dog_app

October 27, 2018

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

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

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

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

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

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

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

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

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

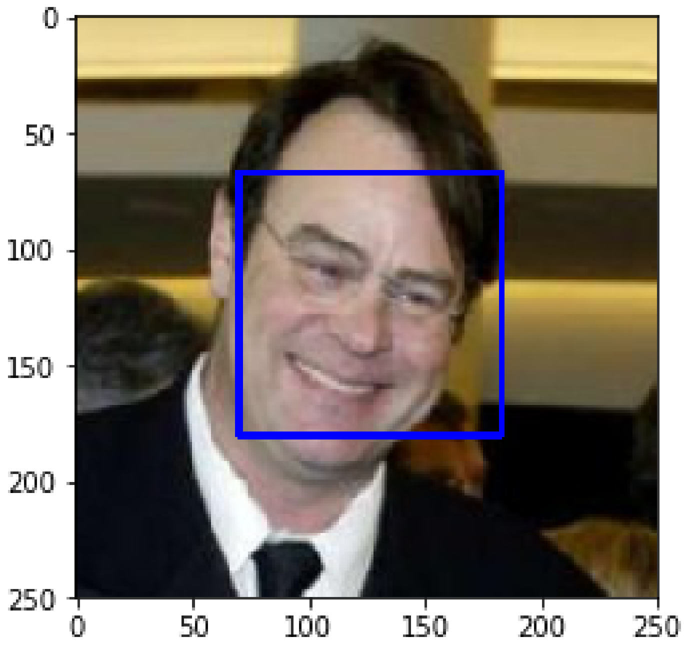
## Step 1: Detect Humans

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

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

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

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

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

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

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

        # get bounding box for each detected face
        for (x,y,w,h) in faces:
            # add bounding box to color image
            cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)
        # convert BGR image to RGB for plotting
        cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

Answer: The accuracy of 100 human images in human face detector: 98.00%. The accuracy of 100 dog images in human face detector: 17.00%

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

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

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        human_counter = 0
        dog_counter = 0
        for human_path, dog_path in zip(range(100), range(100)):
            if(face_detector(human_files_short[human_path])):
                human_counter += 1
            if(face_detector(dog_files_short[dog_path])):
                dog_counter += 1
        print("the percentage of 100 human images in human face detector: %.2f%%" %float((human_
        print("the percentage of 100 dog images in human face detector: %.2f%%" %float((dog_coun
```

```
the percentage of 100 human images in human face detector: 98.00%
the percentage of 100 dog images in human face detector: 17.00%
```

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

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

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

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

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

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:05<00:00, 97926926.02it/s]
```

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

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

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

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

```
In [17]: from PIL import Image
         import torchvision.transforms as transforms
         from torchvision import datasets
         from torch.autograd import Variable

         def VGG16_predict(img_path):
             '''
             Use pre-trained VGG-16 model to obtain index corresponding to
```

```
predicted ImageNet class for image at specified path

Args:
    img_path: path to an image

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

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

#normalize = transforms.Normalize(
   #mean=[0.485, 0.456, 0.406],
   #std=[0.229, 0.224, 0.225]
#)
#data_transform = transforms.Compose([#transforms.RandomResizedCrop(224),
                                     #transforms.Resize((224,224)),
                                     #transforms.ToTensor(),
                                     #normalize
                                     #])
#image = data_transform(image)[:3,:,:].unsqueeze(0)

normalize = transforms.Normalize(
        mean=[0.485, 0.456, 0.406],
        std=[0.229, 0.224, 0.225])

image_size = 224
loader = transforms.Compose([transforms.Resize((image_size,image_size)), transforms
                            normalize])
def image_loader(image_path):
    ### load image, returns tensor
    image = Image.open(image_path)
    image = loader(image).float()
    image = Variable(image, requires_grad=False)
    image = image.unsqueeze(0)  #for vgg 16 or resnet-50?
    if use_cuda:
        return image.cuda()
    else:
        return image
image = image_loader(img_path)



output = VGG16(image)
if use_cuda:
```

```
            output = output.cuda()
        _, pred = torch.max(output.data, 1)
        index = pred.item()

        ### *** find the labels for ImageNet class, should be length 151 - 268

        return index # 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 [19]: print("image path: ", dog_files[265])
         print("test:", VGG16_predict(dog_files[100]))

image path:  /data/dog_images/train/024.Bichon_frise/Bichon_frise_01714.jpg
test: 236
```

```
In [20]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             if(VGG16_predict(img_path) in range(151,269)):
                 return True
             else:
                 return False
             # altervative:
             # pred = VGG16_predict(img_path)
             # return ((pred <= 268) & (pred >= 151))
```

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: 1) 100% accuracy for human_files_short images in dog_detector.

