mexican hairless'. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

Use these ideas to complete the dog_detector function below, which returns True if a dog is detected in an image (and False if not).

```
In [9]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.
            pred=VGG16_predict(img_path)
            if pred >= 151 and pred <= 268:
                return True
            else:
                return False

In [10]: dog_detector(dog_files[0])

Out[10]: True
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your dog_detector function.
- What percentage of the images in human_files_short have a detected dog?
- What percentage of the images in dog_files_short have a detected dog?

Answer:

```
In [11]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         counter_human = 0
         counter_dog   = 0

         for human_file in tqdm(human_files_short):
             if(dog_detector(human_file)):
                 counter_human +=1
         for dog_file in tqdm(dog_files_short):
             if(dog_detector(dog_file)):
                 counter_dog +=1
         print("Detected dogs in human files ",counter_human,"%")
         print("Detected dogs in dogs files ",counter_dog,"%")

100%|| 100/100 [00:03<00:00, 29.73it/s]
100%|| 100/100 [00:04<00:00, 21.63it/s]

Detected dogs in human files  0 %
Detected dogs in dogs files  100 %
```

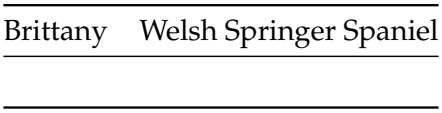
We suggest VGG-16 as a potential network to detect dog images in your algorithm, but you are free to explore other pre-trained networks (such as Inception-v3, ResNet-50, etc). Please use the code cell below to test other pre-trained PyTorch models. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [12]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.
```

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)

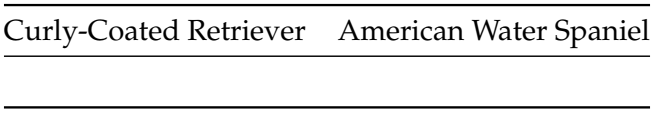
Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 10%. In Step 4 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

We mention that the task of assigning breed to dogs from images is considered exceptionally challenging. To see why, consider that *even a human* would have trouble distinguishing between a Brittany and a Welsh Springer Spaniel.



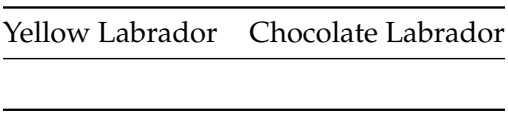
Brittany Welsh Springer Spaniel

It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).



Curly-Coated Retriever American Water Spaniel

Likewise, recall that labradors come in yellow, chocolate, and black. Your vision-based algorithm will have to conquer this high intra-class variation to determine how to classify all of these different shades as the same breed.



Yellow Labrador Chocolate Labrador

We also mention that random chance presents an exceptionally low bar: setting aside the fact that the classes are slightly imabalanced, a random guess will provide a correct answer roughly 1 in 133 times, which corresponds to an accuracy of less than 1%.

Remember that the practice is far ahead of the theory in deep learning. Experiment with many different architectures, and trust your intuition. And, of course, have fun!

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dog_images/train`, `dog_images/valid`, and `dog_images/test`, respectively). You may find this documentation on custom datasets to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of transforms!

In [13]:
```
import os
from torchvision import datasets

### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
data_dir = "/data/dog_images/"
num_workers = 0
batch_size = 10
data_transforms = {
    'train' : transforms.Compose([
    transforms.Resize(256),
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(), # randomly flip and rotate
    transforms.RandomRotation(15),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    # no need of image augmentation for the validation test set
    'valid' : transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    'test' : transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
}


train_dir = data_dir + '/train'
valid_dir = data_dir + '/valid'
test_dir = data_dir + '/test'

image_datasets = {
    'train' : datasets.ImageFolder(root=train_dir,transform=data_transforms['train']),
    'valid' : datasets.ImageFolder(root=valid_dir,transform=data_transforms['valid']),
    'test' : datasets.ImageFolder(root=test_dir,transform=data_transforms['test'])
```

```
}

# Loading Dataset
loaders_scratch = {
    'train' : torch.utils.data.DataLoader(image_datasets['train'],batch_size = batch_si
    'valid' : torch.utils.data.DataLoader(image_datasets['valid'],batch_size = batch_si
    'test' : torch.utils.data.DataLoader(image_datasets['test'],batch_size = batch_size
}
```

Question 3: Describe your chosen procedure for preprocessing the data. - How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why? - Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

Answer: 1. The code resizes the image to an image of 256 x 256, then it center crops imag to a size of 224 X 224 (as for VGG16 the input to cov1 layer is of fixed size 224 x 224), the image is then normalized as this the requirement for f

2. Yes! Image augmentation will give randomness to the dataset so, it prevents overfitting. For training data I have applied flip and rotation for validation and test these augmentation are not applied

1.1.8 (IMPLEMENTATION) Model Architecture

Create a CNN to classify dog breed. Use the template in the code cell below.

