dog_app

May 23, 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

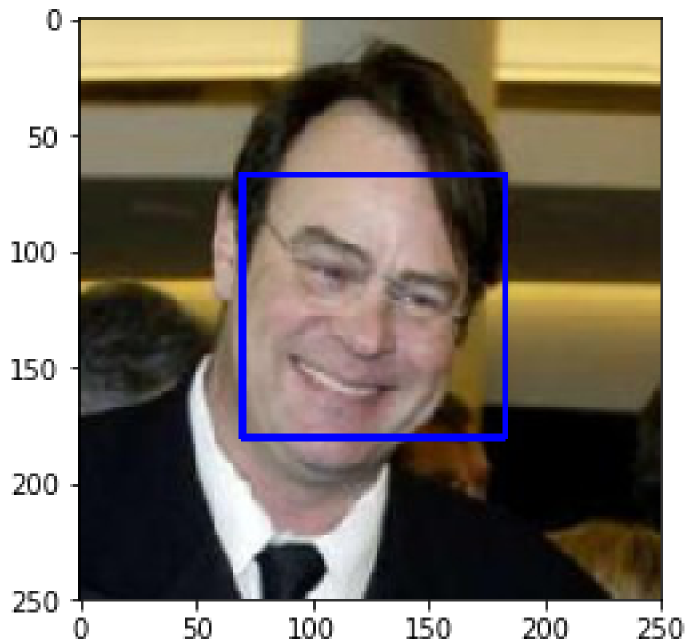
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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))
```

```python
# get bounding box for each detected face
for (x,y,w,h) in faces:
    # add bounding box to color image
    cv2.rectangle(img,(x,y),(x+w,y+h),(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) Percentage of the first 100 images in human_files have a detected human face 98 % Percentage of the first 100 images in dog_files have a detected human face 17 %

```
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.
        human_faces=0
        dog_faces=0
        for i in range(100):
            if face_detector(human_files[i]):
                human_faces+=1
            if face_detector(dog_files[i]):
                dog_faces+=1
        print('Percentage of the first 100 images in human_files have a detected human face',hum
        print('Percentage of the first 100 images in dog_files have a detected human face',dog_f
```

```
Percentage of the first 100 images in human_files have a detected human face 98 %
Percentage of the first 100 images in dog_files have a detected human face 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 [ ]:
```

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

        # 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 [00:10<00:00, 52809828.21it/s]
```

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 [6]: 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
            im = Image.open(img_path).convert('RGB')
            transfer=transforms.Compose([transforms.Resize((224,224)),transforms.ToTensor()])
            im=transfer(im)[:3,:,:].unsqueeze(0)
            return  torch.max(VGG16(im.cuda()),1)[1].item() # predicted class index
```

```
In [7]: print(VGG16_predict(dog_files[1]))
```

```
254
```

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.
            dog_type=VGG16_predict(img_path)
            return dog_type<=268 and dog_type>=151 # 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: Percentage of the first 100 images in human_files have a detected dog face 0 % Percentage of the first 100 images in dog_files have a detected dog face 94 %

In [9]:
```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
human_faces3, dog_faces3 = 0,0
for i in range(100):
    if dog_detector(human_files[i]):
        human_faces3+=1
    if dog_detector(dog_files[i]):
        dog_faces3+=1
print('Percentage of the first 100 images in human_files have a detected dog face',human
print('Percentage of the first 100 images in dog_files have a detected dog face',dog_fac
```

```
Percentage of the first 100 images in human_files have a detected dog face 0 %
Percentage of the first 100 images in dog_files have a detected dog face 94 %
```

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

         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes
         # Loading directory paths for train, test and validation set
         directory='/data/dog_images'
         dog_traindir = os.path.join(directory, 'train')
         dog_testdir = os.path.join(directory, 'test')
         dog_validdir = os.path.join(directory, 'valid')
```

```
In [12]: normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])

         batch_size=10 # batch size

         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         # load train, test and validation sets as dataloader and apply necessary transform
         train_loader = torch.utils.data.DataLoader(
                 datasets.ImageFolder(dog_traindir, transforms.Compose([
                     transforms.RandomResizedCrop(224),
                     transforms.RandomHorizontalFlip(),
                     transforms.ToTensor(),
                     normalize,
                 ])), batch_size=batch_size, shuffle=True, pin_memory=True)
```

