dog_app

December 11, 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
        import torch.nn.functional as F

        # 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

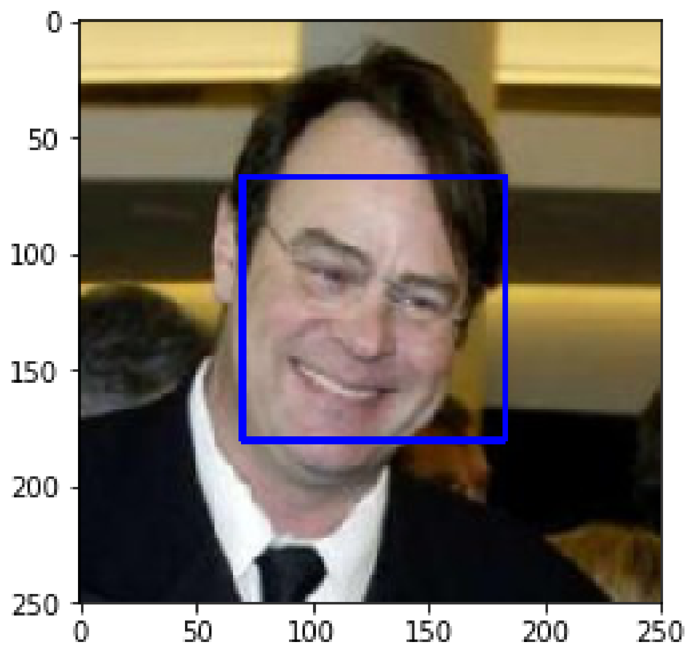
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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
```

```python
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: Result shown in print statement below.

In [5]:
```
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.

num_human = 0
num_dog = 0

for img in human_files_short:
    if face_detector(img): num_human += 1

for img in dog_files_short:
    if face_detector(img): num_dog += 1

print("Percentage of human faces detected in human images:", (num_human/100.0)*100, "%")
print("Percentage of human faces detected in dog images:", (num_dog/100.0)*100, "%")
```

```
Percentage of human faces detected in human images: 0.98
Percentage of human faces detected in dog images: 0.17
```

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 [ ]:
```
### (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 [37]:
```
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 [44]:
```
from PIL import Image
import torchvision.transforms as transforms
```

```
import torchvision.datasets as datasets

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

    #numpy_img = cv2.imread(img_path)

    img = Image.open(img_path)
    #plt.imshow(img)
    data_transform = transforms.Compose([transforms.RandomResizedCrop(224),
                                         transforms.ToTensor(),
                                        transforms.Normalize([0.4, 0.4, 0.4], [0.225, 0
                                        ])
    img = data_transform(img)
    if(use_cuda):
        img = img.cuda()
    values = VGG16(img.unsqueeze_(0))
    values = F.sigmoid(values)
    top_pred, top_index = values.topk(1)
    top_index = top_index.cpu()
    return top_index[0][0].numpy() # 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 [6]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.
```

```
    index = VGG16_predict(img_path)

    return index in range(151, 269)
```

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: Anser is shown under the code block below.

```
In [95]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

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

         num_human = 0
         num_dog = 0

         for img in human_files_short:
             if dog_detector(img): num_human += 1

         for img in dog_files_short:
             if dog_detector(img): num_dog += 1

         print("Percentage of human images predicted to be dogs:", (num_human/100.0)*100, "%")
         print("Percentage of dog images predicted to be dogs:", (num_dog/100.0)*100, "%")
```

```
Percentage of human images predicted to be dogs: 3.0 %
Percentage of dog images predicted to be dogs: 95.0 %
```

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 [ ]: ### (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 [7]: import os
        from torchvision import datasets
        from PIL import ImageFile

        ImageFile.LOAD_TRUNCATED_IMAGES = True

        ### TODO: Write data loaders for training, validation, and test sets
        ## Specify appropriate transforms, and batch_sizes
        train_transforms = transforms.Compose([transforms.RandomResizedCrop(224),
                                               transforms.RandomRotation(25),
```

```
                                     transforms.RandomHorizontalFlip(),
                                     transforms.ToTensor(),
                                     transforms.Normalize([0.485, 0.456, 0.406], [0.229
valid_transforms = transforms.Compose([transforms.Resize(250),
                                      transforms.CenterCrop(224),
                                      transforms.ToTensor(),
                                      transforms.Normalize([0.485, 0.456, 0.406], [0.22
test_transforms = transforms.Compose([transforms.Resize(250),
                                     transforms.CenterCrop(224),
                                     transforms.ToTensor(),
                                     transforms.Normalize([0.485, 0.456, 0.406], [0.229

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

train_loader = torch.utils.data.DataLoader(train_data, batch_size=32, shuffle=True)
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=32, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=32, 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:

1- for the training data set, I added a radom recrop and resized them to 224 to be inline with the VGG16 CNN. I feel making the images bigger than 224 would be too computationally intensive to process.

