dog_app

July 18, 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

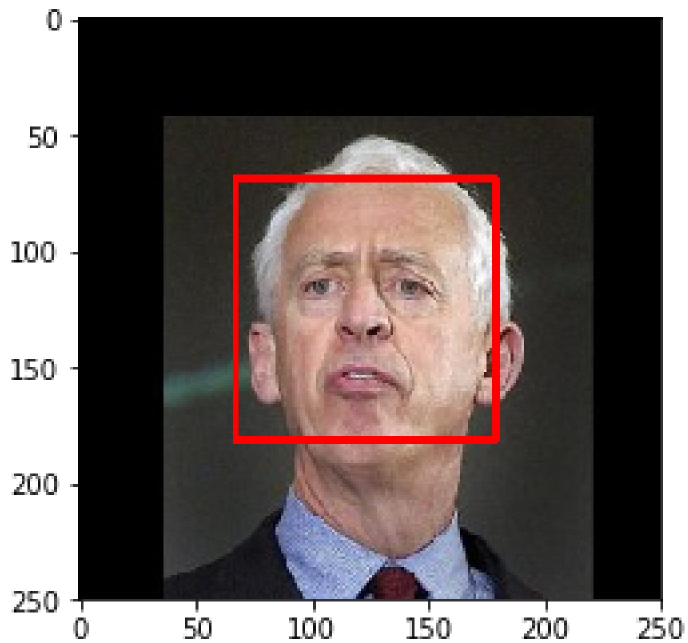
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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[3])
        # 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))
```

```python
# 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),(0,0,255),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) - 98% of the human images were correctly identified as human. - 17% of the dog images were incorrectly identified as human.

```
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.
        import pandas as pd
        df = pd.DataFrame(columns=['path','orig_label','detected_label'])

        df['path'] = list(human_files_short) + list(dog_files_short)
        df['orig_label'] = len(list(human_files_short))*['human'] + len(list(dog_files_short))*[
        df['detected_label'] = df['path'].apply(lambda x: face_detector(x))
        df['detected_label'] = df['detected_label'].replace(True, 'human').replace(False, 'no_hu
```

```
In [5]: (df['detected_label'][df['orig_label'] == 'human']).value_counts()

Out[5]: human       98
        no_human     2
        Name: detected_label, dtype: int64
```

```
In [6]: (df['detected_label'][df['orig_label'] == 'dog']).value_counts()
```

```
Out[6]: no_human    83
        human       17
        Name: detected_label, dtype: int64
```

```
In [7]: # df[df['detected_label'] != df['orig_label']]
```

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 [8]: ### (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 [9]: 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()
            print('using GPU')
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 99812881.89it/s]


using GPU
```

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 [10]:
```
from PIL import Image
import torchvision.transforms as transforms

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

    global VGG16

    img = Image.open(img_path)

#     cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    transform = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
        ])

    VGG16.eval()

    img = transform(img).float()
    img = img.unsqueeze(0)

#     PIL_image = Image.fromarray(cv_rgb)
#     oy = transform(PIL_image).unsqueeze(0)
#     oy.shape
```

```
    if use_cuda:
        img = img.cuda()
    pred, idx = VGG16(img).max(1)
    return  idx.item() # predicted class index
```

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

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? - 0% - What percentage of the images in `dog_files_short` have a detected dog? - 100%

Answer:

```
In [12]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         df = pd.DataFrame(columns=['path','orig_label','detected_label'])

         df['path'] = list(human_files_short) + list(dog_files_short)
         df['orig_label'] = len(list(human_files_short))*['human'] + len(list(dog_files_short))*
         df['detected_label'] = df['path'].apply(lambda x: dog_detector(x))
         df['detected_label'] = df['detected_label'].replace(True, 'dog').replace(False, 'no_dog

         print((df['detected_label'][df['orig_label'] == 'human']).value_counts())
         print((df['detected_label'][df['orig_label'] == 'dog']).value_counts())
```