```
val_loader = torch.utils.data.DataLoader(
        datasets.ImageFolder(dog_validdir, transforms.Compose([
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            normalize,
        ])), batch_size=batch_size, shuffle=False, pin_memory=True)
test_loader = torch.utils.data.DataLoader(
        datasets.ImageFolder(dog_testdir, transforms.Compose([
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            normalize,
        ])), batch_size = batch_size, shuffle=True, pin_memory=True)
```

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: The image is resized to a size of 224x224. I used different method like resizing and croppinng to acheive this. A 224x224 is the typical image size used by several algorithms like VGG16, VGG19, and ResNet. The bigger the size, the more will be the number of parameters. more parameters require more computational capacity along with more data(to avoid overfitting) to train.

Data augumentation like cropping and horizontal flipping are applied are applied to the image. This reduces the problem of overfitting as the network will find difficult to see the same inputs twice.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [13]: 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 1
                 self.conv1 = nn.Conv2d(in_channels=3, out_channels=16, kernel_size=(3,3), strid

                 # Convolutional layer 2
                 self.conv2 = nn.Conv2d(in_channels=16, out_channels=32, kernel_size=(3,3), stri
```

```
        # Convolutional layer 3
        self.conv3 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=(3,3), stri

        # adding pooling layers
        self.pool = nn.MaxPool2d(kernel_size=(2,2))

        # adding fully connected layers

        self.fc1 = nn.Linear(28*28*64, 512)
        self.fc2 = nn.Linear(512, 133)  # 133 is the total dog classes

        # adding dropout layer
        self.dropout = nn.Dropout(p=0.50)

    def forward(self, x):
        ## Define forward behavior
        # adding convolution layers with relu function and max pooling layer
        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)

        # Flattening the tensor to feed fully connected layers
        x = x.view(-1, 28*28*64)

        # Fully connected layer with dropout
        x = self.dropout(x)
        x = F.relu(self.fc1(x))
        x = self.dropout(x)

        # Final classification layer without dropout
        x = F.relu(self.fc2(x))


        return x

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

# instantiate the CNN
model_scratch = Net()

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

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

Answer: After doing research on the internet and trialing with various algorithms found this architecture reasonable enough to generate a minimum of 10% accuracy on testset.

The architecture uses three conv layers with max pooling and relu activation. Since a bigger filter would require more dataset to train, a 3x3 filter along with stride and padding 1 is 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 = optim.SGD(model_scratch.parameters(), lr=0.05)

         # Convert input prameters into a dictionary
         loaders_scratch = {'train': train_loader,
                           'valid': val_loader,
                           'test': test_loader}
```

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
```

```
            optimizer.zero_grad() # Clear gradients from previous iterations

            loss=criterion(model(data),target) # Calculate loss by comparing output and

            loss.backward() # Backward propogation

            optimizer.step() # Updating weights

            # update average train loss
            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()

            loss=criterion(model(data),target) # Calculate loss by comparing output and

            ## update the average validation loss
            valid_loss = valid_loss + ((1/(batch_idx+1)) * (loss.data - valid_loss))

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

        ## TODO: save the model if validation loss has decreased
        if valid_loss < valid_loss_min:
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss

    # return trained model
    return model


# train the model
model_scratch = train(30, 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: 4.876889        Validation Loss: 4.815633
Epoch: 2         Training Loss: 4.807037        Validation Loss: 4.683533
Epoch: 3         Training Loss: 4.735791        Validation Loss: 4.617987
Epoch: 4         Training Loss: 4.679414        Validation Loss: 4.555187
Epoch: 5         Training Loss: 4.628987        Validation Loss: 4.576148
Epoch: 6         Training Loss: 4.590697        Validation Loss: 4.448036
Epoch: 7         Training Loss: 4.554931        Validation Loss: 4.395374
Epoch: 8         Training Loss: 4.530359        Validation Loss: 4.422163
Epoch: 9         Training Loss: 4.494457        Validation Loss: 4.273407
Epoch: 10         Training Loss: 4.463776        Validation Loss: 4.226034
Epoch: 11         Training Loss: 4.407685        Validation Loss: 4.162330
Epoch: 12         Training Loss: 4.383894        Validation Loss: 4.320835
Epoch: 13         Training Loss: 4.370617        Validation Loss: 4.134310
Epoch: 14         Training Loss: 4.340639        Validation Loss: 4.376750
Epoch: 15         Training Loss: 4.320387        Validation Loss: 4.054208
Epoch: 16         Training Loss: 4.286091        Validation Loss: 4.132864
Epoch: 17         Training Loss: 4.272337        Validation Loss: 4.012395
Epoch: 18         Training Loss: 4.248261        Validation Loss: 4.021903
Epoch: 19         Training Loss: 4.235969        Validation Loss: 3.950958
Epoch: 20         Training Loss: 4.198729        Validation Loss: 3.927627
Epoch: 21         Training Loss: 4.196881        Validation Loss: 3.949890
Epoch: 22         Training Loss: 4.154321        Validation Loss: 3.906886
Epoch: 23         Training Loss: 4.187503        Validation Loss: 4.010851
Epoch: 24         Training Loss: 4.181023        Validation Loss: 3.916038
Epoch: 25         Training Loss: 4.150012        Validation Loss: 3.891261
Epoch: 26         Training Loss: 4.190104        Validation Loss: 3.882200
Epoch: 27         Training Loss: 4.133167        Validation Loss: 3.749115
Epoch: 28         Training Loss: 4.112965        Validation Loss: 3.811909
Epoch: 29         Training Loss: 4.155428        Validation Loss: 3.819365
Epoch: 30         Training Loss: 4.105296        Validation Loss: 3.750196
```

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]:
```python
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: 3.732507


