dog_app

June 9, 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

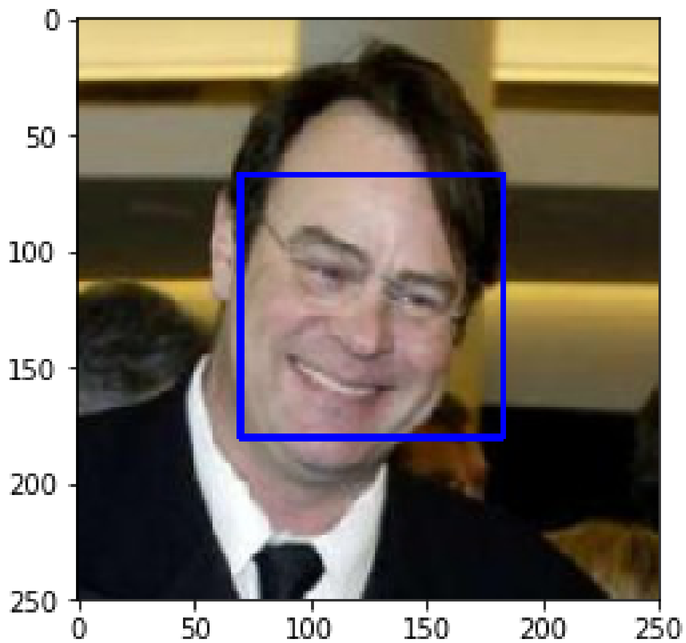
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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. #-#-#
        human_face_count=sum([face_detector(x) for x in human_files_short])
        dog_face_count=sum([face_detector(x) for x in dog_files_short])

        ## TODO: Test the performance of the face_detector algorithm
        print("Percentage of Human face detected is {}%".format(human_face_count*100/len(human_f
        print("Percentage of Dog face detected is {}%".format(dog_face_count*100/len(dog_files_s
        ## on the images in human_files_short and dog_files_short.
```

```
Percentage of Human face detected is 98.0%
Percentage of Dog face detected is 17.0%
```

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 [5]: import torch
        import torchvision.models as models
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        # 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()
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 94011227.09it/s]
```

```
In [8]: #Practice
        from PIL import Image
        image=Image.open(dog_files[0]).convert('RGB')
        in_transform=transforms.Compose([transforms.Resize(256),
                                         transforms.RandomCrop(224),
                                            transforms.ToTensor(),
                                            transforms.Normalize((0.485, 0.456, 0.406),(0.229, 0

        image = in_transform(image)[:3,:,:].unsqueeze(0)
        print(image.shape)
        with torch.no_grad():
            output=VGG16.forward(image.to('cuda'))
        #print(output.max())
        output.max(1)
```

```
torch.Size([1, 3, 224, 224])
```

```
Out[8]: (tensor([ 28.0390], device='cuda:0'), tensor([ 243], device='cuda:0'))
```

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

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

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

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

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

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

    image=Image.open(img_path).convert('RGB')
    in_transform=transforms.Compose([transforms.Resize(256),
                                     transforms.RandomCrop(224),
                                        transforms.ToTensor(),
                                        transforms.Normalize((0.485, 0.456, 0.406),(0.229, 0

    image = in_transform(image)[:3,:,:].unsqueeze(0)
    VGG16.eval()
    with torch.no_grad():
        output=VGG16.forward(image.to(device))
    VGG16.train()
    return output.max(1)[1] # predicted class index

VGG16_predict(human_files_short[7])
```

Out[7]:
```
tensor([ 400], device='cuda:0')
```

1.1.5 (IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary, you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all categories from `'Chihuahua'` to `'Mexican hairless'`. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

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

```
In [9]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.
            predict_idx=VGG16_predict(img_path)
            if predict_idx < 269 and predict_idx > 150:
                return True
            return False # true/false
```

```
In [10]: dog_detector(human_files[6])
```

```
Out[10]: 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 [11]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         detect_dog_h=sum([dog_detector(x) for x in human_files_short])
         detect_dog_d=sum([dog_detector(x) for x in dog_files_short])
         print("Percentage of Dog detected from human files {}%".format(detect_dog_h*100/len(hum
         print("Percentage of Dog detected from dog files {}%".format(detect_dog_d*100/len(dog_f
```

