dog_app

May 21, 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

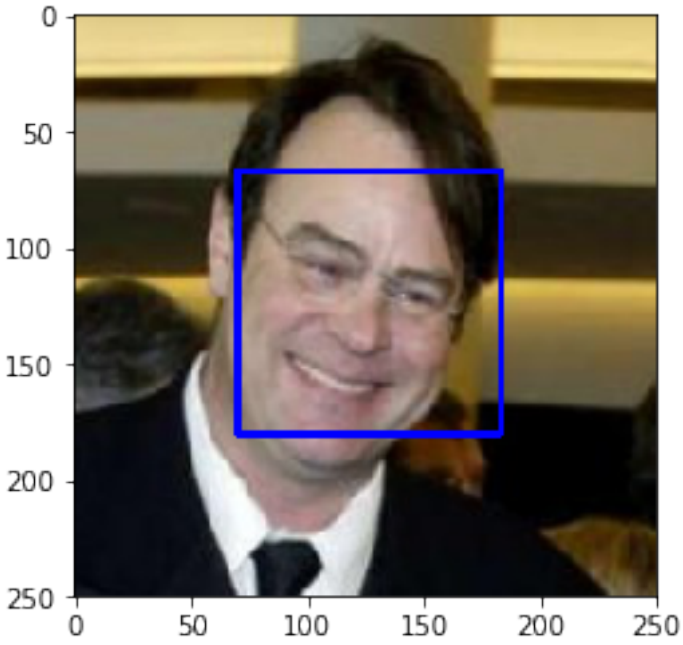
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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.

        import sys

        def detect_human_face(detect_files):
            class_total = list(0. for i in range(len(detect_files)))
            class_correct = list(0. for i in range(len(detect_files)))
            for i in range(len(detect_files)):
                class_total[i] += 1
                if face_detector(detect_files[i]) == True:
                    class_correct[i] += 1

                accuracy = 100. * np.sum(class_correct) / len(detect_files)
                sys.stdout.write('\rTest Accuracy: %2d%% Evaluated: (%2d/%2d )' % (
                    accuracy,
                    np.sum(class_total), len(detect_files) ))
                sys.stdout.flush()
```

```
    return accuracy

print("\n\nWhat percentage of the first 100 images in human_files have a detected human
print("\nHuman Faces Detected in human files: %2d%%" % detect_human_face(human_files_sho

print("\n\nWhat percentage of the first 100 images in dog_files have a detected human fa
print("\nHuman Faces Detected in dog files: %2d%%" % detect_human_face(dog_files_short)
```

```
What percentage of the first 100 images in human_files have a detected human face?
Test Accuracy: 98% Evaluated: (100/100 )
Human Faces Detected in human files: 98%


What percentage of the first 100 images in dog_files have a detected human face?
Test Accuracy: 17% Evaluated: (100/100 )
Human Faces Detected in dog files: 17%
```

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, ImageFile
        import torchvision.transforms as transforms
        from torch.autograd import Variable
        ImageFile.LOAD_TRUNCATED_IMAGES = True

        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

            img = Image.open(img_path)
            loader = transforms.Compose([transforms.Resize([224,224]), transforms.ToTensor()])
            #imgplot = plt.imshow(img)
            img = loader(img).float()
            img = Variable(img)
            x = img.unsqueeze(0)
            #print(x.shape)
            model = VGG16
            if use_cuda:
                model, x = model.cuda(), x.cuda()
```

```
    output = model.forward(x)
    output = torch.exp(output)
    probs, classes = output.topk(1, dim=1)
    #print(probs.item(), classes.item())
    # TODO: Define transforms for the training data and testing data

    return classes.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 [8]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.
            model_class = VGG16_predict(img_path)
            is_dog = False
            if model_class >= 152 and model_class <= 268:
                is_dog = True
            return is_dog # true/false
```

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 [9]: ### TODO: Test the performance of the dog_detector function
        ### on the images in human_files_short and dog_files_short.


        import sys

        def detect_dog_accuracy(detect_files):
            class_total = list(0. for i in range(len(detect_files)))
            class_correct = list(0. for i in range(len(detect_files)))
            for i in range(len(detect_files)):
                class_total[i] += 1
                if dog_detector(detect_files[i]) == True:
                    class_correct[i] += 1
```

