dog_app

March 31, 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 [31]:
```
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

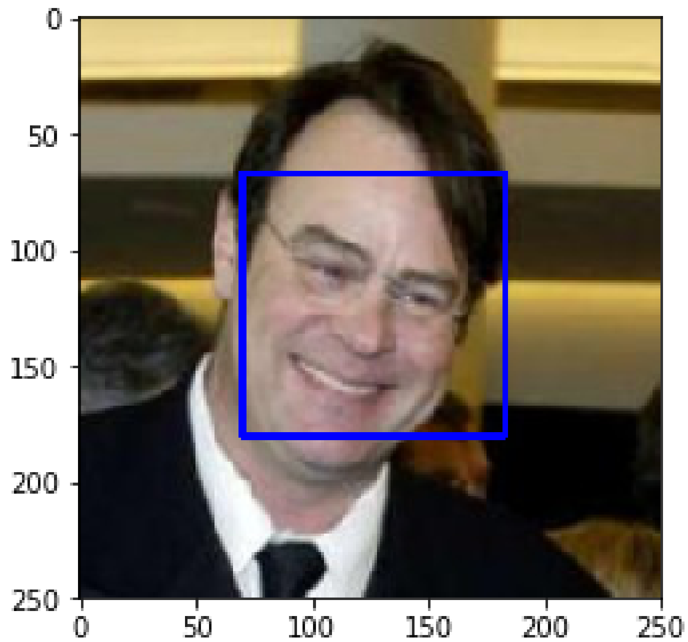
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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 [32]:
```
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 [33]: # 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 [34]: #Create a function to generate number of true entries in a boolean matrix. Algorithm co

         def number_true(array):
             count = 0
             for i in array:
                 if i == True:
                     count +=1
             return count

         #assign result to variable, otherwise count is destroyed after function concludes
         x = number_true([True, False, True])

         percentageCorrect = x/3

         print(percentageCorrect)
```

```
0.6666666666666666
```

```
In [35]: 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.

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

         #vectorize and create a boolean matrix for both human_files and dog_files. Creates matr
```

```
x = lambda x: face_detector(x)

truefalsearray= np.vectorize(x)

array1 = truefalsearray(human_files_short)

array2 = truefalsearray(dog_files_short)

#Apply the function to both arrays and print out the results

count1 = number_true(array1)

percentageCorrect1 = count1/len(array1)

count2 = number_true(array2)

percentageCorrect2 = count2/len(array2)


#Output the total percentage of correct classifications
print("The Percentage of Correct Classifications for humans is", percentageCorrect1, "%

print("The Percentage of Correct Classifications for dogs is", percentageCorrect2, "%")
```

```
The Percentage of Correct Classifications for humans is 0.98 %
The Percentage of Correct Classifications for dogs is 0.17 %
```

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

```
In [36]: ### (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 [37]: import torch
         import torchvision.models as models

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

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

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

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

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

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

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

```
In [38]: #import for use of imshow function. File was used in udacity pytorch challenge

         #imports for image processing
         import PIL
         from PIL import Image
         from PIL import PngImagePlugin

         #imports for data transformation
         import torchvision.transforms as transforms
```

```
In [39]: # From pytorch udacity challenge. Preprocess an image using transforms.

         # Transform the image to tensor
         def process_image(image):
             ''' Scales, crops, and normalizes a PIL image for a PyTorch model,
                 returns an Numpy array
             '''

             # TODO: Process a PIL image for use in a PyTorch model

             img = Image.open(image)
             img_loader = transforms.Compose([transforms.Resize(256),
                                              transforms.CenterCrop(224),
                                              transforms.ToTensor(),
```

```
                                                transforms.Normalize([.485, .456, .406],
                                                                     [.229, .224, .225])])
    img = img_loader(img)
    img = np.array(img)
    return img
```

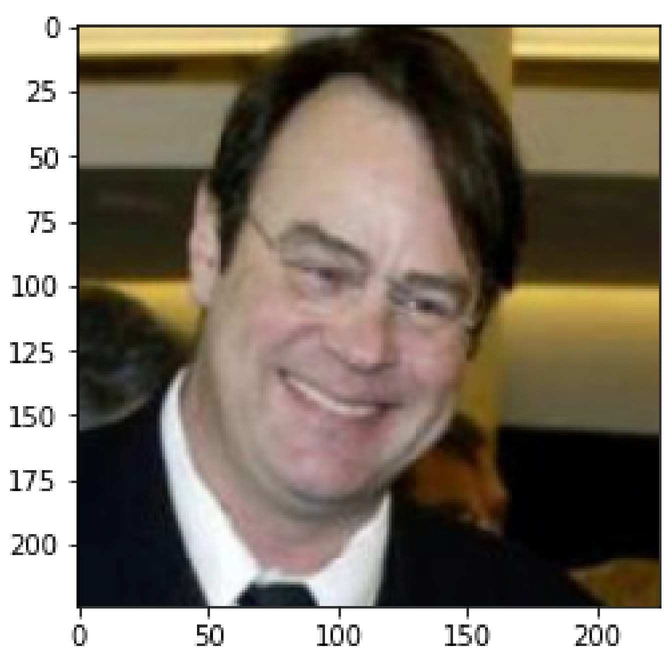
In [40]:
```
#Now this needs to be transformed into a pytorch tensor to be used by the VGG network.

#transform image form numpy to torch tensor
x = process_image(human_files[0])

x = torch.from_numpy(x).float()

x
```