```
Percentage of Dog detected from human files 0.0%
Percentage of Dog detected from dog files 100.0%
```

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 [72]:
```
import os
from torchvision import datasets

batch_size=128

data_dir = '/data/dog_images/'
train_dir = os.path.join(data_dir, 'train/')
valid_dir=os.path.join(data_dir,'valid/')
test_dir = os.path.join(data_dir, 'test/')
```

```
train_transform = transforms.Compose([transforms.Resize(256),
                                      transforms.RandomHorizontalFlip(),
                                       transforms.RandomRotation(10),
                                      transforms.CenterCrop(224),
                                       transforms.ToTensor(),
                                     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.
                                      ])
test_valid_transform = transforms.Compose([
                                      transforms.Resize(256),
                                      transforms.CenterCrop(224),
                                       transforms.ToTensor(),
                                     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.
                                      ])
train_data=datasets.ImageFolder(train_dir,transform=train_transform)
valid_data=datasets.ImageFolder(valid_dir,transform=test_valid_transform)
test_data=datasets.ImageFolder(test_dir,transform=test_valid_transform)
print("Train Images: {}, Validation Images:{} , Test Images: {}".format(len(train_data)
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,shuffle=Tr
num_workers=0)
valid_loader = torch.utils.data.DataLoader(train_data,batch_size=32 )
test_loader = torch.utils.data.DataLoader(train_data,batch_size=32)
```

```
Train Images: 6680, Validation Images:835 , Test Images: 836
```

In [50]:
```
n_classes = len(train_data.classes)
n_classes
```

Out[50]: 133

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 resized using transforms library function Resize.I resized to 256x256 size and applied centre cropping of 224 on resized images. Bigger pixel values allows to learn much feature information Convolution layers can be applied. I augmented dataset because it prevents overfitting ans size of dataset is small. So augment helps in learning.

1.1.8 (IMPLEMENTATION) Model Architecture

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

In [73]:
```
import torch.nn as nn
import torch.nn.functional as F
```

```python
# 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)
        self.conv2=nn.Conv2d(16,32,3,padding=1)
        self.conv3=nn.Conv2d(32,64,3,padding=1)
        self.conv4=nn.Conv2d(64,128,3,padding=1)
        self.conv5=nn.Conv2d(128,256,3,padding=1)
        self.pool=nn.MaxPool2d(2,2)
        self.fc1=nn.Linear(7*7*256,1024)
        self.fc2=nn.Linear(1024,512)
        self.fc3=nn.Linear(512,n_classes)
        self.dropout=nn.Dropout(0.2)
    def forward(self, x):
        ## Define forward behavior
        x=F.relu(self.conv1(x))
        x=self.pool(x)

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

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

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

        x=F.relu(self.conv5(x))
        x=self.pool(x)

        x=x.view(x.shape[0],-1)
        x=F.relu(self.fc1(x))
        x=self.dropout(x)
        x=F.relu(self.fc2(x))
        x=self.dropout(x)
        x=self.fc3(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: Test accuracy atleast 10 percent required hence simple model will be good.I designed 5 layer convolution each follwed by pooling layer and 3 fully connected layer with dropout. Size is reduced by 224x224x3->112x112x16->112x112x32->56x56x32 ->56x56x64->28x28x64 -> 28x28x128 -> 14x14x128 -> 14x14x128->7x7x128-> Flatten->1024->512->133 classes I just implemented basic few layers of VGG i think this gives atleast 10% accuracy

I used CrossEntropy pytorch loss function which uses logSoftmax for output and Negative Log loss.Hence last layer has no activation function. While predicting softmax can be applied and class probabilites can be displayed

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 [74]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.Adam(model_scratch.parameters(),lr=0.001)
```

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 [76]: from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True
         def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

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

                 ###################
                 # train the model #
                 ###################
                 model.train()
                 for batch_idx, (data, target) in enumerate(loaders['train']):
                     # move to GPU
```

```
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
            optimizer.zero_grad()
            output=model.forward(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()
                with torch.no_grad():
                    output=model.forward(data)
                    loss=criterion(output,target)
                    valid_loss+= ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

            ## update the average validation 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

loaders_scratch={'train':train_loader,
                'test':test_loader,
                'valid':valid_loader}
# train the model
```