In [14]:
```
import torch.nn as nn
import torch.nn.functional as F

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Follow the architecture of VGG-16
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
        self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
        self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
        self.conv5 = nn.Conv2d(128, 256, 3, padding=1)

        self.fc1 = nn.Linear(256 * 7 * 7, 133)
        self.max_pool = nn.MaxPool2d(2, 2,ceil_mode=True)

        self.dropout = nn.Dropout(0.20)

        self.conv_bn1 = nn.BatchNorm2d(16)
        self.conv_bn2 = nn.BatchNorm2d(32)
        self.conv_bn3 = nn.BatchNorm2d(64)
        self.conv_bn4 = nn.BatchNorm2d(128)
```

```
                self.conv_bn5 = nn.BatchNorm2d(256)

            def forward(self, x):
                ## Define forward behavior
                x = F.relu(self.conv1(x))
                x = self.max_pool(x)
                x = self.conv_bn1(x)

                x = F.relu(self.conv2(x))
                x = self.max_pool(x)
                x = self.conv_bn2(x)

                x = F.relu(self.conv3(x))
                x = self.max_pool(x)
                x = self.conv_bn3(x)

                x = F.relu(self.conv4(x))
                x = self.max_pool(x)
                x = self.conv_bn4(x)

                x = F.relu(self.conv5(x))
                x = self.max_pool(x)
                x = self.conv_bn5(x)

                x = x.view(-1, 256 * 7 * 7)

                x = self.dropout(x)
                x = self.fc1(x)
                return x
        #-#-# You do NOT have to modify the code below this line. #-#-#

        # instantiate the CNN
        model_scratch = Net()

        print(model_scratch)

        # move tensors to GPU if CUDA is available
        if use_cuda:
            model_scratch.cuda()
```

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (fc1): Linear(in_features=12544, out_features=133, bias=True)
  (max_pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=True)
```

```
  (dropout): Dropout(p=0.2)
  (conv_bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn5): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)
```

Question 4: Outline the steps you took to get to your final CNN architecture and your reasoning at each step.

Answer: 1. I decided to follow the original VGG16 paper (Simonyan K, Zisserman A 2015) for the neural network architecture. I took the simplest model from the VGG16 paper (Table 1, Column A) and further modified it.

2. I chose to have 5 convolutional layers with a kernel size of 3x3 and a padding of 1, which gradually increases the number of feature maps, but keeps the size. In between every convolutional layer, there is a maxpool layer with a 2x2 kernel and a stride of 2, that halfs the size of all featuremaps. After 5 convolutions and maxpool layers we end up with 256 7x7 feature maps.

```
self.conv1   # input: 3x224x224, output: 16x224x224
self.pool1   # input: 16x224x224, output: 16x112x112

self.conv2   # input: 16x112x112, output: 32x112x112
self.pool2   # input: 32x112x112, output: 32x56x56

self.conv3   # input: 32x56x56, output: 64x56x56
self.pool3   # input: 64x56x56, output: 64x28x28

self.conv4   # input: 64x28x28, output: 128x28x28
self.pool4   # input: 128x28x28, output: 128x14x14

self.conv5   # input: 128x14x14, output: 256x14x14
self.pool5   # input: 256x14x14, output: 256x7x7
```

3. Each conv layer goes through RELU activation and then it is maxpooled. I also added natch normalization after every pooling layer

4. The produced feature maps are then flattened to a vector of length (256 * 7 * 7) = 12545 and fed into the fully connected (FC) layer for classification. I have choosen only one fully connected layer as it was sufficient for desired accuracy and also added a dropout before FC layer to avoid overfitting

5. A further deviation from the paper, is that the last layer in my network is a FC layer, not a softmax layer. This is because for training, I used PyTorch's CrossEntropyLoss() class, that combines a log-softmax output-layer activation and a negative log-likelihood loss-function.

6. When testing the neural net, the output of the network is fed into a softmax function to obtain class probabilities.

1.1.9 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_scratch`, and the optimizer as `optimizer_scratch` below.

In [15]:
```
import torch.optim as optim

