dog_app

June 7, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

In this notebook, some template code has already been provided for you, and you will need to implement additional functionality to successfully complete this project. You will not need to modify the included code beyond what is requested. Sections that begin with **'(IMPLEMENTATION)'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section, and the specifics of the implementation are marked in the code block with a 'TODO' statement. Please be sure to read the instructions carefully!

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the Jupyter Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to **File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. Markdown cells can be edited by double-clicking the cell to enter edit mode.

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.

Step 0: Import Datasets

Make sure that you've downloaded the required human and dog datasets:

Note: if you are using the Udacity workspace, you *DO NOT* need to re-download these - they can be found in the `/data` folder as noted in the cell below.

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

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

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

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

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

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

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

Step 1: Detect Humans

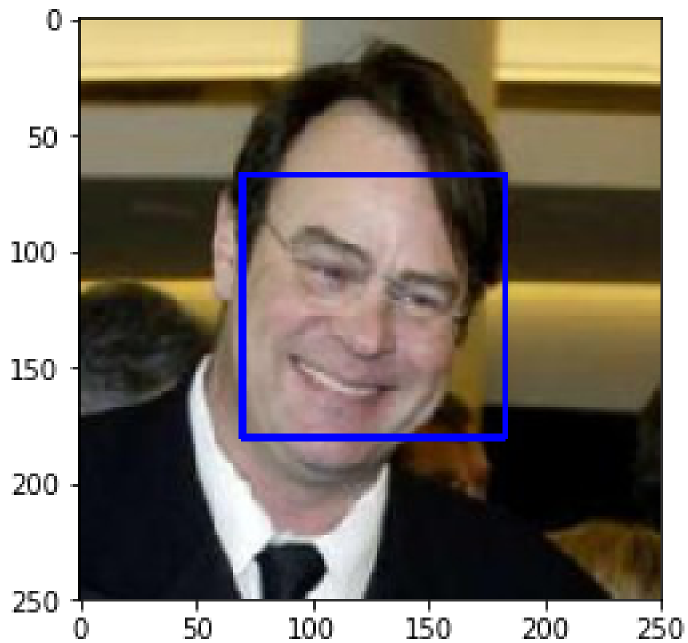
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

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

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

```
In [3]: # returns "True" if face is detected in image stored at img_path
        def face_detector(img_path):
            img = cv2.imread(img_path)
            gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
            faces = face_cascade.detectMultiScale(gray)
            return len(faces) > 0
```

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

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

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

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

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

        ## TODO: Test the performance of the face_detector algorithm

        human_face_count = 0
        human_dog_face_count = 0

        for image in tqdm(human_files_short):
            if face_detector(image):
                human_face_count += 1

        for image in tqdm(dog_files_short):
            if face_detector(image):
                human_dog_face_count += 1

        print(f"% of Human Faces detected in first 100 human_files is: {human_face_count}")
        print(f" % of Human Faces detected in first 100 dog_files is: {human_dog_face_count}")
        ## on the images in human_files_short and dog_files_short.
```

```
100%|| 100/100 [00:02<00:00, 35.58it/s]
100%|| 100/100 [00:30<00:00,  3.32it/s]
```

```
% of Human Faces detected in first 100 human_files is: 98
 % of Human Faces detected in first 100 dog_files is: 17
```

We suggest the face detector from OpenCV as a potential way to detect human images in your algorithm, but you are free to explore other approaches, especially approaches that make use of deep learning :). Please use the code cell below to design and test your own face detection algorithm. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [5]: ### (Optional)
        ### TODO: Test performance of anotherface detection algorithm.
        ### Feel free to use as many code cells as needed.
```