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

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

```
Epoch: 1 	Training Loss: 4.885863 	Validation Loss: 4.865993
Validation loss decreased (inf --> 4.865993).  Saving model ...
Epoch: 2 	Training Loss: 4.839109 	Validation Loss: 4.753596
Validation loss decreased (4.865993 --> 4.753596).  Saving model ...
Epoch: 3 	Training Loss: 4.663292 	Validation Loss: 4.542077
Validation loss decreased (4.753596 --> 4.542077).  Saving model ...
Epoch: 4 	Training Loss: 4.521924 	Validation Loss: 4.369443
Validation loss decreased (4.542077 --> 4.369443).  Saving model ...
Epoch: 5 	Training Loss: 4.333635 	Validation Loss: 4.170733
Validation loss decreased (4.369443 --> 4.170733).  Saving model ...
Epoch: 6 	Training Loss: 4.168627 	Validation Loss: 4.065391
Validation loss decreased (4.170733 --> 4.065391).  Saving model ...
Epoch: 7 	Training Loss: 4.064358 	Validation Loss: 3.891009
Validation loss decreased (4.065391 --> 3.891009).  Saving model ...
Epoch: 8 	Training Loss: 3.929457 	Validation Loss: 3.800073
Validation loss decreased (3.891009 --> 3.800073).  Saving model ...
Epoch: 9 	Training Loss: 3.850594 	Validation Loss: 3.712322
Validation loss decreased (3.800073 --> 3.712322).  Saving model ...
Epoch: 10 	Training Loss: 3.731941 	Validation Loss: 3.575859
Validation loss decreased (3.712322 --> 3.575859).  Saving model ...
Epoch: 11 	Training Loss: 3.640988 	Validation Loss: 3.432724
Validation loss decreased (3.575859 --> 3.432724).  Saving model ...
Epoch: 12 	Training Loss: 3.514543 	Validation Loss: 3.378550
Validation loss decreased (3.432724 --> 3.378550).  Saving model ...
Epoch: 13 	Training Loss: 3.427125 	Validation Loss: 3.271568
Validation loss decreased (3.378550 --> 3.271568).  Saving model ...
Epoch: 14 	Training Loss: 3.361814 	Validation Loss: 3.175006
Validation loss decreased (3.271568 --> 3.175006).  Saving model ...
Epoch: 15 	Training Loss: 3.219424 	Validation Loss: 2.960063
Validation loss decreased (3.175006 --> 2.960063).  Saving model ...
Epoch: 16 	Training Loss: 3.107123 	Validation Loss: 3.084494
Epoch: 17 	Training Loss: 3.035323 	Validation Loss: 2.808926
Validation loss decreased (2.960063 --> 2.808926).  Saving model ...
Epoch: 18 	Training Loss: 2.904166 	Validation Loss: 2.530186
Validation loss decreased (2.808926 --> 2.530186).  Saving model ...
Epoch: 19 	Training Loss: 2.801481 	Validation Loss: 2.405451
Validation loss decreased (2.530186 --> 2.405451).  Saving model ...
Epoch: 20 	Training Loss: 2.653235 	Validation Loss: 2.208256
Validation loss decreased (2.405451 --> 2.208256).  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 [77]: 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: 2.207077


Test Accuracy: 40% (2702/6680)
```

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 [78]:
```
## TODO: Specify data loaders
import os
from torchvision import datasets

batch_size=128

data_dir = '/data/dog_images/'
train_dir = os.path.join(data_dir, 'train/')
valid_dir=os.path.join(data_dir,'valid/')
test_dir = os.path.join(data_dir, 'test/')
train_transform = transforms.Compose([transforms.Resize(256),
                                     transforms.RandomHorizontalFlip(),
                                      transforms.RandomRotation(10),
                                     transforms.CenterCrop(224),
                                      transforms.ToTensor(),
                                    transforms.Normalize((0.485, 0.456, 0.406),(0.229,
                                     ])
test_valid_transform = transforms.Compose([
                                     transforms.Resize(256),
                                     transforms.CenterCrop(224),
                                      transforms.ToTensor(),
                                    transforms.Normalize((0.485, 0.456, 0.406),(0.229,
                                     ])
train_data=datasets.ImageFolder(train_dir,transform=train_transform)
valid_data=datasets.ImageFolder(valid_dir,transform=test_valid_transform)
test_data=datasets.ImageFolder(test_dir,transform=test_valid_transform)
print("Train Images: {}, Validation Images:{} , Test Images: {}".format(len(train_data)
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,shuffle=Tr
num_workers=0)
valid_loader = torch.utils.data.DataLoader(train_data,batch_size=32 )
test_loader = torch.utils.data.DataLoader(train_data,batch_size=32)
```

```
Train Images: 6680, Validation Images:835 , Test Images: 836
```