2) 1% percent for human_files_short images in dog_detector

```
In [21]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.

         human_files_short = human_files[:100]
         dog_files_short = dog_files[:100]
         human_counter = 0
         dog_counter = 0
         for human_path, dog_path in zip(range(100), range(100)):
             if(dog_detector(human_files_short[human_path])):
                 human_counter += 1
             if(dog_detector(dog_files_short[dog_path])):
                 dog_counter += 1
         print("the accuracy of 100 human images in dog detector: %.2f%%" %float((human_counter/
         print("the accuracy of 100 dog images in dog detector: %.2f%%" %float((dog_counter/100)
```

```
the accuracy of 100 human images in dog detector: 1.00%
the accuracy of 100 dog images in dog detector: 100.00%
```

- the accuracy of 100 human images in dog detector alexnet is: 0.01
- the accuracy of 100 dog images in dog detector alexnet is: 0.95

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

        # define VGG16 model
        net50 = models.resnet50(pretrained=True)
        ## switch to evaluation mode
        net50.eval()
        ## use train to fine tuning
        #model.train()
        # check if CUDA is available
        use_cuda = torch.cuda.is_available()

        # Freeze training for all "features" layers
        #for param in net50.features.parameters():
        #    param.require_grad = False

        # move model to GPU if CUDA is available
        if use_cuda:
            net50 = net50.cuda()
```

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:05<00:00, 17523484.23it/s]
```

```
In [6]: from PIL import Image
        import torchvision.transforms as transforms
```

```
from torchvision import datasets
Image.LOAD_TRUNCATED_IMAGES = True
from torch.autograd import Variable


def net50_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 resnet-50 model's prediction
    '''

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image
    #image = Image.open(img_path).convert('RGB')
   # normalize = transforms.Normalize(
   #    mean=[0.485, 0.456, 0.406],
   #    std=[0.229, 0.224, 0.225]
    #)
    #data_transform = transforms.Compose([transforms.Resize(224,224),
                                         ##transforms.RandomResizedCrop(224),
                                         #transforms.ToTensor(),
                                         #normalize
                                         #])
    #output = data_transform(image)[:3,:,:].unsqueeze(0)
    #output = net50(output)

    ## pre-process image
    normalize = transforms.Normalize(
            mean=[0.485, 0.456, 0.406],
            std=[0.229, 0.224, 0.225])

    image_size = 224
    loader = transforms.Compose([transforms.Resize((image_size,image_size)),
                                 #transforms.RandomResizedCrop(image_size),
                                 transforms.ToTensor(),
                                normalize])
    def image_loader(image_path):
        ### load image, returns tensor
        image = Image.open(image_path)
        image = loader(image).float()
        image = Variable(image, requires_grad=False)
```

```
            image = image.unsqueeze(0)  #for vgg 16 or resnet-50?
            if use_cuda:
                return image.cuda()
            else:
                return image
        image_tensor = image_loader(img_path)

        output = net50(image_tensor)
        #print(output.data.shape)
        _, pred = torch.max(output.data, 1)
        index = pred.item()

        ### *** find the labels for ImageNet class, should be length 151 - 268

        return index # predicted class index
```

```
In [7]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector_net50(img_path):
            pred = net50_predict(img_path)
            return ((pred <= 268) & (pred >= 151))
            #if(net50_predict(img_path) in range(151,269)):
            #    return True
            #else:
            #    return False
```

```
In [8]: human_files_short = human_files[:100]
        dog_files_short = dog_files[:100]

        human_counter = 0
        dog_counter = 0
        for human_path, dog_path in zip(range(100), range(100)):
            if(dog_detector_net50(human_files_short[human_path])):
                human_counter += 1
            if(dog_detector_net50(dog_files_short[dog_path])):
                dog_counter += 1
        print("the accuracy of 100 human images in resnet - 50 dog detector: %.2f%%" %float((hum
        print("the accuracy of 100 dog images in resnet - 50 dog detector: %.2f%%" %float((dog_c
```

```
the accuracy of 100 human images in resnet - 50 dog detector: 0.00%
the accuracy of 100 dog images in resnet - 50 dog detector: 100.00%
```

- the accuracy of 100 human images in dog detector alexnet is: 1%
- the accuracy of 100 dog images in dog detector alexnet is: 96%
- the accuracy of 100 human images in dog detector resnet - 50 is: 0.00
- the accuracy of 100 dog images in dog detector resnet - 50 is: 100%

## 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 [40]: import os
         import torch
         from torchvision import datasets
         import torchvision.transforms as transforms
```

```
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

# number of subprocesses to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 100

# define the transformation
normalize = transforms.Normalize(
    mean=[0.485, 0.456, 0.406],
    std=[0.229, 0.224, 0.225]
)

transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomHorizontalFlip(), # randomly flip and rotate
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    normalize
    ])

### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
# prepare data loaders (combine dataset and sampler)

train_data = datasets.ImageFolder('/data/dog_images/train/', transform=transform)
valid_data = datasets.ImageFolder('/data/dog_images/valid/', transform=transform)
test_data = datasets.ImageFolder('/data/dog_images/test/', transform=transform)



loaders_scratch = {}
loaders_scratch['train'] = torch.utils.data.DataLoader(train_data, batch_size=batch_siz
                                                  shuffle=True,
                                                  num_workers=num_workers,
                                                 )
loaders_scratch['valid'] = torch.utils.data.DataLoader(valid_data, batch_size=batch_siz
                                                  shuffle=True,
                                                  num_workers=num_workers)
loaders_scratch['test'] = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
                                                  shuffle=True,
                                                  num_workers=num_workers)
```

```
In [41]: loaders_scratch['train']
         for batch_idx, (data, target) in enumerate(loaders_scratch['test']):
            print(batch_idx, data.shape, "return the batch size = 80 class indices for 80 image
            if(batch_idx > 5):
                break
```