Out[40]:
```
tensor([[[ 1.9235,  1.9407,  1.9407,  ...,  1.9920,  2.0092,  2.0092],
         [ 1.9235,  1.9407,  1.9235,  ...,  2.0092,  2.0092,  2.0092],
         [ 1.8722,  1.8893,  1.8722,  ...,  1.9749,  1.9749,  1.9749],
         ...,
         [-1.9809, -1.9809, -1.9638,  ..., -0.6452, -0.6623, -0.7479],
         [-1.9809, -1.9809, -1.9638,  ..., -0.6109, -0.6452, -0.7308],
         [-1.9809, -1.9638, -1.9638,  ..., -0.5767, -0.6109, -0.7479]],

        [[ 1.7108,  1.7108,  1.7108,  ...,  1.7633,  1.7808,  1.7808],
         [ 1.6933,  1.7108,  1.6933,  ...,  1.7808,  1.7808,  1.7808],
         [ 1.6408,  1.6583,  1.6408,  ...,  1.7458,  1.7458,  1.7458],
         ...,
         [-1.8431, -1.8431, -1.8256,  ..., -0.9503, -0.9328, -1.0028],
         [-1.8431, -1.8431, -1.8256,  ..., -0.9503, -0.9328, -1.0203],
         [-1.8431, -1.8256, -1.8256,  ..., -0.9328, -0.9503, -1.0553]],

        [[ 0.7576,  0.7402,  0.7402,  ...,  0.6531,  0.6705,  0.6705],
         [ 0.7402,  0.7402,  0.7228,  ...,  0.6705,  0.6705,  0.6705],
         [ 0.6705,  0.6879,  0.6705,  ...,  0.6356,  0.6356,  0.6356],
         ...,
         [-1.4559, -1.4559, -1.4384,  ..., -1.5779, -1.5779, -1.6476],
         [-1.4559, -1.4559, -1.4384,  ..., -1.5779, -1.5779, -1.6476],
         [-1.4559, -1.4384, -1.4384,  ..., -1.5604, -1.5953, -1.6999]]])
```

In [41]:
```
#I want to see what the actual image looks like. Lets use the helper.py file and the im


def imshow(image, ax=None, title=None):
    """Imshow for Tensor."""
    if ax is None:
        fig, ax = plt.subplots()

    # PyTorch tensors assume the color channel is the first dimension
```

```
    # but matplotlib assumes is the third dimension
    image = image.numpy().transpose((1, 2, 0))

    # Undo preprocessing
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    image = std * image + mean

    # Image needs to be clipped between 0 and 1 or it looks like noise when displayed
    image = np.clip(image, 0, 1)

    ax.imshow(image)

    return ax

imshow(x)
```

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1adc162208>



In [42]:
```
from PIL import Image
import torchvision.transforms as transforms

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

```
    Args:
        img_path: path to an image

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

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image
    img = process_image(img_path)

    img = torch.from_numpy(img)

    #This line is important. Adds an extra singleton dimension so that convolutional ne
    img = img.unsqueeze_(0)

    #move image to the GPU
    if use_cuda:
        img = img.to('cuda')

    output = VGG16(img)

    _, preds_tensor = torch.max(output, 1)

    preds= np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tenso

    return preds # predicted class index
```

In [43]:
```
#Test the image function above with a sample image
VGG16_predict(human_files[0])
```

Out[43]:
```
array(834)
```

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 [44]:
```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    img = process_image(img_path)
```

```
            img = torch.from_numpy(img)

            #This line is important. Adds an extra singleton dimension so that convolutional ne
            img = img.unsqueeze_(0)

            #move to GPU
            if use_cuda:
                img = img.to('cuda')

            output = VGG16(img)

            _, preds_tensor = torch.max(output, 1)

            preds= np.squeeze(preds_tensor.cuda().numpy()) if not use_cuda else np.squeeze(pred

            dog_indices =  list(range(151, 269))

            if preds in dog_indices:
                Boolean = True
            else:
                Boolean = False# predicted class index

            return Boolean # true/false
```

```
In [45]: #test the dog_detector on one image from each before extrapolating to whole dataset.

         #We expect true for dog_files and false for human_files

         Dog = dog_detector(dog_files_short[1])

         print("The Boolean for Dog is: ", Dog)

         Human = dog_detector(human_files_short[2])

         print("The Boolean for Human is: ", Human)
```

```
The Boolean for Dog is:  True
The Boolean for Human is:  False
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

Answer:

```
In [46]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

         #vectorize and create a boolean matrix for both human_files and dog_files.
         x = lambda x: dog_detector(x)

         truefalsearray= np.vectorize(x)

         array1 = truefalsearray(human_files_short)

         totaltrue1 = number_true(array1)

         percentageCorrect1 = totaltrue1/len(array1)

         array2 = truefalsearray(dog_files_short)

         totaltrue2 = number_true(array2)

         percentageCorrect2 = totaltrue2/len(array2)


         print("The total correct percentage classification for humans is: ", percentageCorrect1

         print("The total correct percentage classification is dogs is: ", percentageCorrect2)
```

```
The total correct percentage classification for humans is:  0.02
The total correct percentage classification is dogs is:  1.0
```

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 [47]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.
```

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)

Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 10%. In Step 4 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

We mention that the task of assigning breed to dogs from images is considered exceptionally challenging. To see why, consider that *even a human* would have trouble distinguishing between a Brittany and a Welsh Springer Spaniel.

Brittany	Welsh Springer Spaniel

It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).

Curly-Coated Retriever	American Water Spaniel

Likewise, recall that labradors come in yellow, chocolate, and black. Your vision-based algorithm will have to conquer this high intra-class variation to determine how to classify all of these different shades as the same breed.

Yellow Labrador	Chocolate Labrador

We also mention that random chance presents an exceptionally low bar: setting aside the fact that the classes are slightly imabalanced, a random guess will provide a correct answer roughly 1 in 133 times, which corresponds to an accuracy of less than 1%.

Remember that the practice is far ahead of the theory in deep learning. Experiment with many different architectures, and trust your intuition. And, of course, have fun!

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

In [11]:
```
# importing required modules
from zipfile import ZipFile

# specifying the zip file name
file_name = "dogImages.zip"

# opening the zip file in READ mode
with ZipFile(file_name, 'r') as zip:
    # printing all the contents of the zip file
    zip.printdir()

    # extracting all the files
    print('Extracting all the files now...')
    zip.extractall()
    print('Done!')
```

```
---------------------------------------------------------------------------

FileNotFoundError                         Traceback (most recent call last)

<ipython-input-11-0edcf8d3f2c3> in <module>()
      7 
      8 # opening the zip file in READ mode
----> 9 with ZipFile(file_name, 'r') as zip:
     10     # printing all the contents of the zip file
     11     zip.printdir()


/opt/conda/lib/python3.6/zipfile.py in __init__(self, file, mode, compression, allowZip6
   1088             while True:
   1089                 try:
-> 1090                     self.fp = io.open(file, filemode)
   1091                 except OSError:
   1092                     if filemode in modeDict:


FileNotFoundError: [Errno 2] No such file or directory: 'dogImages.zip'
```

In [48]:
```python
import os
from torchvision import transforms
from torchvision import datasets
from torch.utils.data.sampler import SubsetRandomSampler

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

# number of subprocesses to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 20
# percentage of training set to use as validation
valid_size = 0.2

# convert data to a normalized torch.FloatTensor

transforms1 = transforms.Compose([
                transforms.Resize(256),
                transforms.CenterCrop(224),
                transforms.ToTensor(),
                transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])
```

```
transforms2 = transforms.Compose([transforms.RandomHorizontalFlip(45),
    transforms.RandomVerticalFlip(p=.25),
    transforms.Resize(256),
     transforms.CenterCrop(224),
     transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
     ])



 # choose the training and test datasets
train_data = datasets.ImageFolder('dogImages/train', transform = transforms2)

valid_data = datasets.ImageFolder('dogImages/valid', transform = transforms1)

test_data = datasets.ImageFolder('dogImages/test', transform = transforms1)

# obtain training indices that will be used for validation
#num_train = len(train_data)
#indices = list(range(num_train))
#np.random.shuffle(indices)
#split = int(np.floor(valid_size * num_train))
#train_idx, valid_idx = indices[split:], indices[:split]

# define samplers for obtaining training and validation batches
#train_sampler = SubsetRandomSampler(train_idx)
#valid_sampler = SubsetRandomSampler(valid_idx)

# prepare data loaders (combine dataset and sampler)
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,  shuffle
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size)

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: resizing is done by resizing image to 256 and then cropping to 224 for all datasets.

input tensor: 224 x 224 x 3 x 1

The image size is 224 x 224

3 comes from the number of color channels: red, green and blue

1 comes from the singleton dimension needed so that the image can be accepted by the network.

Augmenting the dataset was done with random vertical flips and random horizontal flips at 45 degrees. This creates a bigger dataset that can be used by the network.

1.1.8 (IMPLEMENTATION) Model Architecture

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

In [68]:
```
import torch.nn as nn
import torch.nn.functional as F


hidden_1 = 6280

hidden_2 = 6280

num_classes = 133

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN

        #convolutional layer (sees 224 x 224 x 3)
        self.conv1 = nn.Conv2d(3, 16, 3, padding = 1)

        #convolutional layer (sees 112 x 112 x 16 )
        self.conv2 = nn.Conv2d(16,32, 3, padding = 1 )

        #convolutional layer( sees 56 x 56 x 32)
        self.conv3 = nn.Conv2d(32, 64,3, padding = 1)

        #convolutional layer (sees 28 x 28 x 64)
        self.conv4 = nn.Conv2d(64, 128, 3, padding = 1 )

        #convolutional layer (sees 14 x 14 x 128)
        self.conv5 = nn.Conv2d(128, 256, 3, padding = 1)

        #Define a maxpool block to reduce dimensionality
        self.pool = nn.MaxPool2d(2,2)

        #Batchnorm layer

        self.conv1_bn = nn.BatchNorm2d(16)

        self.conv2_bn = nn.BatchNorm2d(32)

        self.conv3_bn = nn.BatchNorm2d(64)

        self.conv4_bn = nn.BatchNorm2d(128)
```

```
        self.conv5_bn = nn.BatchNorm2d(256)

        #Linear Layer 1 (depth of layer * x dim * y dim, hidden1)
        self.fc1 = nn.Linear(256*7*7, hidden_1)

        #Linear Layer 2 (hidden1 -> hidden 2)
        self.fc2 = nn.Linear(hidden_1, hidden_2)

        #Linear layer 3 (hidden_2 -> num_classes)

        self.fc3 = nn.Linear(hidden_2, num_classes)

        self.dropout = nn.Dropout(.75)


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

        x = self.pool(F.relu(self.conv1_bn(self.conv1(x))))
        x = self.pool(F.relu(self.conv2_bn(self.conv2(x))))
        x = self.pool(F.relu(self.conv3_bn(self.conv3(x))))
        x = self.pool(F.relu(self.conv4_bn(self.conv4(x))))
        x = self.pool(F.relu(self.conv5_bn(self.conv5(x))))

        # flatten image input

        x = x.view(-1, 256*7*7)

        #x = x.view(x.size(0), -1)
        #add dropout layer
        x = self.dropout(x)

        #Add first hidden layer
        x = F.relu(self.fc1(x))

        #add second layer
        x = F.relu(self.fc2(x))

        #add final layer
        x = F.relu(self.fc3(x))

        return x

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

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

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

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

Answer:

Defining the convolutional layers comes first. I thought of creating 5 convolutional layers to capture as much spatial information as possible without overfitting. The 5 convolutional layers will reduce the size of the image from 224 x 224 x 3 to 256 * 7 * 7. So the depth of the image is 256 and the image x and y dimensions are 7 and 7. The maxpool layer downsizes the image by 2 in dimensions. I chose 2 because it evenly divides the size of the picture for all the layers. I applied batch normalization to all the convolutional layers. This allows the layers to learn more independently of each other. The next step is the linear layers. There are three layers after the convolutional layers. The first hidden layer takes an input of 256 * 7 * 7 and goes to a hidden layer 1 that is half of the size of the input. From hidden layer 1 to hidden layer 2 its the same size. From hidden layer 2 it goes to the num of classes which is 133. I added a dropout of p = .75 to prevent overfitting. The overfitting tended to be aggressive so I had to make this value high.

```
In [49]: from PIL import ImageFile

         ImageFile.LOAD_TRUNCATED_IMAGES = True
```

1.1.9 (IMPLEMENTATION) Specify Loss Function and Optimizer

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

```
In [50]: import torch.optim as optim


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

         ### TODO: select optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr = .01)


        ---------------------------------------------------------------------------

        NameError                                 Traceback (most recent call last)

        <ipython-input-50-1ca6ac024c0f> in <module>()
          6
          7 ### TODO: select optimizer
    ----> 8 optimizer_scratch = optim.SGD(model_scratch.parameters(), lr = .01)


        NameError: name 'model_scratch' is not defined
```

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 [16]:
```
def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
    """returns trained model"""
    # initialize tracker for minimum validation loss
    valid_loss_min = np.Inf

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

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo

            #clear all gradients of all optimized variables
            optimizer.zero_grad()


            #forward pass: compute predicted outputs by passing inputs to the model
            output = model(data)

            #calculate the loss after each epoch
            loss = criterion(output, target)

            # backward pass: compute gradient of the loss with respect to model paramet
            loss.backward()

             # perform a single optimization step (parameter update)
            optimizer.step()

            #calculate average training loss
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss)
        ######################
        # validate the model #
        ######################
        model.eval()
```

```
            for batch_idx, (data, target) in enumerate(loaders['valid']):
                # move to GPU
                if use_cuda:
                    data, target = data.cuda(), target.cuda()

                output = model.forward(data)

                loss = criterion(output, target)

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

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

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

                torch.save(model.state_dict(), 'model_scratch.pt')

                valid_loss_min = valid_loss


        # return trained model
        return model


    # train the model
    model_scratch = train(100, 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: 4.885881         Validation Loss: 4.871780
Validation loss decreased (inf --> 4.871780). Saving model ...
Epoch: 2         Training Loss: 4.863862         Validation Loss: 4.847791
Validation loss decreased (4.871780 --> 4.847791). Saving model ...
Epoch: 3         Training Loss: 4.836558         Validation Loss: 4.816994
Validation loss decreased (4.847791 --> 4.816994). Saving model ...
Epoch: 4         Training Loss: 4.794854         Validation Loss: 4.765638
```

```
Validation loss decreased (4.816994 --> 4.765638). Saving model ...
Epoch: 5        Training Loss: 4.733595        Validation Loss: 4.698181
Validation loss decreased (4.765638 --> 4.698181). Saving model ...
Epoch: 6        Training Loss: 4.646353        Validation Loss: 4.627349
Validation loss decreased (4.698181 --> 4.627349). Saving model ...
Epoch: 7        Training Loss: 4.579050        Validation Loss: 4.653726
Epoch: 8        Training Loss: 4.534204        Validation Loss: 4.574209
Validation loss decreased (4.627349 --> 4.574209). Saving model ...
Epoch: 9        Training Loss: 4.489618        Validation Loss: 4.616945
Epoch: 10        Training Loss: 4.444829        Validation Loss: 4.569105
Validation loss decreased (4.574209 --> 4.569105). Saving model ...
Epoch: 11        Training Loss: 4.403931        Validation Loss: 4.542284
Validation loss decreased (4.569105 --> 4.542284). Saving model ...
Epoch: 12        Training Loss: 4.349702        Validation Loss: 4.544345
Epoch: 13        Training Loss: 4.290429        Validation Loss: 4.489958
Validation loss decreased (4.542284 --> 4.489958). Saving model ...
Epoch: 14        Training Loss: 4.228899        Validation Loss: 4.382352
Validation loss decreased (4.489958 --> 4.382352). Saving model ...
Epoch: 15        Training Loss: 4.166518        Validation Loss: 4.345833
Validation loss decreased (4.382352 --> 4.345833). Saving model ...
Epoch: 16        Training Loss: 4.115632        Validation Loss: 4.598235
Epoch: 17        Training Loss: 4.063317        Validation Loss: 4.455419
Epoch: 18        Training Loss: 4.013216        Validation Loss: 4.357820
Epoch: 19        Training Loss: 3.962344        Validation Loss: 4.258581
Validation loss decreased (4.345833 --> 4.258581). Saving model ...
Epoch: 20        Training Loss: 3.908684        Validation Loss: 4.392301
Epoch: 21        Training Loss: 3.859600        Validation Loss: 4.392736
Epoch: 22        Training Loss: 3.785444        Validation Loss: 4.137693
Validation loss decreased (4.258581 --> 4.137693). Saving model ...
Epoch: 23        Training Loss: 3.743584        Validation Loss: 4.239990
Epoch: 24        Training Loss: 3.690438        Validation Loss: 4.224137
Epoch: 25        Training Loss: 3.620386        Validation Loss: 4.217593
Epoch: 26        Training Loss: 3.564887        Validation Loss: 4.336804
Epoch: 27        Training Loss: 3.475382        Validation Loss: 4.122360
Validation loss decreased (4.137693 --> 4.122360). Saving model ...
Epoch: 28        Training Loss: 3.431602        Validation Loss: 4.152305
Epoch: 29        Training Loss: 3.373595        Validation Loss: 4.283181
Epoch: 30        Training Loss: 3.309971        Validation Loss: 4.131425
Epoch: 31        Training Loss: 3.279777        Validation Loss: 3.945060
Validation loss decreased (4.122360 --> 3.945060). Saving model ...
Epoch: 32        Training Loss: 3.228582        Validation Loss: 4.148028
Epoch: 33        Training Loss: 3.161027        Validation Loss: 4.294967
Epoch: 34        Training Loss: 3.106294        Validation Loss: 4.137928
Epoch: 35        Training Loss: 3.047109        Validation Loss: 4.018641
Epoch: 36        Training Loss: 2.980718        Validation Loss: 3.917309
Validation loss decreased (3.945060 --> 3.917309). Saving model ...
Epoch: 37        Training Loss: 2.927348        Validation Loss: 3.872347
Validation loss decreased (3.917309 --> 3.872347). Saving model ...
```

```
Epoch: 38         Training Loss: 2.886775         Validation Loss: 4.206933
Epoch: 39         Training Loss: 2.817142         Validation Loss: 3.995087
Epoch: 40         Training Loss: 2.752473         Validation Loss: 4.924351
```

```
    ---------------------------------------------------------------------------

    KeyboardInterrupt                         Traceback (most recent call last)

    <ipython-input-16-45acc30012be> in <module>()
     79 # train the model
     80 model_scratch = train(100, loaders_scratch, model_scratch, optimizer_scratch,
---> 81                       criterion_scratch, use_cuda, 'model_scratch.pt')
     82
     83 # load the model that got the best validation accuracy


    <ipython-input-16-45acc30012be> in train(n_epochs, loaders, model, optimizer, criterion,
     13         ###################
     14         model.train()
---> 15         for batch_idx, (data, target) in enumerate(loaders['train']):
     16             # move to GPU
     17             if use_cuda:


    /opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in __next__(self)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)


    /opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in <listcomp>(.0)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)


    /opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
    101         sample = self.loader(path)
    102         if self.target_transform is not None:
--> 103             sample = self.transform(sample)
    104         if self.target_transform is not None:
    105             target = self.target_transform(target)
```

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/transform
 47     def __call__(self, img):
 48         for t in self.transforms:
---> 49             img = t(img)
 50         return img
 51


/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/transform
173             PIL Image: Rescaled image.
174         """
--> 175         return F.resize(img, self.size, self.interpolation)
176
177     def __repr__(self):


/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/transform
202             oh = size
203             ow = int(size * w / h)
--> 204             return img.resize((ow, oh), interpolation)
205     else:
206         return img.resize(size[::-1], interpolation)


/opt/conda/lib/python3.6/site-packages/PIL/Image.py in resize(self, size, resample)
1710             return self.convert('RGBa').resize(size, resample).convert('RGBA')
1711
-> 1712         return self._new(self.im.resize(size, resample))
1713
1714     def rotate(self, angle, resample=NEAREST, expand=0, center=None,


KeyboardInterrupt:
```

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 [17]: 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: 4.194744


Test Accuracy: 16% (135/836)
```

Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)
You will now use transfer learning to create a CNN that can identify dog breed from images. Your CNN must attain at least 60% accuracy on the test set.

1.1.12 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dogImages/train`, `dogImages/valid`, and `dogImages/test`, respectively).

If you like, **you are welcome to use the same data loaders from the previous step**, when you created a CNN from scratch.

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

```python
import os
from torchvision import transforms
from torchvision import datasets
from torch.utils.data.sampler import SubsetRandomSampler

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

# number of subprocesses to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 32
# percentage of training set to use as validation
valid_size = 0.2

# convert data to a normalized torch.FloatTensor

transforms1 = transforms.Compose([
                transforms.Resize(256),
                transforms.CenterCrop(224),
                transforms.ToTensor(),
                transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

transforms2 = transforms.Compose([transforms.RandomHorizontalFlip(45),
    transforms.RandomVerticalFlip(p=.25),
    transforms.Resize(256),
     transforms.CenterCrop(224),
     transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
     ])



 # choose the training and test datasets
train_data = datasets.ImageFolder('dogImages/train', transform = transforms2)

valid_data = datasets.ImageFolder('dogImages/valid', transform = transforms1)

test_data = datasets.ImageFolder('dogImages/test', transform = transforms1)

# obtain training indices that will be used for validation
#num_train = len(train_data)
#indices = list(range(num_train))
#np.random.shuffle(indices)
#split = int(np.floor(valid_size * num_train))
#train_idx, valid_idx = indices[split:], indices[:split]
```

```
    # define samplers for obtaining training and validation batches
    #train_sampler = SubsetRandomSampler(train_idx)
    #valid_sampler = SubsetRandomSampler(valid_idx)

    # prepare data loaders (combine dataset and sampler)
    train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,  shuffle =
    valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size)
    test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size)

    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 [11]: import torch
         import torchvision.models as models
         import torch.nn as nn

         ## TODO: Specify model architecture
         model_transfer = models.resnet152(pretrained=True)

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



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



         classifier = nn.Sequential(nn.Linear(2048, 133))


         model_transfer.fc = classifier


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

```
Downloading: "https://download.pytorch.org/models/resnet152-b121ed2d.pth" to /root/.torch/models
100%|| 241530880/241530880 [00:02<00:00, 81666186.57it/s]
```

```
In [12]: #for param in model_transfer.parameters():
         #    param.requires_grad = False
```

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

From the pytorch challenge, great results were acquired from resnet152. The final classifier layer will be deleted and replaced with a linear layer to take an input of 2048 features and output of 133 which is the num of classes. the pretrained model's parameters for all layers besides the fc classifier will be frozen with param.requires_grad = False.

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 [13]: import torch.optim as optim

         criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.fc.parameters(), lr = .01)
```

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

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

                 ###################
                 # train the model #
                 ###################
                 model.train()
                 for batch_idx, (data, target) in enumerate(loaders['train']):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## find the loss and update the model parameters accordingly
                     ## record the average training loss, using something like
                     ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo

                     #clear all gradients of all optimized variables
```

```
        optimizer.zero_grad()


        #forward pass: compute predicted outputs by passing inputs to the model
        output = model(data)

        #calculate the loss after each epoch
        loss = criterion(output, target)

        # backward pass: compute gradient of the loss with respect to model paramet
        loss.backward()

         # perform a single optimization step (parameter update)
        optimizer.step()

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

        output = model.forward(data)

        loss = criterion(output, target)

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

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

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

        torch.save(model.state_dict(), 'model_transfer.pt')
```

```
                valid_loss_min = valid_loss

        # return trained model
        return model
```

In [22]:
```
# train the model
model_transfer =  train(10, loaders_transfer, model_transfer, optimizer_transfer, crite

# 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: 0.566293         Validation Loss: 0.368341
Validation loss decreased (inf --> 0.368341). Saving model ...
Epoch: 2        Training Loss: 0.547878         Validation Loss: 0.368949
Epoch: 3        Training Loss: 0.543130         Validation Loss: 0.366751
Validation loss decreased (0.368341 --> 0.366751). Saving model ...
Epoch: 4        Training Loss: 0.546110         Validation Loss: 0.360248
Validation loss decreased (0.366751 --> 0.360248). Saving model ...
Epoch: 5        Training Loss: 0.539950         Validation Loss: 0.367883
```

```
    ---------------------------------------------------------------------------

    KeyboardInterrupt                         Traceback (most recent call last)

    <ipython-input-22-032006872482> in <module>()
      1
      2 # train the model
----> 3 model_transfer =  train(10, loaders_transfer, model_transfer, optimizer_transfer, cr
      4
      5 # load the model that got the best validation accuracy (uncomment the line below)


    <ipython-input-19-93455affad30> in train(n_epochs, loaders, model, optimizer, criterion,
     43         ######################
     44         model.eval()
---> 45         for batch_idx, (data, target) in enumerate(loaders['valid']):
     46             # move to GPU
     47             if use_cuda:


    /opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in __next__(self)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
```

```
    266                 batch = pin_memory_batch(batch)


    /opt/conda/lib/python3.6/site-packages/torch/utils/data/dataloader.py in <listcomp>(.0)
    262         if self.num_workers == 0:  # same-process loading
    263             indices = next(self.sample_iter)  # may raise StopIteration
--> 264             batch = self.collate_fn([self.dataset[i] for i in indices])
    265             if self.pin_memory:
    266                 batch = pin_memory_batch(batch)


    /opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
     99         """
    100         path, target = self.samples[index]
--> 101         sample = self.loader(path)
    102         if self.transform is not None:
    103             sample = self.transform(sample)


    /opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
    145         return accimage_loader(path)
    146     else:
--> 147         return pil_loader(path)
    148
    149


    /opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/datasets/
    128     with open(path, 'rb') as f:
    129         img = Image.open(f)
--> 130         return img.convert('RGB')
    131
    132


    /opt/conda/lib/python3.6/site-packages/PIL/Image.py in convert(self, mode, matrix, dithe
    858                 return self.copy()
    859
--> 860         self.load()
    861
    862         if matrix:


    /opt/conda/lib/python3.6/site-packages/PIL/ImageFile.py in load(self)
    232
    233                         b = b + s
--> 234                         n, err_code = decoder.decode(b)
    235                         if n < 0:
```

```
    236                               break

    KeyboardInterrupt:
```

```
In [14]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

1.1.16 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 60%.

```
In [15]: 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))
```

```
In [18]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.378318


Test Accuracy: 89% (747/836)
```

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 [37]:
```
class_names = [item[4:].replace("_", " ") for item in test_data.classes]

print(class_names[6])
```

```
American foxhound
```

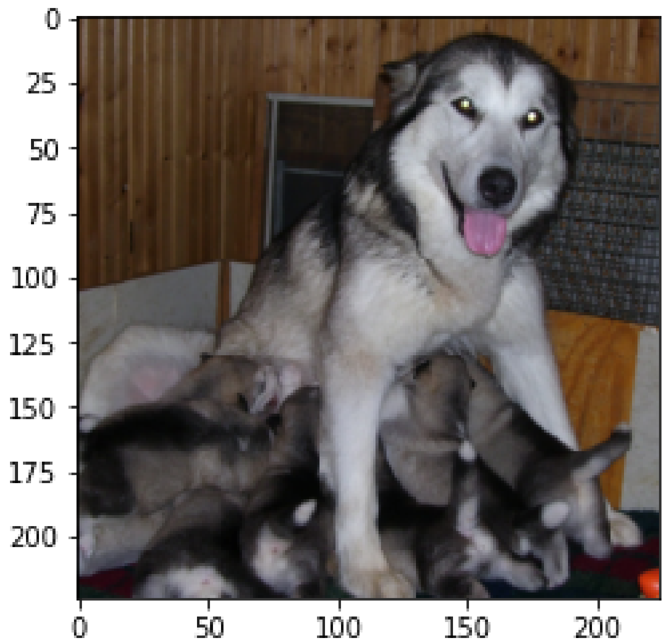
In [27]:
```
### TODO: Write a function that takes a path to an image as input
### and returns the dog breed that is predicted by the model.

# 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 test_data.classes]

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

    '''
    Use pre-trained VGG-16 model to obtain index corresponding to
    predicted ImageNet class for image at specified path

    Args:
        img_path: path to an image

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

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image
    img = process_image(img_path)

    img = torch.from_numpy(img)

    #This line is important. Adds an extra singleton dimension so that convolutional ne
    img = img.unsqueeze_(0)

    #move image to the GPU
    if use_cuda:
        img = img.to('cuda')

    output = model_transfer(img)

    _, preds_tensor = torch.max(output, 1)
```

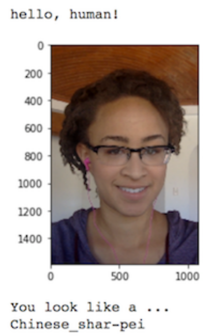
```
        preds= np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tenso

        preds = class_names[preds]


        return preds # predicted class index
```

```
In [28]: x= predict_breed_transfer(dog_files[968])

         print(x)

         y = process_image(dog_files[968])

         y = torch.from_numpy(y)

         imshow(y)
```

```
Smooth fox terrier
```

```
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1adc9c5208>
```





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 [29]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.

def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    if face_detector(img_path) == True:
        print("you are a human")

        x = process_image(img_path)

        x = torch.from_numpy(x).float()

        imshow(x)

        print("You look like a ... ")
        print(predict_breed_transfer(img_path))

    elif dog_detector(img_path) == True:
        print("you are a dog!")

        x = process_image(img_path)
```

```
            x = torch.from_numpy(x).float()

            imshow(x)

            print("You look like a ... ")

            print(predict_breed_transfer(img_path))
        else:
            print("I am not sure what you are!")

            x = process_image(img_path)

            x = torch.from_numpy(x).float()

            imshow(x)

            print("You look like a ... ")

            print(predict_breed_transfer(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)

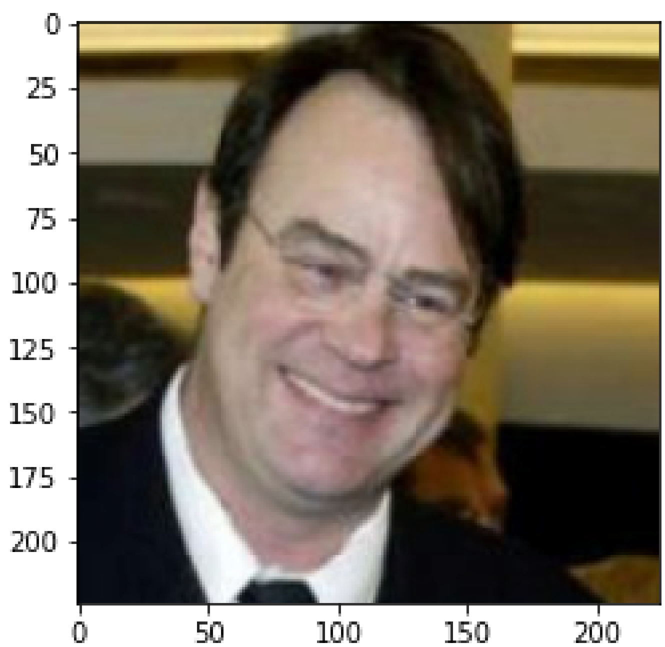
1. Sandwich the image between the print statements.
2. have the images horizontally placed instead of vertically.
3. Train the network more for more accurate results.

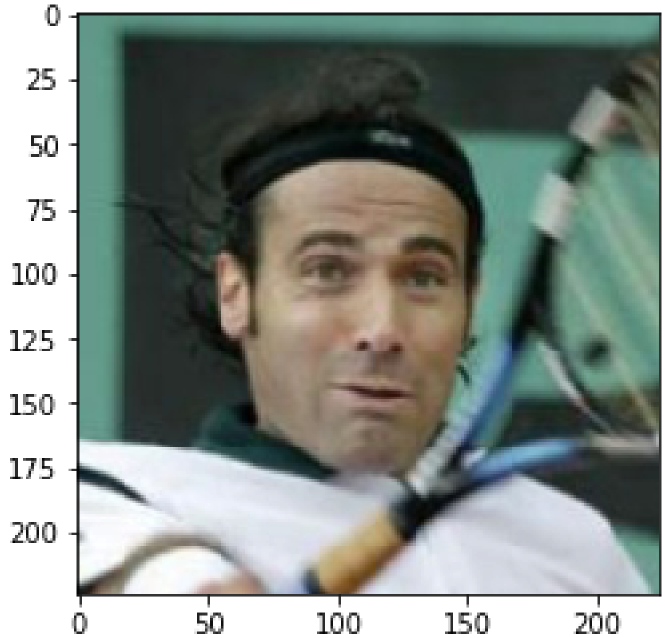
All in all, output is not what I was hoping for.

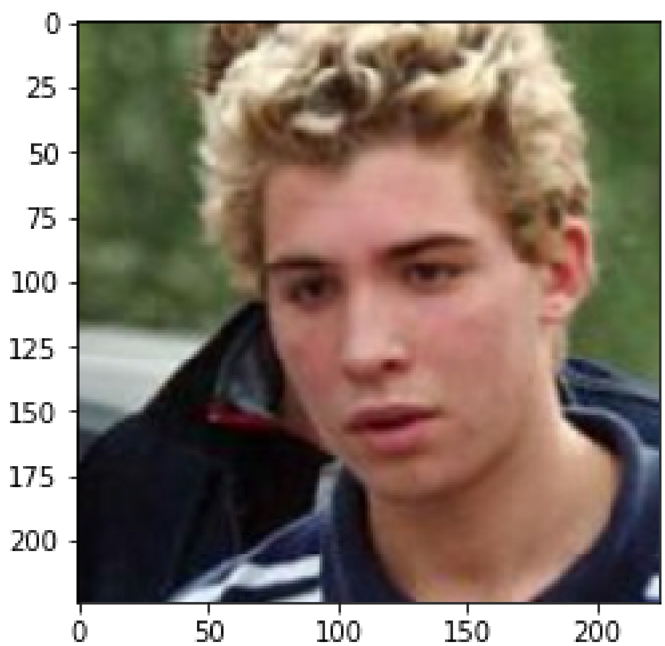
In [30]:
```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as needed.
```

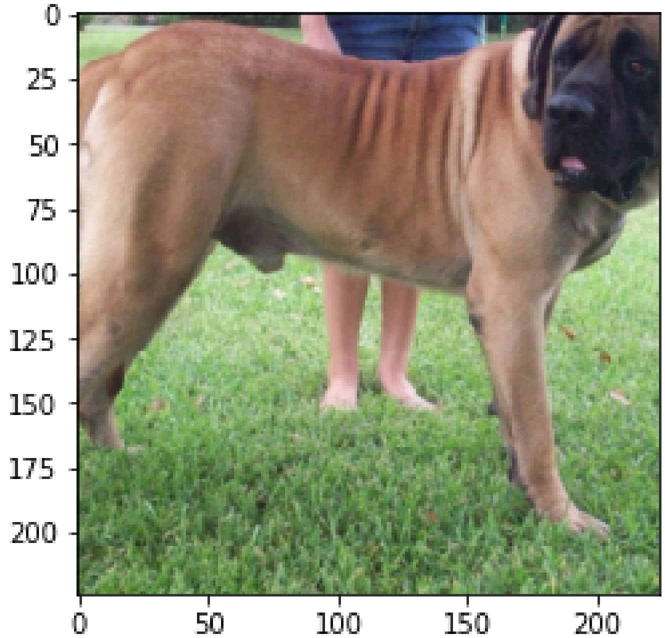
```
## suggested code, below
for file in np.hstack((human_files[:3], dog_files[:3])):
    run_app(file)
```

```
you are a human
You look like a ...
Dachshund
you are a human
You look like a ...
Dachshund
you are a human
You look like a ...
Dachshund
you are a dog!
You look like a ...
Smooth fox terrier
you are a dog!
You look like a ...
Dachshund
you are a dog!
You look like a ...
Dachshund
```

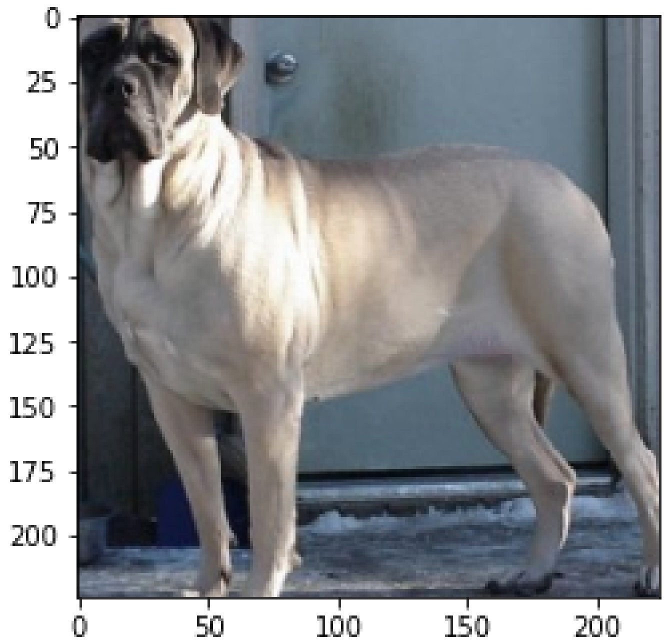




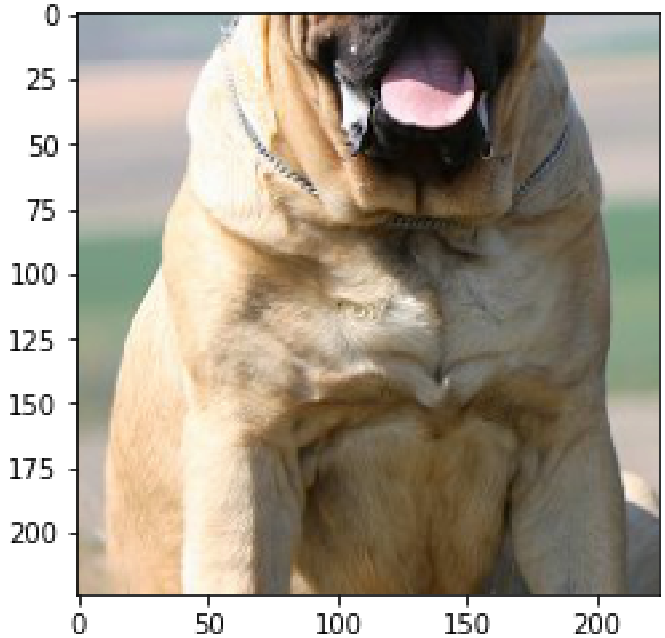




0
25
50
75
100
125
150
175
200
0
50
100
150
200



0
25
50
75
100
125
150
175
200
0
50
100
150
200




```
In [ ]:
```