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 [101]: 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.parameters():
              param.requires_grad=False
          classifier = nn.Sequential(nn.Linear(25088, 4096),
                        nn.ReLU(),
                        nn.Dropout(0.5),
                        nn.Linear(4096, 512),
                        nn.ReLU(),
                        nn.Dropout(0.5),
                        nn.Linear(512, n_classes))
          model_transfer.classifier = classifier
          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: Here i am using VGG model architecture. Transfer learning is best method when dataset is small. Here target class have similarity to pretrained VGG classses. Here i am freezing weights of pretrained vgg model and applying fully connected at end to our target classes. 2 Fully connected layers and output layer to 133 classes is added. Only these layers are trained here. ImageNet dataset have dog breeds in it so because similarity i used pre-trained VGG

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 [103]: criterion_transfer = nn.CrossEntropyLoss()
          optimizer_transfer = optim.Adam(model_transfer.classifier.parameters(),lr=0.001)
```

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 [104]: # train the model
          loaders_transfer={'train':train_loader,
                            'test':test_loader,
```

```
                     'valid':valid_loader}
model_transfer =train(6, loaders_transfer, model_transfer, optimizer_transfer, criteri

# 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: 4.422135         Validation Loss: 2.339518
Validation loss decreased (inf --> 2.339518).  Saving model ...
Epoch: 2        Training Loss: 2.617875         Validation Loss: 1.108658
Validation loss decreased (2.339518 --> 1.108658).  Saving model ...
Epoch: 3        Training Loss: 1.896538         Validation Loss: 0.795392
Validation loss decreased (1.108658 --> 0.795392).  Saving model ...
Epoch: 4        Training Loss: 1.564978         Validation Loss: 0.610499
Validation loss decreased (0.795392 --> 0.610499).  Saving model ...
Epoch: 5        Training Loss: 1.376737         Validation Loss: 0.490609
Validation loss decreased (0.610499 --> 0.490609).  Saving model ...
Epoch: 6        Training Loss: 1.225193         Validation Loss: 0.427196
Validation loss decreased (0.490609 --> 0.427196).  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%.

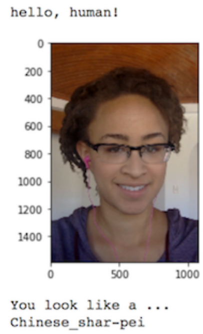
```
In [105]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.425209


Test Accuracy: 87% (5855/6680)
```

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 [115]: ### 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]
          model_transfer.load_state_dict(torch.load('model_transfer.pt'))
          def predict_breed_transfer(img_path):
              # load the image and return the predicted breed
              image=Image.open(img_path).convert('RGB')
              in_transform=transforms.Compose([transforms.Resize(256),
                                               transforms.RandomCrop(224),
```



Sample Human Output

```
                                        transforms.ToTensor(),
                                        transforms.Normalize((0.485, 0.456, 0.406),(0.229

    image = in_transform(image)[:3,:,:].unsqueeze(0)
    #if use_cuda:
     #   image.cuda()
    model_transfer.eval()
    with torch.no_grad():
        output=model_transfer(image.to('cuda'))
    model_transfer.train()



    return class_names[output.data.max(1, keepdim=True)[1]]
```

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 [122]: ### 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 face_detector(img_path):
```