2- slight rotations and a random horizontle flip to the training images to traing the model in a more general sense and prevent overfitting.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [8]: import torch.nn as nn
        import torch.nn.functional as F
        from PIL import ImageFile

        ImageFile.LOAD_TRUNCATED_IMAGES = True

        # 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.pool = nn.MaxPool2d(2, 2)
        #sees 3x224x224
        self.conv1 = nn.Conv2d(3, 32, 3, stride=1, padding=1)
        #sees 32x112x112
        self.conv2 = nn.Conv2d(32, 64, 3, stride=1, padding=1)
        #sees 64x56x56
        self.conv3 = nn.Conv2d(64, 128, 3, stride=1, padding=1)

        #sees 128x28x28
        self.fc1 = nn.Linear(128*28*28, 5000)
        #self.fc2 = nn.Linear(10000, 1000)
        self.fc2 = nn.Linear(5000, 133)

        self.dropout = nn.Dropout(0.3)

    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))

        x = x.view(-1, 128*28*28)

        x = self.dropout(x)
        x = self.dropout(F.relu(self.fc1(x)))
        x = F.log_softmax(self.fc2(x), dim=1)

        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: I used three layers of Convolutional Layers, each one increasing the depth by 2 times. I also added a Max Pooling Layer between each Convolutional Layer to reduce the image (x,y) size by 4 times each layer. I wanted to reduce the amount of training time and resource needed to train the nextwork. I feel if the network is too complex, it would require a very diverse set of training data to train it efficiently, which is not provided for this project. It would also take a long time to train. For the Classification layers, two Linear Layers seemed enough to correctly classify the images coming from the Convelutional 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 [9]: import torch.optim as optim

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

        ### 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 [11]: 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)

                 ######################
```

```python
            # 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)

                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(), 'model_scratch.pt')
                valid_loss_min = valid_loss

        # return trained model
        return model


    # train the model
    model_scratch = train(50, 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: 3.930555         Validation Loss: 4.016954
Validation loss decreased (inf --> 4.016954).  Saving model ...
Epoch: 2         Training Loss: 3.912657         Validation Loss: 3.970589
Validation loss decreased (4.016954 --> 3.970589).  Saving model ...
Epoch: 3         Training Loss: 3.897342         Validation Loss: 3.951663
Validation loss decreased (3.970589 --> 3.951663).  Saving model ...
Epoch: 4         Training Loss: 3.872250         Validation Loss: 3.932456
Validation loss decreased (3.951663 --> 3.932456).  Saving model ...
Epoch: 5         Training Loss: 3.862670         Validation Loss: 3.909735
```

```
Validation loss decreased (3.932456 --> 3.909735).  Saving model ...
Epoch: 6 	Training Loss: 3.847470 	Validation Loss: 4.074210
Epoch: 7 	Training Loss: 3.828098 	Validation Loss: 3.944402
Epoch: 8 	Training Loss: 3.812625 	Validation Loss: 3.892892
Validation loss decreased (3.909735 --> 3.892892).  Saving model ...
Epoch: 9 	Training Loss: 3.754788 	Validation Loss: 3.914458
Epoch: 10 	Training Loss: 3.774062 	Validation Loss: 3.941662
Epoch: 11 	Training Loss: 3.761803 	Validation Loss: 3.890871
Validation loss decreased (3.892892 --> 3.890871).  Saving model ...
Epoch: 12 	Training Loss: 3.722484 	Validation Loss: 3.902412
Epoch: 13 	Training Loss: 3.703076 	Validation Loss: 3.847429
Validation loss decreased (3.890871 --> 3.847429).  Saving model ...
Epoch: 14 	Training Loss: 3.688095 	Validation Loss: 4.046023
Epoch: 15 	Training Loss: 3.684423 	Validation Loss: 3.867375
Epoch: 16 	Training Loss: 3.633354 	Validation Loss: 3.853862
Epoch: 17 	Training Loss: 3.634608 	Validation Loss: 3.928805
Epoch: 18 	Training Loss: 3.601822 	Validation Loss: 3.847548
Epoch: 19 	Training Loss: 3.577527 	Validation Loss: 3.905504
Epoch: 20 	Training Loss: 3.558463 	Validation Loss: 3.947457
```

```
In [10]: model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

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 [12]: 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: 3.802461


Test Accuracy: 13% (112/836)
```

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 [21]: ## TODO: Specify data loaders
         import os
         from torchvision import datasets
         from PIL import ImageFile

         ImageFile.LOAD_TRUNCATED_IMAGES = True

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes
         train_transforms = transforms.Compose([transforms.RandomResizedCrop(224),
                                               transforms.RandomRotation(25),
                                               transforms.RandomHorizontalFlip(),
                                               transforms.ToTensor(),
                                               transforms.Normalize([0.485, 0.456, 0.406], [0.22
         valid_transforms = transforms.Compose([transforms.Resize(250),
                                                transforms.CenterCrop(224),
                                                transforms.ToTensor(),
```

```
                                       transforms.Normalize([0.485, 0.456, 0.406], [0.2
test_transforms = transforms.Compose([transforms.Resize(250),
                                      transforms.CenterCrop(224),
                                      transforms.ToTensor(),
                                      transforms.Normalize([0.485, 0.456, 0.406], [0.22

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

train_loader = torch.utils.data.DataLoader(train_data, batch_size=32, shuffle=True)
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=32, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=32, shuffle=True)

loaders_transfer = {'train':train_loader,
                    'valid':valid_loader,
                    'test': test_loader}
```

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 [14]: 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

         model_transfer.classifier[6] = nn.Linear(4096, 133)

         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: This model has been trained on ImageNet, and includes most of the dog breeds we want to predict for this project at a good accuracy. Since the data is similar, and the sampling data is not that large, just changing the last layer in the Classifications to suite the need for the 133 different dog breeds should be sufficient.

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 [15]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(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 [18]: 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)
                     loss = criterion(output, target)

                     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_transfer = train(10, loaders_transfer, model_transfer, optimizer_transfer, criter

    # 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: 1.369668         Validation Loss: 0.515744
Validation loss decreased (inf --> 0.515744).  Saving model ...
Epoch: 2         Training Loss: 1.310454         Validation Loss: 0.554303
Epoch: 3         Training Loss: 1.272651         Validation Loss: 0.498454
Validation loss decreased (0.515744 --> 0.498454).  Saving model ...
Epoch: 4         Training Loss: 1.224111         Validation Loss: 0.468328
Validation loss decreased (0.498454 --> 0.468328).  Saving model ...
Epoch: 5         Training Loss: 1.217319         Validation Loss: 0.437390
Validation loss decreased (0.468328 --> 0.437390).  Saving model ...
Epoch: 6         Training Loss: 1.140273         Validation Loss: 0.464163
Epoch: 7         Training Loss: 1.127225         Validation Loss: 0.480209
Epoch: 8         Training Loss: 1.091141         Validation Loss: 0.434144
Validation loss decreased (0.437390 --> 0.434144).  Saving model ...
Epoch: 9         Training Loss: 1.104810         Validation Loss: 0.458181
Epoch: 10         Training Loss: 1.043573         Validation Loss: 0.495154
```

```
In [17]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

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%.

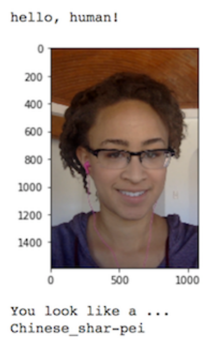
In [22]:
```
def test(loaders, model, criterion, use_cuda):

    # 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))


test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.469420


Test Accuracy: 85% (713/836)
```

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 [50]:
```
### 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 train_data.classes]
```



Sample Human Output

```
def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    img = Image.open(img_path)
    data_transform = transforms.Compose([transforms.Resize(250),
                                         transforms.CenterCrop(224),
                                         transforms.ToTensor(),
                                         transforms.Normalize([0.485, 0.456, 0.406], [0.22
                                         ])
    img = data_transform(img)
    if(use_cuda):
        img = img.cuda()
    values = model_transfer(img.unsqueeze_(0))
    values = F.sigmoid(values)
    top_pred, top_index = values.topk(1)
    top_index = top_index.cpu()
    pred = class_names[top_index[0][0].numpy()]
    return pred
```

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 [26]: ### 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
    is_human = face_detector(img_path)
    is_dog = dog_detector(img_path)
    img = Image.open(img_path)

    if(is_dog):
        dog_pred = predict_breed_transfer(img_path)
        print("Hello dog!")
        plt.imshow(img)
        print("You look like a..." + dog_pred + "!")
    elif(is_human):
        dog_pred = predict_breed_transfer(img_path)
        print("Hello human!")
        plt.imshow(img)
        print("You look like a..." + dog_pred + "!")
    else:
        print("Hello Unidentified Object")
        plt.imshow(img)
        print("Unfortunately my amazing AI predicts that you are neither human nor dog

    return None
```

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:

1- Changing the whole Classification layer in the VGG16 model and retraining it might have made the model more accurate instead only changing the last layer.

2- Adding more diverse transforms to the training data would have trained the model more efficeintly and reduced the overfitting.

3- Having a bigger training set for the model would have helped.

```
In [51]: ## 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.
```

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

```
Hello human!
You look like a...Brittany!
Hello human!
You look like a...Dachshund!
Hello human!
You look like a...Curly-coated retriever!
Hello dog!
You look like a...Mastiff!
Hello dog!
You look like a...Mastiff!
Hello dog!
You look like a...Bullmastiff!
```