```
            accuracy = 100. * np.sum(class_correct) / len(detect_files)
            sys.stdout.write('\rTest Accuracy: %2d%% Evaluated: (%2d/%2d )' % (
                accuracy,
                np.sum(class_total), len(detect_files) ))
            sys.stdout.flush()

        return accuracy

    print("\n\nWhat percentage of the images in human_files_short have a detected dog?")
    print("\nDog Detected in human files: %2d%%" % detect_dog_accuracy(human_files_short) )

    print("\n\nWhat percentage of the first 100 images in dog_files have a detected human fa
    print("\nDog Detected in dog files: %2d%%" % detect_dog_accuracy(dog_files_short) )
```

```
What percentage of the images in human_files_short have a detected dog?
Test Accuracy:  0% Evaluated: (100/100 )
Dog Detected in human files:  0%


What percentage of the first 100 images in dog_files have a detected human face?
Test Accuracy: 91% Evaluated: (100/100 )
Dog Detected in dog files: 91%
```

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 [10]: ### (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 [11]: import os
         from torchvision import datasets
         from torch.utils.data.sampler import SubsetRandomSampler

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


         data_dir = '/data/dog_images'

         # TODO: Define transforms for the training data and testing data
         train_transform = transforms.Compose([
                                         transforms.RandomResizedCrop(224),
                                         transforms.RandomHorizontalFlip(),
                                         transforms.RandomRotation(20),
                                         transforms.ToTensor(),
```

```
                                ])
transform = transforms.Compose([
                                transforms.CenterCrop(224),
                                transforms.ToTensor(),
                                ])

# number of subprocesses to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 10


# Pass transforms in here, then run the next cell to see how the transforms look
train_data = datasets.ImageFolder(data_dir + '/train', transform=train_transform)
valid_data = datasets.ImageFolder(data_dir + '/valid', transform=transform)
test_data = datasets.ImageFolder(data_dir + '/test', transform=transform)


loaders_scratch = {}

loaders_scratch['train'] = torch.utils.data.DataLoader(train_data, batch_size=batch_siz
                                                       num_workers=num_workers, shuffl
loaders_scratch['valid'] = torch.utils.data.DataLoader(valid_data, batch_size=batch_siz
                                                       num_workers=num_workers, shuffl
loaders_scratch['test'] = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
                                                      num_workers=num_workers, shuffle=T
```

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:

- Using Cropping to 224 and using RandomResizedCrop, RandomHorizontalFlip and RandomRotation on training set scaled to 224 to to allow for better generalization
- Converting to tensor

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [12]: 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__()
```

```
        ## Define layers of a CNN

        # convolutional layer (sees 224x224x3 image tensor)
        self.conv_bn1 = nn.BatchNorm2d(3)
        self.conv1 = nn.Conv2d(3, 16, 3, padding = 1 )


        # convolutional layer (sees 112x112x16 image tensor)
        self.conv_bn2 = nn.BatchNorm2d(16)
        self.conv2 = nn.Conv2d(16, 32, 3, padding = 1)

        # convolutional layer (sees 56x56x32 image tensor)
        self.conv_bn3 = nn.BatchNorm2d(32)
        self.conv3 = nn.Conv2d(32, 64, 3, padding = 1)

        # convolutional layer (sees 28x28x64 image tensor)
        self.conv_bn4 = nn.BatchNorm2d(64)
        self.conv4 = nn.Conv2d(64, 128, 3, padding = 1)

        # convolutional layer (sees 14x14x128 image tensor)
        self.conv_bn5 = nn.BatchNorm2d(128)
        self.conv5 = nn.Conv2d(128, 256, 3, padding = 1 )

        # max pooling layer
        self.pool = nn.MaxPool2d(2, 2)

        self.dropout = nn.Dropout(0.25)

        # linear layer (256 * 7 * 7 -> 512)
        self.fc1 = nn.Linear(256 * 7 * 7, 512)
        self.fc2 = nn.Linear(512, 133)



    def forward(self, x):
        ## Define forward behavior
        # add sequence of convolutional and max pooling layers
        x = self.pool(F.relu(self.conv1(self.conv_bn1(x))))
        x = self.pool(F.relu(self.conv2(self.conv_bn2(x))))
        x = self.pool(F.relu(self.conv3(self.conv_bn3(x))))
        x = self.pool(F.relu(self.conv4(self.conv_bn4(x))))
        x = self.pool(F.relu(self.conv5(self.conv_bn5(x))))

        # flatten image input
        x = x.view(-1, 256 * 7 * 7)
        # add dropout layer
        x = self.dropout(x)
        # add second hidden layer
```

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

```
In [13]: model_scratch
```

```
Out[13]: Net(
           (conv_bn1): BatchNorm2d(3, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
           (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
           (conv_bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats
           (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
           (conv_bn3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats
           (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
           (conv_bn4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats
           (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
           (conv_bn5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stat
           (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
           (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
           (dropout): Dropout(p=0.25)
           (fc1): Linear(in_features=12544, out_features=512, bias=True)
           (fc2): Linear(in_features=512, out_features=133, bias=True)
         )
```

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

Answer:

- Use of five convolution layers.
- Each convolution layer is followed by a max pooling layer.
- Two linear layer are used.
- Relu activations are used.
- Dropouts with the probability of 0.25 are used.

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 [14]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = torch.optim.SGD(model_scratch.parameters(), lr=0.0012)

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

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 [15]: 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()
                     output = model(data)
                     loss = criterion(output, target)
                     loss.backward()
                     optimizer.step()
                     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
                ## valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_lo
                #print(target.shape)
                output = model(data)
                loss = criterion(output, target)
                #valid_loss += loss.item()*data.size(0)
                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


# train the model
model_scratch = train(28, 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: 4.885713         Validation Loss: 4.869355
Validation loss decreased (inf --> 4.869355).  Saving model ...
Epoch: 2         Training Loss: 4.865140         Validation Loss: 4.853119
Validation loss decreased (4.869355 --> 4.853119).  Saving model ...
Epoch: 3         Training Loss: 4.845236         Validation Loss: 4.821589
Validation loss decreased (4.853119 --> 4.821589).  Saving model ...
Epoch: 4         Training Loss: 4.819544         Validation Loss: 4.776275
Validation loss decreased (4.821589 --> 4.776275).  Saving model ...
Epoch: 5         Training Loss: 4.780870         Validation Loss: 4.711902
Validation loss decreased (4.776275 --> 4.711902).  Saving model ...
Epoch: 6         Training Loss: 4.719491         Validation Loss: 4.626669
Validation loss decreased (4.711902 --> 4.626669).  Saving model ...
```

```
Epoch: 7         Training Loss: 4.647398         Validation Loss: 4.540485
Validation loss decreased (4.626669 --> 4.540485).  Saving model ...
Epoch: 8         Training Loss: 4.590881         Validation Loss: 4.465695
Validation loss decreased (4.540485 --> 4.465695).  Saving model ...
Epoch: 9         Training Loss: 4.547703         Validation Loss: 4.416389
Validation loss decreased (4.465695 --> 4.416389).  Saving model ...
Epoch: 10         Training Loss: 4.484097         Validation Loss: 4.369986
Validation loss decreased (4.416389 --> 4.369986).  Saving model ...
Epoch: 11         Training Loss: 4.451431         Validation Loss: 4.336476
Validation loss decreased (4.369986 --> 4.336476).  Saving model ...
Epoch: 12         Training Loss: 4.428040         Validation Loss: 4.281644
Validation loss decreased (4.336476 --> 4.281644).  Saving model ...
Epoch: 13         Training Loss: 4.386063         Validation Loss: 4.274120
Validation loss decreased (4.281644 --> 4.274120).  Saving model ...
Epoch: 14         Training Loss: 4.359249         Validation Loss: 4.251663
Validation loss decreased (4.274120 --> 4.251663).  Saving model ...
Epoch: 15         Training Loss: 4.329841         Validation Loss: 4.235172
Validation loss decreased (4.251663 --> 4.235172).  Saving model ...
Epoch: 16         Training Loss: 4.311805         Validation Loss: 4.213553
Validation loss decreased (4.235172 --> 4.213553).  Saving model ...
Epoch: 17         Training Loss: 4.277680         Validation Loss: 4.256864
Epoch: 18         Training Loss: 4.249313         Validation Loss: 4.198720
Validation loss decreased (4.213553 --> 4.198720).  Saving model ...
Epoch: 19         Training Loss: 4.226342         Validation Loss: 4.139011
Validation loss decreased (4.198720 --> 4.139011).  Saving model ...
Epoch: 20         Training Loss: 4.215135         Validation Loss: 4.106677
Validation loss decreased (4.139011 --> 4.106677).  Saving model ...
Epoch: 21         Training Loss: 4.190475         Validation Loss: 4.120155
Epoch: 22         Training Loss: 4.172596         Validation Loss: 4.050540
Validation loss decreased (4.106677 --> 4.050540).  Saving model ...
Epoch: 23         Training Loss: 4.134459         Validation Loss: 4.054695
Epoch: 24         Training Loss: 4.108360         Validation Loss: 4.053494
Epoch: 25         Training Loss: 4.086386         Validation Loss: 4.120769
Epoch: 26         Training Loss: 4.088747         Validation Loss: 4.013413
Validation loss decreased (4.050540 --> 4.013413).  Saving model ...
Epoch: 27         Training Loss: 4.065163         Validation Loss: 4.045581
Epoch: 28         Training Loss: 4.032333         Validation Loss: 3.972853
Validation loss decreased (4.013413 --> 3.972853).  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 [16]: 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: 3.920208


Test Accuracy: 10% (86/836)
```

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 [17]: ## TODO: Specify data loaders
         loaders_transfer = loaders_scratch.copy()
```

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

         ## TODO: Specify model architecture
         # Load the pretrained model from pytorch
         model_transfer = models.vgg16(pretrained=True)

         n_inputs = model_transfer.classifier[6].in_features

         # add last linear layer (n_inputs -> 5 flower classes)
         # new layers automatically have requires_grad = True
         last_layer = nn.Linear(n_inputs, 133)

         model_transfer.classifier[6] = last_layer

         for param in model_transfer.features.parameters():
             param.requires_grad = False


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

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. Used VGG16
2. Freezed all the network gradients for the transfered layers
3. Applied a fully connected layer that outputs 133 as the output as per the dog breed classes

The architecture is suitable for the current problem as it allows the reuse of pre-trained network in the classification task

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 [19]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr=0.001)

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

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 [26]:
```
# train the model

        n_epochs = 28
        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: 1.699504         Validation Loss: 1.488134
Validation loss decreased (inf --> 1.488134).  Saving model ...
Epoch: 2         Training Loss: 1.681134         Validation Loss: 1.511250
Epoch: 3         Training Loss: 1.670899         Validation Loss: 1.522071
Epoch: 4         Training Loss: 1.636934         Validation Loss: 1.490601
Epoch: 5         Training Loss: 1.634342         Validation Loss: 1.488185
Epoch: 6         Training Loss: 1.602757         Validation Loss: 1.469399
Validation loss decreased (1.488134 --> 1.469399).  Saving model ...
Epoch: 7         Training Loss: 1.624927         Validation Loss: 1.459689
Validation loss decreased (1.469399 --> 1.459689).  Saving model ...
Epoch: 8         Training Loss: 1.589251         Validation Loss: 1.469750
Epoch: 9         Training Loss: 1.574223         Validation Loss: 1.454606
Validation loss decreased (1.459689 --> 1.454606).  Saving model ...
Epoch: 10         Training Loss: 1.601614         Validation Loss: 1.453024
Validation loss decreased (1.454606 --> 1.453024).  Saving model ...
Epoch: 11         Training Loss: 1.547146         Validation Loss: 1.436549
Validation loss decreased (1.453024 --> 1.436549).  Saving model ...
Epoch: 12         Training Loss: 1.581334         Validation Loss: 1.437981
Epoch: 13         Training Loss: 1.540520         Validation Loss: 1.449573
Epoch: 14         Training Loss: 1.546347         Validation Loss: 1.424575
Validation loss decreased (1.436549 --> 1.424575).  Saving model ...
Epoch: 15         Training Loss: 1.528198         Validation Loss: 1.433123
Epoch: 16         Training Loss: 1.502424         Validation Loss: 1.418449
Validation loss decreased (1.424575 --> 1.418449).  Saving model ...
Epoch: 17         Training Loss: 1.547975         Validation Loss: 1.419549
Epoch: 18         Training Loss: 1.496855         Validation Loss: 1.404684
Validation loss decreased (1.418449 --> 1.404684).  Saving model ...
Epoch: 19         Training Loss: 1.504769         Validation Loss: 1.396958
Validation loss decreased (1.404684 --> 1.396958).  Saving model ...
Epoch: 20         Training Loss: 1.505398         Validation Loss: 1.406497
Epoch: 21         Training Loss: 1.464507         Validation Loss: 1.400022
Epoch: 22         Training Loss: 1.463712         Validation Loss: 1.421770
Epoch: 23         Training Loss: 1.446510         Validation Loss: 1.401493
Epoch: 24         Training Loss: 1.463616         Validation Loss: 1.410450
Epoch: 25         Training Loss: 1.411890         Validation Loss: 1.412464
Epoch: 26         Training Loss: 1.425671         Validation Loss: 1.390291
```