```
no_dog    100
Name: detected_label, dtype: int64
dog    100
Name: detected_label, dtype: int64
```

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 [13]: ### (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 [14]: import os
         from torchvision import datasets

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes

         # number of subprocesses to use for data loading
         num_workers = 0
         batch_size = 32

         transform = transforms.Compose([transforms.RandomRotation(15),
                                         transforms.CenterCrop(224),
                                         transforms.ToTensor(),
                                         transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
                                        ])
         test_transforms = transforms.Compose([transforms.Resize(255),
                                               transforms.CenterCrop(224),
                                               transforms.ToTensor(),
                                               transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5,
                                              ])

         train_data = datasets.ImageFolder('/data/dog_images/train/', transform=transform)
         valid_data = datasets.ImageFolder('/data/dog_images/valid/', transform=test_transforms)
         test_data = datasets.ImageFolder('/data/dog_images/test/', transform=test_transforms)

         train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,
                                                    num_workers=num_workers, shuffle=True)
         valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size,
                                                    num_workers=num_workers, shuffle=True)
         test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
                                                    num_workers=num_workers, shuffle=True)
         loaders_scratch = {'train' : train_loader, 'valid': valid_loader, 'test': test_loader}
```

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: - I decided to center crop training data,and resize and also center crop the validation and testing data - I decided to augment the data set through random rotatio, I'd like to see the performance before without applying additional augmentaiton methods like flips and translations.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [15]: import torch.nn as nn
         import torch.nn.functional as F
```

```python
n_breeds = 133

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)  # 16*224*224
        self.pool = nn.MaxPool2d(2, 2) # 16*112*112
        self.batchnorm1 = nn.BatchNorm2d(16)

        self.conv2 = nn.Conv2d(16, 32, 3, padding=1) # 32*112*112
        # with max pool2d 32*56*56
        self.batchnorm2 = nn.BatchNorm2d(32)

        self.conv3 = nn.Conv2d(32, 64, 3, padding=1) # 64*56*56
        # with max pool2d 64*28*28
        self.batchnorm3 = nn.BatchNorm2d(64)

        self.conv4 = nn.Conv2d(64, 128, 3, padding=1) # 128*28*28
        # with max pool2d 128*14*14
        self.batchnorm4 = nn.BatchNorm2d(128)

        self.dropout = nn.Dropout(0.25)

        self.fc1 = nn.Linear(128*14*14, 1024)
        self.batchnorm_fc1 = nn.BatchNorm1d(1024)

        self.fc2 = nn.Linear(1024, n_breeds)

    def forward(self, x):
        ## Define forward behavior

        x = self.pool(F.relu(self.conv1(x)))
        x = self.batchnorm1(x)

        x = self.pool(F.relu(self.conv2(x)))
        x = self.batchnorm2(x)

        x = self.pool(F.relu(self.conv3(x)))
        x = self.batchnorm3(x)

        x = self.pool(F.relu(self.conv4(x)))
        x = self.batchnorm4(x)

        #drop out and shape tranform
        x = self.dropout(x.view(-1,128*14*14))
```

```
        #fc1
        x = self.dropout(F.relu(self.fc1(x)))
        x = self.batchnorm_fc1(x)

        #fc2
        x = self.fc2(x)
        return x

#-#-# You so NOT have to modify the code below this line. #-#-#

# instantiate the CNN
model_scratch = Net()

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

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

Answer: following the general architctures shown in class I included 4 convilutional layers, and two fully connected layers, while max pooling after every convultional layer, and using dropout with relu activation between the convlutional layers and the fully connected layers.

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 [16]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch =  optim.Adagrad(model_scratch.parameters(), lr=0.01)
```

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 [20]: from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

In [21]: 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
        optimizer.zero_grad()
        output = model(data)
        loss = criterion(output, target)
        loss.backward()
        optimizer.step()
        ## record the average training loss, using something like
        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)
        # calculate the batch loss
        loss = criterion(output, target)
        # update average validation loss
        valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)

    # 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
```

In [22]:
```
n_epochs = 6
model_scratch = train(n_epochs, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1 	Training Loss: 4.382576 	Validation Loss: 4.300640
Validation loss decreased (inf --> 4.300640).  Saving model ...
Epoch: 2 	Training Loss: 3.923810 	Validation Loss: 4.182365
Validation loss decreased (4.300640 --> 4.182365).  Saving model ...
Epoch: 3 	Training Loss: 3.577131 	Validation Loss: 4.152959
Validation loss decreased (4.182365 --> 4.152959).  Saving model ...
Epoch: 4 	Training Loss: 3.196566 	Validation Loss: 4.076169
Validation loss decreased (4.152959 --> 4.076169).  Saving model ...
Epoch: 5 	Training Loss: 2.788756 	Validation Loss: 4.057329
Validation loss decreased (4.076169 --> 4.057329).  Saving model ...
Epoch: 6 	Training Loss: 2.325181 	Validation Loss: 4.014776
Validation loss decreased (4.057329 --> 4.014776).  Saving model ...
```