```
0 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
1 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
2 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
3 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
4 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
5 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
6 torch.Size([100, 3, 224, 224]) return the batch size = 80 class indices for 80 images: torch.S
```

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 use transforms.Resize(224) because it does not change the content of the image compared to cropping. * The input tensor is normalized. The size would be (batch_size,244,244,3) corresponding to 3 RGB channels * I argument the data in order for the network to learn a more generalized pattern rather than memorized the informations. I use random flip and rotations.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [42]: # takes in a module and applies the specified weight initialization
         def weights_init_normal(m):
             classname = m.__class__.__name__
             # for every Linear layer in a model..
             if classname.find('Linear') != -1:
                 # get the number of the inputs
                 n = m.in_features
                 y = (1.0/np.sqrt(n))
                 m.weight.data.normal_(0, y)
                 m.bias.data.fill_(0)
```

```
In [43]: 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
                 ## two efficitive structures: either 4 convolutional layer with kernel size 2,
        ## or 3 convolutional layer with kernel size 3
        # convolutional layer (sees 224x224x3 image tensor)
        self.conv1 = nn.Conv2d(3, 16, 2, padding=1)
        # convolutional layer (sees 112x112x16 tensor)
        self.conv2 = nn.Conv2d(16, 64, 2, padding=1)
        # convolutional layer (sees 56x56x32 tensor)
        self.conv3 = nn.Conv2d(64, 128, 2, padding=1)
        ## convolutional layer (sees 28x28x64 tensor)
        self.conv4 = nn.Conv2d(128, 256,2, padding=1)
        # max pooling layer
        self.pool = nn.MaxPool2d(2, 2)
        # global average pooling layer, the ouput size is [28 X 28] the size of the
        #input H X W of the feature map
        self.avgpool = nn.AdaptiveAvgPool2d(14)
        ## apply the batch normalization before the softmax
        self.batchnorm = nn.BatchNorm1d(256)
        # linear layer (64 * 4 * 4 -> 500)
        self.fc1 = nn.Linear(256 * 14 * 14, 256)
        # linear layer (500 -> 10)
        self.fc2 = nn.Linear(256, 133)
        # dropout layer (p=0.25)
        self.dropout_2 = nn.Dropout(0.25)
        self.dropout_1 = nn.Dropout(0.1)


    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        #x = self.dropout_1(x)
        x = self.pool(F.relu(self.conv2(x)))
        #x = self.dropout_1(x)
        x = self.pool(F.relu(self.conv3(x)))
        x = self.dropout_1(x)
        x = self.pool(F.relu(self.conv4(x)))
        x = self.dropout_1(x)
        x = self.avgpool(x)
        # flatten image input
        x = x.view(-1, 256 * 14 * 14)
        # x = x.view(x.size(0), -1)
        # add dropout layer
        x = self.dropout_2(x)
        # add 1st hidden layer, with relu activation function
        x = F.relu(self.fc1(x))

        x = self.batchnorm(x)
        # add dropout layer
        x = self.dropout_2(x)
        # add 2nd hidden layer, with ? activation function
```

```
            ## nn.LogSoftmax(dim=1)
            x = self.fc2(x)

            return x

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

    # instantiate the CNN
    model_scratch = Net()
    ### add weight initialization from normal distribution, can be improved?
    model_scratch.apply(weights_init_normal)
    print(model_scratch)

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 64, kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(64, 128, kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(128, 256, kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (avgpool): AdaptiveAvgPool2d(output_size=14)
  (batchnorm): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (fc1): Linear(in_features=50176, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=133, bias=True)
  (dropout_2): Dropout(p=0.25)
  (dropout_1): Dropout(p=0.1)
)
```

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

Answer: Firstly, we have a series of convolutional layers and apply max pooling layers to detect features from the input image, Relu activation functions are applied for each convolutional layers to turn all negative pixel values into zeros. Then we flatten the image to a one dimensional tensor, before apply the fully connected layers. The number of output classes are equal to the total amount of dog breeds. Finally, we can apply the softmax activation function to generate a series of probabilities corresponding to the predicted classes. The class with the highest probability are the most likely dog breed of the input image. Moreover, between each fully connnected layers, I apply the dropout layer to mitigate the overfitting, it should be noted that max pooling layers are there to prevent overfitting as well.

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 [44]: import torch.optim as optim