### TODO: select loss function
criterion_scratch = nn.CrossEntropyLoss()

### TODO: select optimizer
optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.005)
```

1.1.10 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters at filepath `'model_scratch.pt'`.

In [16]:
```
# the following import is required for training to be robust to truncated images
import numpy as np
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
    """returns trained model"""
    # initialize tracker for minimum validation loss
    valid_loss_min = np.Inf

    for epoch in range(1, n_epochs+1):
        # initialize variables to monitor training and validation loss
        train_loss = 0.0
        valid_loss = 0.0

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
            optimizer.zero_grad()
            # forward pass
            output = model(data)
            # Loss
            loss = criterion(output, target)
```

```
            # backward pass
            loss.backward()
            # Optimization
            optimizer.step()
            # update training loss
            # train_loss += loss.item()*data.size(0)
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss
            output = model(data)
            loss = criterion(output, target)
            # update average validation loss
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)


            # calculate average losses
        train_loss = train_loss/len(loaders['train'].dataset)
        valid_loss = valid_loss/len(loaders['valid'].dataset)


        # print training/validation statistics
        print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
            epoch,
            train_loss,
            valid_loss
            ))

        ## TODO: save the model if validation loss has decreased
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
            valid_loss_min,
            valid_loss))
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss

    # return trained model
    return model


# train the model
```

```
        model_scratch = train(20, loaders_scratch, model_scratch, optimizer_scratch,
                              criterion_scratch, use_cuda, 'model_scratch.pt')

        # load the model that got the best validation accuracy
        model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

```
Epoch: 1         Training Loss: 0.000705         Validation Loss: 0.005220
Validation loss decreased (inf --> 0.005220).  Saving model ...
Epoch: 2         Training Loss: 0.000680         Validation Loss: 0.005005
Validation loss decreased (0.005220 --> 0.005005).  Saving model ...
Epoch: 3         Training Loss: 0.000657         Validation Loss: 0.004926
Validation loss decreased (0.005005 --> 0.004926).  Saving model ...
Epoch: 4         Training Loss: 0.000641         Validation Loss: 0.004896
Validation loss decreased (0.004926 --> 0.004896).  Saving model ...
Epoch: 5         Training Loss: 0.000629         Validation Loss: 0.004792
Validation loss decreased (0.004896 --> 0.004792).  Saving model ...
Epoch: 6         Training Loss: 0.000613         Validation Loss: 0.004719
Validation loss decreased (0.004792 --> 0.004719).  Saving model ...
Epoch: 7         Training Loss: 0.000601         Validation Loss: 0.004640
Validation loss decreased (0.004719 --> 0.004640).  Saving model ...
Epoch: 8         Training Loss: 0.000592         Validation Loss: 0.004724
Epoch: 9         Training Loss: 0.000582         Validation Loss: 0.004488
Validation loss decreased (0.004640 --> 0.004488).  Saving model ...
Epoch: 10         Training Loss: 0.000574         Validation Loss: 0.004481
Validation loss decreased (0.004488 --> 0.004481).  Saving model ...
Epoch: 11         Training Loss: 0.000564         Validation Loss: 0.004424
Validation loss decreased (0.004481 --> 0.004424).  Saving model ...
Epoch: 12         Training Loss: 0.000555         Validation Loss: 0.004519
Epoch: 13         Training Loss: 0.000548         Validation Loss: 0.004340
Validation loss decreased (0.004424 --> 0.004340).  Saving model ...
Epoch: 14         Training Loss: 0.000541         Validation Loss: 0.004293
Validation loss decreased (0.004340 --> 0.004293).  Saving model ...
Epoch: 15         Training Loss: 0.000533         Validation Loss: 0.004276
Validation loss decreased (0.004293 --> 0.004276).  Saving model ...
Epoch: 16         Training Loss: 0.000523         Validation Loss: 0.004166
Validation loss decreased (0.004276 --> 0.004166).  Saving model ...
Epoch: 17         Training Loss: 0.000516         Validation Loss: 0.004195
Epoch: 18         Training Loss: 0.000510         Validation Loss: 0.004184
Epoch: 19         Training Loss: 0.000505         Validation Loss: 0.004078
Validation loss decreased (0.004166 --> 0.004078).  Saving model ...
Epoch: 20         Training Loss: 0.000497         Validation Loss: 0.004079
```