Test Accuracy: 13% (113/836)
```

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
```

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
         model_transfer = models.resnet50(pretrained=True) # Load Resnet50 model
         model_transfer.fc = nn.Linear(model_transfer.fc.in_features, 133) # Set the number of c

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

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:01<00:00, 91140942.56it/s]
```

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: For the final CNN architecture i used ResNet50 model. - I choose this model because the model is aproven technique for image classification. - As the model allows skip connection it avoids vanishing gradients. - It has 50 layers and computational time is acceptable. - It has a top-1 error of 23.85 and a top-5 error of 7.13

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() # Define loss function
         optimizer_transfer = optim.SGD(model_transfer.fc.parameters(), lr=0.05) # Define SGD Op
```

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 [20]: n_epochs=10
         # train the model
         model_transfer = train(n_epochs, loaders_scratch, model_transfer, optimizer_transfer, c

         # 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: 2.721474         Validation Loss: 0.877535
Epoch: 2         Training Loss: 1.512138         Validation Loss: 0.636815
Epoch: 3         Training Loss: 1.275879         Validation Loss: 0.558789
Epoch: 4         Training Loss: 1.189196         Validation Loss: 0.576259
Epoch: 5         Training Loss: 1.138169         Validation Loss: 0.523055
Epoch: 6         Training Loss: 1.075857         Validation Loss: 0.513188
Epoch: 7         Training Loss: 1.062099         Validation Loss: 0.478975
Epoch: 8         Training Loss: 1.020700         Validation Loss: 0.456885
```

```
Epoch: 9        Training Loss: 1.022305        Validation Loss: 0.489375
Epoch: 10        Training Loss: 0.981760        Validation Loss: 0.528315
```

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 [21]: test(loaders_scratch, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.466678


Test Accuracy: 86% (723/836)
```

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.

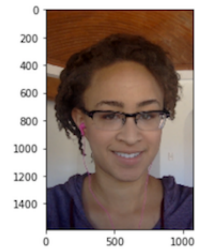
```
In [22]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.

         # 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 loaders_scratch['train'].dataset.

         def predict_breed_transfer(img_path,model,class_names):
             # load the image and return the predicted breed
             im = Image.open(img_path).convert('RGB') # Load image

             transfer=transforms.Compose([transforms.Resize((224,224)),transforms.ToTensor()]) #

             im=transfer(im)[:3,:,:].unsqueeze(0)

             index=torch.max(model(im.cuda()),1)[1].item() # predicted class index

             return class_names[index]
```

```
In [23]: predict_breed_transfer(dog_files[500],model_transfer,class_names)
```

```
Out[23]: 'Papillon'
```

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

```
hello, human!
```




```
You look like a ...
Chinese_shar-pei
```

Sample Human Output

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 [28]: ### TODO: Write your algorithm.
         ### Feel free to use as many code cells as needed.
         import matplotlib.pyplot as plt
         def plot_image(img_path):
             file = Image.open(img_path).convert('RGB')
             plt.imshow(file)
             plt.show()

         def run_app(img_path):