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

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

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

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

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

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

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

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

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

```
In [7]: from PIL import Image
        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

            img = Image.open(img_path)

            #transforms and utilize the normalization for pretrained models
            transform = transforms.Compose([
                transforms.Resize(225),
                transforms.CenterCrop(224),
                transforms.ToTensor(),
                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])
            ])

            #apply transforms on the image
            img = transform(img)
            img = torch.unsqueeze(img, 0)
            if use_cuda:
                img = img.cuda()
            #Predictions on the Image
            pred = VGG16(img)

            #index of the pred image
            idx = torch.argmax(pred)

            # return predicted class index
            return idx.item()
```

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.

            idx = VGG16_predict(img_path)

            if idx in range(151, 269):
                return True
            else:
                return False
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

Answer:

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

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

        dog_face_in_human_count = 0
        dog_face_in_dog_count = 0

        for image in tqdm(human_files_short):
            if dog_detector(image):
                dog_face_in_human_count += 1

        for image in tqdm(dog_files_short):
            if dog_detector(image):
                dog_face_in_dog_count += 1

        print( f" % of Dog Faces detected in first 100 human_files is: {dog_face_in_human_count}
        print( f" % of Dog Faces detected in first 100 dog_files is: {dog_face_in_dog_count}")

100%|| 100/100 [00:03<00:00, 29.00it/s]
100%|| 100/100 [00:04<00:00, 25.31it/s]
```

```
% of Dog Faces detected in first 100 human_files is: 1
% of Dog Faces detected in first 100 dog_files is: 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 [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 [ ]:

In [11]:
```
import os
from torchvision import datasets
import torchvision.transforms as transforms

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

from PIL import ImageFile
#
ImageFile.LOAD_TRUNCATED_IMAGES = True
data_dir = '/data/dog_images'
batch_size = 20

#data transforms

data_transforms = {
    'train': transforms.Compose([
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.RandomRotation(15),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    'valid': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
```

```
    ]),
}

num_workers = 0
image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x), data_transforms[x]
                  for x in ['train', 'valid', 'test']}

loaders_data = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size = batch_si
                                               shuffle = True, num_workers = num_workers
                  for x in ['train', 'valid', 'test']}

dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'valid', 'test']}
class_names = image_datasets['train'].classes
n_classes = len(class_names)


#print the numbers of classes, data in test, validation and training
print(f"No. of images in training: {dataset_sizes['train']}")
print(f"No. of images in validation: {dataset_sizes['valid']}")
print(f"No. of images in testing: {dataset_sizes['test']}")
print(f"No. of Classes (breeds): {n_classes}")
```

```
No. of images in training: 6680
No. of images in validation: 835
No. of images in testing: 836
No. of Classes (breeds): 133
```

Question 3: Describe your chosen procedure for preprocessing the data. - How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why?

- Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

Answer: - I have resized the images to **224x224** pixels following the Imagenet standards

- Yes, I have decided to augmented them by rotation (**RandomRotation of 15 degrees**) for the training dataset as this would help the model to genralize. Further added a(**RandomHorizontalFlip**) then transformed the images into Tensors. Finally Normalized the image with mean and standard deviation. These tensors will be fed to the cnn network

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [15]: 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

        # Input to cnn : 224x224x3 image tensor a RGB image
        #convolutional layer with 16 filters, each filter having a width and height of
        #output channel increase by a factor of 2 image size decreases by 2

        self.conv1 = nn.Conv2d(3, 16, 3, padding = 1 )
        # cnn layer -->112x112x16 image tensor
        self.conv2 = nn.Conv2d(16, 32, 3, padding = 1)
        # cnn layer --> 56x56x32 image tensor
        self.conv3 = nn.Conv2d(32, 64, 3, padding = 1)
        # cnn layer -->28x28x64 image tensor
        self.conv4 = nn.Conv2d(64, 128, 3, padding = 1)
        # cnn layer -->14x14x128 image tensor
        self.conv5 = nn.Conv2d(128, 256, 3, padding = 1 )