1.1.11 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 10%.

```
In [17]: def test(loaders, model, criterion, use_cuda):

             # monitor test loss and accuracy
             test_loss = 0.
             correct = 0.
             total = 0.

             model.eval()
             for batch_idx, (data, target) in enumerate(loaders['test']):
                 # move to GPU
                 if use_cuda:
                     data, target = data.cuda(), target.cuda()
                 # forward pass: compute predicted outputs by passing inputs to the model
                 output = model(data)
                 # calculate the loss
                 loss = criterion(output, target)
                 # update average test loss
                 test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
                 # convert output probabilities to predicted class
                 pred = output.data.max(1, keepdim=True)[1]
                 # compare predictions to true label
                 correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
                 total += data.size(0)

             print('Test Loss: {:.6f}\n'.format(test_loss))

             print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
                 100. * correct / total, correct, total))

         # call test function
         test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.244610


Test Accuracy: 21% (182/836)
```

Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)

You will now use transfer learning to create a CNN that can identify dog breed from images. Your CNN must attain at least 60% accuracy on the test set.

1.1.12 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dogImages/train`, `dogImages/valid`, and `dogImages/test`, respectively).

If you like, **you are welcome to use the same data loaders from the previous step**, when you created a CNN from scratch.

```
In [18]: ## TODO: Specify data loaders
         import os
         from torchvision import datasets

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes
         data_dir = "/data/dog_images/"
         num_workers = 0
         batch_size = 10
         data_transforms = {
             'train' : transforms.Compose([
             transforms.Resize(256),
             transforms.RandomResizedCrop(224),
             transforms.RandomHorizontalFlip(), # randomly flip and rotate
             transforms.RandomRotation(15),
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
             ]),
             # no need of image augmentation for the validation test set
             'valid' : transforms.Compose([
             transforms.Resize(256),
             transforms.CenterCrop(224),
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
             ]),
             'test' : transforms.Compose([
             transforms.Resize(256),
             transforms.CenterCrop(224),
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
             ]),
         }


         train_dir = data_dir + '/train'
         valid_dir = data_dir + '/valid'
         test_dir = data_dir + '/test'

         image_datasets = {
             'train' : datasets.ImageFolder(root=train_dir,transform=data_transforms['train']),
             'valid' : datasets.ImageFolder(root=valid_dir,transform=data_transforms['valid']),
             'test' : datasets.ImageFolder(root=test_dir,transform=data_transforms['test'])
         }

         class_names = image_datasets['train'].classes
```

```
        # Loading Dataset
        loaders_transfer= {
            'train' : torch.utils.data.DataLoader(image_datasets['train'],batch_size = batch_si
            'valid' : torch.utils.data.DataLoader(image_datasets['valid'],batch_size = batch_si
            'test' : torch.utils.data.DataLoader(image_datasets['test'],batch_size = batch_size
        }
```

1.1.13 (IMPLEMENTATION) Model Architecture

Use transfer learning to create a CNN to classify dog breed. Use the code cell below, and save your initialized model as the variable `model_transfer`.

```
In [19]: import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         model_transfer = models.vgg16(pretrained=True)
         # Freeze the pre-trained weights
         for param in model_transfer.features.parameters():
             param.required_grad = False

         # Get the input of the last layer of VGG-16
         n_inputs = model_transfer.classifier[6].in_features

         # Create a new layer(n_inputs -> 133)
         # The new layer's requires_grad will be automatically True.
         last_layer = nn.Linear(n_inputs, 133)

         # Change the last layer to the new layer.
         model_transfer.classifier[6] = last_layer

         # Print the model.
         print(model_transfer)

         if use_cuda:
             model_transfer = model_transfer.cuda()
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace)
```

```
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace)
    (2): Dropout(p=0.5)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace)
    (5): Dropout(p=0.5)
    (6): Linear(in_features=4096, out_features=133, bias=True)
  )
)
```

Question 5: Outline the steps you took to get to your final CNN architecture and your reasoning at each step. Describe why you think the architecture is suitable for the current problem.

Answer: 1. Pulled up the PreTrained VGG-16 model. The full dataset has 13,233 dog images, which is not large enough to train a deep learning model from scratch. Therefore, transfer learning with VGG-16 (a convolutional neural network that is trained on more than a million images from the ImageNet database) is used to achieve relatively good accuracy with less training time. 2. We don't wanna modify the features it already has in pretaraining so freezed the features parameter 3. We are interested in modifying the classifier part that is the fully connected layer, so created a new Linear layer and attached it as the classifier (FC Layer) of VGG-16 4. This architecture is chosen because it gives relatevely better accuracy in less training time

1.1.14 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_transfer`, and the optimizer as `optimizer_transfer` below.

```
In [20]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(),lr=0.001,momentum
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters at filepath `'model_transfer.pt'`.