         # specify loss function (categorical cross-entropy)
         criterion_scratch = nn.CrossEntropyLoss()

         # specify optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.025, momentum=0.9)
         #optimizer_scratch = optim.RMSprop(model_scratch.parameters(), lr=0.1)
         #optimizer_scratch = torch.optim.Adam(model_scratch.parameters(), lr=0.01)
```

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 [45]: 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']):
                 #for batch_idx, (data, target) in enumerate(train_loader):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## find the loss and update the model parameters accordingly
                     ## record the average training loss, using something like
                     ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
                     optimizer.zero_grad()
                     # 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 paramet
                     loss.backward()
                     # perform a single optimization step (parameter update)
                     optimizer.step()
                     # update training 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']):
        #for batch_idx, (data, target) in enumerate(valid_loader):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss

            output = model(data)
            # calculate the batch loss
            loss = criterion(output, target)
            # update average validation loss
            #valid_loss += loss.item()*data.size(0)
            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
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
            valid_loss_min,
            valid_loss))
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss
    # 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: 4.781500        Validation Loss: 4.601139
Validation loss decreased (inf --> 4.601139).  Saving model ...
Epoch: 2        Training Loss: 4.440815        Validation Loss: 4.361509
Validation loss decreased (4.601139 --> 4.361509).  Saving model ...
Epoch: 3        Training Loss: 4.244933        Validation Loss: 4.287996
Validation loss decreased (4.361509 --> 4.287996).  Saving model ...
Epoch: 4        Training Loss: 4.067500        Validation Loss: 4.324405
Epoch: 5        Training Loss: 3.907982        Validation Loss: 4.102394
Validation loss decreased (4.287996 --> 4.102394).  Saving model ...
Epoch: 6        Training Loss: 3.750396        Validation Loss: 3.968072
Validation loss decreased (4.102394 --> 3.968072).  Saving model ...
Epoch: 7        Training Loss: 3.588984        Validation Loss: 4.001078
Epoch: 8        Training Loss: 3.414987        Validation Loss: 3.733730
Validation loss decreased (3.968072 --> 3.733730).  Saving model ...
Epoch: 9        Training Loss: 3.223705        Validation Loss: 3.811717
Epoch: 10        Training Loss: 3.097919        Validation Loss: 3.769402
Epoch: 11        Training Loss: 2.908973        Validation Loss: 3.800385
Epoch: 12        Training Loss: 2.714174        Validation Loss: 3.788274
Epoch: 13        Training Loss: 2.567910        Validation Loss: 3.863041
Epoch: 14        Training Loss: 2.399887        Validation Loss: 3.839105
Epoch: 15        Training Loss: 2.184856        Validation Loss: 3.653557
Validation loss decreased (3.733730 --> 3.653557).  Saving model ...
Epoch: 16        Training Loss: 2.027077        Validation Loss: 3.842007
```

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

        KeyboardInterrupt                         Traceback (most recent call last)

        <ipython-input-45-afa9ac548d58> in <module>()
         76 # train the model
         77 model_scratch = train(100, loaders_scratch, model_scratch, optimizer_scratch,
    ---> 78                       criterion_scratch, use_cuda, 'model_scratch.pt')
         79 
         80 # load the model that got the best validation accuracy


        <ipython-input-45-afa9ac548d58> in train(n_epochs, loaders, model, optimizer, criterion,
         13         ###################
         14         model.train()
    ---> 15         for batch_idx, (data, target) in enumerate(loaders['train']):
         16         #for batch_idx, (data, target) in enumerate(train_loader):
         17             # move to GPU


        /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.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
    204             return img.resize((ow, oh), interpolation)
    205     else:
--> 206         return img.resize(size[::-1], interpolation)
    207
    208


    /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 [33]: 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))

         # load the model that got the best validation accuracy
         model_scratch.load_state_dict(torch.load('model_scratch.pt'))
         model_scratch.eval()
         # call test function
         test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.559543


Test Accuracy: 21% (177/836)
```

## 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 [9]: import os
        import torch
        from torchvision import datasets
        import torchvision.transforms as transforms

        from PIL import ImageFile
        ImageFile.LOAD_TRUNCATED_IMAGES = True

        # number of subprocesses to use for data loading
        num_workers = 0
        # how many samples per batch to load
        batch_size = 20

        # define the transformation
        normalize = transforms.Normalize(
            mean=[0.485, 0.456, 0.406],
            std=[0.229, 0.224, 0.225]
        )

        transform = transforms.Compose([
            transforms.Resize((224, 224)),
            transforms.RandomHorizontalFlip(), # randomly flip and rotate
            transforms.RandomRotation(30),
            transforms.ToTensor(),
            normalize
            ])

        ## Specify appropriate transforms, and batch_sizes
        # prepare data loaders (combine dataset and sampler)
```

```
data_transfer = {}
data_transfer['train'] = datasets.ImageFolder('/data/dog_images/train/', transform=trans
data_transfer['valid'] = datasets.ImageFolder('/data/dog_images/valid/', transform=trans
data_transfer['test'] = datasets.ImageFolder('/data/dog_images/test/', transform=transfo


loaders_transfer = {}
loaders_transfer['train'] = torch.utils.data.DataLoader(data_transfer['train'], batch_si
                                            shuffle=True,
                                            num_workers=num_workers,
                                           )
loaders_transfer['valid'] = torch.utils.data.DataLoader(data_transfer['valid'], batch_si
                                            shuffle=True,
                                            num_workers=num_workers)
loaders_transfer['test'] = torch.utils.data.DataLoader(data_transfer['test'], batch_size
                                            shuffle=True,
                                            num_workers=num_workers)
```

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 [10]: import torchvision.models as models
         import torch.nn as nn
         ### try different models like: VGG - 16, ResNet-50, Inception V3
         ## TODO: Specify model architecture

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

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

```
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=1000, bias=True)
)
```

```
In [11]: # optionally, Freeze training for all "features" layers, not required for fine tuning
         #for param in model_transfer.features.parameters():
         #    param.require_grad = False
         #for param in model_transfer.parameters():
         #    param.require_grad = False
         print("the number of output features:")
         model_transfer.fc.in_features
```

```
the number of output features:
```

```
Out[11]: 2048
```

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 dog detection has been performed with VGG19, Alexnet, InceptionV3, and ResNet-50 with pretrained features on Imagenet. It has been found that ResNet-50 (pretrained on Imagenet) provided the best accuracy on detecting dogs with identical hyper-parameter settings. Since we have a relevant large dataset, I use the fine-tuning for the transfer learning model, and the weights are initialized as the pretrained model weights. The last fully connected layer has been replaced with customized output classes of 133, corresponding to the number of dog breeds. I also compared the fine-tuning with freezed features (end of convNet), the result shows that the fine-tuning provide better initial loss, and faster convergence rates. Resnet-50 has Conv2d, BatchNorm2d, AvgPool2d, maxpool2d, Relu and other layers.

```
In [12]: n_inputs = model_transfer.fc.in_features
```

```
        # new layers automatically have requires_grad = True
        last_layer = nn.Linear(n_inputs, 133)

        model_transfer.fc = last_layer

        # check to see that your last layer produces the expected number of outputs
        print("the number of output features:", model_transfer.fc.out_features)
```

```
the number of output features: 133
```

```
In [13]: ## for customized fine tune
         # fix the parameter for first 2 stacks of Convs of pre-trained model
         #for param in list(model.parameters())[:8]:
         #    param.requires_grad = False

         # filter out the parameters to be fine tuned
         #params = filter(lambda p: p.requires_grad, model.parameters())

         # only pass the parameters which did not freezed to the optimizer
         #optimizer = optim.SGD(params, lr=0.0001, momentum, weigth_decay)
```

```
In [14]: # ** optionally, randomize the weights in fully connected layer.
         ## takes in a module and applies the specified weight initialization
         #def weights_init_normal(m):
         #    classname = m.__class__.__name__
         #    # for every Linear layer in a model..
         #    if classname.find('Linear') != -1:
         #        # get the number of the inputs
         #        n = m.in_features
         #        y = (1.0/np.sqrt(n))
         #        m.weight.data.normal_(0, y)
         #        m.bias.data.fill_(0)

         #model_transfer.apply(weights_init_normal)
```

```
In [15]: ## pass model to GPU
         if use_cuda:
             model_transfer = model_transfer.cuda()
```

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 [16]: import torch.optim as optim
         # specify loss function (categorical cross-entropy)
         criterion_transfer = nn.CrossEntropyLoss()
         # specify optimizer (stochastic gradient descent) and learning rate = 0.0001
```

```
        # end of conv net
        #optimizer_transfer = optim.SGD(model_transfer.fc.parameters(), lr=0.001)
        # fine tune
        optimizer_transfer = optim.SGD(model_transfer.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 [17]: import numpy as np
         n_epochs = 25

         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']):
                 #for batch_idx, (data, target) in enumerate(train_loader):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## find the loss and update the model parameters accordingly
                     ## record the average training loss, using something like
                     ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
                     optimizer.zero_grad()
                     # 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 paramet
                     loss.backward()
                     # perform a single optimization step (parameter update)
                     optimizer.step()
                     # update training 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']):
        #for batch_idx, (data, target) in enumerate(valid_loader):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss

            output = model(data)
            # calculate the batch loss
            loss = criterion(output, target)
            # update average validation loss
            #valid_loss += loss.item()*data.size(0)
            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
        if valid_loss <= valid_loss_min:
            print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
            valid_loss_min,
            valid_loss))
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss
    # return trained model
    return model


# train the model
model_transfer = train(n_epochs, loaders_transfer, model_transfer,
                       optimizer_transfer, criterion_transfer,
                       use_cuda, 'model_transfer.pt')

# 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: 4.760524        Validation Loss: 4.522728
Validation loss decreased (inf --> 4.522728).  Saving model ...
Epoch: 2        Training Loss: 4.360328        Validation Loss: 4.041355
Validation loss decreased (4.522728 --> 4.041355).  Saving model ...
Epoch: 3        Training Loss: 3.898192        Validation Loss: 3.502767
Validation loss decreased (4.041355 --> 3.502767).  Saving model ...
Epoch: 4        Training Loss: 3.431360        Validation Loss: 2.970050
Validation loss decreased (3.502767 --> 2.970050).  Saving model ...
Epoch: 5        Training Loss: 2.989043        Validation Loss: 2.522160
Validation loss decreased (2.970050 --> 2.522160).  Saving model ...
Epoch: 6        Training Loss: 2.625334        Validation Loss: 2.166278
Validation loss decreased (2.522160 --> 2.166278).  Saving model ...
Epoch: 7        Training Loss: 2.313761        Validation Loss: 1.897904
Validation loss decreased (2.166278 --> 1.897904).  Saving model ...
Epoch: 8        Training Loss: 2.068531        Validation Loss: 1.662966
Validation loss decreased (1.897904 --> 1.662966).  Saving model ...
Epoch: 9        Training Loss: 1.848648        Validation Loss: 1.453926
Validation loss decreased (1.662966 --> 1.453926).  Saving model ...
Epoch: 10        Training Loss: 1.688178        Validation Loss: 1.317163
Validation loss decreased (1.453926 --> 1.317163).  Saving model ...
Epoch: 11        Training Loss: 1.535612        Validation Loss: 1.201614
Validation loss decreased (1.317163 --> 1.201614).  Saving model ...
Epoch: 12        Training Loss: 1.416561        Validation Loss: 1.120222
Validation loss decreased (1.201614 --> 1.120222).  Saving model ...
Epoch: 13        Training Loss: 1.312083        Validation Loss: 1.022242
Validation loss decreased (1.120222 --> 1.022242).  Saving model ...
Epoch: 14        Training Loss: 1.208640        Validation Loss: 0.935591
Validation loss decreased (1.022242 --> 0.935591).  Saving model ...
Epoch: 15        Training Loss: 1.148791        Validation Loss: 0.894218
Validation loss decreased (0.935591 --> 0.894218).  Saving model ...
Epoch: 16        Training Loss: 1.078137        Validation Loss: 0.847263
Validation loss decreased (0.894218 --> 0.847263).  Saving model ...
Epoch: 17        Training Loss: 1.005048        Validation Loss: 0.807856
Validation loss decreased (0.847263 --> 0.807856).  Saving model ...
Epoch: 18        Training Loss: 0.956798        Validation Loss: 0.760979
Validation loss decreased (0.807856 --> 0.760979).  Saving model ...
Epoch: 19        Training Loss: 0.916996        Validation Loss: 0.723424
Validation loss decreased (0.760979 --> 0.723424).  Saving model ...
Epoch: 20        Training Loss: 0.873570        Validation Loss: 0.705879
Validation loss decreased (0.723424 --> 0.705879).  Saving model ...
Epoch: 21        Training Loss: 0.836981        Validation Loss: 0.684980
Validation loss decreased (0.705879 --> 0.684980).  Saving model ...
Epoch: 22        Training Loss: 0.800122        Validation Loss: 0.648343
Validation loss decreased (0.684980 --> 0.648343).  Saving model ...
Epoch: 23        Training Loss: 0.760539        Validation Loss: 0.645117
Validation loss decreased (0.648343 --> 0.645117).  Saving model ...
Epoch: 24        Training Loss: 0.720099        Validation Loss: 0.601550
Validation loss decreased (0.645117 --> 0.601550).  Saving model ...
```