             ## handle cases for a human face, dog, and neither
             # Plot the image for better visualization


             breed=predict_breed_transfer(img_path,model_transfer,class_names) # Predict the bre

             if dog_detector(img_path):
                 print("Hello dog! \n Your predicted breed is...\n", breed,"\n\n")
                 plot_image(img_path)
             elif face_detector(img_path):
                 print("Hello human!")
                 plot_image(img_path)
                 print("You look like a...\n", breed,"\n\n")
             else:
                 print("The image has neither human nor dog. \n\n")
```

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.

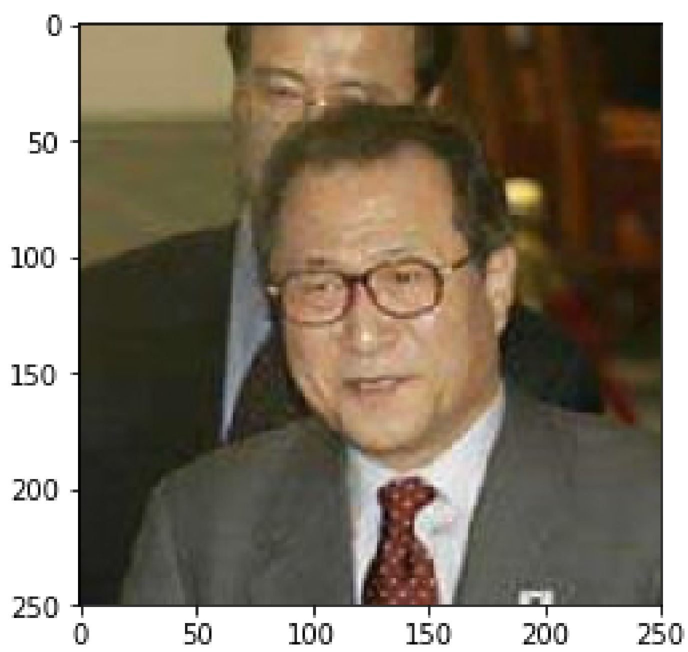
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement) The test set had an accuracy of 84%. This means that the predicted output might have an error.

The following steps can be taken to improve the efficiency - The number of epochs to train data can be increased. - Use a more deep algorithms like ResNeXt-101-32x8d at the cost of computational complexity. - Increase the size of the training dataset

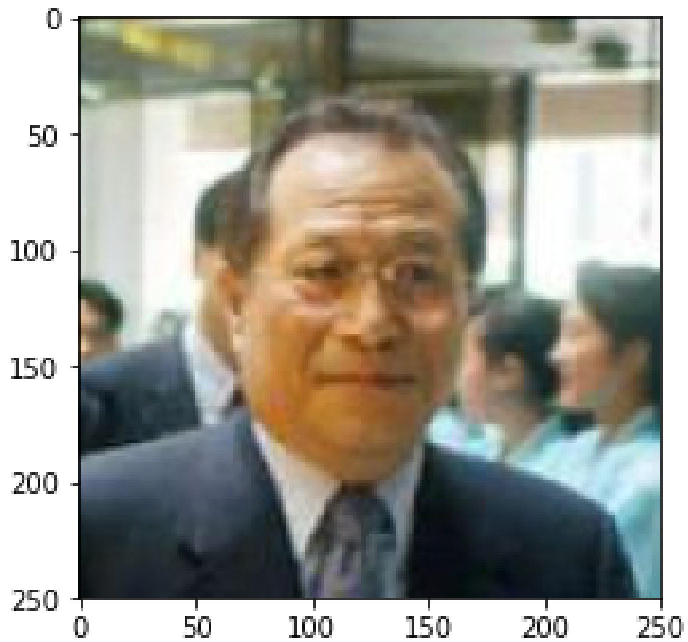
```
In [29]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

         ## suggested code, below
         for file in np.hstack((human_files[10:13], dog_files[10:13])):
             run_app(file)
```

```
Hello human!
```



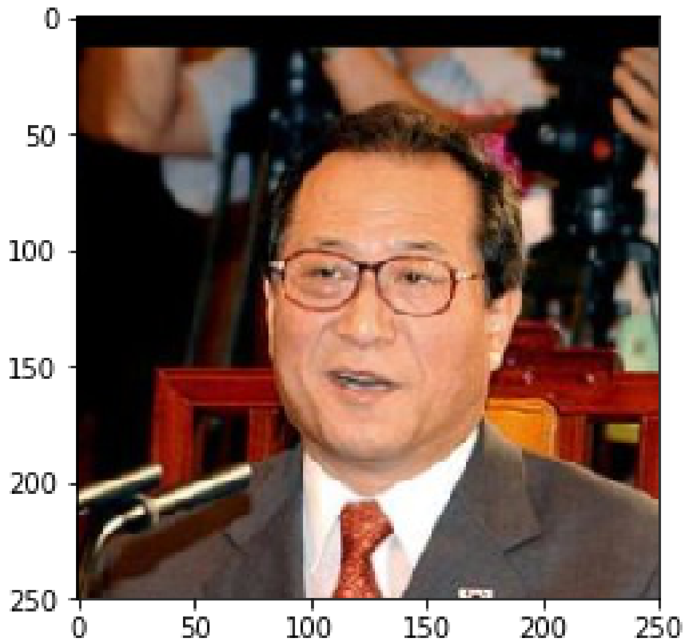
```
You look like a...
 Pharaoh hound
```