```
In [21]: import numpy as np
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True
         # train the model
         n_epochs = 5


         def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

             for epoch in range(1, n_epochs+1):
                 # initialize variables to monitor training and validation loss
                 train_loss = 0.0
                 valid_loss = 0.0

                 ###################
                 # train the model #
                 ###################
                 model.train()
                 for batch_idx, (data, target) in enumerate(loaders['train']):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## find the loss and update the model parameters accordingly
                     ## record the average training loss, using something like
                     ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
                     optimizer.zero_grad()
                     # forward pass
                     output = model(data)
                     # Loss
                     loss = criterion(output, target)
                     # backward pass
                     loss.backward()
                     # Optimization
```

```
            optimizer.step()
            # update training loss
            # train_loss += loss.item()*data.size(0)
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)


        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()

            output = model(data)
            loss = criterion(output, target)
            # update average validation loss
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)


            # calculate average losses
        train_loss = train_loss/len(loaders['train'].dataset)
        valid_loss = valid_loss/len(loaders['valid'].dataset)



        # print training/validation statistics
        print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
            epoch,
            train_loss,
            valid_loss
            ))

        ## TODO: save the model if validation loss has decreased
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
            valid_loss_min,
            valid_loss))
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss

    # return trained model
    return model


model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,
```

```
        # load the model that got the best validation accuracy (uncomment the line below)
        model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
Epoch: 1         Training Loss: 0.000353         Validation Loss: 0.001030
Validation loss decreased (inf --> 0.001030).  Saving model ...
Epoch: 2         Training Loss: 0.000244         Validation Loss: 0.000790
Validation loss decreased (0.001030 --> 0.000790).  Saving model ...
Epoch: 3         Training Loss: 0.000227         Validation Loss: 0.000757
Validation loss decreased (0.000790 --> 0.000757).  Saving model ...
Epoch: 4         Training Loss: 0.000217         Validation Loss: 0.000658
Validation loss decreased (0.000757 --> 0.000658).  Saving model ...
Epoch: 5         Training Loss: 0.000208         Validation Loss: 0.000674
```

1.1.16 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 60%.

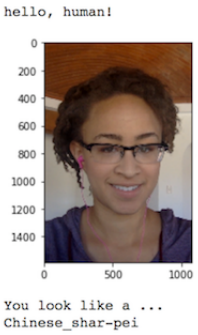
```
In [22]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.675994


Test Accuracy: 81% (680/836)
```

1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

Write a function that takes an image path as input and returns the dog breed (`Affenpinscher`, `Afghan hound`, etc) that is predicted by your model.

```
In [23]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.

         # list of class names by index, i.e. a name can be accessed like class_names[0]
         class_names = [item[4:].replace("_", " ") for item in image_datasets['train'].classes]

         # Load the trained model 'model_transfer.pt'
         model_transfer.load_state_dict(torch.load('model_transfer.pt', map_location='cpu'))
         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             image = Image.open(img_path).convert('RGB')
             prediction_transform = transforms.Compose([transforms.Resize(size=(224, 224)),
                                                        transforms.ToTensor(),
                                                        transforms.Normalize(mean=[0.485, 0.456, 0.406], s

             # discard the transparent, alpha channel (that's the :3) and add the batch dimensio
             image = prediction_transform(image)[:3,:,:].unsqueeze(0)
```



Sample Human Output

```
    image = image.cuda()


    model_transfer.eval()
    idx = torch.argmax(model_transfer(image))
    return class_names[idx]
```

```
In [24]: predict_breed_transfer(dog_files[0])
```

```
Out[24]: 'Bullmastiff'
```

Step 5: Write your Algorithm

Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then, - if a **dog** is detected in the image, return the predicted breed. - if a **human** is detected in the image, return the resembling dog breed. - if **neither** is detected in the image, provide output that indicates an error.

You are welcome to write your own functions for detecting humans and dogs in images, but feel free to use the `face_detector` and `human_detector` functions developed above. You are **required** to use your CNN from Step 4 to predict dog breed.

Some sample output for our algorithm is provided below, but feel free to design your own user experience!

1.1.18 (IMPLEMENTATION) Write your Algorithm

```
In [25]: ### TODO: Write your algorithm.
         ### Feel free to use as many code cells as needed.