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

        #Droput of .20
        self.dropout = nn.Dropout(0.2)

        self.conv_bn1 = nn.BatchNorm2d(224,3)
        self.conv_bn2 = nn.BatchNorm2d(16)
        self.conv_bn3 = nn.BatchNorm2d(32)
        self.conv_bn4 = nn.BatchNorm2d(64)
        self.conv_bn5 = nn.BatchNorm2d(128)
        self.conv_bn6 = nn.BatchNorm2d(256)

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

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

```
                x = self.conv_bn4(x)
                x = self.pool(F.relu(self.conv4(x)))
                x = self.conv_bn5(x)
                x = self.pool(F.relu(self.conv5(x)))
                x = self.conv_bn6(x)

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

               # fully connected layers
                x = F.relu(self.fc1(x))
                x = self.dropout(x)
                x = self.fc2(x)
                return x

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

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

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (dropout): Dropout(p=0.2)
  (conv_bn1): BatchNorm2d(224, eps=3, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (fc1): Linear(in_features=12544, out_features=512, bias=True)
  (fc2): Linear(in_features=512, out_features=133, bias=True)
)
```

Question 4: Outline the steps you took to get to your final CNN architecture and your reason-

ing at each step.
Answer:

- CNN has 5 convolution layers and 2 fully connected layers. The input paramters to the cnn are defined above (Kernel size = 3, stride = 1 and padding = 1)
- Each convolutional layer changes the output of the previous layer to generate a new set of filters. and it generates much more filters in my case 16/32/64/128/256 filters respectively
- The network utilize max pooling layer of 2*2.
- Relu activations are used after each layers excpet in the final one
- Dropout is applied with the probability of 0.20,to overcome the overfitting problem.
- Batch normalization is applied after the max pooling.

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 [16]: import torch.optim as optim

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

         # specify optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.001, momentum=0.9)
```

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 [18]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

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

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

```
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        ## find the loss and update the model parameters accordingly
        ## record the average training loss, using something like
        ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
        # clear the gradients
        optimizer.zero_grad()
        # forward pass
        output = model(data)
        # calculate the batch loss
        loss = criterion(output, target)
        # backward pass
        loss.backward()
        optimizer.step()
        # update training 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()
        ## update the average validation loss
        # calculate the batch loss
        output = model(data)
        loss = criterion(output, target)
        # update 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:
        print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
        valid_loss_min,
        valid_loss))
        torch.save(model.state_dict(), save_path)
        valid_loss_min = valid_loss
```

```python
    # return trained model
    return model


# train the model

n_epochs = 35
loaders_scratch = loaders_data
model_scratch = train(n_epochs, 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: 4.748436 	Validation Loss: 4.490994
Validation loss decreased (inf --> 4.490994).  Saving model ...
Epoch: 2 	Training Loss: 4.483682 	Validation Loss: 4.270331
Validation loss decreased (4.490994 --> 4.270331).  Saving model ...
Epoch: 3 	Training Loss: 4.316967 	Validation Loss: 4.087558
Validation loss decreased (4.270331 --> 4.087558).  Saving model ...
Epoch: 4 	Training Loss: 4.174576 	Validation Loss: 4.061221
Validation loss decreased (4.087558 --> 4.061221).  Saving model ...
Epoch: 5 	Training Loss: 4.086576 	Validation Loss: 3.925786
Validation loss decreased (4.061221 --> 3.925786).  Saving model ...
Epoch: 6 	Training Loss: 3.980169 	Validation Loss: 3.771525
Validation loss decreased (3.925786 --> 3.771525).  Saving model ...
Epoch: 7 	Training Loss: 3.900100 	Validation Loss: 3.752803
Validation loss decreased (3.771525 --> 3.752803).  Saving model ...
Epoch: 8 	Training Loss: 3.831213 	Validation Loss: 3.608454
Validation loss decreased (3.752803 --> 3.608454).  Saving model ...
Epoch: 9 	Training Loss: 3.771993 	Validation Loss: 3.525111
Validation loss decreased (3.608454 --> 3.525111).  Saving model ...
Epoch: 10 	Training Loss: 3.697834 	Validation Loss: 3.595663
Epoch: 11 	Training Loss: 3.673644 	Validation Loss: 3.512602
Validation loss decreased (3.525111 --> 3.512602).  Saving model ...
Epoch: 12 	Training Loss: 3.605539 	Validation Loss: 3.483999
Validation loss decreased (3.512602 --> 3.483999).  Saving model ...
Epoch: 13 	Training Loss: 3.547174 	Validation Loss: 3.402950
Validation loss decreased (3.483999 --> 3.402950).  Saving model ...
Epoch: 14 	Training Loss: 3.477463 	Validation Loss: 3.427480
Epoch: 15 	Training Loss: 3.435679 	Validation Loss: 3.252339
Validation loss decreased (3.402950 --> 3.252339).  Saving model ...
Epoch: 16 	Training Loss: 3.356348 	Validation Loss: 3.263912
Epoch: 17 	Training Loss: 3.343296 	Validation Loss: 3.172007
Validation loss decreased (3.252339 --> 3.172007).  Saving model ...
Epoch: 18 	Training Loss: 3.295691 	Validation Loss: 3.198979
```

