

dog_app

July 2, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

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

Step 0: Import Datasets

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

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

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

Note: If you are using a Windows machine, you are encouraged to use [7zip](#) to extract the folder.

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

```
In [2]: import numpy as np
        from glob import glob

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

        # 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 [3]: 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 [4]: # 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 [5]: from tqdm import tqdm

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

##-## Do NOT modify the code above this line. ##-##
Detected_human_face = 0
Detected_dog_face = 0

for face in human_files_short:
    if face_detector(face) == True :
        Detected_human_face = Detected_human_face + 1
for face in dog_files_short:
    if face_detector(face) == True :
        Detected_dog_face = Detected_dog_face + 1
## TODO: Test the performance of the face_detector algorithm
## on the images in human_files_short and dog_files_short.
print("From first 100 Human images ",Detected_human_face,"% were Detected Human")
print("From first 100 Dog images ",Detected_dog_face,"% Were Detected Human")

From first 100 Human images  98 % were Detected Human
From first 100 Dog images  17 % Were Detected Human
```

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 [6]: ### (Optional)  
        ### TODO: Test performance of another face 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 [7]: 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 [8]: 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
Loaded_image = Image.open(img_path)
transformer = transforms.Compose([transforms.RandomResizedCrop(224), transforms.ToTensor()])
tensor_image = transformer(Loaded_image).unsqueeze_(0)
VGG16.eval()
with torch.no_grad():
    output = VGG16(tensor_image.cuda())
    prediction = torch.argmax(output).item()
VGG16.train()

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 [9]: ### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    Predict = VGG16_predict(img_path)
    if Predict >= 151 and Predict <= 268 :
        return True
    else:
        return False

```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your `dog_detector` function.

- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?

Answer:

```
In [10]: ### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
Detected_human = 0
Detected_dogs = 0
for i in range(0, len(human_files_short)-1):
    if(dog_detector(human_files_short[i])==False):
        Detected_human +=1
for j in range(0, len(dog_files_short)-1):
    if(dog_detector(dog_files_short[j])==True):
        Detected_dogs +=1
print('Dogs in human files are',100-(Detected_human/len(human_files_short))*100,"%")
print('Dogs in dog files ',(Detected_dogs/len(dog_files_short))*100,"%")

Dogs in human files are 3.0 %
Dogs in dog files 96.0 %
```

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 [ ]: ### (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
------------------------	------------------------

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 imbalanced, 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 [13]: import torchvision.transforms as transforms
         from torchvision import datasets

         num_workers = 0
         batch_size = 10

         data_dir = '/data/dog_images'
         ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes
         data_transforms = {
             'train' : transforms.Compose([
                 transforms.Resize(256),
                 transforms.RandomResizedCrop(224),
                 transforms.RandomHorizontalFlip(), # randomly flip and rotate
                 transforms.RandomRotation(10),
                 transforms.ToTensor(),
                 transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
             ]),

             'valid' : transforms.Compose([
```



```

        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),

    'test' : transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
}
train_dir = data_dir + '/train'
valid_dir = data_dir + '/valid'
test_dir = data_dir + '/test'

image_datasets = {
    'train' : datasets.ImageFolder(root=train_dir,transform=data_transforms['train']),
    'valid' : datasets.ImageFolder(root=valid_dir,transform=data_transforms['valid']),
    'test' : datasets.ImageFolder(root=test_dir,transform=data_transforms['test'])
}
loaders_scratch = {
    'train' : torch.utils.data.DataLoader(image_datasets['train'],batch_size = batch_size),
    'valid' : torch.utils.data.DataLoader(image_datasets['valid'],batch_size = batch_size),
    'test' : torch.utils.data.DataLoader(image_datasets['test'],batch_size = batch_size)
}
print(loaders_scratch['train'])

```

<torch.utils.data.dataloader.DataLoader object at 0x7fe1fd2215f8>

Question 3: Describe your chosen procedure for preprocessing the data. - How does your code resize the images (by cropping, stretching, etc)? What size did you pick for the input tensor, and why? - Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