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             img = Image.open(img_path)
             plt.imshow(img)
             plt.show()

             if dog_detector(img_path) is True:
```

```
        prediction = predict_breed_transfer(img_path)
        print("A dog has been detected which most likely to be {0} breed".format(predic
    elif face_detector(img_path) > 0:
        prediction = predict_breed_transfer(img_path)
        print("This is a Human who looks like a {0}".format(prediction))
    else:
        print("Neither Human nor Dog")
```

Step 6: Test Your Algorithm

In this section, you will take your new algorithm for a spin! What kind of dog does the algorithm think that *you* look like? If you have a dog, does it predict your dog's breed accurately? If you have a cat, does it mistakenly think that your cat is a dog?

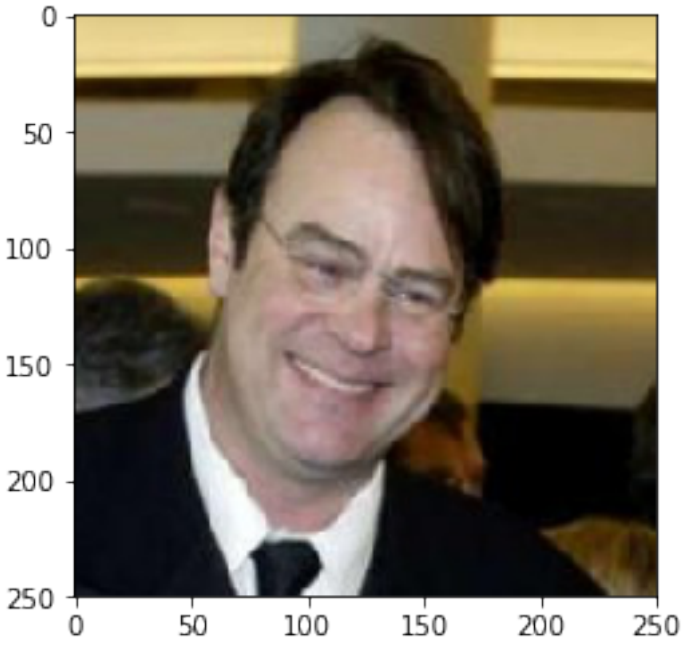
1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

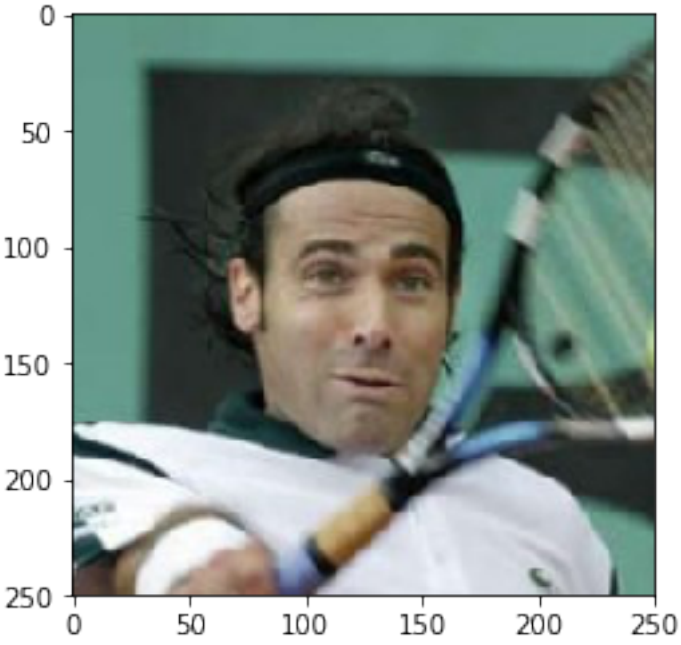
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement)

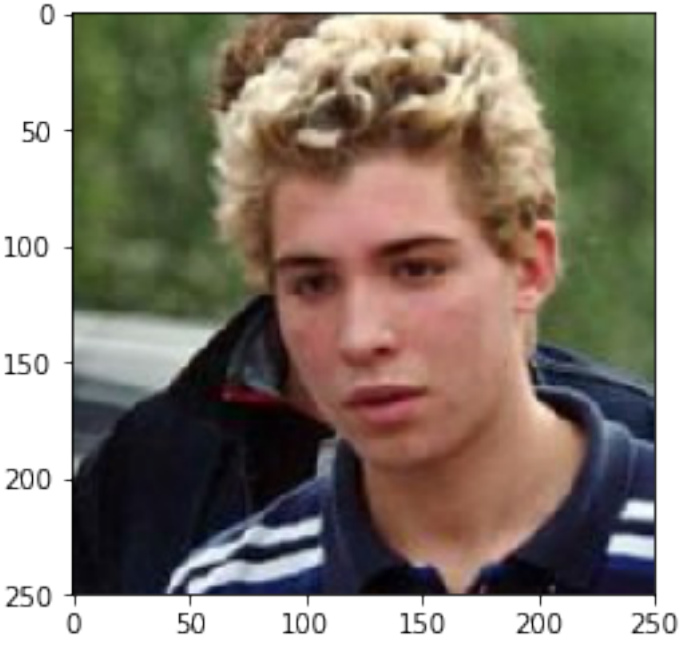
In [26]:
```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as needed.