```
            print("Hey..human")
            plt.imshow(Image.open(img_path))
            plt.show()
            print("No offence..\nYou look like a ..{}".format(predict_breed_transfer(img_p
            print("**********************************************")
        elif dog_detector(img_path):
            print("Hey..doggy")
            plt.imshow(Image.open(img_path))
            plt.show()
            print("I think you are {} breed".format(predict_breed_transfer(img_path)))
            print("**********************************************")
        else:
            print("Sorry..No dogs or humans detected :)")
```

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!

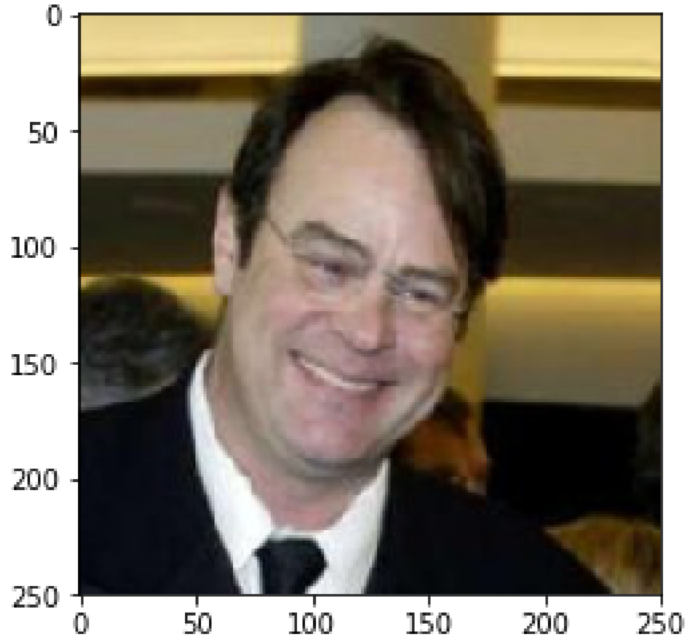
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

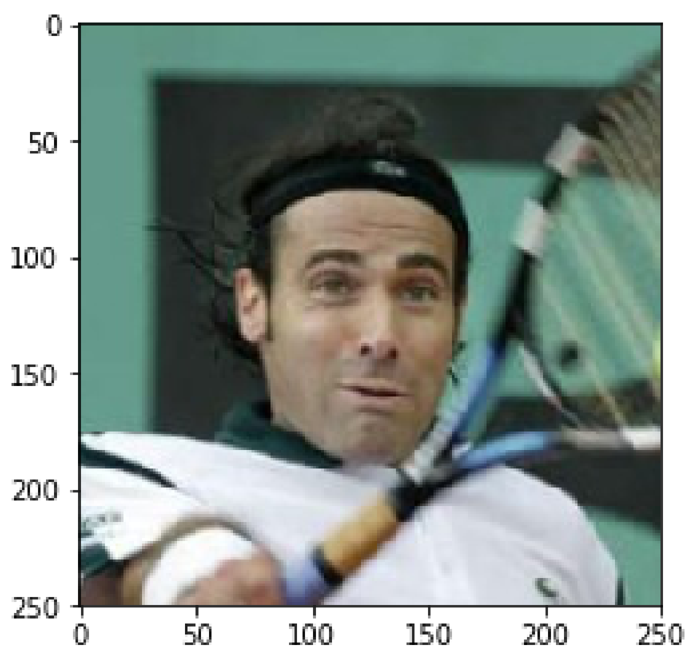
Answer: (Three possible points for improvement)
Output is better but it took longer time to train. For training 20 epochs it took me 1 hour.
(1) Other pretrained models can be applied (ResNets,etc)
(2) More dataset can be added to increase accuracy
(3) Different learning rate can be applied and train longer