Answer: I have augmented the dataset by random flipping, and transformed using ToTensor, with the fixed size of images 224.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```

In [14]: import torch.nn as nn
import torch.nn.functional as F

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

```

```

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3, 64, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
        self.conv3 = nn.Conv2d(128, 256, kernel_size=3, padding=1)
        self.conv4 = nn.Conv2d(256, 512, kernel_size=3, padding=1)
        self.conv5 = nn.Conv2d(512, 512, kernel_size=3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.fc1 = nn.Linear(25088, 512)
        self.fc2 = nn.Linear(512, 512)
        self.fc3 = nn.Linear(512, 133)
        self.dropout = nn.Dropout(0.5)

    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))
        x = self.pool(F.relu(self.conv4(x)))
        x = self.pool(F.relu(self.conv5(x)))
        x = x.view(-1, 25088)
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = F.relu(self.fc2(x))
        x = self.dropout(x)
        x = 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: choosed 5 Convolutional layers, kernel of 3 size, Max pooling layers of 2x2 are applied. Batch normalization is applied after each max pool layer.

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 [15]: import torch.optim as optim

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

        ### TODO: select optimizer
        optimizer_scratch = optim.Adam(model_scratch.parameters(), lr=0.001)
```

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

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

                #####
                # train the model #
                #####
                model.train()
                for batch_idx, (data, target) in enumerate(loaders['train']):
                    # move to GPU
                    if use_cuda:
                        data, target = data.cuda(), target.cuda()
                    ## find the loss and update the model parameters accordingly
                    ## record the average training loss, using something like
                    ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))
                    # clear the gradients of all optimized variables
                    optimizer.zero_grad()
                    # forward pass: compute predicted outputs by passing inputs to the model
                    output = model(data)
                    # calculate the batch loss
                    loss = criterion(output, target)
                    # backward pass: compute gradient of the loss with respect to model parameters
                    loss.backward()
```

```

        # perform a single optimization step (parameter update)
        optimizer.step()
        # update training loss
        # train_loss += loss.item()*data.size(0)
        train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))

#####
# validate the model #
#####
model.eval()

for batch_idx, (data, target) in enumerate(loaders['valid']):
    # move to GPU
    if use_cuda:
        data, target = data.cuda(), target.cuda()
    ## update the average validation loss
    # forward pass: compute predicted outputs by passing inputs to the model
    output = model(data)
    # calculate the batch loss
    loss = criterion(output, target)
    # update average validation loss
    valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

# calculate average losses
train_loss = train_loss/len(loaders['train'].dataset)
valid_loss = valid_loss/len(loaders['valid'].dataset)

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

# return trained model
return model

# train the model

```

```

model_scratch = train(10, loaders_scratch, model_scratch, optimizer_scratch, criterion_

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

```

```

Epoch: 1      Training Loss: 0.000731      Validation Loss: 0.005835
Validation loss decreased (inf --> 0.005835). Saving model ...
Epoch: 2      Training Loss: 0.000729      Validation Loss: 0.005834
Validation loss decreased (0.005835 --> 0.005834). Saving model ...
Epoch: 3      Training Loss: 0.000729      Validation Loss: 0.005834
Epoch: 4      Training Loss: 0.000729      Validation Loss: 0.005835
Epoch: 5      Training Loss: 0.000729      Validation Loss: 0.005835
Epoch: 6      Training Loss: 0.000729      Validation Loss: 0.005834
Epoch: 7      Training Loss: 0.000729      Validation Loss: 0.005834
Epoch: 8      Training Loss: 0.000729      Validation Loss: 0.005835
Epoch: 9      Training Loss: 0.000729      Validation Loss: 0.005834
Epoch: 10     Training Loss: 0.000729      Validation Loss: 0.005834

```

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 [18]: 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: 4.860718

Test Accuracy: 1% (10/836)

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 [26]: import os
import numpy as np
from PIL import Image
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms, models
## TODO: Specify data loaders
data_dir = '/data/dog_images'

train_transforms = transforms.Compose([transforms.Resize(size=258),
                                       transforms.RandomHorizontalFlip(),
                                       transforms.RandomRotation(10),
                                       transforms.CenterCrop(224),
                                       transforms.ToTensor(),
                                       transforms.Normalize([0.485, 0.456, 0.406],
                                                            [0.229, 0.224, 0.225])])

validTest_transforms = transforms.Compose([transforms.Resize(size=258),
                                           transforms.CenterCrop(224),

```

```

        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],
                              [0.229, 0.224, 0.225])))

train_dataset = datasets.ImageFolder(os.path.join(data_dir, 'train'), transform=train_t
valid_dataset = datasets.ImageFolder(os.path.join(data_dir, 'valid'), transform=validTe
test_dataset = datasets.ImageFolder(os.path.join(data_dir, 'test'), transform=validTest

trainLoader = torch.utils.data.DataLoader(train_dataset,
                                           batch_size=128,
                                           shuffle=True,
                                           num_workers=0)

validLoader = torch.utils.data.DataLoader(valid_dataset,
                                           batch_size=128,
                                           shuffle=True,
                                           num_workers=0)

testLoader = torch.utils.data.DataLoader(test_dataset,
                                           batch_size=16,
                                           shuffle=False,
                                           num_workers=0)

loaders = {'train':trainLoader,'test':testLoader,'valid':validLoader}
print('training images: ',len(train_dataset))
print('test images: ',len(test_dataset))
print('validaion images: ',len(valid_dataset))

```

```

training images: 6680
test images: 836
validaion images: 835

```

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 [23]: import torchvision.models as models
import torch.nn as nn
## TODO: Specify model architecture
use_cuda = torch.cuda.is_available()
model_transfer = models.resnet50(pretrained=True)
for param in model_transfer.parameters():
    param.requires_grad = False
model_transfer.fc = nn.Linear(2048, 133, bias=True)
fc_parameters = model_transfer.fc.parameters()
for param in fc_parameters:
    param.requires_grad = True

```

```

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

```

Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/100%|| 102502400/102502400 [00:01<00:00, 53444608.31it/s]

```

ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
  )
)
(layer2): Sequential(
  (0): Bottleneck(

```



```

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

```

```

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

```

```

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

```

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

Answer: The classifier used is pre architected and pre trained ResNet model. It is pre tuned so that we don't have to worry for features which makes it suitable for this problem

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 [24]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.fc.parameters(), lr=0.001)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. [Save the final model parameters](#) at filepath `'model_transfer.pt'`.

```
In [27]: n_epochs = 10
         def train(n_epochs, loader, model, optimizer, criterion, use_cuda, save_path):
             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
                 model.train()
                 for batch_i, (data, target) in enumerate(loader['train']):
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     optimizer.zero_grad()
                     output = model(data)
                     loss = criterion(output, target)
                     loss.backward()
                     optimizer.step()
                     train_loss = train_loss + ((1 / (batch_i + 1)) * (loss.data - train_loss))

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

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

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

```

        train_loss,
        valid_loss
    ))

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

    return model

# train the model
model_transfer = train(n_epochs, loaders, model_transfer, optimizer_transfer, criterion)

# 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, Batch 1 loss: 4.895345
Epoch: 1      Training Loss: 4.903930      Validation Loss: 4.880250
Validation loss decreased (inf --> 4.880250). Saving model
Epoch 2, Batch 1 loss: 4.859437
Epoch: 2      Training Loss: 4.840901      Validation Loss: 4.814876
Validation loss decreased (4.880250 --> 4.814876). Saving model
Epoch 3, Batch 1 loss: 4.799450
Epoch: 3      Training Loss: 4.780416      Validation Loss: 4.759712
Validation loss decreased (4.814876 --> 4.759712). Saving model
Epoch 4, Batch 1 loss: 4.759193
Epoch: 4      Training Loss: 4.724835      Validation Loss: 4.699985
Validation loss decreased (4.759712 --> 4.699985). Saving model
Epoch 5, Batch 1 loss: 4.675133
Epoch: 5      Training Loss: 4.668806      Validation Loss: 4.649217
Validation loss decreased (4.699985 --> 4.649217). Saving model
Epoch 6, Batch 1 loss: 4.650366
Epoch: 6      Training Loss: 4.616624      Validation Loss: 4.598540
Validation loss decreased (4.649217 --> 4.598540). Saving model
Epoch 7, Batch 1 loss: 4.580531
Epoch: 7      Training Loss: 4.564011      Validation Loss: 4.552738
Validation loss decreased (4.598540 --> 4.552738). Saving model
Epoch 8, Batch 1 loss: 4.578467
Epoch: 8      Training Loss: 4.511509      Validation Loss: 4.496191
Validation loss decreased (4.552738 --> 4.496191). Saving model
Epoch 9, Batch 1 loss: 4.487164
Epoch: 9      Training Loss: 4.464613      Validation Loss: 4.457799
Validation loss decreased (4.496191 --> 4.457799). Saving model
Epoch 10, Batch 1 loss: 4.447391

```

```
Epoch: 10           Training Loss: 4.412097           Validation Loss: 4.391196
Validation loss decreased (4.457799 --> 4.391196).  Saving model
```

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 [29]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
         test(loaders, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 4.386758
```

```
Test Accuracy: 23% (195/836)
```

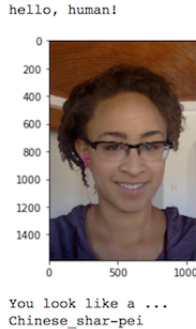
1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

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

# list of class names by index, i.e. a name can be accessed like class_names[0]
class_names = [item[4:].replace("_", " ") for item in train_dataset.classes]
model_transfer.load_state_dict(torch.load('model_transfer.pt'))
def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    img = Image.open(img_path)
    normalize = transforms.Normalize(mean=(0.485, 0.456, 0.406),
                                     std=(0.229, 0.224, 0.225))
    preprocess = transforms.Compose([transforms.Resize(258),
                                    transforms.CenterCrop(224),
                                    transforms.ToTensor(),
                                    normalize])
    img_tensor = preprocess(img).unsqueeze_(0)
    if use_cuda:
        img_tensor = img_tensor.cuda()
    model_transfer.eval()
    with torch.no_grad():
        output = model_transfer(img_tensor)
        prediction = torch.argmax(output).item()
    model_transfer.train()
    breed = class_names[prediction]

    return breed
```



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

def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    image = Image.open(img_path)
    if(face_detector(img_path)):
        print("It looks like Human Detected\n")
        plt.imshow(image)
        plt.show()

    elif(dog_detector(img_path)):
        print("It looks like Dog detected")
        plt.imshow(image)
        plt.show()
        prediction = predict_breed_transfer(img_path)
        print("Dog Breed: {0}".format(prediction))
    else:
        print("I can Not Detect any dog or human")
```

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) . I can train it on more dataset so that i can make better predictions | |

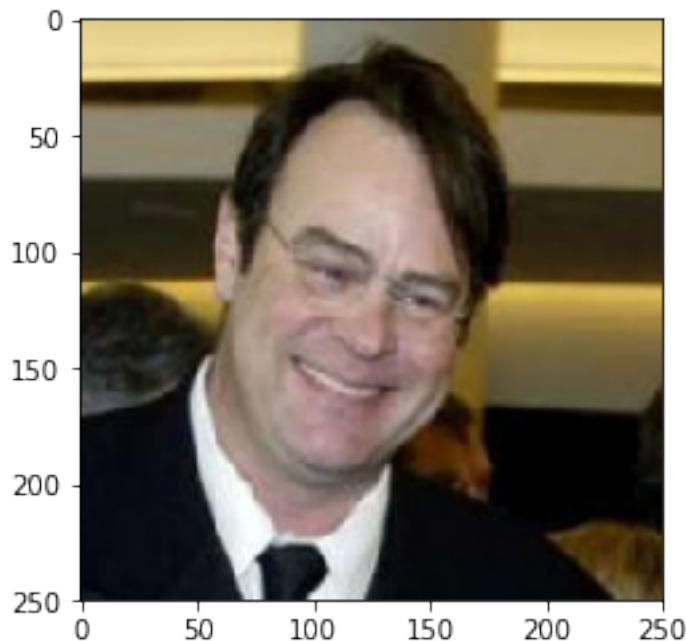
| | can Build a neural network | |

| | I can tune Hyperparameters | |

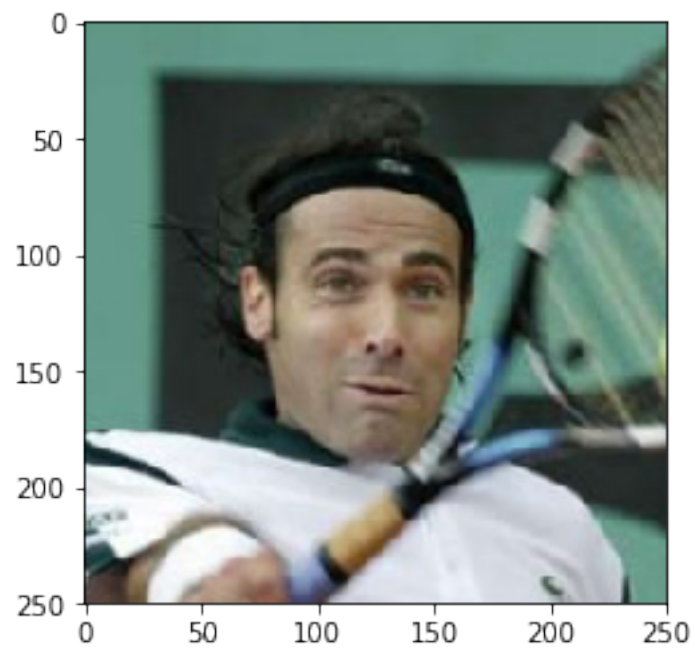
```
In [35]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
         ## Feel free to use as many code cells as needed.

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

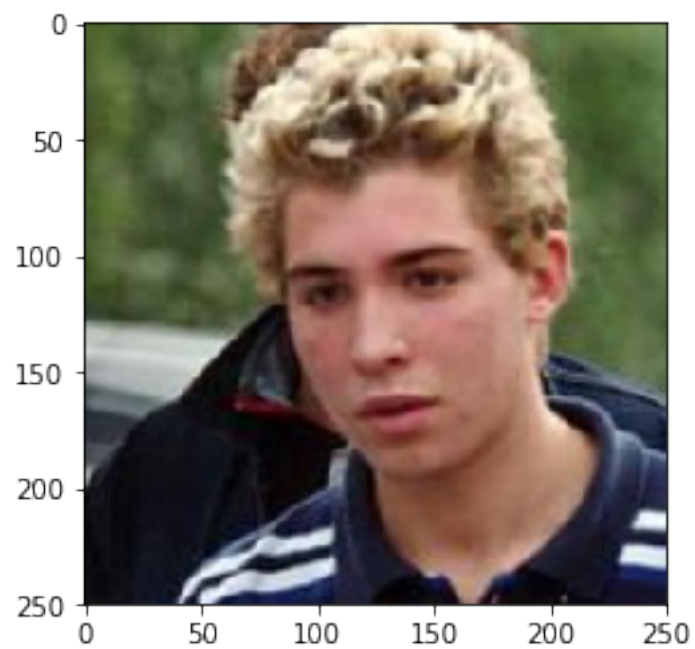
It looks like Human Detected



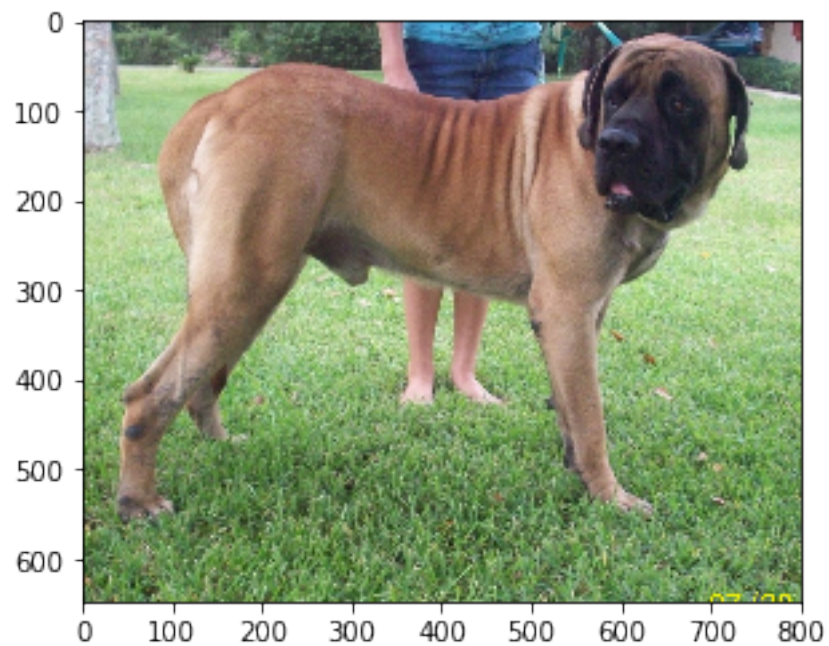
It looks like Human Detected



It looks like Human Detected

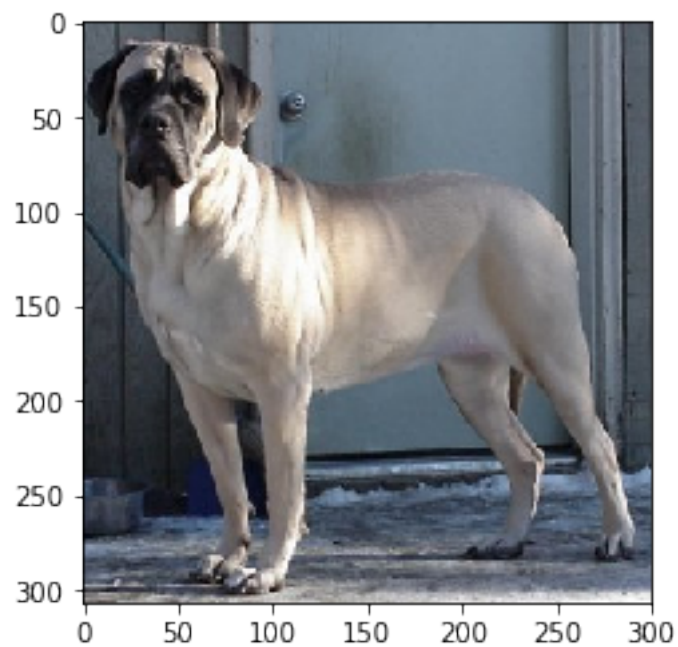


It looks like Dog detected

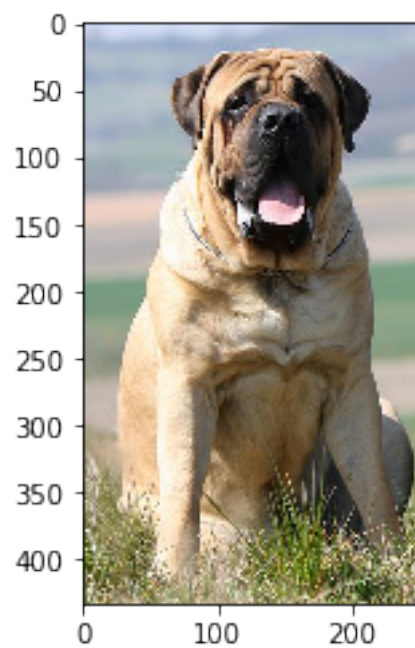


Dog Breed: Bullmastiff

It looks like Dog detected



Dog Breed: Bullmastiff
It looks like Dog detected



Dog Breed: Bullmastiff

In []: *# Working Well.*