## suggested code, below
for file in np.hstack((human_files[:3], dog_files[:3])):
    run_app(file)
```



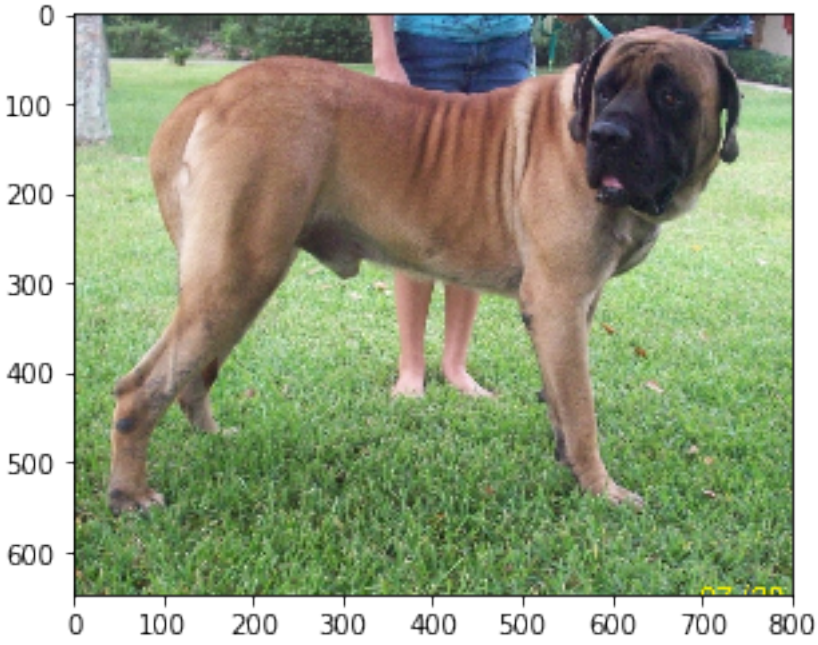
```
This is a Human who looks like a Beagle
```



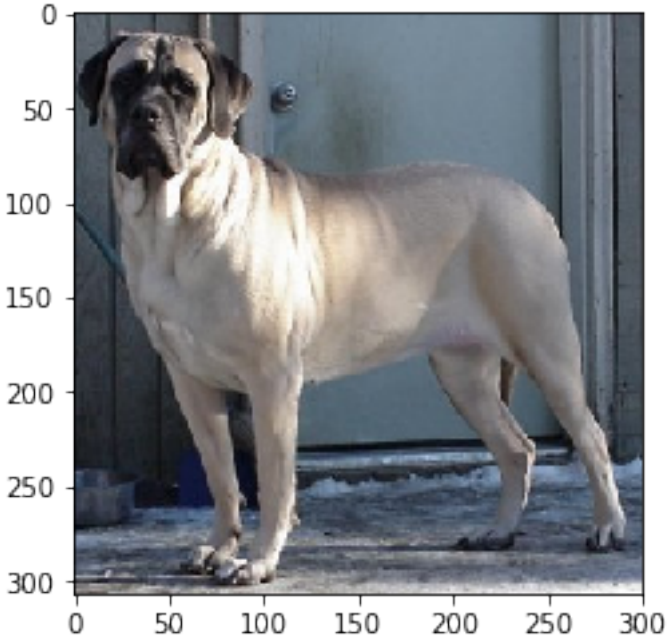

```
This is a Human who looks like a Dachshund
```



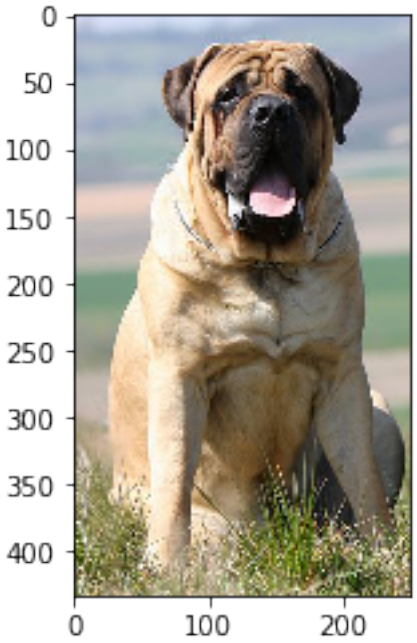
```
This is a Human who looks like a Portuguese water dog
```