```
Epoch: 19         Training Loss: 3.289752        Validation Loss: 3.076001
Validation loss decreased (3.172007 --> 3.076001).  Saving model ...
Epoch: 20         Training Loss: 3.183255        Validation Loss: 3.053718
Validation loss decreased (3.076001 --> 3.053718).  Saving model ...
Epoch: 21         Training Loss: 3.158794        Validation Loss: 3.066228
Epoch: 22         Training Loss: 3.097327        Validation Loss: 3.148269
Epoch: 23         Training Loss: 3.074307        Validation Loss: 3.056688
Epoch: 24         Training Loss: 3.068527        Validation Loss: 2.977883
Validation loss decreased (3.053718 --> 2.977883).  Saving model ...
Epoch: 25         Training Loss: 3.006848        Validation Loss: 3.029471
Epoch: 26         Training Loss: 2.949154        Validation Loss: 2.908468
Validation loss decreased (2.977883 --> 2.908468).  Saving model ...
Epoch: 27         Training Loss: 2.928885        Validation Loss: 2.985412
Epoch: 28         Training Loss: 2.893171        Validation Loss: 2.930684
Epoch: 29         Training Loss: 2.856885        Validation Loss: 2.817039
Validation loss decreased (2.908468 --> 2.817039).  Saving model ...
Epoch: 30         Training Loss: 2.827268        Validation Loss: 2.891276
Epoch: 31         Training Loss: 2.787215        Validation Loss: 2.836779
Epoch: 32         Training Loss: 2.756763        Validation Loss: 2.768382
Validation loss decreased (2.817039 --> 2.768382).  Saving model ...
Epoch: 33         Training Loss: 2.707659        Validation Loss: 2.685337
Validation loss decreased (2.768382 --> 2.685337).  Saving model ...
Epoch: 34         Training Loss: 2.670494        Validation Loss: 2.732625
Epoch: 35         Training Loss: 2.660668        Validation Loss: 2.758169
```

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 [19]: def test(loaders, model, criterion, use_cuda):

             # monitor test loss and accuracy
             test_loss = 0.
             correct = 0.
             total = 0.

             model.eval()
             for batch_idx, (data, target) in enumerate(loaders['test']):
                 # move to GPU
                 if use_cuda:
                     data, target = data.cuda(), target.cuda()
                 # forward pass: compute predicted outputs by passing inputs to the model
                 output = model(data)
                 # calculate the loss
                 loss = criterion(output, target)
                 # update average test loss
```

```
            test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
            # convert output probabilities to predicted class
            pred = output.data.max(1, keepdim=True)[1]
            # compare predictions to true label
            correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
            total += data.size(0)

        print('Test Loss: {:.6f}\n'.format(test_loss))

        print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
            100. * correct / total, correct, total))

    # call test function
    test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 2.662227


Test Accuracy: 30% (257/836)
```

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 [ ]: ## 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 [20]: import torchvision.models as models
         import torch.nn as nn

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

         # Freeze weights
```

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


num_features = model_transfer.fc.in_features

#retrieve the fully model and replace the last layer we have 133 classes

model_transfer.fc = nn.Linear(num_features, 133)

print(model_transfer)


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, 90886192.30it/s]


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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      )
    )
    (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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      )
    )
    (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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_stats=True)
      )
    )
    (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
```

```
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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_stats=True)
      )
    )
    (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (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=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (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_stats=True)
      (relu): ReLU(inplace)
    )
```

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

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:

- downloaded resnet50
- Model has multiple convolution layers with batch normalization, positioned well to produce good feature maps
- Freezed all the weights
- Changed the last layer with new linear layer
- Once training the last layer the model should perform well

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 [21]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adam(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 [25]: # train the model
         #model_transfer = # train(n_epochs, loaders_transfer, model_transfer, optimizer_transfe

         # load the model that got the best validation accuracy (uncomment the line below)
         #model_transfer.load_state_dict(torch.load('model_transfer.pt'))

         use_cuda = torch.cuda.is_available()
         n_epochs = 35
         loaders_transfer = loaders_data
         model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,

         # load the model that got the best validation accuracy (uncomment the line below)
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

```
Epoch: 1        Training Loss: 2.784400        Validation Loss: 0.921440
Validation loss decreased (inf --> 0.921440).  Saving model ...
Epoch: 2        Training Loss: 1.476399        Validation Loss: 0.694371
Validation loss decreased (0.921440 --> 0.694371).  Saving model ...
Epoch: 3        Training Loss: 1.324259        Validation Loss: 0.612826
```

```
Validation loss decreased (0.694371 --> 0.612826).  Saving model ...
Epoch: 4 	Training Loss: 1.247753 	Validation Loss: 0.546889
Validation loss decreased (0.612826 --> 0.546889).  Saving model ...
Epoch: 5 	Training Loss: 1.189999 	Validation Loss: 0.558195
Epoch: 6 	Training Loss: 1.158284 	Validation Loss: 0.577564
Epoch: 7 	Training Loss: 1.112632 	Validation Loss: 0.544920
Validation loss decreased (0.546889 --> 0.544920).  Saving model ...
Epoch: 8 	Training Loss: 1.083200 	Validation Loss: 0.531057
Validation loss decreased (0.544920 --> 0.531057).  Saving model ...
Epoch: 9 	Training Loss: 1.086882 	Validation Loss: 0.478748
Validation loss decreased (0.531057 --> 0.478748).  Saving model ...
Epoch: 10 	Training Loss: 1.103998 	Validation Loss: 0.566955
Epoch: 11 	Training Loss: 1.085731 	Validation Loss: 0.581186
Epoch: 12 	Training Loss: 1.084617 	Validation Loss: 0.614660
Epoch: 13 	Training Loss: 1.098471 	Validation Loss: 0.605814
Epoch: 14 	Training Loss: 1.030051 	Validation Loss: 0.515123
Epoch: 15 	Training Loss: 1.044326 	Validation Loss: 0.618534
Epoch: 16 	Training Loss: 1.044043 	Validation Loss: 0.599697
Epoch: 17 	Training Loss: 1.047254 	Validation Loss: 0.580215
Epoch: 18 	Training Loss: 1.025260 	Validation Loss: 0.603088
Epoch: 19 	Training Loss: 1.007038 	Validation Loss: 0.576497
Epoch: 20 	Training Loss: 1.004583 	Validation Loss: 0.544563
Epoch: 21 	Training Loss: 0.992934 	Validation Loss: 0.606000
Epoch: 22 	Training Loss: 0.973981 	Validation Loss: 0.487672
Epoch: 23 	Training Loss: 1.033656 	Validation Loss: 0.613230
Epoch: 24 	Training Loss: 1.013029 	Validation Loss: 0.591409
Epoch: 25 	Training Loss: 0.986257 	Validation Loss: 0.589346
Epoch: 26 	Training Loss: 0.999525 	Validation Loss: 0.560033
Epoch: 27 	Training Loss: 0.999886 	Validation Loss: 0.590397
Epoch: 28 	Training Loss: 0.982180 	Validation Loss: 0.642958
Epoch: 29 	Training Loss: 0.993848 	Validation Loss: 0.613944
Epoch: 30 	Training Loss: 0.953055 	Validation Loss: 0.567777
Epoch: 31 	Training Loss: 0.981019 	Validation Loss: 0.599526
Epoch: 32 	Training Loss: 0.939059 	Validation Loss: 0.576597
Epoch: 33 	Training Loss: 0.921627 	Validation Loss: 0.683792
Epoch: 34 	Training Loss: 0.963769 	Validation Loss: 0.613968
Epoch: 35 	Training Loss: 0.960022 	Validation Loss: 0.623691
```

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

```
Test Loss: 0.510182
```

```
Test Accuracy: 84% (706/836)
```

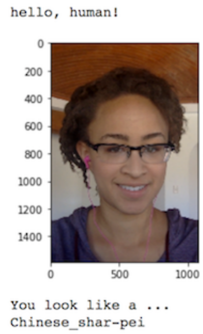
1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

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 [29]: ### 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 image_datasets['train'].classes]

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             img = Image.open(img_path)

             transform = transforms.Compose([
                 transforms.Resize(225),
                 transforms.CenterCrop(224),
                 transforms.ToTensor(),
                 transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                      std=[0.229, 0.224, 0.225])
             ])

             img = transform(img)
             img = torch.unsqueeze(img, 0)
             if use_cuda:
                 img = img.cuda()

             ps = model_transfer(img)
             idx = torch.argmax(ps)

             return class_names[idx]
```

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.



Sample Human Output

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

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             if dog_detector(img_path):
                 img = Image.open(img_path)
                 plt.imshow(img)
                 plt.show()
                 print("This Dog is :")
                 print(predict_breed_transfer(img_path))

             elif face_detector(img_path):
                 print("Hello, Human !")
                 img = Image.open(img_path)
                 plt.imshow(img)
                 plt.show()
                 print("You look like a.........:")
                 print(predict_breed_transfer(img_path))

             else:
                 print("Neither Dog nor Human face is detected")
                 plt.imshow(img)
```

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)

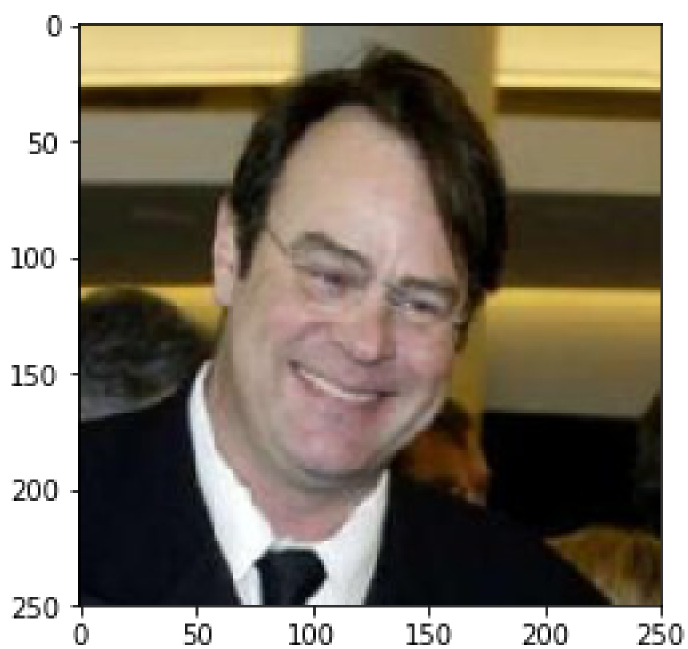
- The transfer model is performing fine, better than the scratch model with 84% accuracy

Improving the model :

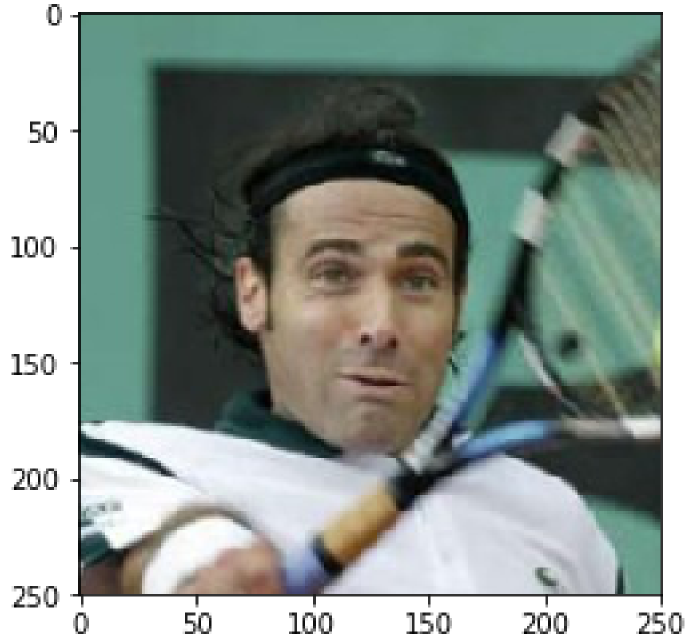
- during the training phase after epoch 9 the validation loss did not decrease! I would try diffrent hyperparameter for learning rate, the default value is quite low
- Randomly Shuffle the dataset
- Explore a diffrent pretrained model
- utilize SGD with momentum as the optimzer instead of Adam optimizer to cheeck if the accuracy improves further
- utilize K-fold cross validation

```
In [41]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

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

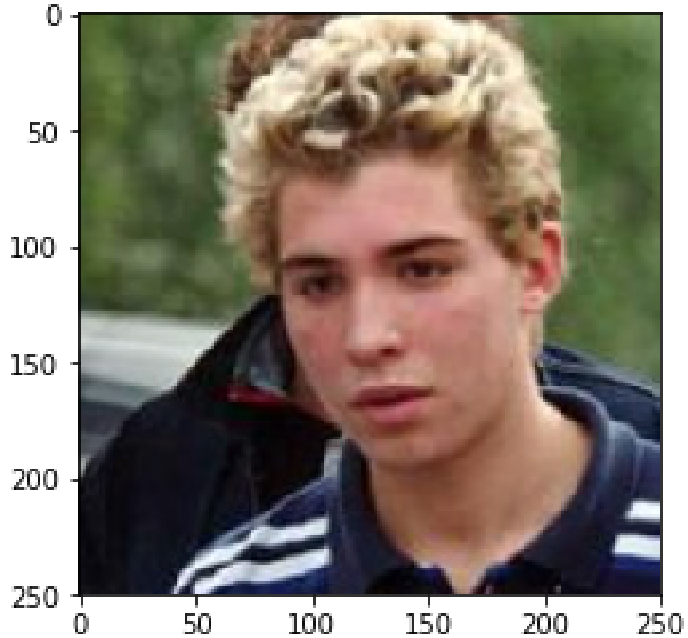
```
Hello, Human !
```



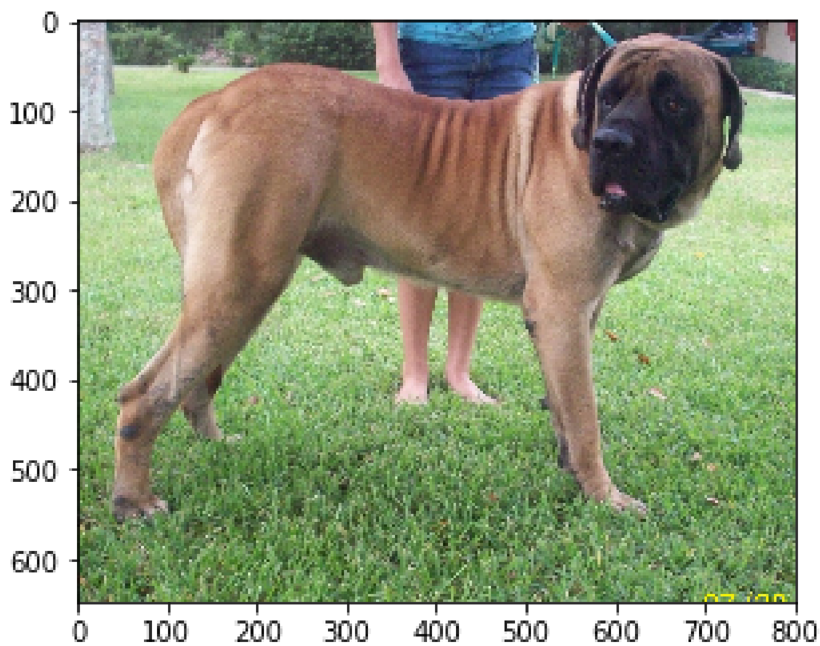
```
You look like a...:
Clumber spaniel
Hello, Human !
```



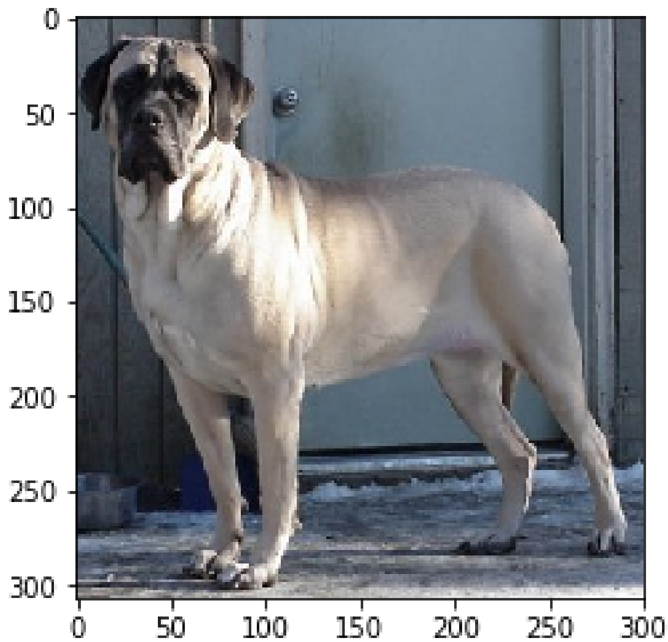

```
You look like a...:
Dachshund
Hello, Human !
```



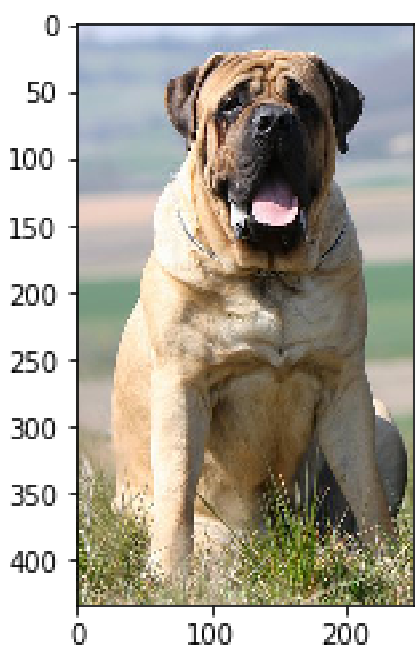
You look like a...:
American water spaniel



```
This Dog is :
Mastiff
```




```
This Dog is :
Mastiff
```



```
This Dog is :
Bullmastiff
```

```
In [ ]:
```