```
Validation loss decreased (1.396958 --> 1.390291).  Saving model ...
Epoch: 27         Training Loss: 1.444316         Validation Loss: 1.387098
Validation loss decreased (1.390291 --> 1.387098).  Saving model ...
Epoch: 28         Training Loss: 1.419371         Validation Loss: 1.383291
Validation loss decreased (1.387098 --> 1.383291).  Saving model ...
```

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%.

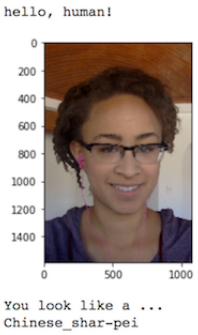
```
In [27]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 1.433428


Test Accuracy: 61% (510/836)
```

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 [28]: ### 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': loaders_transfer['train'].dataset }
         # 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
             img = Image.open(img_path)
             loader = transforms.Compose([transforms.Resize([224,224]), transforms.ToTensor()])
             #imgplot = plt.imshow(img)
             img = loader(img).float()
             img = Variable(img)
             x = img.unsqueeze(0)
             #print(x.shape)
             model = model_transfer
             if use_cuda:
                 model, x = model.cuda(), x.cuda()

             output = model.forward(x)
             output = torch.exp(output)
             probs, classes = output.topk(1, dim=1)
             #print(probs.item(), classes.item())
             # TODO: Define transforms for the training data and testing data
```



Sample Human Output

```
    return class_names[classes.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 [29]:
```
### 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

    #if a dog is detected in the image, return the predicted breed.
    if dog_detector(img_path) == True:
        print('\nHello, dog!')
        breed = predict_breed_transfer(img_path)
        plt.imshow(Image.open(img_path))
        plt.axis('off')
        plt.show()
        print( 'your predicted breed is ...\n%s\n' % breed )
        return
    #if a human is detected in the image, return the resembling dog breed.
    elif face_detector(img_path) == True:
        print('\nHello, human!')
```

```
            breed = predict_breed_transfer(img_path)
            plt.imshow(Image.open(img_path))
            plt.axis('off')
            plt.show()
            print( 'You look like a ....\n%s' % breed )
            return
        #if neither is detected in the image, provide output that indicates an error.
        else:
            print('No dog or human face detected on image: %s' % (img_path) )
            plt.imshow(Image.open(img_path))
            plt.axis('off')
            plt.show()
            return
```

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:

Accuracy achieved:

Other methods that could be applied to improve accuracy would be:

1. Testing additional or a variety of learning rates
2. Altering the training using various additional methods for better generalization
3. Testing additional pre-existing networks to understand which one may work even better

In [30]:
```
## 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 ...
Alaskan malamute

Hello, human!

```
You look like a ...
Ibizan hound

Hello, human!
```

```
You look like a ...
Poodle

Hello, dog!
```

```
your predicted breed is ...
Bullmastiff


Hello, dog!
```

```
your predicted breed is ...
Mastiff


Hello, dog!
```

```
your predicted breed is ...
Bullmastiff


In [ ]:
```