dog_app

March 11, 2019

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.
Step 0: Import Datasets
Make sure that you've downloaded the required human and dog datasets: * Download the dog dataset. Unzip the folder and place it in this project's home directory, at the location `/dog_images`.

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

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

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

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

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

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

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

Step 1: Detect Humans

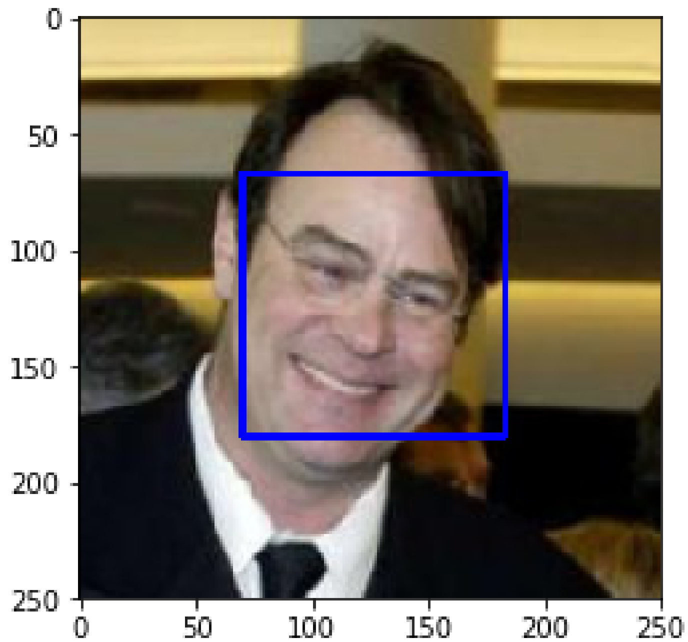
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

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

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

Answer: The algorithm detects 98% of human faces in 100 human images and 1% percent of dog faces in 100 dog images The performance looks great in 100 images

```
In [51]: from tqdm import tqdm_notebook as tqdm

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

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

         #-#-# Do NOT modify the code above this line. #-#-#
         human_counter = 0
         dog_counter = 0
         for ii, (h_f, d_f) in enumerate(tqdm(zip(human_files_short, dog_files_short))):
             human_face = face_detector(h_f)
             dog_face = face_detector(d_f)
             if human_face:
                 human_counter += 1
             elif dog_face:
                 dog_counter += 1
             #if ii==9:
         print('human face detected {} with {}% percformance'.format(human_counter, human_counte
         print('chance for not detecting dog face is {}%'.format(dog_counter/100 * 100))
```

```
HBox(children=(IntProgress(value=1, bar_style='info', max=1), HTML(value='')))



human face detected 98 with 98.0% percformance
chance for not detecting dog face is 1.0%
```

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

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

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

        # 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 [00:04<00:00, 124572843.77it/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

        #process the image first before use with this helper function
        def process_image(img_path):
             ## Load and pre-process an image from the given img_path
            img_transform = transforms.Compose([transforms.RandomResizedCrop(224),
                                                transforms.ToTensor(),
                                                transforms.Normalize((0.485, 0.456, 0.406),
                                                                     (0.229, 0.224, 0.225))
                                               ])
            image = Image.open(img_path)


            #transform an image
            image = img_transform(image).unsqueeze(0)

            return image


        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
            image = process_image(img_path)

            ## Return the *index* of the predicted class for that image
            if use_cuda:
                image = image.cuda()

            out = VGG16(image)
            ps = torch.exp(out)
            #get the prediction with the class ignored
            _, prediction = torch.topk(ps, 1)

            return prediction # predicted class index
```

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.

            pred = VGG16_predict(img_path)

            if pred.item() 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: low of 95.0% and high of 100.0% performance, it detected 100 dogs out 100 dog images and 0.0% of human image is detected out of 100 human images . this is so reasonable given how VGG net detect face features with 98% accuracy, it has a pretrained optimal weights to identify either, or

```
In [15]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

         human_det, dog_det = [0,0]

         for ii, (h_file, d_file) in tqdm(enumerate(zip(human_files_short, dog_files_short))):
             dog = dog_detector(d_file)
             human = dog_detector(h_file)
             if dog:
                 dog_det += 1
             elif human:
                 human_det += 1

         print("{}% of dog in dog images of {}".format(dog_det * len(dog_files_short) / len(dog_
         print("{}% of dog in human images of {}".format(human_det * len(human_files_short) / le
```

```
HBox(children=(IntProgress(value=1, bar_style='info', max=1), HTML(value='')))
```

```
100.0% of dog in dog images of 100
0.0% of dog in human images of 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`.

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

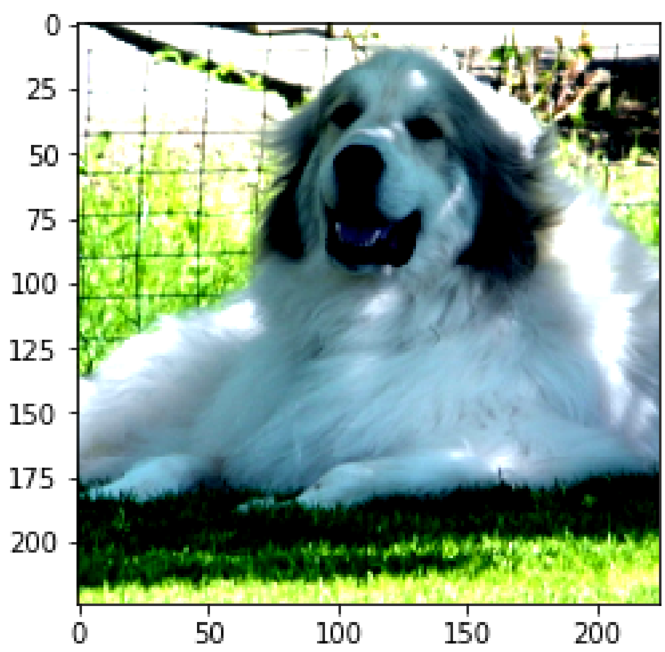
Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dog_images/train`, `dog_images/valid`, and `dog_images/test`, respectively). You may find this documentation on custom datasets to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of transforms!