```
A dog has been detected which most likely to be Bullmastiff breed
```

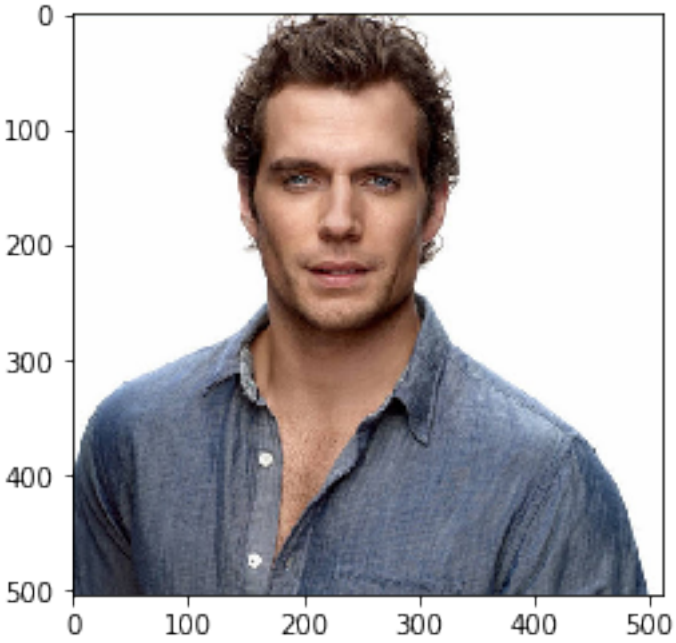


```
A dog has been detected which most likely to be Bullmastiff breed
```




```
A dog has been detected which most likely to be Bullmastiff breed
```

```
In [52]: # Checking with my Images
         path_prefix = './assets/'
         external_human_files = list(map(lambda x: path_prefix + x, ['human1.jpeg', 'human2.jpeg
         external_dog_files = list(map(lambda x: path_prefix + x, ['dog1.jpeg', 'dog2.jpeg', 'do

In [53]: for file in np.hstack((external_human_files, external_dog_files)):
             run_app(file)
```



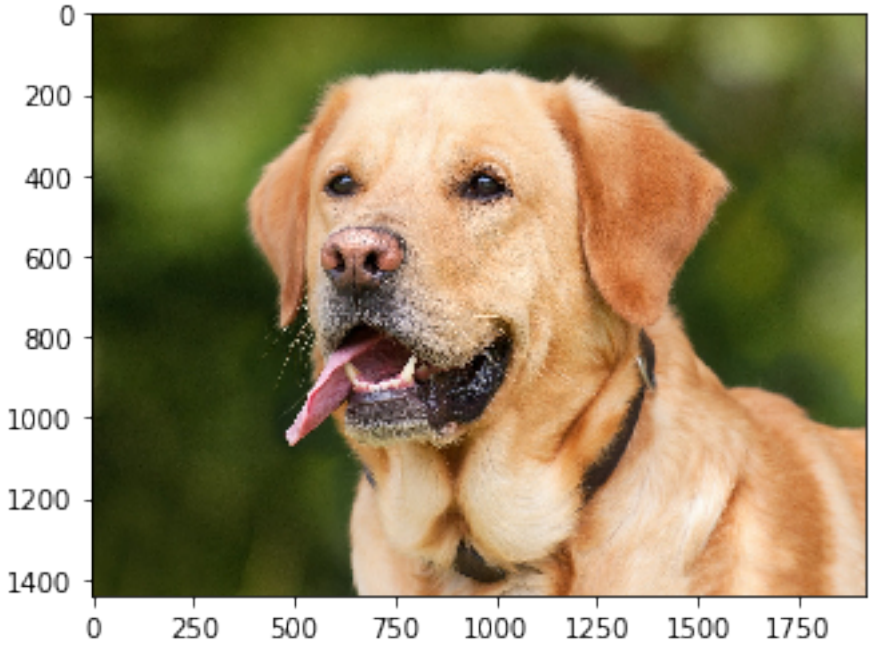

```
This is a Human who looks like a Briard
```

```
This is a Human who looks like a German shorthaired pointer
```


```
This is a Human who looks like a Poodle
```

A dog has been detected which most likely to be Nova scotia duck tolling retriever breed

A dog has been detected which most likely to be French bulldog breed



A dog has been detected which most likely to be Labrador retriever breed

In [ ]: