dog_app

February 19, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.
Step 0: Import Datasets
Make sure that you've downloaded the required human and dog datasets:
Note: if you are using the Udacity workspace, you *DO NOT* need to re-download these - they can be found in the `/data` folder as noted in the cell below.

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

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

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

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

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

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

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

Step 1: Detect Humans

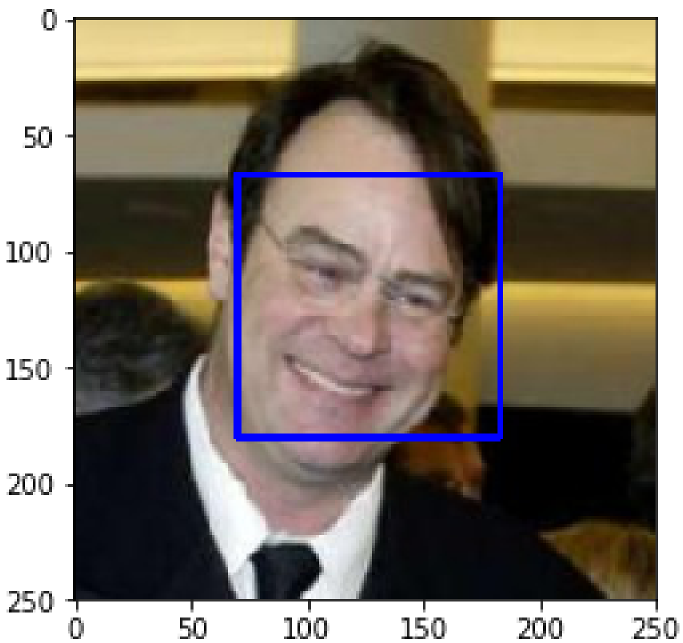
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

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

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

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

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

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

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.

        human_number = 0
        dog_number = 0
        for i in range(0,len(human_files_short)):
            if face_detector(human_files_short[i]):
                human_number += 1
            if face_detector(dog_files_short[i]):
                dog_number += 1
        print('Performance of the face_detector algorithm:')
        print('Percentage of the first 100 images in human_files that detected human face:{:.2f}
        print('Percentage of the first 100 images in dog_files that detected human face:{:.2f}%'
```

```
Performance of the face_detector algorithm:
Percentage of the first 100 images in human_files that detected human face:98.00%
Percentage of the first 100 images in dog_files that detected human face:17.00%
```

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

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

```
In [5]: import torch
        import torchvision.models as models

        # 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 [00:08<00:00, 67498950.51it/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 [6]: from PIL import Image
        import torchvision.transforms as transforms

        def VGG16_predict(img_path):
            '''
            Use pre-trained VGG-16 model to obtain index corresponding to
            predicted ImageNet class for image at specified path

            Args:
                img_path: path to an image

            Returns:
                Index corresponding to VGG-16 model's prediction
            '''

            ## TODO: Complete the function.
            ## Load and pre-process an image from the given img_path
            ## Return the *index* of the predicted class for that image
            image = Image.open(img_path).convert('RGB')
            in_transform = transforms.Compose([transforms.Resize((224,224)),
                                        transforms.ToTensor(),
                                        transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0
                                        ])
            image = in_transform(image).unsqueeze(0)
            VGG16.cpu()
            VGG16.eval()
            final_output = VGG16(image)
            prob = torch.exp(final_output)
            top_prob, top_class = prob.topk(1, dim=1)

            return top_class.item() # predicted class index
        #print(VGG16_predict(human_files[10])) # checking if function run correctly
```

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 [7]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.
            indices = VGG16_predict(img_path)
            r = range (151,268)
```

```
        if indices in r:
            return True
        else:
            return False
    #print(dog_detector(dog_files[152])) # checking if function run correctly
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

Answer:

Percentage of the images in `human_files_short` that detected dog:`0.00%` Percentage of the images in `dog_files_short` that detected dog:`100.00%`

```
In [8]: ### TODO: Test the performance of the dog_detector function
        ### on the images in human_files_short and dog_files_short.
        dog_number = 0
        human_number = 0
        for i in range(0,len(human_files_short)):
            if dog_detector(human_files_short[i]):
                human_number += 1
            if dog_detector(dog_files_short[i]):
                dog_number += 1

        print('Percentage of the images in human_files_short that detected dog:{:.2f}%'.format(h
        print('Percentage of the images in dog_files_short that detected dog:{:.2f}%'.format(dog

Percentage of the images in human_files_short that detected dog:0.00%
Percentage of the images in dog_files_short that detected dog:100.00%
```

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 [9]: import os
        from torchvision import datasets

        ### TODO: Write data loaders for training, validation, and test sets
        ## Specify appropriate transforms, and batch_sizes
        train_dir = '/data/dog_images/train'
        test_dir = '/data/dog_images/test'
        valid_dir = '/data/dog_images/valid'

        train_transform = transforms.Compose([transforms.RandomHorizontalFlip(),
                                              transforms.RandomRotation(45),
                                              transforms.RandomResizedCrop(256),
```

```
                                        transforms.ToTensor(),
                                        transforms.Normalize([0.5, 0.5, 0.5],
                                                             [0.5, 0.5, 0.5])])
test_transform = transforms.Compose([transforms.Resize(256),
                                        transforms.CenterCrop(256),
                                        transforms.ToTensor(),
                                        transforms.Normalize([0.5, 0.5, 0.5],
                                                             [0.5, 0.5, 0.5])])
valid_transform = transforms.Compose([transforms.Resize(256),
                                        transforms.CenterCrop(256),
                                        transforms.ToTensor(),
                                        transforms.Normalize([0.5, 0.5, 0.5],
                                                             [0.5, 0.5, 0.5])])

# create dataset
train_data = datasets.ImageFolder(train_dir, transform=train_transform)
test_data = datasets.ImageFolder(valid_dir, transform=test_transform)
valid_data = datasets.ImageFolder(valid_dir, transform=valid_transform)

# dataloaders
my_batch_size = 64

train_loader = torch.utils.data.DataLoader(train_data, batch_size=my_batch_size, shuffle
test_loader = torch.utils.data.DataLoader(test_data, batch_size=my_batch_size, shuffle=T
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=my_batch_size, shuffle

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: - Code resizes the image by: - randomly flipping the image along horizontal axis with the 0.5 probability being flipped - rotating the image by 45 degrees - croppig image to 256 x 256 size with default aspect ratio. This size was chosen as a nice representation of a square (width x height) - Data set was augmented using transformation from a previous bullet. Dataset was augmented because by doing so we are expending our training data set. It will give the data some geometric variation. Data augmentation will will also help prevent from overfitting (because model sees a lot of new images). As a result it should be better in generalizing and overall we should get a better performance on a test dataset.

1.1.8 (IMPLEMENTATION) Model Architecture

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

In [21]:
```
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
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
        self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.fc1 = nn.Linear(4 * 64 * 16 * 16, 1000)
        self.fc2 = nn.Linear(1000, 133)
        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))
        x = x.view(-1, 4 * 64 * 16 * 16) #image flattening
        x = self.dropout(x) # 1st dropout layer
        x = F.relu(self.fc1(x)) # hidden layer, with relu activation function
        x = self.dropout(x) # 2nd dropout layer
        x = self.fc2(x) # yet another hidden layer, with relu activation function

        return x

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

# instantiate the CNN
model_scratch = Net()

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

In [22]:
```
print(model_scratch)
```

```
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))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=65536, out_features=1000, bias=True)
  (fc2): Linear(in_features=1000, out_features=133, bias=True)
```

```
  (dropout): Dropout(p=0.2)
)
```

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

Answer:

1. Cretae three Convolutional Layers for features extraction:
`(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))`
2. After each of the Convolutional Layer and and Poiling, the layer size will then decrease by half:
`(pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)`
3. Create two fully connected layers with 133 output (133 dog's categories):
`(fc1): Linear(in_features=65536, out_features=1000, bias=True)` `(fc2): Linear(in_features=900, out_features=133, bias=True)` 4. Dropout is used with 0.3 probability to minimize overfitting:
`(dropout): Dropout(p=0.2)`

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 [23]: import torch.optim as optim
         import torch.nn as nn

         ### TODO: select loss function
         criterion_scratch = nn.CrossEntropyLoss() # useful when outputing character class score

         ### TODO: select optimizer
         # optimizer_scratch = optim.Adam(model_scratch.parameters(), lr=0.1)
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.1)
```

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

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

```
        valid_loss = 0.0

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
            optimizer.zero_grad() # zero gradients (clearing gradients)
            output = model(data) # output prediction
            loss = criterion(output, target)# loss batch
            loss.backward() # perform backprop and and update weights
            optimizer.step() # optimization step
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss
            output = model(data)
            loss = criterion(output, target)
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss)


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

        ## TODO: save the model if validation loss has decreased
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss

    # return trained model
```

```python
    print("Done with training and validation!!!")
    return model


# train the model
model_scratch = train(30, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')

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

```
Epoch: 1         Training Loss: 4.882170         Validation Loss: 4.849853
Validation loss decreased (inf --> 4.849853).  Saving model ...
Epoch: 2         Training Loss: 4.826301         Validation Loss: 4.735191
Validation loss decreased (4.849853 --> 4.735191).  Saving model ...
Epoch: 3         Training Loss: 4.691152         Validation Loss: 4.727820
Validation loss decreased (4.735191 --> 4.727820).  Saving model ...
Epoch: 4         Training Loss: 4.615850         Validation Loss: 4.532625
Validation loss decreased (4.727820 --> 4.532625).  Saving model ...
Epoch: 5         Training Loss: 4.578701         Validation Loss: 4.679669
Epoch: 6         Training Loss: 4.539591         Validation Loss: 4.694114
Epoch: 7         Training Loss: 4.511318         Validation Loss: 4.460907
Validation loss decreased (4.532625 --> 4.460907).  Saving model ...
Epoch: 8         Training Loss: 4.455799         Validation Loss: 4.405567
Validation loss decreased (4.460907 --> 4.405567).  Saving model ...
Epoch: 9         Training Loss: 4.438338         Validation Loss: 4.619535
Epoch: 10         Training Loss: 4.398119         Validation Loss: 4.245244
Validation loss decreased (4.405567 --> 4.245244).  Saving model ...
Epoch: 11         Training Loss: 4.351612         Validation Loss: 4.278226
Epoch: 12         Training Loss: 4.326964         Validation Loss: 4.370104
Epoch: 13         Training Loss: 4.283459         Validation Loss: 4.153362
Validation loss decreased (4.245244 --> 4.153362).  Saving model ...
Epoch: 14         Training Loss: 4.242263         Validation Loss: 4.162258
Epoch: 15         Training Loss: 4.220447         Validation Loss: 4.281980
Epoch: 16         Training Loss: 4.196184         Validation Loss: 5.327575
Epoch: 17         Training Loss: 4.169785         Validation Loss: 4.591059
Epoch: 18         Training Loss: 4.220480         Validation Loss: 4.090458
Validation loss decreased (4.153362 --> 4.090458).  Saving model ...
Epoch: 19         Training Loss: 4.102777         Validation Loss: 4.023499
Validation loss decreased (4.090458 --> 4.023499).  Saving model ...
Epoch: 20         Training Loss: 4.070781         Validation Loss: 4.190574
Epoch: 21         Training Loss: 4.041007         Validation Loss: 4.468907
Epoch: 22         Training Loss: 4.048665         Validation Loss: 3.801460
Validation loss decreased (4.023499 --> 3.801460).  Saving model ...
Epoch: 23         Training Loss: 3.966794         Validation Loss: 3.887326
Epoch: 24         Training Loss: 3.939949         Validation Loss: 4.119043
Epoch: 25         Training Loss: 3.918787         Validation Loss: 4.272644
Epoch: 26         Training Loss: 3.895032         Validation Loss: 4.017144
```

```
Epoch: 27         Training Loss: 3.869854        Validation Loss: 3.958123
Epoch: 28         Training Loss: 3.846146        Validation Loss: 4.033047
Epoch: 29         Training Loss: 3.803643        Validation Loss: 3.955742
Epoch: 30         Training Loss: 3.786479        Validation Loss: 3.939665
Done with training and validation!!!
```

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 [25]: 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: 3.859382


Test Accuracy: 10% (89/835)
```

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 [26]: ## TODO: Specify data loaders
         # loaders_transfer = loaders_scratch.copy() # might be a cause of mismatch matric error

         train_dir = '/data/dog_images/train'
         test_dir = '/data/dog_images/test'
         valid_dir = '/data/dog_images/valid'

         train_transforms = transforms.Compose([transforms.RandomRotation(30),
                                                transforms.RandomHorizontalFlip(),
                                                transforms.RandomResizedCrop(224),
                                                transforms.ToTensor(),
                                                transforms.Normalize([0.485, 0.456, 0.406],
                                                                     [0.229, 0.224, 0.225])])
         valid_transforms = transforms.Compose([transforms.Resize(255),
                                                transforms.CenterCrop(224),
                                                transforms.ToTensor(),
                                                transforms.Normalize([0.485, 0.456, 0.406],
                                                                     [0.229, 0.224, 0.225])])
         test_transforms = transforms.Compose([transforms.Resize(255),
                                                transforms.CenterCrop(224),
                                                transforms.ToTensor(),
                                                transforms.Normalize([0.485, 0.456, 0.406],
                                                                     [0.229, 0.224, 0.225])])

         # create dataset
         train_data = datasets.ImageFolder(train_dir, transform=train_transforms)
         valid_data = datasets.ImageFolder(valid_dir, transform=valid_transforms)
         test_data = datasets.ImageFolder(valid_dir, transform=test_transforms)

         # dataloaders
         my_batch_size = 64

         train_loader = torch.utils.data.DataLoader(train_data, batch_size=my_batch_size, shuffl
         valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=my_batch_size, shuffl
```

```
test_loader = torch.utils.data.DataLoader(test_data, batch_size=my_batch_size, shuffle=

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

1.1.13 (IMPLEMENTATION) Model Architecture

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

In [27]:
```
import torchvision.models as models
import torch.nn as nn

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

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

#model_transfer.fc = nn.Linear(8192, 133, bias=True)
model_transfer.fc = nn.Linear(2048, 133, bias=True)
fc_parameters = model_transfer.fc.parameters()

for param in fc_parameters:
    param.requires_grad = True

if use_cuda:
    model_transfer = model_transfer.cuda()

print(model_transfer)
```

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:05<00:00, 17560721.77it/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:

Pretrained ResNet50 (50 layer Residual Network) has been chosen for multiple reasons:

- Before emerging of ResNet, it was super difficult to training very deep neural networks due to the problem of vanishing gradients
- Increases and improves the classification/recognition accuracy
- Solves more and more complex tasks
- Successfully trains extremely deep neural networks with 150+layers
- Won ImageNet world level image classification challenges
  More info can be found He, Kaiming, et al. and Akiba, Takuya, et al.

ResNet50 is a good choise as provided dog images are RGB images with a different sizes. ResNet model consists of 3 input channels - perfect for RGB images.

Last layer has been replaced by sub linear layers:
`Sequential(nn.Linear(2048, 133, bias=True)`

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 [28]: import torch.optim as optim
         import torch.nn as nn
```

```
criterion_transfer = nn.CrossEntropyLoss() # useful when outputing character class scor
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 [29]:
```
# train the model
n_epochs = 20

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: 2.913797         Validation Loss: 1.024065
Validation loss decreased (inf --> 1.024065).  Saving model ...
Epoch: 2         Training Loss: 1.380792         Validation Loss: 0.690890
Validation loss decreased (1.024065 --> 0.690890).  Saving model ...
Epoch: 3         Training Loss: 1.125891         Validation Loss: 0.636775
Validation loss decreased (0.690890 --> 0.636775).  Saving model ...
Epoch: 4         Training Loss: 0.984398         Validation Loss: 0.506386
Validation loss decreased (0.636775 --> 0.506386).  Saving model ...
Epoch: 5         Training Loss: 0.927103         Validation Loss: 0.448137
Validation loss decreased (0.506386 --> 0.448137).  Saving model ...
Epoch: 6         Training Loss: 0.857022         Validation Loss: 0.525056
Epoch: 7         Training Loss: 0.862022         Validation Loss: 0.461756
Epoch: 8         Training Loss: 0.806068         Validation Loss: 0.427679
Validation loss decreased (0.448137 --> 0.427679).  Saving model ...
Epoch: 9         Training Loss: 0.783639         Validation Loss: 0.439271
Epoch: 10         Training Loss: 0.779502         Validation Loss: 0.397852
Validation loss decreased (0.427679 --> 0.397852).  Saving model ...
Epoch: 11         Training Loss: 0.736096         Validation Loss: 0.429247
Epoch: 12         Training Loss: 0.732612         Validation Loss: 0.445865
Epoch: 13         Training Loss: 0.738257         Validation Loss: 0.552284
Epoch: 14         Training Loss: 0.695009         Validation Loss: 0.402541
Epoch: 15         Training Loss: 0.739936         Validation Loss: 0.566044
Epoch: 16         Training Loss: 0.662121         Validation Loss: 0.406110
Epoch: 17         Training Loss: 0.691108         Validation Loss: 0.403463
Epoch: 18         Training Loss: 0.677572         Validation Loss: 0.426504
Epoch: 19         Training Loss: 0.681085         Validation Loss: 0.462001
Epoch: 20         Training Loss: 0.647044         Validation Loss: 0.405785
Done with training and validation!!!
```

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

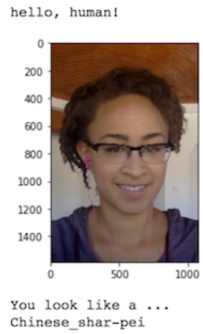
```
Test Loss: 0.403602


Test Accuracy: 86% (721/835)
```

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 [31]: ### 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 data_transfer['train'].classes]
         class_names = [item[4:].replace("_", " ") for item in loaders_transfer['train'].dataset

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             #class_names[:20]
             dog_img = Image.open(img_path).convert('RGB')
             dog_transform = transforms.Compose([transforms.Resize(256),
                                                 transforms.CenterCrop(224),
                                                 transforms.ToTensor(),
                                                 transforms.Normalize([0.5, 0.5, 0.5],
                                                                      [0.5, 0.5, 0.5])])


             dog_img = dog_transform(dog_img).unsqueeze(0)
             dog_img = dog_img.cuda()
             model_transfer.eval()
             idx = torch.argmax(model_transfer(dog_img))

             return class_names[idx]

         print(loaders_transfer['train'].dataset.classes[:20])
```

```
['001.Affenpinscher', '002.Afghan_hound', '003.Airedale_terrier', '004.Akita', '005.Alaskan_mala
```



Sample Human Output

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 [32]:
```
### 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
    image = Image.open(img_path)
    plt.imshow(image)
    plt.show()

    if(dog_detector(img_path)):
        print("Dog has been detected")
        prediction = predict_breed_transfer(img_path)
        print("Predicted dog breed is: {0}".format(prediction))
    elif(face_detector(img_path)):
        print("Human has been Detected")
        prediction = predict_breed_transfer(img_path)
        print("Resembling dog breed is: {0}".format(prediction))
    else:
        print("Neither dog not human has been detected")
```

Step 6: Test Your Algorithm

In this section, you will take your new algorithm for a spin! What kind of dog does the algorithm think that *you* look like? If you have a dog, does it predict your dog's breed accurately? If you have a cat, does it mistakenly think that your cat is a dog?

1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

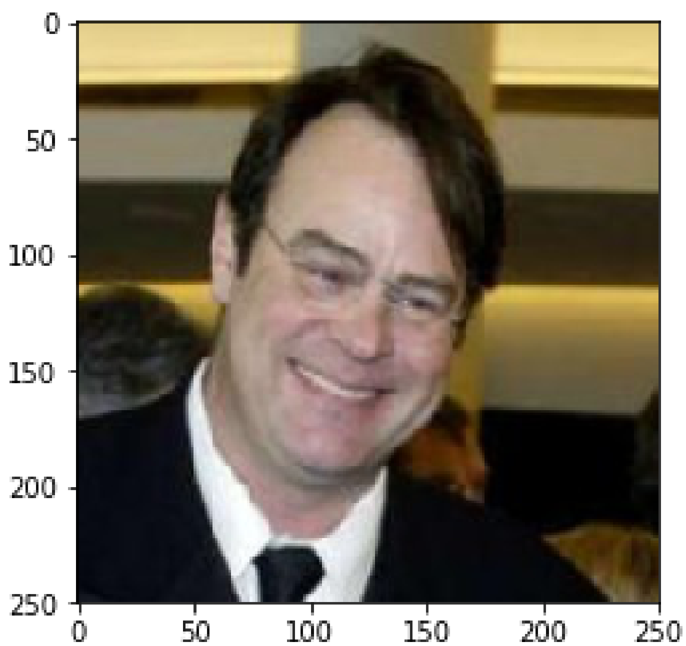
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

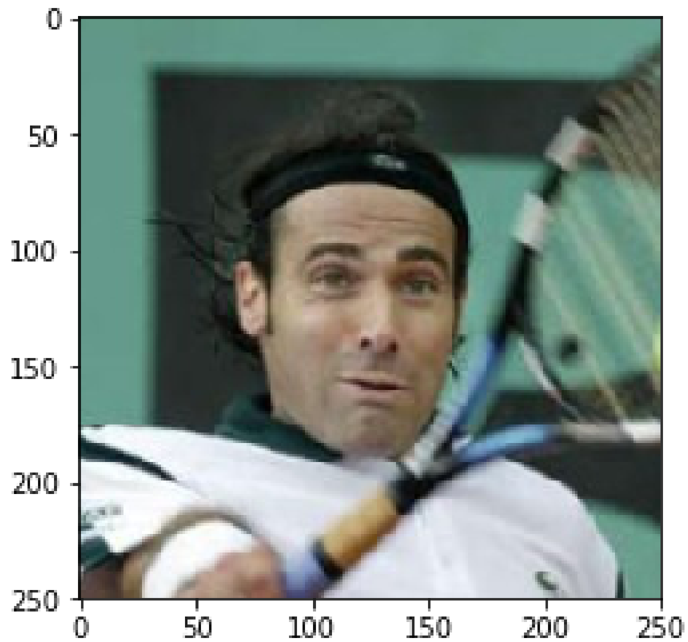
Answer: (Three possible points for improvement)

- Beter tuning and optimization of hyperparameter, specifictly learning rate, minibatch size, number of training iterations (epochs), number of hidden unites and layers
- Much bigger dataset with variety of image tranformations
- Different optimizer and

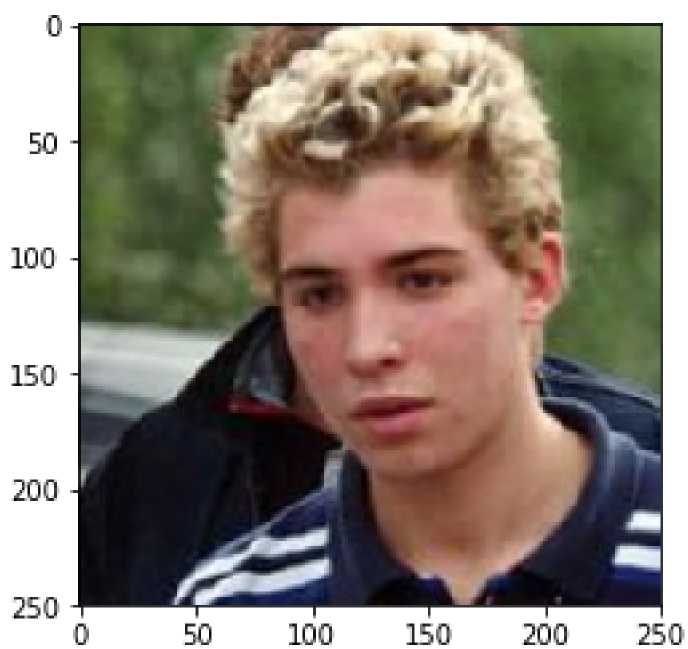
```
In [33]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

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



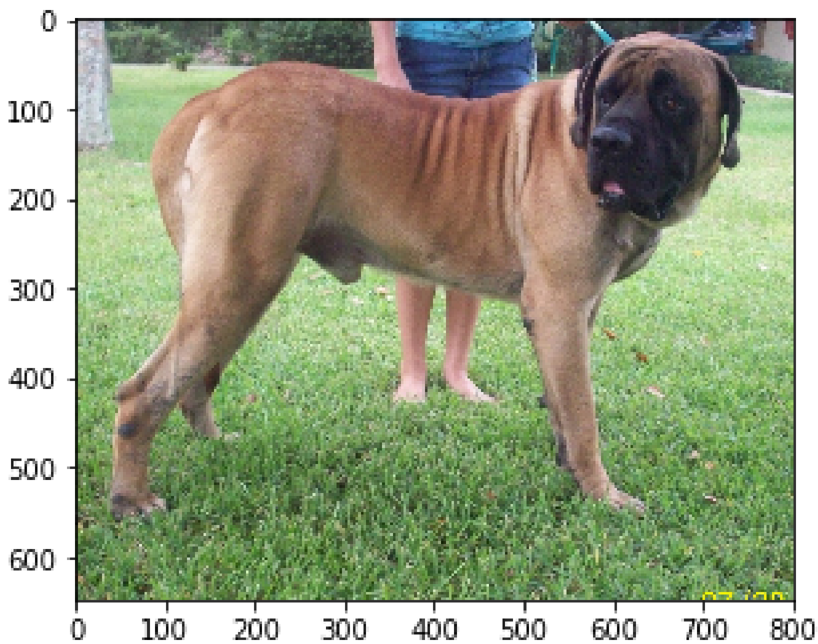
```
Human has been Detected
Resembling dog breed is: Dachshund
```



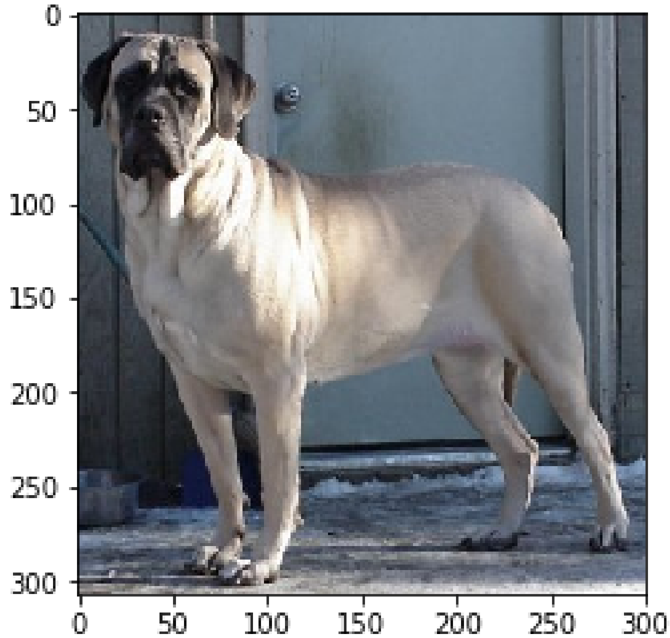

```
Human has been Detected
Resembling dog breed is: American foxhound
```



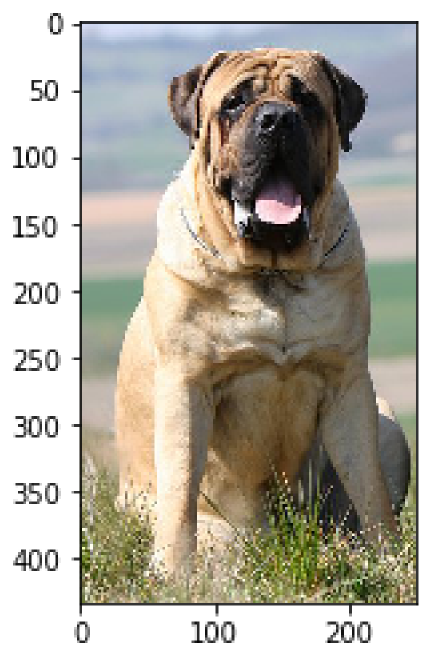
```
Human has been Detected
Resembling dog breed is: Bullmastiff
```




```
Dog has been detected
Predicted dog breed is: Bullmastiff
```




```
Dog has been detected
Predicted dog breed is: Mastiff
```



```
Dog has been detected
Predicted dog breed is: Bullmastiff
```

```
In [ ]:
```