In [8]:
```
#helper display function
def imshow(image, ax=None, title=None, norm=[[0.485, 0.456, 0.406],[0.229, 0.224, 0.225]
    if ax is None:
        fig, ax = plt.subplots()
    if title:
        plt.title(title)
    # PyTorch tensors assume the color channel is first
    # but matplotlib assumes is the third dimension
    image = image.transpose((1, 2, 0))

    # Undo preprocessing
    mean = np.array(norm[0])
    std = np.array(norm[0])
    image = std * image + mean

    # Image needs to be clipped between 0 and 1

    image = np.clip(image, 0, 1)

    ax.imshow(image)

    return ax
```

In [9]:
```
import os
from torchvision import datasets

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

batch_size = 32

data = '/data/dog_images/'
train = os.path.join(data, 'train')
test = os.path.join(data, 'test')
valid = os.path.join(data, 'valid')

#Preprocessing
#training and validation data transformation with Augmentation
train_transform = transforms.Compose([transforms.RandomResizedCrop(224),
                                      transforms.RandomHorizontalFlip(),
                                      transforms.RandomRotation(10),
```

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

#actual test data transformation, without augmentation
test_transform = transforms.Compose([transforms.Resize(225),
                                    transforms.CenterCrop(224),
                                    transforms.ToTensor(),
                                    transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0
#downloading the datasets
train_data = datasets.ImageFolder(train, train_transform)
valid_data = datasets.ImageFolder(valid, train_transform)
test_data =  datasets.ImageFolder(test, test_transform)

#loading the generator

trainloader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, shuffle=Tru
validloader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, shuffle=Tru
testloader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, shuffle=True)

loaders_scratch = {'train':trainloader, 'valid':validloader, 'test':testloader}

image, label= next(iter(loaders_scratch['test']))
img = image[0].numpy()
imshow(img, norm = [[0.5,0.5,0.5], [0.5,0.5,0.5]])
print(img.shape)
```

```
(3, 224, 224)
```



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: 1. I've Randomly resize the training images to create more variation in which a network would learn from, and square all my images (224), I chose to resize all the images to keep them uiniform so the variation factor would only be the hyperparameters not the image dimensions.

2. Yes! I've used image Augmentation(shift of position) that's flip and rotation to feed my network with different positional variations which might positively affect the performance of the network later, if given a shift image with the same sort of style, it'll have it's weights optimized on it already, so it won't have a hard time to converge it.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [10]: #create Weight initialization function to initialize weights explicity
         def weights_init_scratch(m):
             '''m: Module with random weights
                and explicilty initialize the weight using normal distribution.'''

             module_classname = m.__class__.__name__
             # for every Linear layer in a model
             if module_classname.find('Linear') != -1:
                 mean = 0
                 in_features = m.in_features
                 std = 1/np.sqrt(in_features)
                 # initialize module's weights using a normal distribution
                 m.weight.data.normal_(mean, std)
                 # m.bias.data should be 0
                 m.bias.data.fill_(0)
```

```
In [11]: 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, weight_init=None):
                 super(Net, self).__init__()
                 ## Define layers of a CNN
                 #set the kernel size and stride to 2 and padding will result to 1 to keep spati

                 #(sees 244x244x3 tensor)
                 self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
```

```
        #sees (122x122x16 tensor) Kernel and stride of 3, padding 2
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)

        #sees (56x56x32 tensor) kernel size of 3 and padding of 1 crease the spatial ou
        self.conv3 = nn.Conv2d(32, 64, 3, padding = 1)

        #define pooling layer with downsample of 2
        self.pool = nn.MaxPool2d(2,2)

        #define Linear transformation
        #sees (28x28x64)
        self.fc1 = nn.Linear(64*28*28, 1024)
        self.fc2 = nn.Linear(1024, 133)

        #define dropout
        self.dropout = nn.Dropout(0.4)

    def forward(self, x):
        ## Define forward behavior
        #add sequence of convolution with pooling
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))

        #flatten the image (input)
        x = x.view(-1, 64*28*28)

        #pass input through sequence of linear layers and dropouts
        x = self.dropout(F.relu(self.fc1(x)))

        #don't add relu function as softmax will be added using the crossentropyloss
        x = self.dropout(self.fc2(x))

        return x

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

# instantiate the CNN
model_scratch = Net()
#initialize the weights.
model_scratch.apply(weights_init_scratch)

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

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

Answer: steps 1. Used three layers with last layer with depth of 64, they are deep enough given the data size and the need for efficiency. step 2. Defined the kernels size, stride and padding in a sense where they minimally decrease the spatial output volume to keep the number of parameters optimals. step 4. Defined pooing layer using Maxpooling to shrink the size with downsample of 2, to keep most of the relevant information. step 5. Add dropout to prevent linear layers from overfitting(0.4) step 6. add max number of linear layer of 3 which later change to 2 linear layer, because of overfitting. step 7. initialized linear layer's weights using normal distribution in respect to the input features instead of default initialization. It made a huge different.

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 [12]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.008, momentum=0.8)
```

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 [23]: from PIL import ImageFile

         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 tqdm(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()
```

```
            #clean the commulated gradients
            optimizer.zero_grad()
            ## find the loss and update the model parameters accordingly
            score = model(data)
            #calculate the loss
            loss = criterion(score, target)
            #perform backward pass
            loss.backward()
            #update the weight steps
            optimizer.step()
            #accumulate the training loss

            ## record the average training loss, using something like
            #train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss

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

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

        # 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 decreaseing {:.6f}-->{:6f} Saving the model..".forma
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss
    # return trained model
    return model

ImageFile.LOAD_TRUNCATED_IMAGES = True
```

```
In [45]: # train the model
         model_scratch = train(100, loaders_scratch, model_scratch, optimizer_scratch,
                               criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
HBox(children=(IntProgress(value=0), HTML(value='')))


Epoch: 1         Training Loss: 4.881536         Validation Loss: 4.832925
Validation loss decreaseing inf-->4.832925 Saving the model..
Epoch: 2         Training Loss: 4.821130         Validation Loss: 4.736949
Validation loss decreaseing 4.832925-->4.736949 Saving the model..
Epoch: 3         Training Loss: 4.771755         Validation Loss: 4.722067
Validation loss decreaseing 4.736949-->4.722067 Saving the model..
Epoch: 4         Training Loss: 4.724927         Validation Loss: 4.634645
Validation loss decreaseing 4.722067-->4.634645 Saving the model..
Epoch: 5         Training Loss: 4.700912         Validation Loss: 4.604043
Validation loss decreaseing 4.634645-->4.604043 Saving the model..
Epoch: 6         Training Loss: 4.672387         Validation Loss: 4.589789
Validation loss decreaseing 4.604043-->4.589789 Saving the model..
Epoch: 7         Training Loss: 4.643333         Validation Loss: 4.577717
Validation loss decreaseing 4.589789-->4.577717 Saving the model..
Epoch: 8         Training Loss: 4.626854         Validation Loss: 4.557050
Validation loss decreaseing 4.577717-->4.557050 Saving the model..
Epoch: 9         Training Loss: 4.592225         Validation Loss: 4.540246
Validation loss decreaseing 4.557050-->4.540246 Saving the model..
Epoch: 10         Training Loss: 4.582294         Validation Loss: 4.489850
Validation loss decreaseing 4.540246-->4.489850 Saving the model..
Epoch: 11         Training Loss: 4.566668         Validation Loss: 4.514095
Epoch: 12         Training Loss: 4.547650         Validation Loss: 4.388429
Validation loss decreaseing 4.489850-->4.388429 Saving the model..
Epoch: 13         Training Loss: 4.543060         Validation Loss: 4.453534
Epoch: 14         Training Loss: 4.508343         Validation Loss: 4.374008
Validation loss decreaseing 4.388429-->4.374008 Saving the model..
Epoch: 15         Training Loss: 4.496319         Validation Loss: 4.379891
Epoch: 16         Training Loss: 4.484959         Validation Loss: 4.391161
Epoch: 17         Training Loss: 4.478659         Validation Loss: 4.346081
Validation loss decreaseing 4.374008-->4.346081 Saving the model..
Epoch: 18         Training Loss: 4.455123         Validation Loss: 4.347882
Epoch: 19         Training Loss: 4.426649         Validation Loss: 4.328746
Validation loss decreaseing 4.346081-->4.328746 Saving the model..
Epoch: 20         Training Loss: 4.421987         Validation Loss: 4.369238
Epoch: 21         Training Loss: 4.410442         Validation Loss: 4.327862
Validation loss decreaseing 4.328746-->4.327862 Saving the model..
Epoch: 22         Training Loss: 4.393980         Validation Loss: 4.279475
Validation loss decreaseing 4.327862-->4.279475 Saving the model..
Epoch: 23         Training Loss: 4.378014         Validation Loss: 4.322811
Epoch: 24         Training Loss: 4.359455         Validation Loss: 4.290632
Epoch: 25         Training Loss: 4.328636         Validation Loss: 4.243739
```

```
Validation loss decreaseing 4.279475-->4.243739 Saving the model..
Epoch: 26        Training Loss: 4.322799        Validation Loss: 4.163621
Validation loss decreaseing 4.243739-->4.163621 Saving the model..
Epoch: 27        Training Loss: 4.302753        Validation Loss: 4.222687
Epoch: 28        Training Loss: 4.287996        Validation Loss: 4.207547
Epoch: 29        Training Loss: 4.256842        Validation Loss: 4.115352
Validation loss decreaseing 4.163621-->4.115352 Saving the model..
Epoch: 30        Training Loss: 4.266382        Validation Loss: 4.169433
Epoch: 31        Training Loss: 4.248536        Validation Loss: 4.189362
Epoch: 32        Training Loss: 4.236709        Validation Loss: 4.140635
Epoch: 33        Training Loss: 4.221517        Validation Loss: 4.093665
Validation loss decreaseing 4.115352-->4.093665 Saving the model..
Epoch: 34        Training Loss: 4.204654        Validation Loss: 4.107800
Epoch: 35        Training Loss: 4.183634        Validation Loss: 4.136631
Epoch: 36        Training Loss: 4.179335        Validation Loss: 4.114881
Epoch: 37        Training Loss: 4.173853        Validation Loss: 4.052154
Validation loss decreaseing 4.093665-->4.052154 Saving the model..
Epoch: 38        Training Loss: 4.164621        Validation Loss: 4.152158
Epoch: 39        Training Loss: 4.132117        Validation Loss: 4.075137
Epoch: 40        Training Loss: 4.138521        Validation Loss: 3.995711
Validation loss decreaseing 4.052154-->3.995711 Saving the model..
Epoch: 41        Training Loss: 4.104085        Validation Loss: 3.976720
Validation loss decreaseing 3.995711-->3.976720 Saving the model..
Epoch: 42        Training Loss: 4.135204        Validation Loss: 4.010933
Epoch: 43        Training Loss: 4.110487        Validation Loss: 4.029657
Epoch: 44        Training Loss: 4.100555        Validation Loss: 3.979820
Epoch: 45        Training Loss: 4.088951        Validation Loss: 4.059055
Epoch: 46        Training Loss: 4.037337        Validation Loss: 4.007128
Epoch: 47        Training Loss: 4.051743        Validation Loss: 4.004684
Epoch: 48        Training Loss: 4.047150        Validation Loss: 4.007070
Epoch: 49        Training Loss: 4.009610        Validation Loss: 3.981491
Epoch: 50        Training Loss: 3.971740        Validation Loss: 3.925138
Validation loss decreaseing 3.976720-->3.925138 Saving the model..
Epoch: 51        Training Loss: 4.014239        Validation Loss: 3.968796
Epoch: 52        Training Loss: 4.006294        Validation Loss: 3.926167
Epoch: 53        Training Loss: 4.005444        Validation Loss: 3.954841
Epoch: 54        Training Loss: 3.984589        Validation Loss: 3.941978
Epoch: 55        Training Loss: 3.924601        Validation Loss: 3.965921
Epoch: 56        Training Loss: 3.951761        Validation Loss: 3.948007
Epoch: 57        Training Loss: 3.968911        Validation Loss: 3.968909
Epoch: 58        Training Loss: 3.936890        Validation Loss: 3.947856
Epoch: 59        Training Loss: 3.918499        Validation Loss: 3.917351
Validation loss decreaseing 3.925138-->3.917351 Saving the model..
Epoch: 60        Training Loss: 3.929626        Validation Loss: 3.970106
Epoch: 61        Training Loss: 3.932950        Validation Loss: 3.951138
Epoch: 62        Training Loss: 3.873145        Validation Loss: 3.906332
Validation loss decreaseing 3.917351-->3.906332 Saving the model..
Epoch: 63        Training Loss: 3.920498        Validation Loss: 3.934994
```

```
Epoch: 64         Training Loss: 3.866429        Validation Loss: 3.936193
Epoch: 65         Training Loss: 3.855929        Validation Loss: 3.858407
Validation loss decreaseing 3.906332-->3.858407 Saving the model..
Epoch: 66         Training Loss: 3.867110        Validation Loss: 3.836968
Validation loss decreaseing 3.858407-->3.836968 Saving the model..
Epoch: 67         Training Loss: 3.873383        Validation Loss: 3.933701
Epoch: 68         Training Loss: 3.855724        Validation Loss: 3.933807
Epoch: 69         Training Loss: 3.840075        Validation Loss: 3.861718
Epoch: 70         Training Loss: 3.812969        Validation Loss: 3.798855
Validation loss decreaseing 3.836968-->3.798855 Saving the model..
Epoch: 71         Training Loss: 3.824899        Validation Loss: 3.764018
Validation loss decreaseing 3.798855-->3.764018 Saving the model..
Epoch: 72         Training Loss: 3.794700        Validation Loss: 3.893775
Epoch: 73         Training Loss: 3.796968        Validation Loss: 3.838217
Epoch: 74         Training Loss: 3.823378        Validation Loss: 3.909378
Epoch: 75         Training Loss: 3.800723        Validation Loss: 3.917333
Epoch: 76         Training Loss: 3.782760        Validation Loss: 3.900837
Epoch: 77         Training Loss: 3.758612        Validation Loss: 3.832224
Epoch: 78         Training Loss: 3.727787        Validation Loss: 3.867997
Epoch: 79         Training Loss: 3.745050        Validation Loss: 3.825298
Epoch: 80         Training Loss: 3.755486        Validation Loss: 3.887218
Epoch: 81         Training Loss: 3.748495        Validation Loss: 3.792509
Epoch: 82         Training Loss: 3.736626        Validation Loss: 3.853437
Epoch: 83         Training Loss: 3.726776        Validation Loss: 3.832274
Epoch: 84         Training Loss: 3.741711        Validation Loss: 3.809683
Epoch: 85         Training Loss: 3.719096        Validation Loss: 3.849525
Epoch: 86         Training Loss: 3.712649        Validation Loss: 3.751818
Validation loss decreaseing 3.764018-->3.751818 Saving the model..
Epoch: 87         Training Loss: 3.673524        Validation Loss: 3.873482
Epoch: 88         Training Loss: 3.722111        Validation Loss: 3.846647
Epoch: 89         Training Loss: 3.710919        Validation Loss: 3.795715
Epoch: 90         Training Loss: 3.692423        Validation Loss: 3.898527
Epoch: 91         Training Loss: 3.686661        Validation Loss: 3.716529
Validation loss decreaseing 3.751818-->3.716529 Saving the model..
Epoch: 92         Training Loss: 3.666628        Validation Loss: 3.830305
Epoch: 93         Training Loss: 3.629065        Validation Loss: 3.786971
Epoch: 94         Training Loss: 3.652694        Validation Loss: 3.772433
Epoch: 95         Training Loss: 3.662270        Validation Loss: 3.823160
Epoch: 96         Training Loss: 3.688618        Validation Loss: 3.877831
Epoch: 97         Training Loss: 3.637734        Validation Loss: 3.880479
Epoch: 98         Training Loss: 3.650880        Validation Loss: 3.773265
Epoch: 99         Training Loss: 3.603407        Validation Loss: 3.826256
Epoch: 100         Training Loss: 3.584887        Validation Loss: 3.825924
```

In [14]:
```
# load the model that got the best validation accuracy
model_scratch.load_state_dict(torch.load('model_scratch.pt', map_location='cpu'))
```

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 [64]: 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(tqdm((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))
```

```
In [39]: #call test function
         test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
HBox(children=(IntProgress(value=0, max=27), HTML(value='')))



Test Loss: 3.394794


Test Accuracy: 22% (190/836)
```

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 [19]:
```
## TODO: Specify data loaders

image_size = 224

batch_size = 32

data = '/data/dog_images/'
train = os.path.join(data, 'train')
test = os.path.join(data, 'test')
valid = os.path.join(data, 'valid')

norm_mean = [0.485, 0.456, 0.406]
norm_std = [0.229, 0.224, 0.225]

#defining the transform and augmenting the data

train_transform = transforms.Compose([
                                     transforms.Resize(256),
                                     transforms.RandomRotation(10),
                                     transforms.CenterCrop(image_size),
                                     transforms.RandomHorizontalFlip(),
                                     transforms.ToTensor(),
                                     transforms.Normalize(norm_mean,
                                                          norm_std)])

#defining test transform without data augmentation
test_transform = transforms.Compose([
                                     transforms.Resize(256),
                                     transforms.CenterCrop(image_size),
                                     transforms.ToTensor(),
                                     transforms.Normalize(norm_mean,
                                                            norm_std)])

valid_transform = transforms.Compose([transforms.Resize(256),
                                       transforms.CenterCrop(image_size),
                                       transforms.ToTensor(),
```

```
                                              transforms.Normalize(norm_mean,
                                                                   norm_std)])

train_data = datasets.ImageFolder(train, transform = train_transform)
valid_data = datasets.ImageFolder(valid, transform = valid_transform)
test_data = datasets.ImageFolder(test, transform = test_transform)

data_transfer = {'train':train_data, 'valid':valid_data, 'test':test_data}

data = [train_data, valid_data, test_data]
keys = ['train', 'valid', 'test']
loaders_transfer = {i:torch.utils.data.DataLoader(j, batch_size=batch_size, shuffle=Tru
```

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 [15]: def weights_init_transfer(m):
             class_n = m.__class__.__name__
             if class_n.find('Linear') != -1:
                 mean = 0
                 std = 1/np.sqrt(m.in_features)
                 m.weight.data.normal_(mean, std)
                 m.bias.data.fill_(0)
```

```
In [16]: class classifier(nn.Module):
             ### TODO: choose an architecture, and complete the class
             def __init__(self, input_unit, output_unit=133, weight_init=None, ):
                 super(classifier, self).__init__()
                 ## Define classifier
                 self.input_unit = input_unit
                 self.fc1 = nn.Linear(self.input_unit, 512)
                 self.fc2 = nn.Linear(512, 128)
                 self.fc3 = nn.Linear(128, output_unit)

                 self.dropout = nn.Dropout(0.5)

             def forward(self, x):
                 ## Define forward behavior

                 #flatten the image (input)
                 x = x.view(-1, self.input_unit)
                 #pass input through sequence of linear layers and dropouts
                 x = self.dropout(F.relu(self.fc1(x)))
                 x = self.dropout(F.relu(self.fc2(x)))
                 #don't add relu function as softmax will be added using the crossentropyloss
                 x = self.dropout(self.fc3(x))
```

```
        return x

import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture

model_transfer = models.resnet152(pretrained=True)

#freeze the parameters()
for par in model_transfer.parameters():
    par.requires_grad = False
c=0
for child in model_transfer.children():
    c+=1
    if c >= 9:
        #freeze the weights of the lower layers except the fully connected layer which
        for par in child.parameters():
            par.requires_grad = True


#remove the last linear layer and replace it with my own linear layer.(considering the
#get the pretrained network's input unit
in_puts = model_transfer.fc.in_features

#replace the fully connected layer with the new one

new_fcl = classifier(in_puts)

#new_fcl = nn.Linear(in_puts, 133)

model_transfer.fc = new_fcl

#Randomly initialize the weight of the last fully connected layers.
model_transfer.apply(weights_init_transfer)

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

```
Downloading: "https://download.pytorch.org/models/resnet152-b121ed2d.pth" to /root/.torch/models
100%|| 241530880/241530880 [00:01<00:00, 122672665.74it/s]
```

Question 5: Outline the steps you took to get to your final CNN architecture and your reasoning at each step. Describe why you think the architecture is suitable for the current problem.

Answer: I choose resnet152 model as it looks to be performing better in top error chart in torchvison and a little bit lighter than most of the models but not all. The data seems to be small, so

I'll freeze the weight of pretrained model except, the last convolutional and fully connected layers (which I'll create). replace the last linear layer with my own. Initialize the linear layer's weights with normal distribution in respect to the input data. used CrossEntropyLoss which gives me two in one advantages, and some lower learning rate. I chose SGD optimizer with momentum, because it gives some advantage of bouncing around the local minumue might lead to getting momentum toward the global minimume.

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 [61]: from torch.optim import lr_scheduler as lr_sc


         criterion_transfer = nn.CrossEntropyLoss()
         lr = 0.003
         optimizer_transfer = optim.SGD(model_transfer.fc.parameters(), lr, momentum=0.8)
```

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 [24]: # train the model
         n_epochs = 70
         model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,
```

```
HBox(children=(IntProgress(value=0, max=70), HTML(value='')))


Epoch: 1         Training Loss: 4.903919         Validation Loss: 4.813878
Validation loss decreaseing inf-->4.813878 Saving the model..
Epoch: 2         Training Loss: 4.802709         Validation Loss: 4.646449
Validation loss decreaseing 4.813878-->4.646449 Saving the model..
Epoch: 3         Training Loss: 4.669187         Validation Loss: 4.391281
Validation loss decreaseing 4.646449-->4.391281 Saving the model..
Epoch: 4         Training Loss: 4.491480         Validation Loss: 4.063117
Validation loss decreaseing 4.391281-->4.063117 Saving the model..
Epoch: 5         Training Loss: 4.305210         Validation Loss: 3.747999
Validation loss decreaseing 4.063117-->3.747999 Saving the model..
Epoch: 6         Training Loss: 4.140966         Validation Loss: 3.480655
Validation loss decreaseing 3.747999-->3.480655 Saving the model..
Epoch: 7         Training Loss: 4.026899         Validation Loss: 3.229159
Validation loss decreaseing 3.480655-->3.229159 Saving the model..
Epoch: 8         Training Loss: 3.896148         Validation Loss: 2.993914
Validation loss decreaseing 3.229159-->2.993914 Saving the model..
Epoch: 9         Training Loss: 3.786450         Validation Loss: 2.840523
Validation loss decreaseing 2.993914-->2.840523 Saving the model..
Epoch: 10         Training Loss: 3.703591         Validation Loss: 2.620704
```

```
Validation loss decreaseing 2.840523-->2.620704 Saving the model..
Epoch: 11         Training Loss: 3.625480        Validation Loss: 2.565142
Validation loss decreaseing 2.620704-->2.565142 Saving the model..
Epoch: 12         Training Loss: 3.548054        Validation Loss: 2.340242
Validation loss decreaseing 2.565142-->2.340242 Saving the model..
Epoch: 13         Training Loss: 3.540211        Validation Loss: 2.261193
Validation loss decreaseing 2.340242-->2.261193 Saving the model..
Epoch: 14         Training Loss: 3.470314        Validation Loss: 2.193210
Validation loss decreaseing 2.261193-->2.193210 Saving the model..
Epoch: 15         Training Loss: 3.418658        Validation Loss: 2.044484
Validation loss decreaseing 2.193210-->2.044484 Saving the model..
Epoch: 16         Training Loss: 3.410552        Validation Loss: 1.991459
Validation loss decreaseing 2.044484-->1.991459 Saving the model..
Epoch: 17         Training Loss: 3.278982        Validation Loss: 1.885484
Validation loss decreaseing 1.991459-->1.885484 Saving the model..
Epoch: 18         Training Loss: 3.296477        Validation Loss: 1.873967
Validation loss decreaseing 1.885484-->1.873967 Saving the model..
Epoch: 19         Training Loss: 3.302544        Validation Loss: 1.784900
Validation loss decreaseing 1.873967-->1.784900 Saving the model..
Epoch: 20         Training Loss: 3.245257        Validation Loss: 1.638599
Validation loss decreaseing 1.784900-->1.638599 Saving the model..
Epoch: 21         Training Loss: 3.218705        Validation Loss: 1.574252
Validation loss decreaseing 1.638599-->1.574252 Saving the model..
Epoch: 22         Training Loss: 3.196005        Validation Loss: 1.551254
Validation loss decreaseing 1.574252-->1.551254 Saving the model..
Epoch: 23         Training Loss: 3.160427        Validation Loss: 1.520785
Validation loss decreaseing 1.551254-->1.520785 Saving the model..
Epoch: 24         Training Loss: 3.131001        Validation Loss: 1.501896
Validation loss decreaseing 1.520785-->1.501896 Saving the model..
Epoch: 25         Training Loss: 3.078573        Validation Loss: 1.394673
Validation loss decreaseing 1.501896-->1.394673 Saving the model..
Epoch: 26         Training Loss: 3.111917        Validation Loss: 1.378286
Validation loss decreaseing 1.394673-->1.378286 Saving the model..
Epoch: 27         Training Loss: 3.065612        Validation Loss: 1.401725
Epoch: 28         Training Loss: 3.060464        Validation Loss: 1.288982
Validation loss decreaseing 1.378286-->1.288982 Saving the model..
Epoch: 29         Training Loss: 3.048539        Validation Loss: 1.235663
Validation loss decreaseing 1.288982-->1.235663 Saving the model..
Epoch: 30         Training Loss: 3.024668        Validation Loss: 1.277346
Epoch: 31         Training Loss: 3.005724        Validation Loss: 1.288837
Epoch: 32         Training Loss: 2.990692        Validation Loss: 1.167600
Validation loss decreaseing 1.235663-->1.167600 Saving the model..
Epoch: 33         Training Loss: 2.976979        Validation Loss: 1.173318
Epoch: 34         Training Loss: 3.028697        Validation Loss: 1.166017
Validation loss decreaseing 1.167600-->1.166017 Saving the model..
Epoch: 35         Training Loss: 2.961563        Validation Loss: 1.148626
Validation loss decreaseing 1.166017-->1.148626 Saving the model..
Epoch: 36         Training Loss: 2.972399        Validation Loss: 1.104774
```

```
Validation loss decreaseing 1.148626-->1.104774 Saving the model..
Epoch: 37        Training Loss: 2.951366        Validation Loss: 1.082793
Validation loss decreaseing 1.104774-->1.082793 Saving the model..
Epoch: 38        Training Loss: 2.918320        Validation Loss: 1.055253
Validation loss decreaseing 1.082793-->1.055253 Saving the model..
Epoch: 39        Training Loss: 2.959229        Validation Loss: 1.001787
Validation loss decreaseing 1.055253-->1.001787 Saving the model..
Epoch: 40        Training Loss: 2.946078        Validation Loss: 1.027699
Epoch: 41        Training Loss: 2.950186        Validation Loss: 1.098652
Epoch: 42        Training Loss: 2.887367        Validation Loss: 0.957818
Validation loss decreaseing 1.001787-->0.957818 Saving the model..
Epoch: 43        Training Loss: 2.879298        Validation Loss: 0.960254
Epoch: 44        Training Loss: 2.924648        Validation Loss: 0.963256
Epoch: 45        Training Loss: 2.843501        Validation Loss: 0.917697
Validation loss decreaseing 0.957818-->0.917697 Saving the model..
Epoch: 46        Training Loss: 2.859823        Validation Loss: 0.941023
Epoch: 47        Training Loss: 2.882069        Validation Loss: 0.959419
Epoch: 48        Training Loss: 2.882685        Validation Loss: 0.974716
Epoch: 49        Training Loss: 2.830906        Validation Loss: 0.950817
Epoch: 50        Training Loss: 2.820702        Validation Loss: 0.909764
Validation loss decreaseing 0.917697-->0.909764 Saving the model..
Epoch: 51        Training Loss: 2.853886        Validation Loss: 0.916874
Epoch: 52        Training Loss: 2.825505        Validation Loss: 0.800676
Validation loss decreaseing 0.909764-->0.800676 Saving the model..
Epoch: 53        Training Loss: 2.814055        Validation Loss: 0.857791
Epoch: 54        Training Loss: 2.808362        Validation Loss: 0.845692
Epoch: 55        Training Loss: 2.810093        Validation Loss: 0.813360
Epoch: 56        Training Loss: 2.779327        Validation Loss: 0.792318
Validation loss decreaseing 0.800676-->0.792318 Saving the model..
Epoch: 57        Training Loss: 2.785463        Validation Loss: 0.833327
Epoch: 58        Training Loss: 2.807075        Validation Loss: 0.838441
Epoch: 59        Training Loss: 2.827681        Validation Loss: 0.806808
Epoch: 60        Training Loss: 2.734741        Validation Loss: 0.812074
Epoch: 61        Training Loss: 2.788928        Validation Loss: 0.838801
Epoch: 62        Training Loss: 2.766139        Validation Loss: 0.812668
Epoch: 63        Training Loss: 2.747047        Validation Loss: 0.752747
Validation loss decreaseing 0.792318-->0.752747 Saving the model..
Epoch: 64        Training Loss: 2.782073        Validation Loss: 0.727260
Validation loss decreaseing 0.752747-->0.727260 Saving the model..
Epoch: 65        Training Loss: 2.791275        Validation Loss: 0.784925
Epoch: 66        Training Loss: 2.748399        Validation Loss: 0.710551
Validation loss decreaseing 0.727260-->0.710551 Saving the model..
Epoch: 67        Training Loss: 2.785285        Validation Loss: 0.783127
Epoch: 68        Training Loss: 2.800176        Validation Loss: 0.723721
Epoch: 69        Training Loss: 2.747555        Validation Loss: 0.725567
Epoch: 70        Training Loss: 2.761037        Validation Loss: 0.771454
```

```
In [17]: # load the model that got the best validation accuracy (uncomment the line below)
         #little bit modified because I load my model in machines with no Cuda.
         model_transfer.load_state_dict(torch.load('model_transfer.pt', map_location='cpu'))
```

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

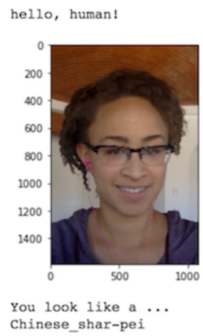
```
HBox(children=(IntProgress(value=0, max=27), HTML(value='')))



Test Loss: 0.748038



Test Accuracy: 86% (725/836)
```

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 [20]: ### 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]

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             model_transfer.cpu()

             image = process_image(img_path)

             out = model_transfer(image)

             pred = out.data.max(1, keepdim=True)[1]

             return class_names[pred]
```

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



Sample Human Output

breed. - if a **human** is detected in the image, return the resembling dog breed. - if **neither** is detected in the image, provide output that indicates an error.

You are welcome to write your own functions for detecting humans and dogs in images, but feel free to use the `face_detector` and `human_detector` functions developed above. You are **required** to use your CNN from Step 4 to predict dog breed.

Some sample output for our algorithm is provided below, but feel free to design your own user experience!

1.1.18 (IMPLEMENTATION) Write your Algorithm

In [21]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.
def display(img_path):
    img = cv2.imread(img_path)
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.imshow(cv_rgb)
    plt.show()



def run_app(img_path):
    ## handle cases for a human face, dog, and neither

    #Check if dog or human face exists

    #check if dog or human exist in the image and return the dog breed or resenble of h
    if dog_detector(img_path): #if dog exists, return the prediction of the breed
        dog_breed = predict_breed_transfer(img_path)
        title = 'A dog is detected and its breed is '+dog_breed
        img = cv2.imread(img_path)
        print(title)
        display(img_path)

    elif face_detector(img_path): #if human exists, return the prediction of dog resemb
        dog_resemble = predict_breed_transfer(img_path)
        title = 'hello human'
```

```
            user_promt = title+"\nI think you look like a dog breed called "+dog_resemble
            print(user_promt)
            display(img_path)

        else: #if neither is detected
            title = "There\'s no dog or human detected in the image"
            print(title)
            display(img_path)
```

Step 6: Test Your Algorithm

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

1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

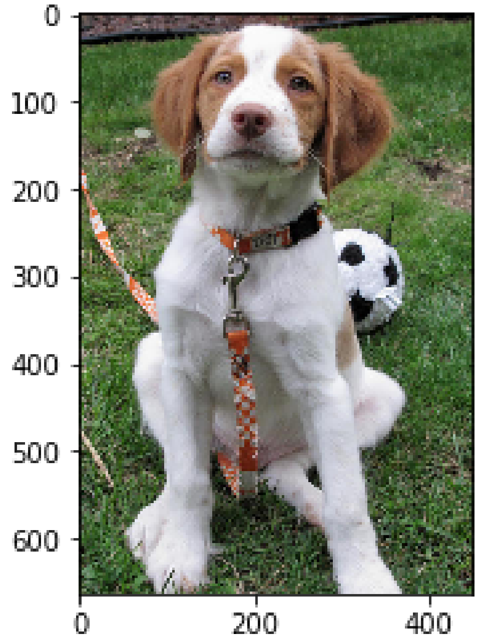
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

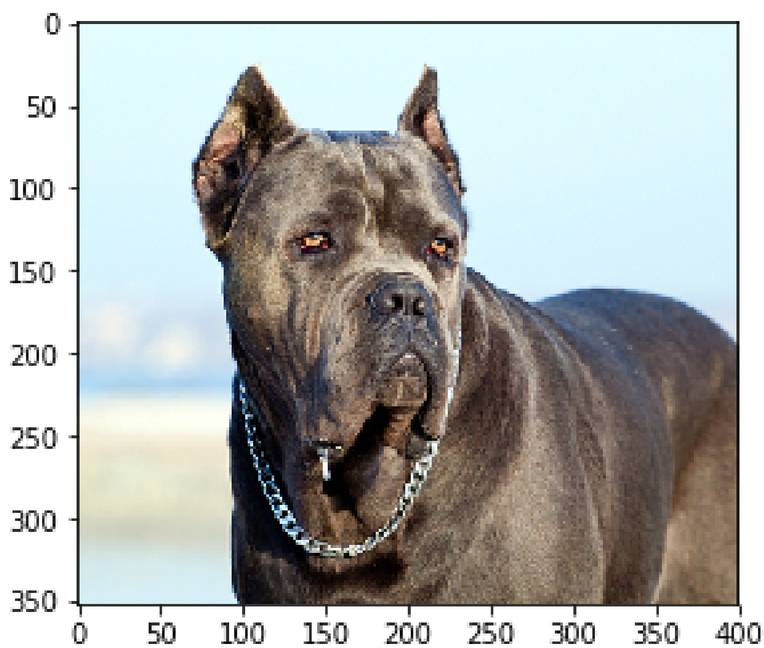
Answer: (Three possible points for improvement) 1. would use another pretrained model, which may take less training time and resouces with a low accuracy. 2. would try learning rate decay, using reschedulers or any learning deacy methods. 3. Would try different optimizer like adam, and the rest out there which may improve the accuracy

```
In [40]: ## 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
         run_app("/home/workspace/dog_project/images/Brittany.jpg")
         run_app("/home/workspace/dog_project/images/dog2.jpg")
         run_app("/home/workspace/dog_project/images/dog1.jpg")

         run_app("/home/workspace/dog_project/images/human1.JPG")
         run_app("/home/workspace/dog_project/images/human2.JPG")

         run_app("/home/workspace/dog_project/images/cat.jpg")
         run_app("/home/workspace/dog_project/images/monkey.jpg")
```

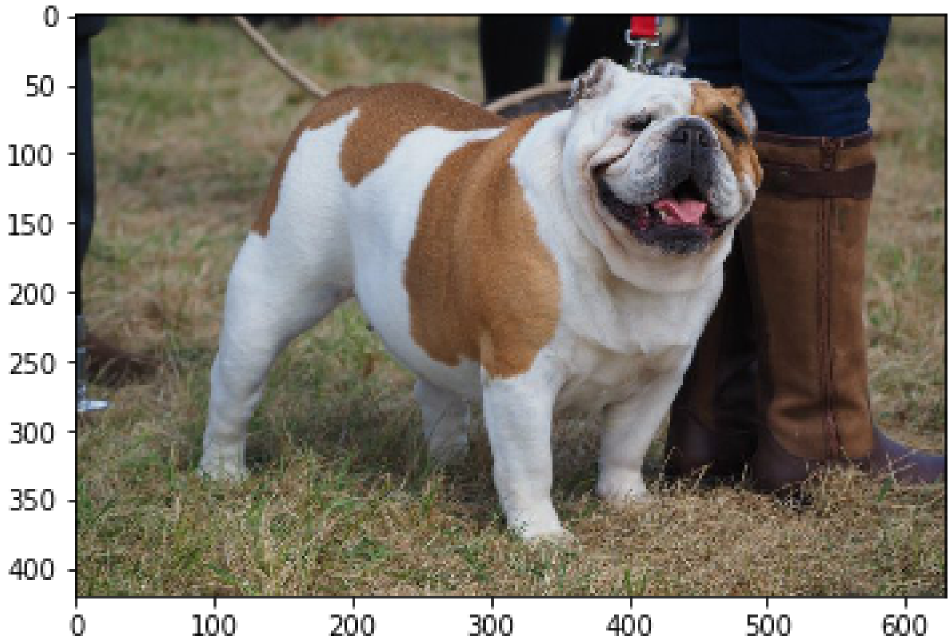
```
A dog is detected and its breed is Dachshund
```



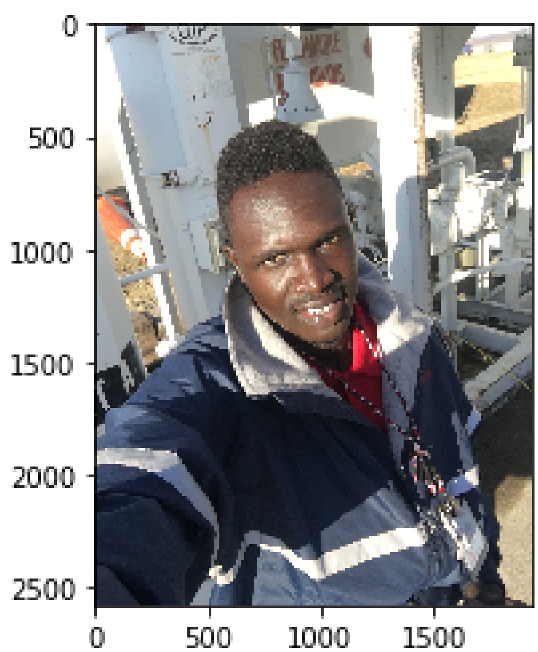

```
A dog is detected and its breed is Portuguese water dog
```



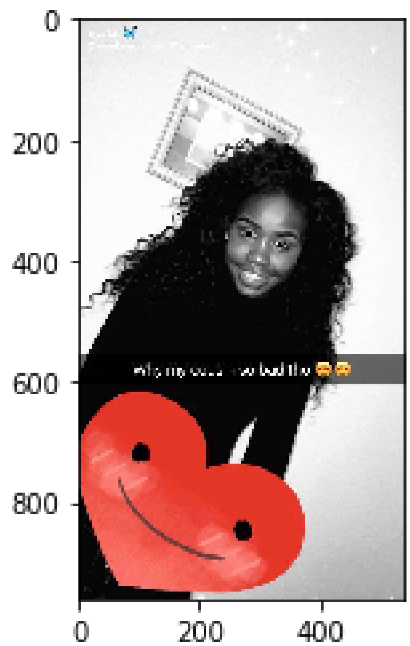
```
A dog is detected and its breed is English cocker spaniel
```



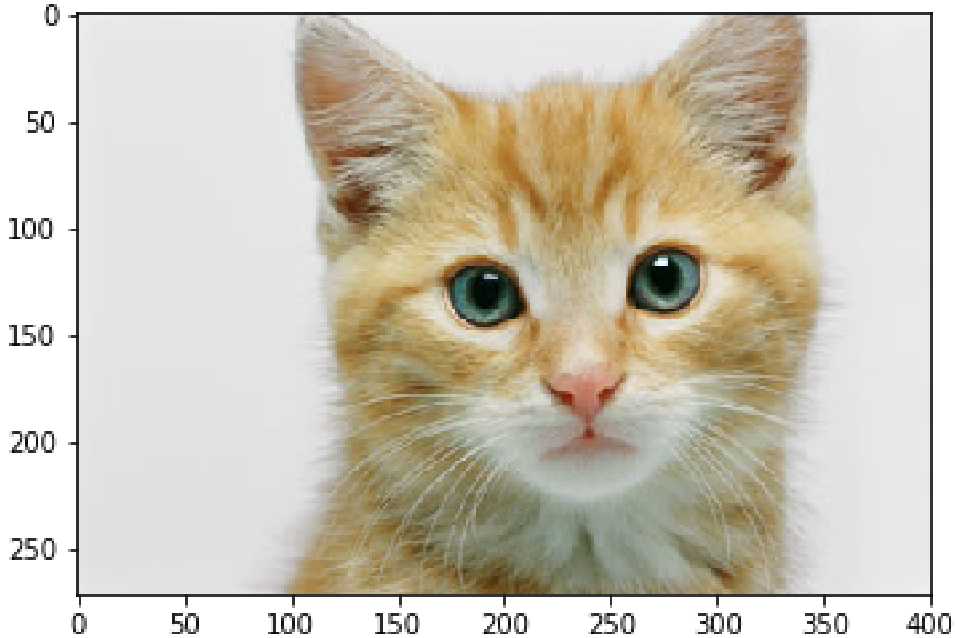
```
hello human
I think you look like a dog breed called Field spaniel
```



```
hello human
I think you look like a dog breed called Bullmastiff
```




```
There's no dog or human detected in the image
```




```
There's no dog or human detected in the image
```