```
Epoch: 25 	Training Loss: 0.699808 	Validation Loss: 0.599644
Validation loss decreased (0.601550 --> 0.599644).  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 [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))

         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
         model_transfer.eval()
         test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.580044


Test Accuracy: 84% (704/836)
```

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 [19]: ## test the number of class names
         class_names = [item[4:].replace("_", " ") for item in data_transfer['train'].classes]
         print(data_transfer['train'].classes[7], class_names[7])
         len(class_names)
```

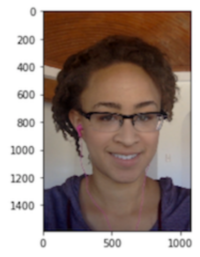
```
008.American_staffordshire_terrier American staffordshire terrier
```

```
Out[19]: 133
```

```
In [20]: def pre_process_image(img_path):
             from PIL import Image
             import torchvision.transforms as transforms
             from torchvision import datasets
             Image.LOAD_TRUNCATED_IMAGES = True
             from torch.autograd import Variable

             ## pre-process image
             normalize = transforms.Normalize(
                     mean=[0.485, 0.456, 0.406],
                     std=[0.229, 0.224, 0.225])

             image_size = 224
             loader = transforms.Compose([transforms.Resize((image_size,image_size)),
                                          #transforms.RandomResizedCrop(image_size),
                                          transforms.ToTensor(),
                                         normalize])
             def image_loader(image_path):
                 ### load image, returns tensor
                 image = Image.open(image_path)
                 image = loader(image).float()
                 image = Variable(image, requires_grad=False)
                 image = image.unsqueeze(0)  #for vgg 16 or resnet-50?
                 if use_cuda:
                     return image.cuda()
                 else:
                     return image
             image_tensor = image_loader(img_path)
             return image_tensor
```

```
In [21]: ### 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]
```

```
hello, human!
```



```
You look like a ...
Chinese_shar-pei
```

Sample Human Output

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

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    #images.numpy()
    # move model inputs to cuda, if GPU available
    #if use_cuda:
    #images = images.cuda()

    ##pre-process image path
    image_tensor = pre_process_image(img_path)
    # get sample outputs
    model_transfer.eval()
    output = model_transfer(image_tensor)
    # convert output probabilities to predicted class
    _, preds_tensor = torch.max(output.data, 1)
    # from the index get the predicted breed name
    pred_breed = class_names[preds_tensor]

    return pred_breed
```

## 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 [22]: def dog_human_detector(img_path):
             if dog_detector_net50(img_path) > 0:
                 is_human = False
                 dog_breed = predict_breed_transfer(img_path)
             # use Haarscascade model to detect whether a human or not
             elif face_detector(img_path) > 0:
                 is_human = True
                 dog_breed = predict_breed_transfer(img_path)
             else :
                  return -1
             return is_human, dog_breed
```

```
In [23]: ### 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
             is_human, dog_breed = dog_human_detector(img_path)
             print("the path of the file:", img_path)
             ## display the image
             img = cv2.imread(img_path)
             cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
             imgplot = plt.imshow(cv_rgb)
             plt.show()
             if(is_human == True):
                 print("Hello human, You look like a ... ",dog_breed)
             else:
                 print("the breed of dog is:", dog_breed)
```

```
In [24]: ### TODO: Write your algorithm.
         ### Feel free to use as many code cells as needed.
         def run_app(img_path):
             dog_breed = predict_breed_transfer(img_path)

             print("the path of the file:", img_path)
             ## Display the image
             img = cv2.imread(img_path)
             cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
             plt.imshow(cv_rgb)
             plt.show()

             ## handle cases for a human face, dog, and neither
             if dog_detector_net50(img_path):
                 print("Hello! The predicted dog breed is: {}".format(dog_breed))
             elif face_detector(img_path):
                 print("Hello human, You look like a ...:{}".format(dog_breed))
             else:
                print("Error, Alien")
                ## return error message and break function
```

## 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!

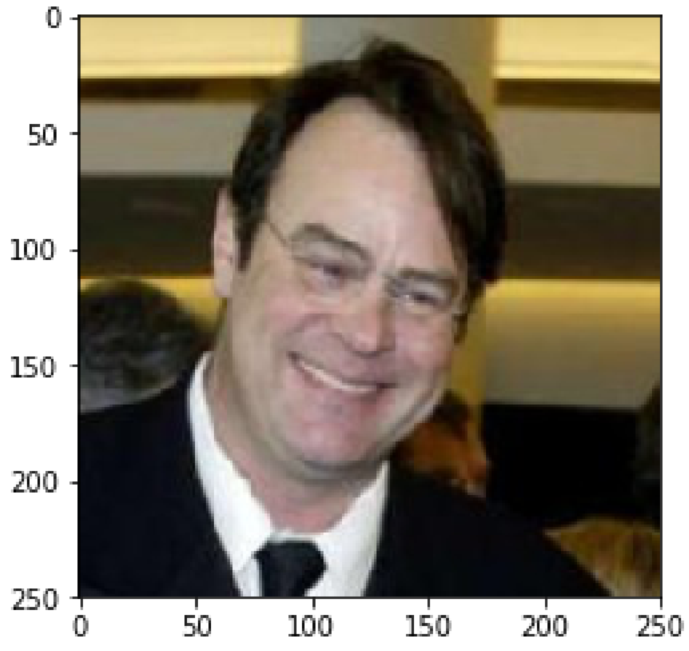
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

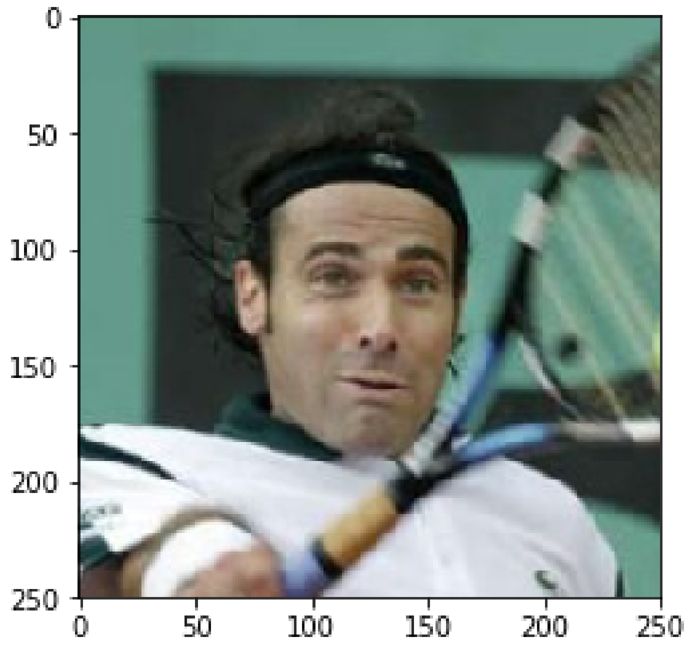
Answer: The output is better than I expected, the test accuracy increased from approximately 21% to 84%. The transfer learning with Resnet-50 together provides a pretty satisfied result when compared to the original CNN I created in section 3. * The improvements can start with data argumentation, to make the model more generalized to fit different type of dogs. We can change the data agumentation parameters to test the accuracy. * The second way is to train the current model on a larger data sets. * The third, we can modify the hyper-parameters (e.g. learning rate) until we have an optimal choices of hyper-parameters. However, this approach is very time consuming, hundres of hours of calculation are expected, alternative solution would be parallel computing. * We can add more dense layers to the pretrained networks, for example, an additional dense layer before the final linear layer would slightly increase the accuracy.

```
In [25]: ## 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.

         ## in online notebook I use existing files instead of my own images
         ## suggested code, below
         for file in np.hstack((human_files[:3], dog_files[:3])):
             run_app(file)
```

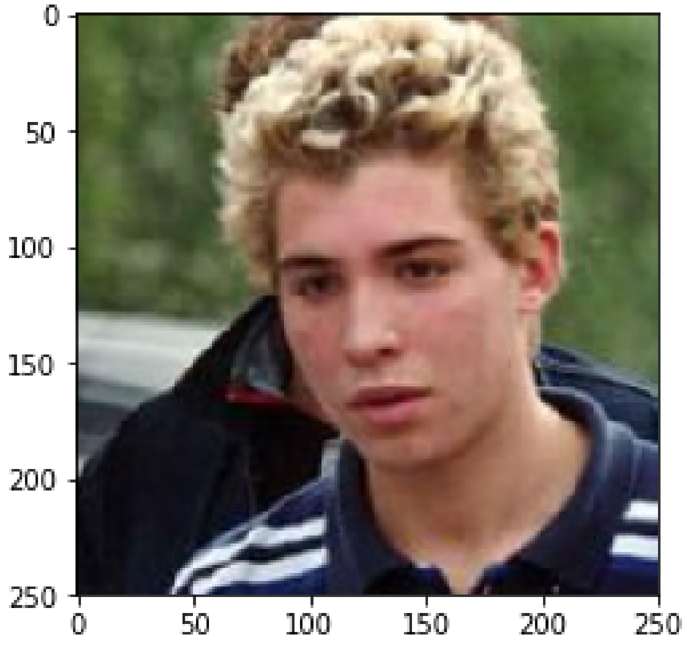
```
the path of the file: /data/lfw/Dan_Ackroyd/Dan_Ackroyd_0001.jpg
```



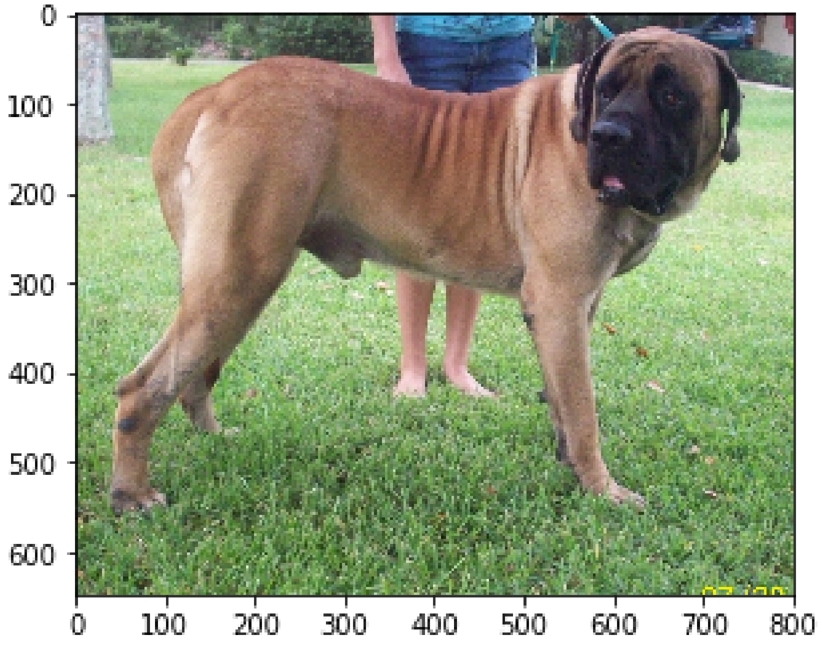
```
Hello human, You look like a ...:Chihuahua
the path of the file: /data/lfw/Alex_Corretja/Alex_Corretja_0001.jpg
```



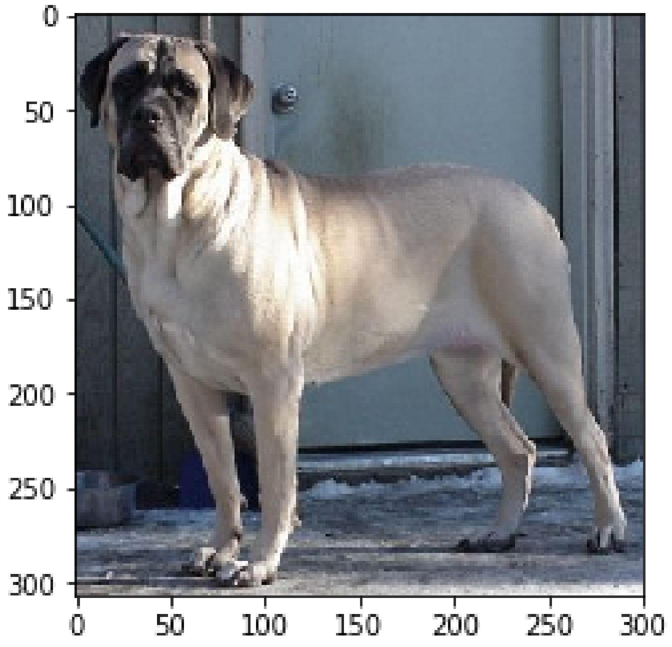
```
Hello human, You look like a ...:Dogue de bordeaux
the path of the file: /data/lfw/Daniele_Bergamin/Daniele_Bergamin_0001.jpg
```



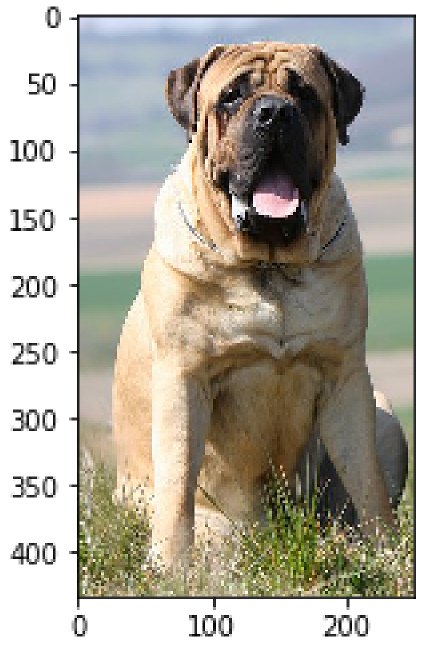
```
Hello human, You look like a ...:Portuguese water dog
the path of the file: /data/dog_images/train/103.Mastiff/Mastiff_06833.jpg
```



```
Hello! The predicted dog breed is: Bullmastiff
the path of the file: /data/dog_images/train/103.Mastiff/Mastiff_06826.jpg
```



```
Hello! The predicted dog breed is: Mastiff
the path of the file: /data/dog_images/train/103.Mastiff/Mastiff_06871.jpg
```



```
Hello! The predicted dog breed is: Bullmastiff
```

In [ ]: