dog_app

February 16, 2019

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: * Download the dog dataset. Unzip the folder and place it in this project's home directory, at the location `/dog_images`.

- Download the human dataset. Unzip the folder and place it in the home directory, at location `/lfw`.

Note: If you are using a Windows machine, you are encouraged to use 7zip to extract the folder.

In the code cell below, we save the file paths for both the human (LFW) dataset and dog dataset in the numpy arrays `human_files` and `dog_files`.

```
In [1]: import numpy as np
        from glob import glob

        # load filenames for human and dog images
        human_files = np.array(glob("/data/lfw/*/*"))
        dog_files = np.array(glob("/data/dog_images/*/*/*"))

        # print number of images in each dataset
        print('There are %d total human images.' % len(human_files))
        print('There are %d total dog images.' % len(dog_files))
```

```
There are 13233 total human images.
There are 8351 total dog images.
```

Step 1: Detect Humans

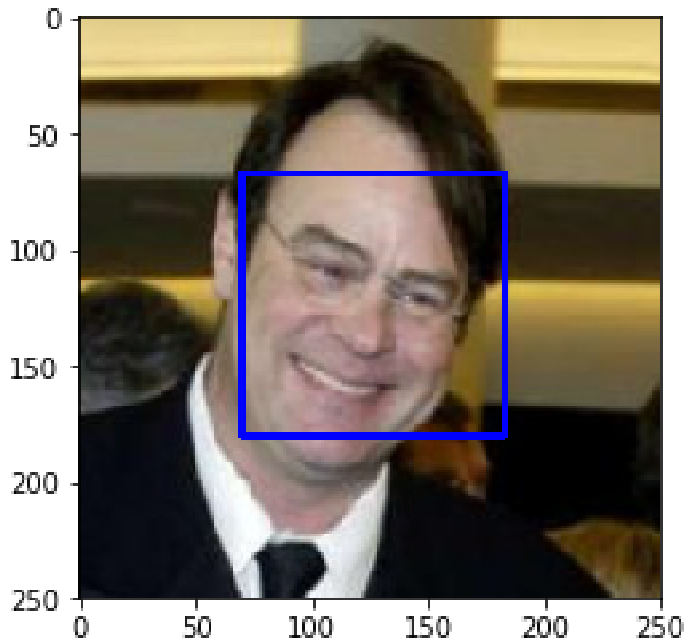
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

OpenCV provides many pre-trained face detectors, stored as XML files on github. We have downloaded one of these detectors and stored it in the `haarcascades` directory. In the next code cell, we demonstrate how to use this detector to find human faces in a sample image.

```
In [2]: import cv2
        import matplotlib.pyplot as plt
        %matplotlib inline

        # extract pre-trained face detector
        face_cascade = cv2.CascadeClassifier('haarcascades/haarcascade_frontalface_alt.xml')

        # load color (BGR) image
        img = cv2.imread(human_files[0])
        # convert BGR image to grayscale
        gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

        # find faces in image
        faces = face_cascade.detectMultiScale(gray)

        # print number of faces detected in the image
        print('Number of faces detected:', len(faces))

        # get bounding box for each detected face
        for (x,y,w,h) in faces:
            # add bounding box to color image
            cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)
```

```
        # convert BGR image to RGB for plotting
        cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

        # display the image, along with bounding box
        plt.imshow(cv_rgb)
        plt.show()
```

```
Number of faces detected: 1
```



Before using any of the face detectors, it is standard procedure to convert the images to grayscale. The `detectMultiScale` function executes the classifier stored in `face_cascade` and takes the grayscale image as a parameter.

In the above code, `faces` is a numpy array of detected faces, where each row corresponds to a detected face. Each detected face is a 1D array with four entries that specifies the bounding box of the detected face. The first two entries in the array (extracted in the above code as `x` and `y`) specify the horizontal and vertical positions of the top left corner of the bounding box. The last two entries in the array (extracted here as `w` and `h`) specify the width and height of the box.

1.1.1 Write a Human Face Detector

We can use this procedure to write a function that returns `True` if a human face is detected in an image and `False` otherwise. This function, aptly named `face_detector`, takes a string-valued file path to an image as input and appears in the code block below.

```
In [3]: # returns "True" if face is detected in image stored at img_path
        def face_detector(img_path):
```

```
        img = cv2.imread(img_path)
        gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
        faces = face_cascade.detectMultiScale(gray)
        return len(faces) > 0
```

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

Question 1: Use the code cell below to test the performance of the `face_detector` function.
- What percentage of the first 100 images in `human_files` have a detected human face?
- What percentage of the first 100 images in `dog_files` have a detected human face?

Ideally, we would like 100% of human images with a detected face and 0% of dog images with a detected face. You will see that our algorithm falls short of this goal, but still gives acceptable performance. We extract the file paths for the first 100 images from each of the datasets and store them in the numpy arrays `human_files_short` and `dog_files_short`.

Answer: (You can print out your results and/or write your percentages in this cell)

```
In [4]: from tqdm import tqdm

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

        #-#-# Do NOT modify the code above this line. #-#-#

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        def face_detection_test(files):
            detection_cnt = 0;
            total_cnt = len(files)
            for file in files:
                detection_cnt += face_detector(file)
            return detection_cnt, total_cnt

In [5]: print("detect face in human_files: {} / {}".format(face_detection_test(human_files_short
        print("detect face in dog_files: {} / {}".format(face_detection_test(dog_files_short)[0]
```

```
detect face in human_files: 98 / 100
detect face in dog_files: 17 / 100
```

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`.

Step 2: Detect Dogs
In this section, we use a pre-trained model to detect dogs in images.

1.1.3 Obtain Pre-trained VGG-16 Model

The code cell below downloads the VGG-16 model, along with weights that have been trained on ImageNet, a very large, very popular dataset used for image classification and other vision tasks. ImageNet contains over 10 million URLs, each linking to an image containing an object from one of 1000 categories.

```
In [6]: import torch
        import torchvision.models as models

        # define VGG16 model
        VGG16 = models.vgg16(pretrained=True)

        # check if CUDA is available
        use_cuda = torch.cuda.is_available()

        # move model to GPU if CUDA is available
        if use_cuda:
            VGG16 = VGG16.cuda()
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:10<00:00, 54027823.51it/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 [7]: from PIL import Image
        import torchvision.transforms as transforms

        def load_image(img_path):
            image = Image.open(img_path).convert('RGB')
            # resize to (244, 244) because VGG16 accept this shape
            in_transform = transforms.Compose([
                                transforms.Resize(size=(244, 244)),
                                transforms.ToTensor()]) # normalizaiton parameters from pytorch

            # discard the transparent, alpha channel (that's the :3) and add the batch dimension
            image = in_transform(image)[:3,:,:].unsqueeze(0)
            return image
```

```
In [8]: 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
            img = load_image(img_path)
            if use_cuda:
                img = img.cuda()
            ret = VGG16(img)
            #print(torch.max(ret,1))
            return torch.max(ret,1)[1].item() # predicted class index
```

```
In [9]: # predict dog using ImageNet class
        VGG16_predict(dog_files_short[10])
```

```
Out[9]: 243
```

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

```
In [11]: print(dog_detector(dog_files_short[0]))
         print(dog_detector(human_files_short[0]))
```

```
True
False
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your `dog_detector` function.
- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?
Answer:

```
In [12]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         def dog_detector_test(files):
             detection_cnt = 0;
             total_cnt = len(files)
             for file in files:
                 detection_cnt += dog_detector(file)
             return detection_cnt, total_cnt
```

```
In [13]: print("detect a dog in human_files: {} / {}".format(dog_detector_test(human_files_short
         print("detect a dog in dog_files: {} / {}".format(dog_detector_test(dog_files_short)[0]
```

```
detect a dog in human_files: 0 / 100
detect a dog in dog_files: 97 / 100
```

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 [20]:
```
import os
from torchvision import datasets
import torchvision.transforms as transforms
import torch
import numpy as np
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

batch_size = 20
num_workers = 0

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

In [15]:
```
normalization = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])
```

```
In [21]: data_transforms = {'train': transforms.Compose([transforms.RandomResizedCrop(224),
                                     transforms.RandomHorizontalFlip(),
                                     transforms.ToTensor(),
                                     normalization]),
                            'val': transforms.Compose([transforms.Resize(224),
                                     transforms.CenterCrop(224),
                                     transforms.ToTensor(),
                                     normalization]),
                            'test': transforms.Compose([transforms.Resize(size=(224,224)),
                                     transforms.ToTensor(),
                                     normalization])
                           }
```

```
In [22]: train_data = datasets.ImageFolder(train_dir, transform=data_transforms['train'])
         valid_data = datasets.ImageFolder(valid_dir, transform=data_transforms['val'])
         test_data = datasets.ImageFolder(test_dir, transform=data_transforms['test'])
```

```
In [23]: train_loader = torch.utils.data.DataLoader(train_data,
                                                    batch_size=batch_size,
                                                    num_workers=num_workers,
                                                    shuffle=True)
         valid_loader = torch.utils.data.DataLoader(valid_data,
                                                    batch_size=batch_size,
                                                    num_workers=num_workers,
                                                    shuffle=False)
         test_loader = torch.utils.data.DataLoader(test_data,
                                                    batch_size=batch_size,
                                                    num_workers=num_workers,
                                                    shuffle=False)
         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:

Preprocessing in Train dataset: I have used RandomResizedCrop & RandomHorizontalFlip for dataaugmentation and preventing overfitting of model on train data.

Preprocessing in Validation dataset: I have ony resized and cropped images for validation data as augmentation is not requried as we are going to use this for validation of model so overfitting issue is not in picture so augmentation not required.

Preprocessing in Test dataset: I have only resized the dataset to 224 x 224 size and as it is for test we dont have to do any manipulation of cropping or augmentation.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [24]: from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         num_classes = 133 # total classes of dog breeds
```

```
In [25]: import torch.nn as nn
         import torch.nn.functional as F
         import numpy as np

         # 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, 32, 3, stride=2, padding=1)
                 self.conv2 = nn.Conv2d(32, 64, 3, stride=2, padding=1)
                 self.conv3 = nn.Conv2d(64, 128, 3, padding=1)

                 # pool
                 self.pool = nn.MaxPool2d(2, 2)

                 # fully-connected
                 self.fc1 = nn.Linear(7*7*128, 500)
                 self.fc2 = nn.Linear(500, num_classes)

                 # drop-out
                 self.dropout = nn.Dropout(0.3)

             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)

                 # flatten
                 x = x.view(-1, 7*7*128)

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

                 x = self.dropout(x)
```

```python
        x = self.fc2(x)
        return x

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

# instantiate the CNN
model_scratch = Net()
print(model_scratch)

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

```
Net(
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=6272, out_features=500, bias=True)
  (fc2): Linear(in_features=500, out_features=133, bias=True)
  (dropout): Dropout(p=0.3)
)
```

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

Answer:

(conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
activation: relu
(pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
activation: relu

> Here the image passed through kernel_size of 3 and stride of 2 and after applying max pooling the image will be downsize by 2

(conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
activation: relu
(pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)

> After this layer the image will be downsize the image more by 2

(conv3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)

> Here in this third conv layer we have stride 1 which won't reduce size of image but after finally passing the image through final maxpool layer will downsize the image by 2 .Hence we have output image downsized by factor of 32 and the depth will be 128 .

(dropout): Dropout(p=0.3)

Dropout is used to avoid overfitting .

Finally passing the output of convolutional layer to fully connected layer. The end layer has output nodes equal to number of classes of dog breed.

(fc1): Linear(in_features=6272, out_features=500, bias=True)
(dropout): Dropout(p=0.3)
(fc2): Linear(in_features=500, out_features=133, bias=True)

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 [31]: import torch.optim as optim

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

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

1.1.10 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters at filepath `'model_scratch.pt'`.

```
In [27]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path, last_val
             """returns trained model"""
             # initialize tracker for minimum validation loss
             if last_validation_loss is not None:
                 valid_loss_min = last_validation_loss
             else:
                 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

        # initialize weights to zero
        optimizer.zero_grad()

        output = model(data)

        # calculate loss
        loss = criterion(output, target)

        # back prop
        loss.backward()

        # grad
        optimizer.step()

        train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

        if batch_idx % 100 == 0:
            print('Epoch %d, Batch %d loss: %.6f' %
              (epoch, batch_idx + 1, 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:
```

```
                torch.save(model.state_dict(), save_path)
                print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
                valid_loss_min,
                valid_loss))
                valid_loss_min = valid_loss

        # return trained model
        return model
```

```
In [32]: # train the model
         model_scratch = train(10, loaders_scratch, model_scratch, optimizer_scratch,
                               criterion_scratch, use_cuda, 'saved_models/model_scratch.pt')
```

```
Epoch 1, Batch 1 loss: 3.908999
Epoch 1, Batch 101 loss: 4.015626
Epoch 1, Batch 201 loss: 3.997042
Epoch 1, Batch 301 loss: 3.995115
Epoch: 1        Training Loss: 3.997056         Validation Loss: 3.876928
Validation loss decreased (inf --> 3.876928).  Saving model ...
Epoch 2, Batch 1 loss: 3.458007
Epoch 2, Batch 101 loss: 3.948977
Epoch 2, Batch 201 loss: 3.951413
Epoch 2, Batch 301 loss: 3.935884
Epoch: 2        Training Loss: 3.936072         Validation Loss: 3.860922
Validation loss decreased (3.876928 --> 3.860922).  Saving model ...
Epoch 3, Batch 1 loss: 3.282301
Epoch 3, Batch 101 loss: 3.915960
Epoch 3, Batch 201 loss: 3.906821
Epoch 3, Batch 301 loss: 3.907014
Epoch: 3        Training Loss: 3.905596         Validation Loss: 3.880639
Epoch 4, Batch 1 loss: 3.964421
Epoch 4, Batch 101 loss: 3.903651
Epoch 4, Batch 201 loss: 3.895406
Epoch 4, Batch 301 loss: 3.894248
Epoch: 4        Training Loss: 3.886576         Validation Loss: 3.794130
Validation loss decreased (3.860922 --> 3.794130).  Saving model ...
Epoch 5, Batch 1 loss: 3.441909
Epoch 5, Batch 101 loss: 3.833393
Epoch 5, Batch 201 loss: 3.857077
Epoch 5, Batch 301 loss: 3.857906
Epoch: 5        Training Loss: 3.869052         Validation Loss: 3.779830
Validation loss decreased (3.794130 --> 3.779830).  Saving model ...
Epoch 6, Batch 1 loss: 3.545855
Epoch 6, Batch 101 loss: 3.834943
Epoch 6, Batch 201 loss: 3.826650
Epoch 6, Batch 301 loss: 3.826591
Epoch: 6        Training Loss: 3.832165         Validation Loss: 3.740736
Validation loss decreased (3.779830 --> 3.740736).  Saving model ...
```

```
Epoch 7, Batch 1 loss: 3.678937
Epoch 7, Batch 101 loss: 3.830055
Epoch 7, Batch 201 loss: 3.823961
Epoch 7, Batch 301 loss: 3.806534
Epoch: 7 	Training Loss: 3.814124 	Validation Loss: 3.739967
Validation loss decreased (3.740736 --> 3.739967).  Saving model ...
Epoch 8, Batch 1 loss: 4.226998
Epoch 8, Batch 101 loss: 3.723239
Epoch 8, Batch 201 loss: 3.755349
Epoch 8, Batch 301 loss: 3.773633
Epoch: 8 	Training Loss: 3.780015 	Validation Loss: 3.746424
Epoch 9, Batch 1 loss: 4.248481
Epoch 9, Batch 101 loss: 3.756952
Epoch 9, Batch 201 loss: 3.736356
Epoch 9, Batch 301 loss: 3.739083
Epoch: 9 	Training Loss: 3.739850 	Validation Loss: 3.728591
Validation loss decreased (3.739967 --> 3.728591).  Saving model ...
Epoch 10, Batch 1 loss: 3.698992
Epoch 10, Batch 101 loss: 3.724628
Epoch 10, Batch 201 loss: 3.732695
Epoch 10, Batch 301 loss: 3.732400
Epoch: 10 	Training Loss: 3.725506 	Validation Loss: 3.706079
Validation loss decreased (3.728591 --> 3.706079).  Saving model ...
```

```
In [33]: # load the model that got the best validation accuracy
         model_scratch.load_state_dict(torch.load('saved_models/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 [34]: 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: 3.804691


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

1.1.13 (IMPLEMENTATION) Model Architecture

Use transfer learning to create a CNN to classify dog breed. Use the code cell below, and save your initialized model as the variable `model_transfer`.

```
In [37]: import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         model_transfer = models.resnet50(pretrained=True)
```

```
In [38]: for param in model_transfer.parameters():
             param.requires_grad = False
```

```
In [39]: model_transfer.fc = nn.Linear(2048, 133, bias=True)
```

```
In [40]: fc_parameters = model_transfer.fc.parameters()
```

```
In [41]: for param in fc_parameters:
             param.requires_grad = True
```

```
In [42]: model_transfer
```

```
Out[42]: ResNet(
           (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
           (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
           (relu): ReLU(inplace)
           (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
           (layer1): Sequential(
             (0): Bottleneck(
               (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
               (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               (relu): ReLU(inplace)
               (downsample): Sequential(
                 (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               )
             )
             (1): Bottleneck(
               (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
               (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               (relu): ReLU(inplace)
             )
             (2): Bottleneck(
               (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
               (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               (relu): ReLU(inplace)
             )
```

```
)
(layer2): Sequential(
  (0): Bottleneck(
    (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
    (downsample): Sequential(
      (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
  )
  (3): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
  )
)
(layer3): Sequential(
  (0): Bottleneck(
    (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
```

```
  (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  (relu): ReLU(inplace)
  (downsample): Sequential(
    (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
    (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  )
)
(1): Bottleneck(
  (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
  (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  (relu): ReLU(inplace)
)
(2): Bottleneck(
  (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
  (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  (relu): ReLU(inplace)
)
(3): Bottleneck(
  (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
  (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  (relu): ReLU(inplace)
)
(4): Bottleneck(
  (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
  (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
  (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  (relu): ReLU(inplace)
)
(5): Bottleneck(
  (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
```

```
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
        (relu): ReLU(inplace)
      )
    )
    (layer4): Sequential(
      (0): Bottleneck(
        (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
        (relu): ReLU(inplace)
        (downsample): Sequential(
          (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
        )
      )
      (1): Bottleneck(
        (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
        (relu): ReLU(inplace)
      )
      (2): Bottleneck(
        (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
        (relu): ReLU(inplace)
      )
    )
    (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
    (fc): Linear(in_features=2048, out_features=133, bias=True)
  )
```

In [43]:
```
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:

I took Resnet50 for image classfication as it uses residual learning where it learns the residuals of the input layer. It allows the Deep Learning Scientists to create deeper layers and reducing vanishing gradients.

I have modified the last layer so that it works for giving output to only 133 classes.

1.1.14 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_transfer`, and the optimizer as `optimizer_transfer` below.

```
In [44]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.fc.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 [45]: 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()

                     # initialize weights to zero
                     optimizer.zero_grad()

                     output = model(data)

                     # calculate loss
                     loss = criterion(output, target)

                     # back prop
                     loss.backward()
```

```
                # grad
                optimizer.step()

                train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

                if batch_idx % 100 == 0:
                    print('Epoch %d, Batch %d loss: %.6f' %
                      (epoch, batch_idx + 1, 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:
                torch.save(model.state_dict(), save_path)
                print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
                valid_loss_min,
                valid_loss))
                valid_loss_min = valid_loss

        # return trained model
        return model
```

```
In [46]: train(20, loaders_transfer, model_transfer, optimizer_transfer, criterion_transfer, use
```

```
Epoch 1, Batch 1 loss: 4.888382
Epoch 1, Batch 101 loss: 4.885850
Epoch 1, Batch 201 loss: 4.852132
Epoch 1, Batch 301 loss: 4.816556
Epoch: 1 	Training Loss: 4.806008 	Validation Loss: 4.629217
```

```
Validation loss decreased (inf --> 4.629217).  Saving model ...
Epoch 2, Batch 1 loss: 4.668130
Epoch 2, Batch 101 loss: 4.647774
Epoch 2, Batch 201 loss: 4.619598
Epoch 2, Batch 301 loss: 4.593101
Epoch: 2         Training Loss: 4.584577         Validation Loss: 4.380966
Validation loss decreased (4.629217 --> 4.380966).  Saving model ...
Epoch 3, Batch 1 loss: 4.318672
Epoch 3, Batch 101 loss: 4.435700
Epoch 3, Batch 201 loss: 4.416689
Epoch 3, Batch 301 loss: 4.395535
Epoch: 3         Training Loss: 4.389947         Validation Loss: 4.134647
Validation loss decreased (4.380966 --> 4.134647).  Saving model ...
Epoch 4, Batch 1 loss: 4.324954
Epoch 4, Batch 101 loss: 4.260853
Epoch 4, Batch 201 loss: 4.230697
Epoch 4, Batch 301 loss: 4.210302
Epoch: 4         Training Loss: 4.200007         Validation Loss: 3.926477
Validation loss decreased (4.134647 --> 3.926477).  Saving model ...
Epoch 5, Batch 1 loss: 4.076292
Epoch 5, Batch 101 loss: 4.058923
Epoch 5, Batch 201 loss: 4.054462
Epoch 5, Batch 301 loss: 4.038502
Epoch: 5         Training Loss: 4.028974         Validation Loss: 3.703760
Validation loss decreased (3.926477 --> 3.703760).  Saving model ...
Epoch 6, Batch 1 loss: 3.821211
Epoch 6, Batch 101 loss: 3.906406
Epoch 6, Batch 201 loss: 3.886961
Epoch 6, Batch 301 loss: 3.866813
Epoch: 6         Training Loss: 3.860204         Validation Loss: 3.492729
Validation loss decreased (3.703760 --> 3.492729).  Saving model ...
Epoch 7, Batch 1 loss: 3.787822
Epoch 7, Batch 101 loss: 3.752785
Epoch 7, Batch 201 loss: 3.725492
Epoch 7, Batch 301 loss: 3.710804
Epoch: 7         Training Loss: 3.702484         Validation Loss: 3.313504
Validation loss decreased (3.492729 --> 3.313504).  Saving model ...
Epoch 8, Batch 1 loss: 3.711968
Epoch 8, Batch 101 loss: 3.567208
Epoch 8, Batch 201 loss: 3.559146
Epoch 8, Batch 301 loss: 3.546472
Epoch: 8         Training Loss: 3.543852         Validation Loss: 3.137055
Validation loss decreased (3.313504 --> 3.137055).  Saving model ...
Epoch 9, Batch 1 loss: 3.431386
Epoch 9, Batch 101 loss: 3.440492
Epoch 9, Batch 201 loss: 3.437513
Epoch 9, Batch 301 loss: 3.419180
Epoch: 9         Training Loss: 3.409115         Validation Loss: 2.979734
```

```
Validation loss decreased (3.137055 --> 2.979734).  Saving model ...
Epoch 10, Batch 1 loss: 3.826253
Epoch 10, Batch 101 loss: 3.327027
Epoch 10, Batch 201 loss: 3.320222
Epoch 10, Batch 301 loss: 3.289873
Epoch: 10         Training Loss: 3.283198         Validation Loss: 2.807588
Validation loss decreased (2.979734 --> 2.807588).  Saving model ...
Epoch 11, Batch 1 loss: 3.262190
Epoch 11, Batch 101 loss: 3.182606
Epoch 11, Batch 201 loss: 3.158441
Epoch 11, Batch 301 loss: 3.152481
Epoch: 11         Training Loss: 3.144997         Validation Loss: 2.668688
Validation loss decreased (2.807588 --> 2.668688).  Saving model ...
Epoch 12, Batch 1 loss: 3.316385
Epoch 12, Batch 101 loss: 3.100871
Epoch 12, Batch 201 loss: 3.068149
Epoch 12, Batch 301 loss: 3.048908
Epoch: 12         Training Loss: 3.046776         Validation Loss: 2.540525
Validation loss decreased (2.668688 --> 2.540525).  Saving model ...
Epoch 13, Batch 1 loss: 2.733607
Epoch 13, Batch 101 loss: 2.960250
Epoch 13, Batch 201 loss: 2.959926
Epoch 13, Batch 301 loss: 2.949531
Epoch: 13         Training Loss: 2.943440         Validation Loss: 2.432476
Validation loss decreased (2.540525 --> 2.432476).  Saving model ...
Epoch 14, Batch 1 loss: 2.684515
Epoch 14, Batch 101 loss: 2.823873
Epoch 14, Batch 201 loss: 2.822641
Epoch 14, Batch 301 loss: 2.820942
Epoch: 14         Training Loss: 2.815055         Validation Loss: 2.289469
Validation loss decreased (2.432476 --> 2.289469).  Saving model ...
Epoch 15, Batch 1 loss: 2.865393
Epoch 15, Batch 101 loss: 2.764222
Epoch 15, Batch 201 loss: 2.745911
Epoch 15, Batch 301 loss: 2.736744
Epoch: 15         Training Loss: 2.731187         Validation Loss: 2.197915
Validation loss decreased (2.289469 --> 2.197915).  Saving model ...
Epoch 16, Batch 1 loss: 2.564109
Epoch 16, Batch 101 loss: 2.675342
Epoch 16, Batch 201 loss: 2.668299
Epoch 16, Batch 301 loss: 2.665821
Epoch: 16         Training Loss: 2.659169         Validation Loss: 2.094008
Validation loss decreased (2.197915 --> 2.094008).  Saving model ...
Epoch 17, Batch 1 loss: 2.677252
Epoch 17, Batch 101 loss: 2.590544
Epoch 17, Batch 201 loss: 2.572642
Epoch 17, Batch 301 loss: 2.568063
Epoch: 17         Training Loss: 2.569607         Validation Loss: 1.992750
```

```
Validation loss decreased (2.094008 --> 1.992750).  Saving model ...
Epoch 18, Batch 1 loss: 2.398603
Epoch 18, Batch 101 loss: 2.519676
Epoch 18, Batch 201 loss: 2.496644
Epoch 18, Batch 301 loss: 2.477833
Epoch: 18         Training Loss: 2.479097         Validation Loss: 1.935906
Validation loss decreased (1.992750 --> 1.935906).  Saving model ...
Epoch 19, Batch 1 loss: 2.526854
Epoch 19, Batch 101 loss: 2.430813
Epoch 19, Batch 201 loss: 2.417607
Epoch 19, Batch 301 loss: 2.419910
Epoch: 19         Training Loss: 2.418494         Validation Loss: 1.815110
Validation loss decreased (1.935906 --> 1.815110).  Saving model ...
Epoch 20, Batch 1 loss: 2.756580
Epoch 20, Batch 101 loss: 2.369330
Epoch 20, Batch 201 loss: 2.378848
Epoch 20, Batch 301 loss: 2.351124
Epoch: 20         Training Loss: 2.353470         Validation Loss: 1.769806
Validation loss decreased (1.815110 --> 1.769806).  Saving model ...
```

```
Out[46]: ResNet(
           (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
           (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
           (relu): ReLU(inplace)
           (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
           (layer1): Sequential(
             (0): Bottleneck(
               (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
               (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               (relu): ReLU(inplace)
               (downsample): Sequential(
                 (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               )
             )
             (1): Bottleneck(
               (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
               (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
               (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
               (relu): ReLU(inplace)
```

```
  )
  (2): Bottleneck(
    (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=F
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
  )
)
(layer2): Sequential(
  (0): Bottleneck(
    (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
    (downsample): Sequential(
      (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (relu): ReLU(inplace)
  )
  (3): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats
```

```
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (relu): ReLU(inplace)
    )
  )
  (layer3): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
```

```
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stat
      (relu): ReLU(inplace)
```

```
        )
      )
      (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
      (fc): Linear(in_features=2048, out_features=133, bias=True)
    )
```

```
In [47]: # load the model that got the best validation accuracy
         model_transfer.load_state_dict(torch.load('saved_models/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 [48]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 1.811930


Test Accuracy: 72% (610/836)
```

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 [55]: ### 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_transfer['train'].dataset
```

```
In [57]: from PIL import Image
         import torchvision.transforms as transforms

         def load_input_image(img_path):
             image = Image.open(img_path).convert('RGB')
             prediction_transform = transforms.Compose([transforms.Resize(size=(224, 224)),
                                              transforms.ToTensor(),
                                              normalization])

             # discard the transparent, alpha channel (that's the :3) and add the batch dimensio
             image = prediction_transform(image)[:3,:,:].unsqueeze(0)
             return image
```

```
In [58]: def predict_breed_transfer(model, class_names, img_path):
             # load the image and return the predicted breed
             img = load_input_image(img_path)
```

```
        model = model.cpu()
        model.eval()
        idx = torch.argmax(model(img))
        return class_names[idx]
```

```
In [59]: for img_file in os.listdir('./images'):
             img_path = os.path.join('./images', img_file)
             predition = predict_breed_transfer(model_transfer, class_names, img_path)
             print("image_file_name: {0}, \t predition breed: {1}".format(img_path, predition))
```

```
image_file_name: ./images/Brittany_02625.jpg,          predition breed: Brittany
image_file_name: ./images/Welsh_springer_spaniel_08203.jpg,          predition breed: Welsh spri
image_file_name: ./images/Labrador_retriever_06449.jpg,          predition breed: Flat-coated re
image_file_name: ./images/sample_human_output.png,          predition breed: Bulldog
image_file_name: ./images/Labrador_retriever_06457.jpg,          predition breed: Labrador retri
image_file_name: ./images/American_water_spaniel_00648.jpg,          predition breed: Curly-coat
image_file_name: ./images/sample_dog_output.png,          predition breed: Italian greyhound
image_file_name: ./images/sample_cnn.png,          predition breed: French bulldog
image_file_name: ./images/Curly-coated_retriever_03896.jpg,          predition breed: Curly-coat
image_file_name: ./images/Labrador_retriever_06455.jpg,          predition breed: Chesapeake bay
```

```
In [ ]:
```

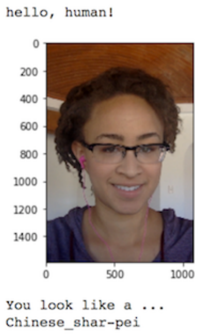
Step 5: Write your Algorithm
Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then, - if a **dog** is detected in the image, return the predicted breed. - if a **human** is detected in the image, return the resembling dog 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

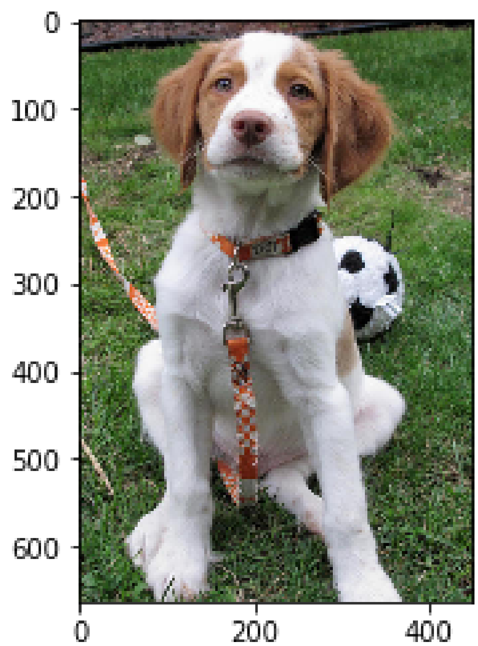
```
In [60]: ### TODO: Write your algorithm.
         ### Feel free to use as many code cells as needed.

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             img = Image.open(img_path)
             plt.imshow(img)
             plt.show()
             if dog_detector(img_path) is True:
                 prediction = predict_breed_transfer(model_transfer, class_names, img_path)
```



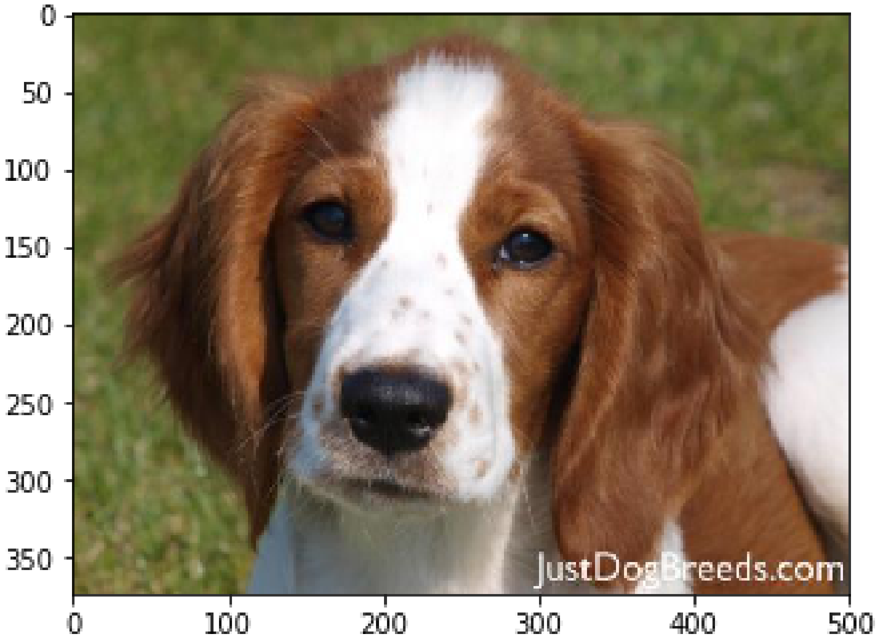
Sample Human Output

```
            print("Dogs Detected!\nIt looks like a {0}".format(prediction))
        elif face_detector(img_path) > 0:
            prediction = predict_breed_transfer(model_transfer, class_names, img_path)
            print("Hello, human!\nIf you were a dog..You may look like a {0}".format(predic
        else:
            print("Error! Can't detect anything..")
```

```
In [61]: for img_file in os.listdir('./images'):
             img_path = os.path.join('./images', img_file)
             run_app(img_path)
```

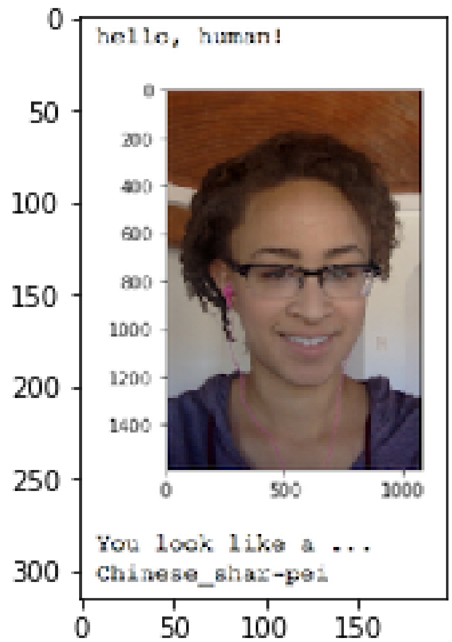


```
Dogs Detected!
It looks like a Brittany
```

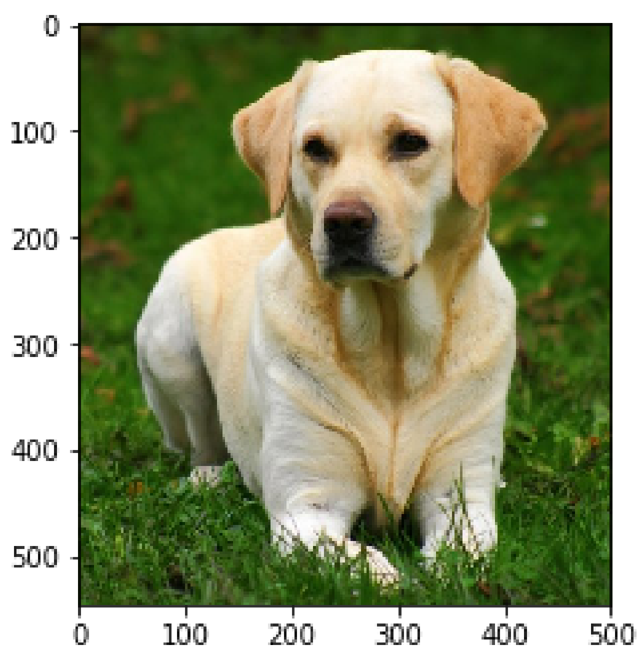



```
Dogs Detected!
It looks like a Welsh springer spaniel
```

```
Dogs Detected!
It looks like a Flat-coated retriever
```

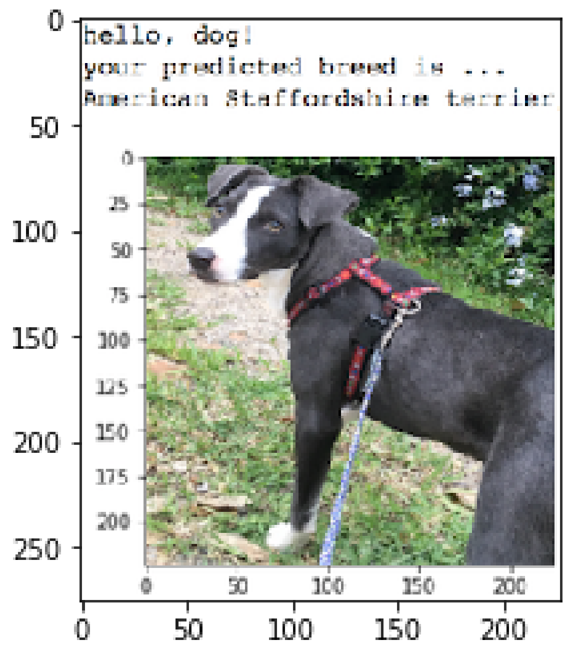



```
Hello, human!
If you were a dog..You may look like a Bulldog
```

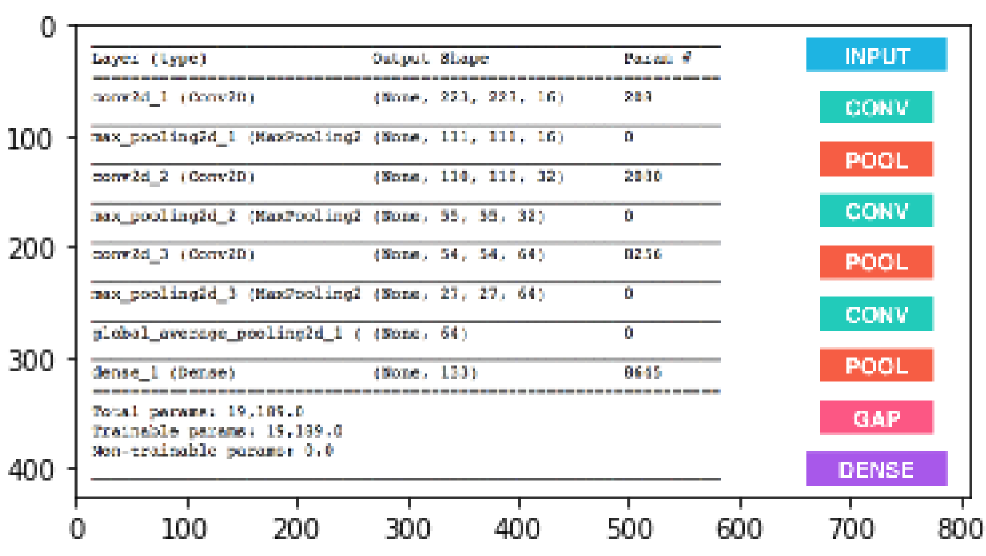


```
Dogs Detected!
It looks like a Labrador retriever
```

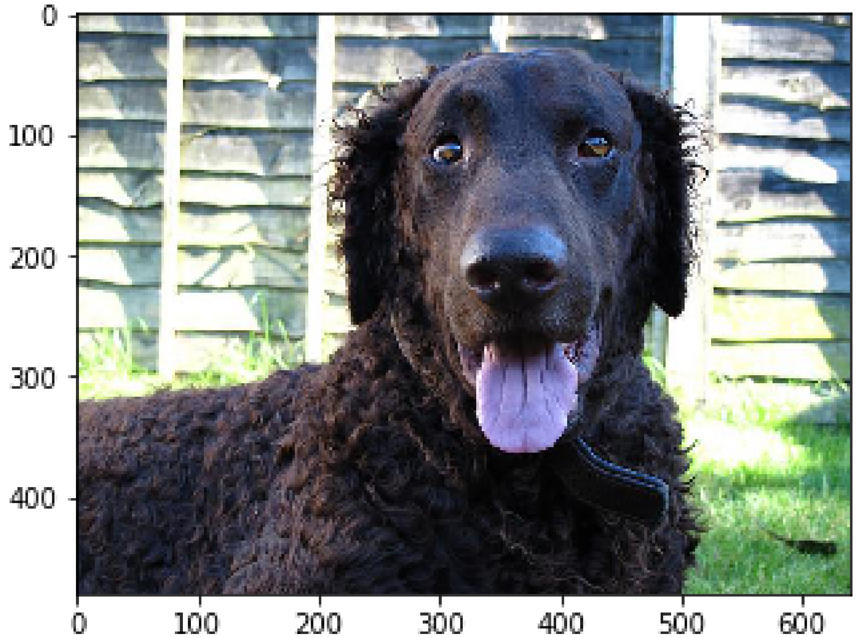

```
Dogs Detected!
It looks like a Curly-coated retriever
```



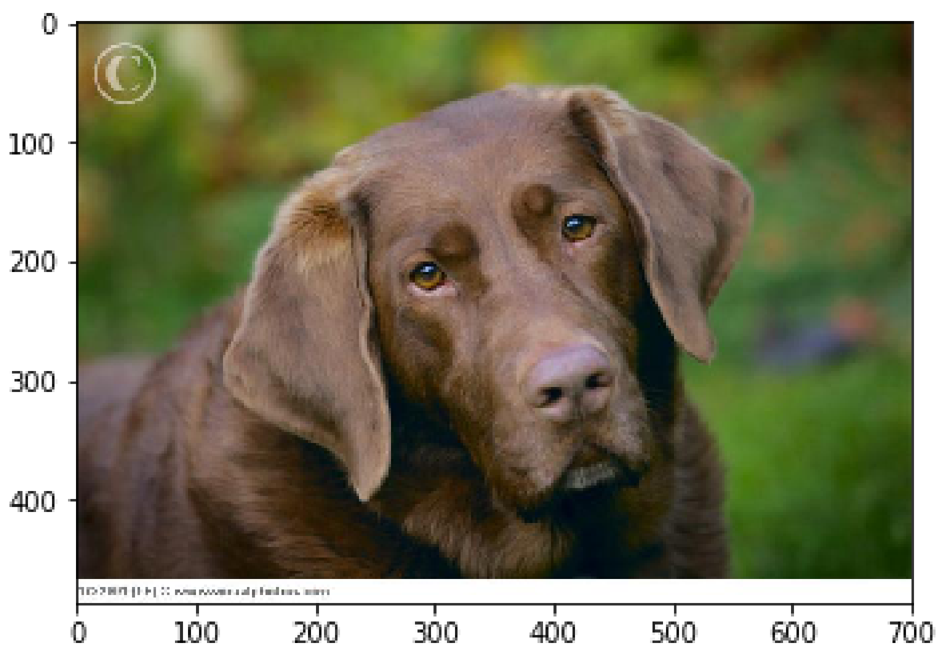
Dogs Detected!
It looks like a Italian greyhound



Error! Can't detect anything..



Dogs Detected!
It looks like a Curly-coated retriever



```
Dogs Detected!
It looks like a Chesapeake bay retriever
```

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.

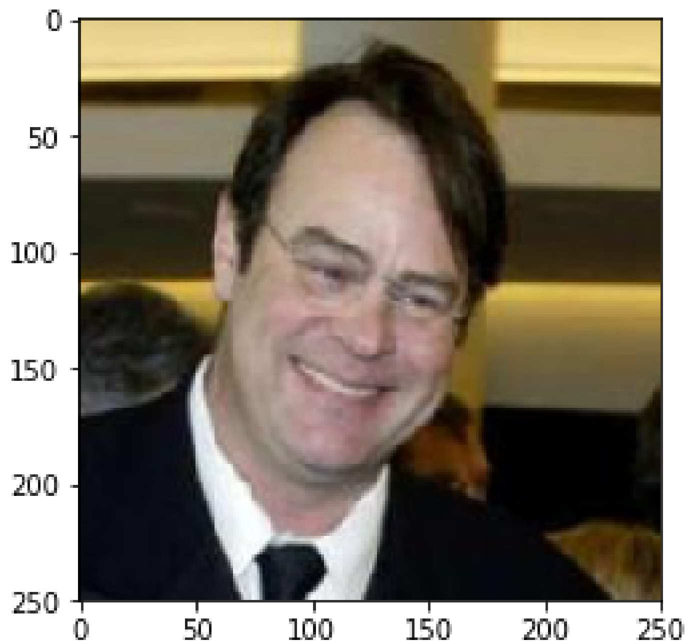
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement)

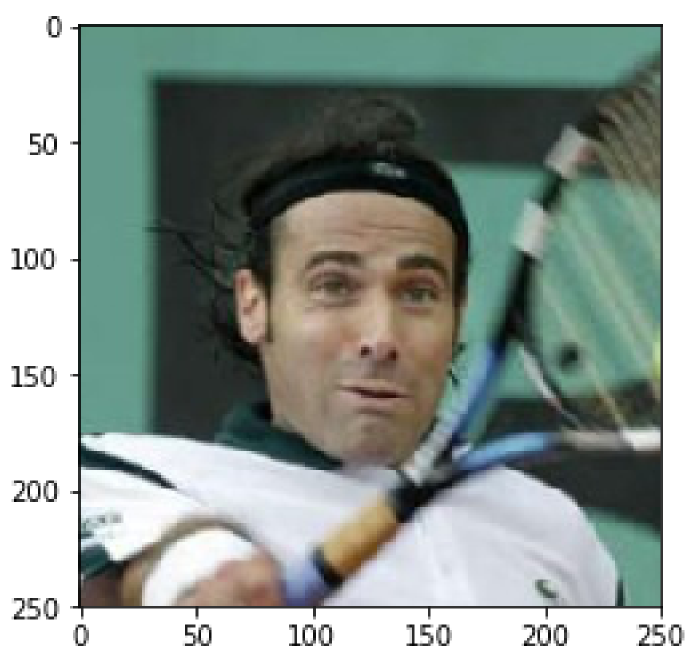
1.ensemble techniques 2.Augmentation like flipping vertically, move left or right, etc 3.Hyper-parameter tunings: weight initializings, learning rates, drop-outs, batch_sizes, and optimizers will be helpful to improve performances.

```
In [63]: my_human_files = ['./my_images/human_1.jpg', './my_images/human_2.jpg', './my_images/hu
         my_dog_files = ['./my_images/dog_shiba.jpeg', './my_images/dog_yorkshire.jpg', './my_im
```

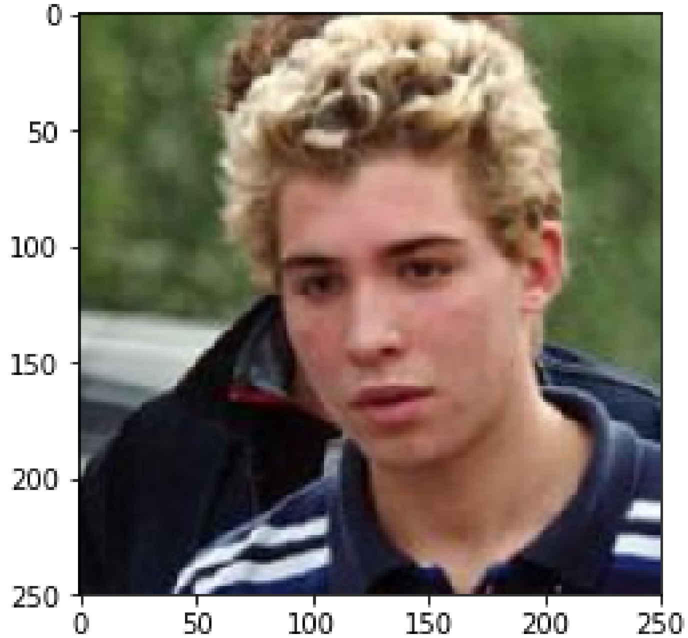
```
In [64]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

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



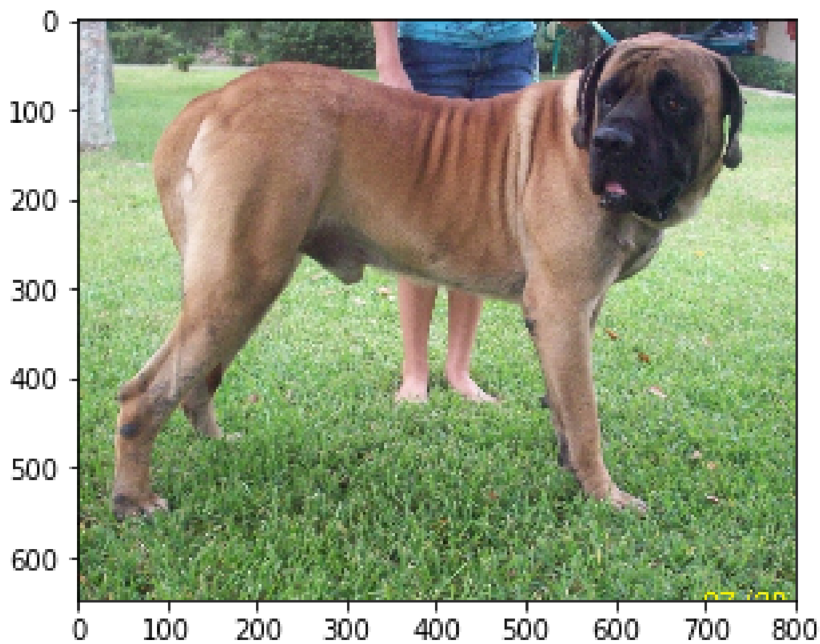
```
Hello, human!
If you were a dog..You may look like a Dachshund
```



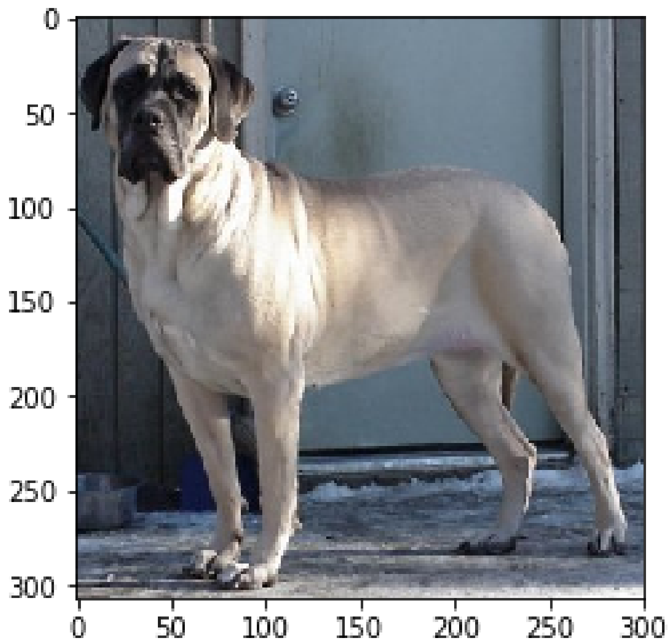
```
Hello, human!
If you were a dog..You may look like a Basenji
```



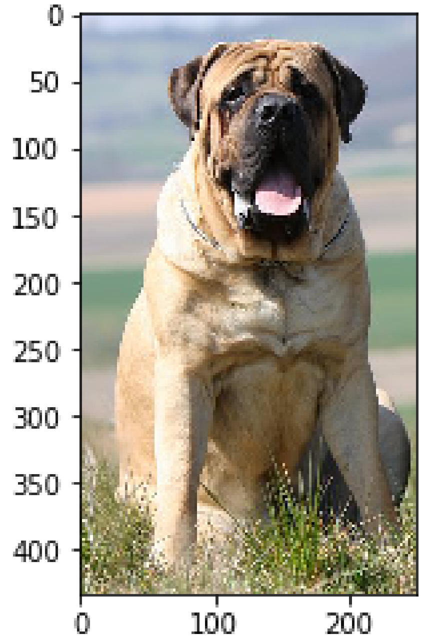

```
Hello, human!
If you were a dog..You may look like a Cane corso
```



```
Dogs Detected!
It looks like a Bullmastiff
```




```
Dogs Detected!
It looks like a Bullmastiff
```




```
Dogs Detected!
It looks like a Bullmastiff
```