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 [23]:
```
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: 3.962036


Test Accuracy: 11% (99/836)
```

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 [24]: ## TODO: Specify data loaders
         loaders_transfer = loaders_scratch
```

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 [25]: import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         model_transfer = models.vgg16(pretrained=True)

         for param in model_transfer.features.parameters():
```

```
        param.requires_grad = False

    print(model_transfer.classifier) # 4096

    n_inputs = 4096

    last_layer = nn.Linear(n_inputs, n_breeds)

    model_transfer.classifier[6] = last_layer

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

```
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=1000, 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: I choose VGG16 because we already saw it perform well and it could serve as a great start. I want to try to freeze the parts that already provide great features and retrain the fully connected layer to detect the dog classes, which should hopefully give better results than the initial model that tried to predict 1000 object classes

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 [26]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adagrad(model_transfer.classifier.parameters(), lr=0.01)
```

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 [27]: n_epochs=10
         model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,

         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
Epoch: 1         Training Loss: 17.076174        Validation Loss: 3.020439
Validation loss decreased (inf --> 3.020439).  Saving model ...
Epoch: 2         Training Loss: 3.644233         Validation Loss: 2.276255
Validation loss decreased (3.020439 --> 2.276255).  Saving model ...
Epoch: 3         Training Loss: 3.115942         Validation Loss: 1.927495
Validation loss decreased (2.276255 --> 1.927495).  Saving model ...
Epoch: 4         Training Loss: 2.671246         Validation Loss: 1.607002
Validation loss decreased (1.927495 --> 1.607002).  Saving model ...
Epoch: 5         Training Loss: 2.328120         Validation Loss: 1.504136
Validation loss decreased (1.607002 --> 1.504136).  Saving model ...
Epoch: 6         Training Loss: 2.044485         Validation Loss: 1.388786
Validation loss decreased (1.504136 --> 1.388786).  Saving model ...
Epoch: 7         Training Loss: 1.866667         Validation Loss: 1.302002
Validation loss decreased (1.388786 --> 1.302002).  Saving model ...
Epoch: 8         Training Loss: 1.667487         Validation Loss: 1.188677
Validation loss decreased (1.302002 --> 1.188677).  Saving model ...
Epoch: 9         Training Loss: 1.528241         Validation Loss: 1.180701
Validation loss decreased (1.188677 --> 1.180701).  Saving model ...
Epoch: 10        Training Loss: 1.398191         Validation Loss: 1.184677
```

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

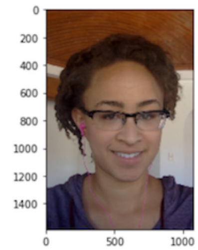
```
Test Loss: 1.264091


Test Accuracy: 64% (540/836)
```

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 [29]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.
         data_transfer = {'train' : train_data, 'valid': valid_data, 'test': test_data}
         # 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 data_transfer['train'].classes]

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
```

hello, human!



You look like a ...
Chinese_shar-pei

Sample Human Output

```
    img = Image.open(img_path)

    transform = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
        ])

    model_transfer.eval()

    img = transform(img).float()
    img = img.unsqueeze(0)

    if use_cuda:
        img = img.cuda()
    pred, idx = model_transfer(img).max(1)
    return  class_names[idx.item()] # predicted class index
```

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 [30]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.
```

```
def disp_image(img_path):
    img = cv2.imread(img_path)
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.imshow(cv_rgb)
    plt.show()
def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    disp_image(img_path)
    if dog_detector(img_path):
        print('Hello dog!')
        print('You look like a ' + predict_breed_transfer(img_path))
    elif face_detector(img_path):
        print('Hello human!')
        print('You look like a ' + predict_breed_transfer(img_path))
    else:
        print('Error, not a dog nor a human.')
```

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!

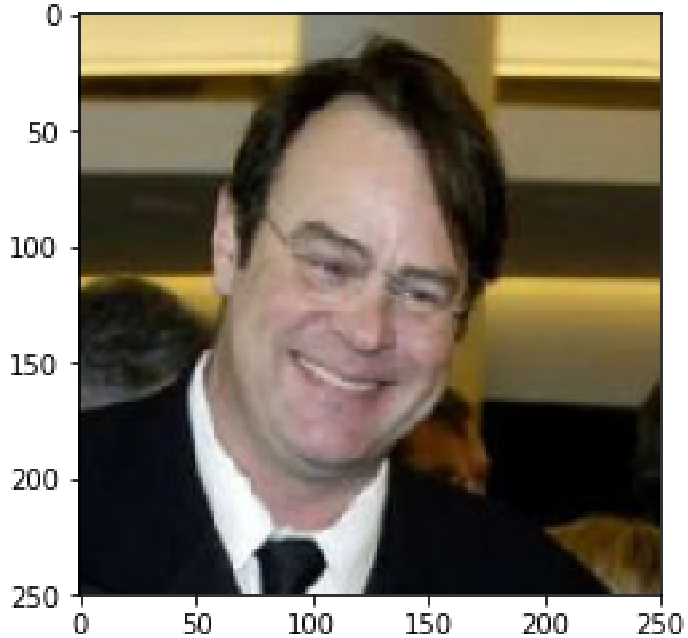
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

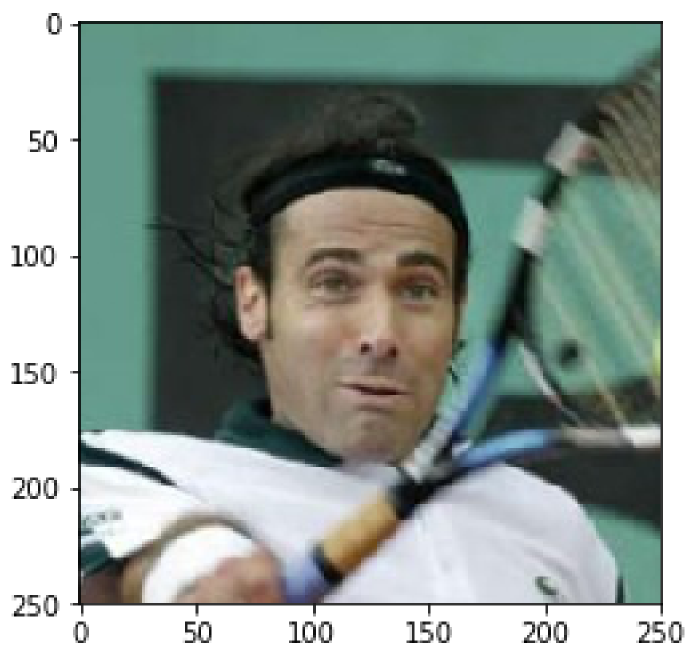
Answer: (Three possible points for improvement) - (first question) the output was better than I expected, I'm gineunely surprised how you can get very decent results quickly through transfer learning

- I think more augmentation methods could improve the model for example, random flipping for the image
- training the model for more epochs also could give better results, I did not try large number of epochs since they take a lot of time, and I already met the required score.
- also perhaps if I introduced random noise to the images, it could improve the performance on the test set

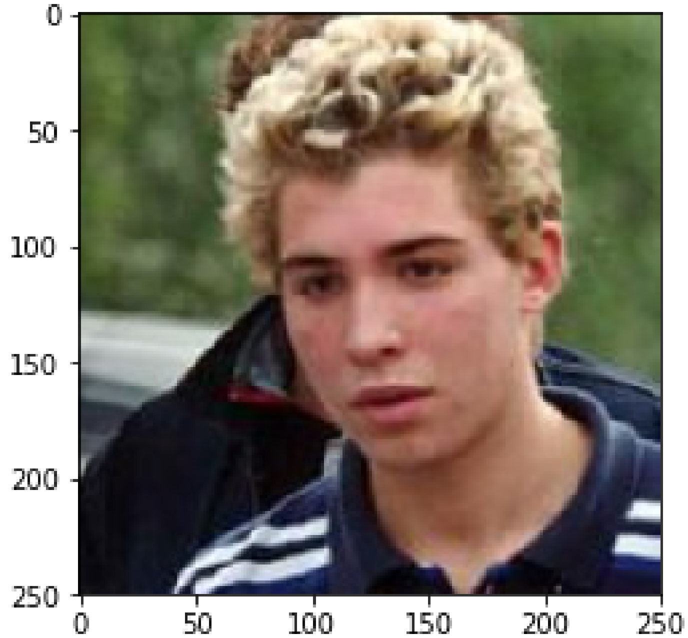
In [31]:
```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as needed.

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



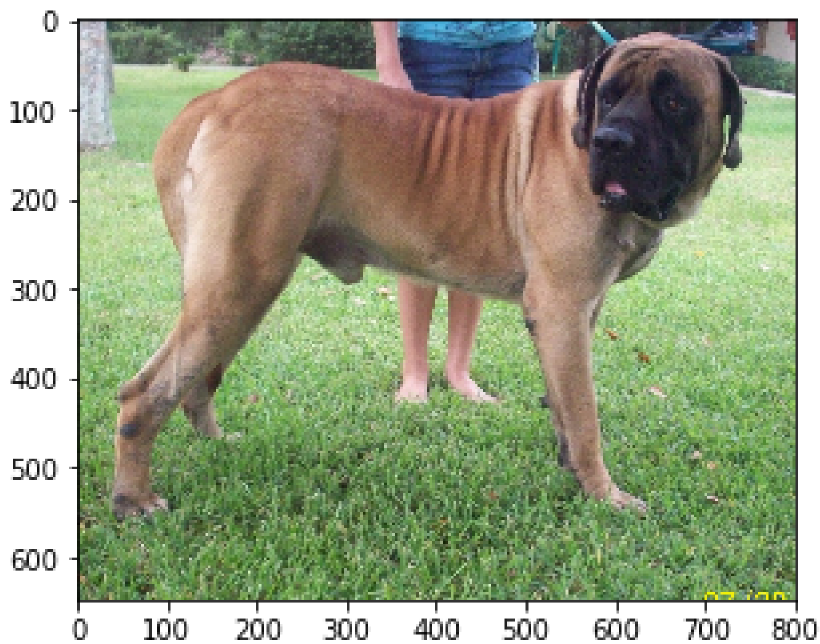

```
Hello human!
You look like a Dogue de bordeaux
```



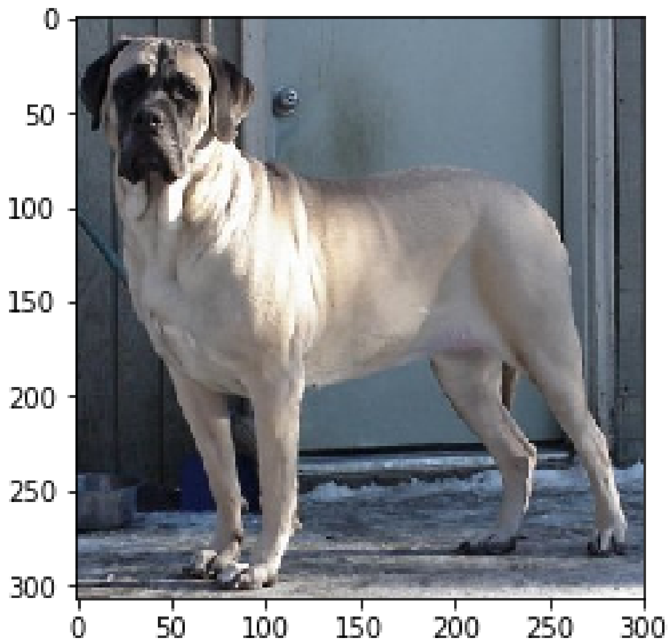
```
Hello human!
You look like a Italian greyhound
```



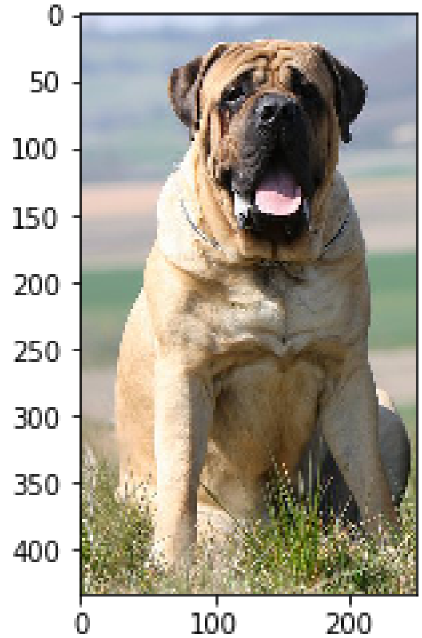

```
Hello human!
You look like a Irish water spaniel
```



```
Hello dog!
You look like a Bullmastiff
```




```
Hello dog!
You look like a Labrador retriever
```




```
Hello dog!
You look like a Mastiff
```