```
In [127]: ## 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[:5])):
              run_app(file)
```

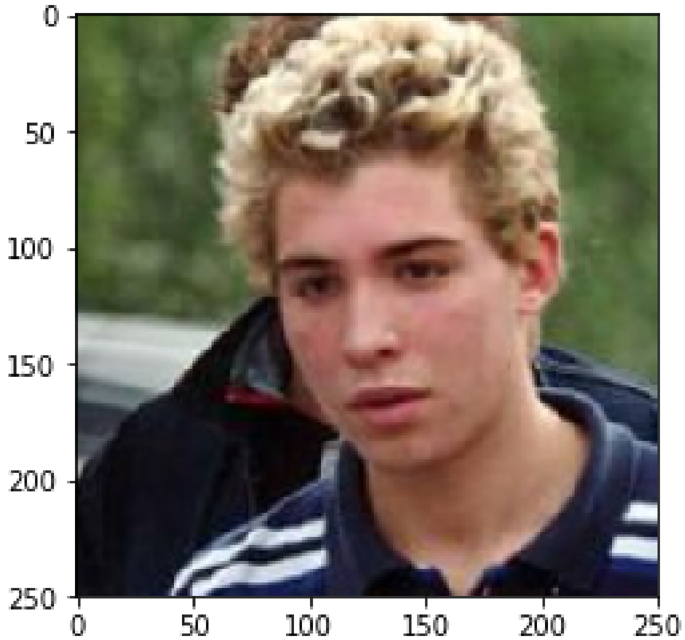
```
Hey..human
```



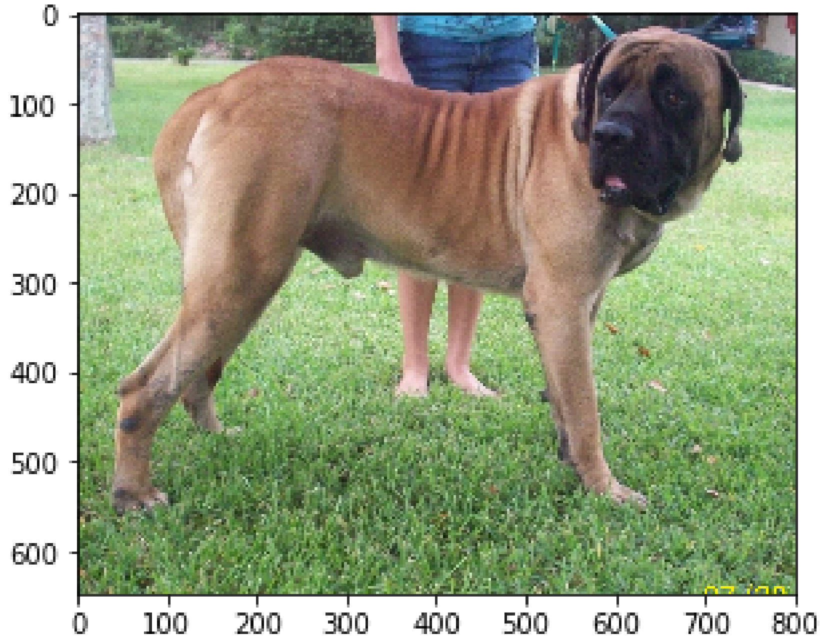

```
No offence..
You look like a ..Boxer
*********************************************
Hey..human
```



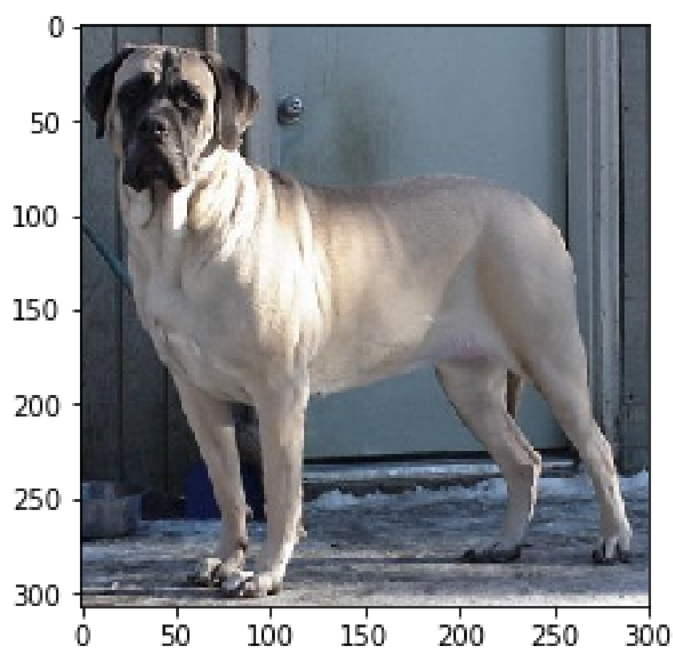
```
No offence..
You look like a ..Italian greyhound
*********************************************
Hey..human
```



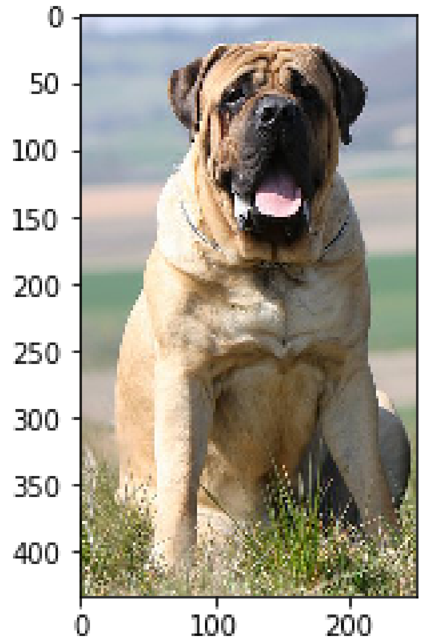

```
No offence..
You look like a ..Dachshund
*********************************************
Hey..doggy
```



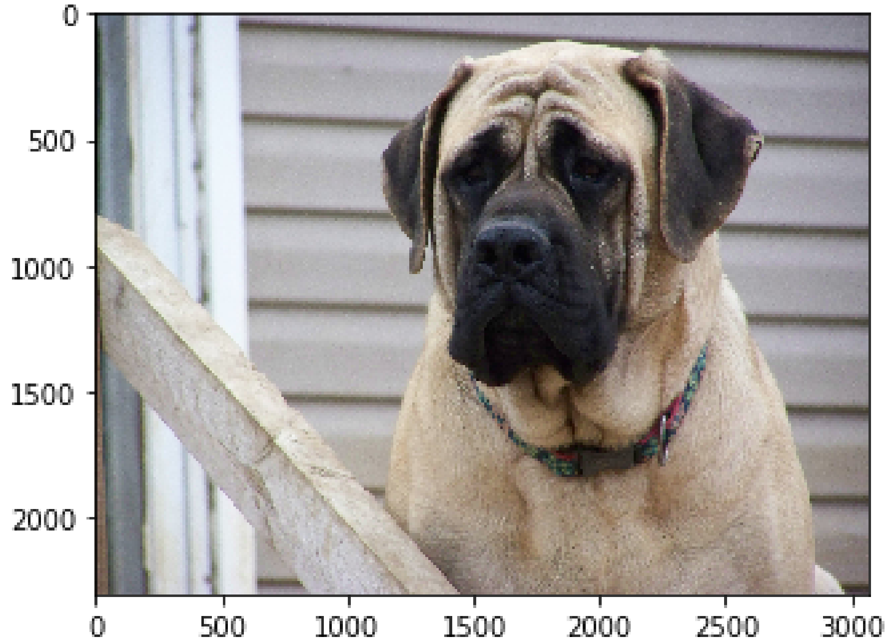
```
I think you are Bullmastiff breed
*********************************************
Hey..doggy
```



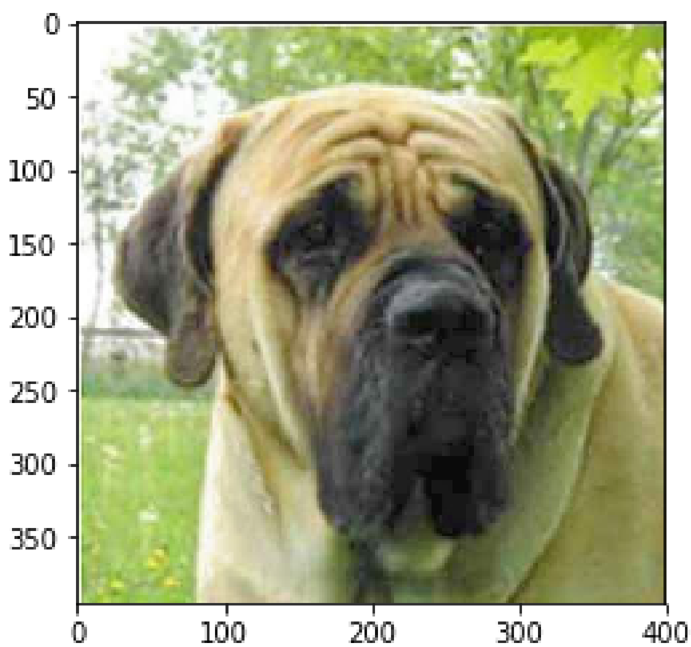
```
I think you are Bullmastiff breed
*********************************************
Hey..doggy
```




```
I think you are Chinese shar-pei breed
*********************************************
Hey..doggy
```




```
I think you are Bullmastiff breed
*********************************************
Hey..doggy
```



```
I think you are Mastiff breed
*********************************************
```

```
In [97]:
```

```
In [96]:
```

```
In [ ]:
```