```
Hello human!
```

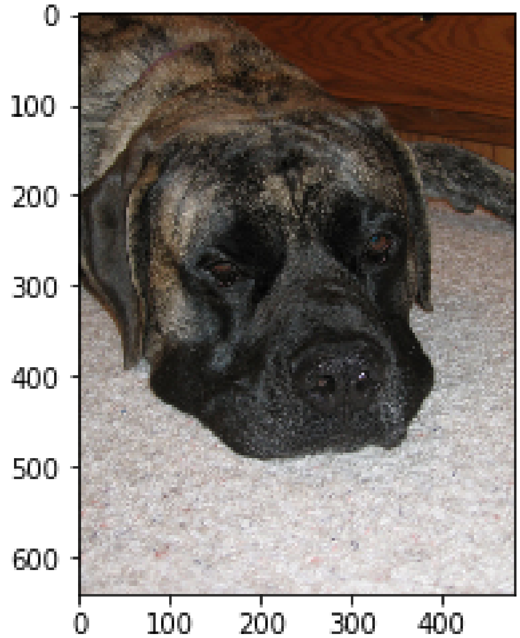



```
You look like a...
 Bearded collie
```

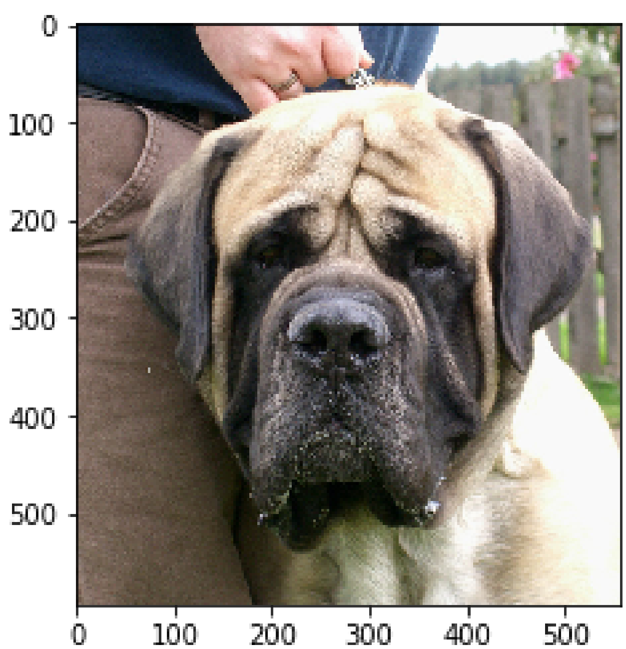
```
Hello human!
```



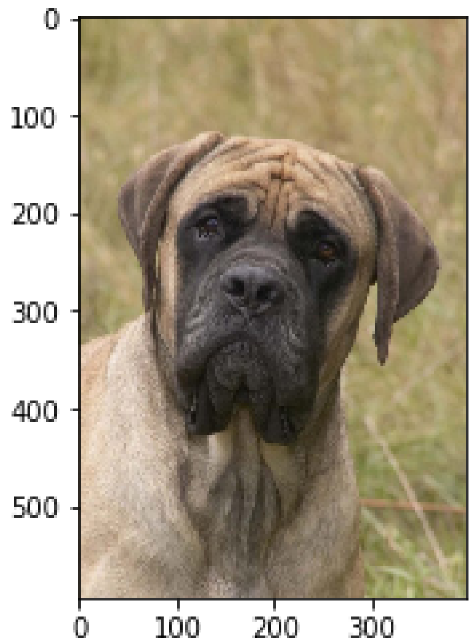

```
You look like a...
 Chihuahua


Hello dog!
 Your predicted breed is...
 Bluetick coonhound
```




```
Hello dog!
 Your predicted breed is...
 Mastiff
```



```
Hello dog!
 Your predicted breed is...
 Cane corso
```



In [ ]: