dog_app

November 15, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

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

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

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

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

```
In [1]: import numpy as np
        from glob import glob
        import cv2
        import matplotlib.pyplot as plt
        from tqdm import tqdm
        import torch
        import torchvision.models as models
        from PIL import Image, ImageFile
        import torchvision.transforms as transforms
        ImageFile.LOAD_TRUNCATED_IMAGES = True
        import os
        from torchvision import datasets
        from torch.utils.data.sampler import SubsetRandomSampler
        import torch.nn as nn
        import torch.nn.functional as F
        import torch.optim as optim
```

```
In [2]: # check if CUDA is available
        use_cuda = torch.cuda.is_available()
```

```
In [31]: # 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.
```

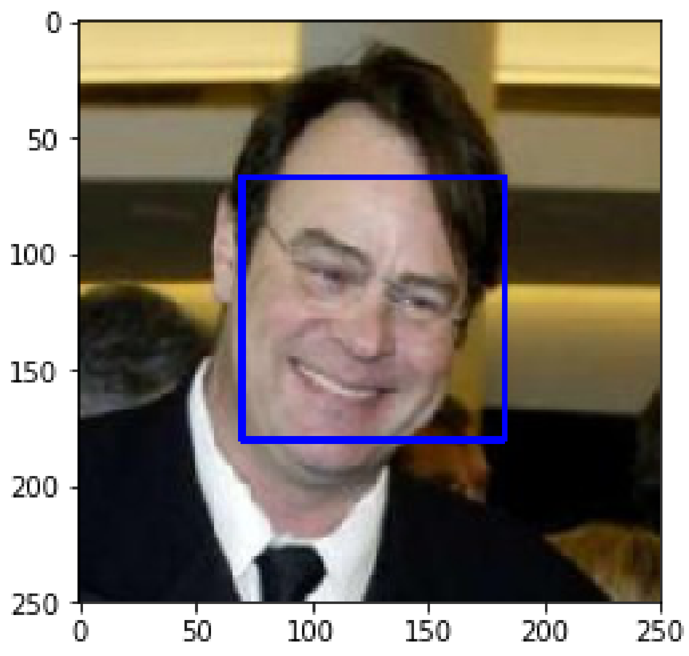
## Step 1: Detect Humans

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 [35]: %matplotlib inline

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

```
In [33]: # returns "True" if face is detected in image stored at img_path
         def face_detector(img_path):
             img = cv2.imread(img_path)
             gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
             faces = face_cascade.detectMultiScale(gray)
             return len(faces) > 0
```

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

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

```
In [5]: 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.
        humanfacelist = []
        dogfacelist = []
        for i in range(100):
            hum = face_detector(human_files_short[i])
            dog = face_detector(dog_files_short[i])
            humanfacelist.append(hum)
            dogfacelist.append(dog)
        print(str(sum(humanfacelist))+"%"+" of the first 100 images in human_files have a detect
        print(str(sum(dogfacelist))+"%"+" of the first 100 images in dog_files have a detected h
```

```
98% of the first 100 images in human_files have a detected human face
17% of the first 100 images in dog_files have a detected human face
```

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 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 [43]: # define VGG16 model
         VGG16 = models.vgg16(pretrained=True)

         # 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 [00:19<00:00, 28327223.18it/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 [41]: 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

             # pre-processing: mini-batches of 3-channel RGB images of shape (3 x H x W),
             # where H and W are expected to be at least 224. The images have to be loaded
             # in to a range of [0, 1] and then normalized using mean = [0.485, 0.456, 0.406]
             # and std = [0.229, 0.224, 0.225]
             img = Image.open(img_path).convert('RGB')
             transform = 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])
        ])
        img = transform(img).unsqueeze(0)

        if use_cuda:
            img = img.cuda()

        # get output
        output = VGG16(img)
        # convert output probabilities to predicted class
        _, preds_tensor = torch.max(output, 1)
        preds = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tens

        return preds # 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 [28]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             ## TODO: Complete the function.
             pred = VGG16_predict(img_path)

             return ((pred>=151) and (pred<=268)) # true/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:
Printed below

```
In [10]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         humans_detected_dogs = []
         dogs_detected_dogs = []
         for i in range(100):
             hum = dog_detector(human_files_short[i])
             dog = dog_detector(dog_files_short[i])
             humans_detected_dogs.append(hum)
             dogs_detected_dogs.append(dog)
```

```
        print(str(sum(humans_detected_dogs))+"%"+" of the images in human_files_short have a de
        print(str(sum(dogs_detected_dogs))+"%"+" of the images in dog_files_short have a detect
```

```
1% of the images in human_files_short have a detected dog
100% of the images in dog_files_short have a detected dog
```

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

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

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

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

Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador

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

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

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

In [3]:
```
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
transform = 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])
])

transform_augm = transforms.Compose([
    transforms.RandomRotation(45),
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                         std=[0.229, 0.224, 0.225])
])

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

num_workers = 0
batch_size = 64

train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, num_worker
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, num_worker
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, num_workers=
```

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:

- The code resizes the image to 256x256. Then, it crops the image in the center to 224x224 which are the dimensions specified in pytorch documentation. Then, I normalize the image using values from pytoch documentation. - I applied augmentation to the training data to make the model generalize better and to prevent overfitting. Applied augmentations are random horizontal filping (with default probability 0.5) and random 10 degrees rotations.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [4]: # define the CNN architecture
        class Net(nn.Module):
            ### TODO: choose an architecture, and complete the class
            def __init__(self):
                super(Net, self).__init__()
                ## Define layers of a CNN
                # convolutional layer input is (224, 224, 3)
                self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
                self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
                self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
                # max pooling layer
                self.pool = nn.MaxPool2d(2, 2)
                # linear layer 224/2/2/2 = 28 (bc 3 max pooling layers)
                self.fc1 = nn.Linear(64 * 28 * 28, 1000)
                # linear layer
                self.fc3 = nn.Linear(1000, 133) # 133 classes
                # dropout layer (p=0.2)
                self.dropout = nn.Dropout(0.2)
                self.batch_norm1D = nn.BatchNorm1d(num_features=1000)

            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)))
                # flatten image input
                x = x.view(-1, 64 * 28 * 28)
                # add dropout layer
                x = self.dropout(x)
                # add 1st hidden layer, with relu activation function
                x = self.dropout(F.relu(self.batch_norm1D(self.fc1(x))))
                # add 2nd hidden layer, with relu activation function
                x = self.fc3(x)
                return x

        #-#-# You do 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()
        print(model_scratch)
```

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=50176, out_features=1000, bias=True)
  (fc3): Linear(in_features=1000, out_features=133, bias=True)
  (dropout): Dropout(p=0.2)
  (batch_norm1D): BatchNorm1d(1000, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tr
)
```

Question 4: Outline the steps you took to get to your final CNN architecture and your reasoning at each step.
Answer:
- The input of the first layer is (224, 224, 3) RGB image and since the kernel is 3x3 and the stripe is 1, we add a padding of 1 to the convolution layers. - Then, in each convolutional layer, I increase the channels but to reduce complexity, I add a max pooling layer in between. The max pooling layers reduce the x and y dimentions of the channels by a factor that I set to 2. Since the input image is 224x224 and I have 3 max pooling layers, the input to the fully connected layer is 28x28. - Lastly, I add fully connected layers to produce the probabilities for the 133 classes. I add dropout layers with probability of 25% between the fully connected layers to avoid overfitting.

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

        ### TODO: select optimizer
        optimizer_scratch = optim.SGD(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 [8]: 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
        # 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 paramete
        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()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = model(data)
        # calculate the batch loss
        loss = criterion(output, target)
        ## update the 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(train_loader.dataset)
    valid_loss = valid_loss/len(valid_loader.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 ...'.for
                valid_loss_min,
                valid_loss))
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss
        # return trained model
        return model

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

```
In [13]: # train the model
         model_scratch = train(20, loaders_scratch, model_scratch, optimizer_scratch,
                               criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1         Training Loss: 4.333205         Validation Loss: 3.998448
Validation loss decreased (inf --> 3.998448).  Saving model ...
Epoch: 2         Training Loss: 3.772750         Validation Loss: 3.827180
Validation loss decreased (3.998448 --> 3.827180).  Saving model ...
Epoch: 3         Training Loss: 3.547476         Validation Loss: 3.689263
Validation loss decreased (3.827180 --> 3.689263).  Saving model ...
Epoch: 4         Training Loss: 3.394024         Validation Loss: 3.568305
Validation loss decreased (3.689263 --> 3.568305).  Saving model ...
Epoch: 5         Training Loss: 3.281266         Validation Loss: 3.531068
Validation loss decreased (3.568305 --> 3.531068).  Saving model ...
Epoch: 6         Training Loss: 3.173690         Validation Loss: 3.530559
Validation loss decreased (3.531068 --> 3.530559).  Saving model ...
Epoch: 7         Training Loss: 3.106951         Validation Loss: 3.497418
Validation loss decreased (3.530559 --> 3.497418).  Saving model ...
Epoch: 8         Training Loss: 3.037456         Validation Loss: 3.461328
Validation loss decreased (3.497418 --> 3.461328).  Saving model ...
Epoch: 9         Training Loss: 2.965735         Validation Loss: 3.447061
Validation loss decreased (3.461328 --> 3.447061).  Saving model ...
Epoch: 10         Training Loss: 2.905399         Validation Loss: 3.390238
Validation loss decreased (3.447061 --> 3.390238).  Saving model ...
Epoch: 11         Training Loss: 2.845196         Validation Loss: 3.472519
Epoch: 12         Training Loss: 2.796148         Validation Loss: 3.337935
Validation loss decreased (3.390238 --> 3.337935).  Saving model ...
Epoch: 13         Training Loss: 2.728541         Validation Loss: 3.428873
```

```
Epoch: 14       Training Loss: 2.694771       Validation Loss: 3.318512
Validation loss decreased (3.337935 --> 3.318512).  Saving model ...
Epoch: 15       Training Loss: 2.632421       Validation Loss: 3.361822
Epoch: 16       Training Loss: 2.601501       Validation Loss: 3.299017
Validation loss decreased (3.318512 --> 3.299017).  Saving model ...
Epoch: 17       Training Loss: 2.538660       Validation Loss: 3.276952
Validation loss decreased (3.299017 --> 3.276952).  Saving model ...
Epoch: 18       Training Loss: 2.495792       Validation Loss: 3.313815
Epoch: 19       Training Loss: 2.455751       Validation Loss: 3.331891
Epoch: 20       Training Loss: 2.410255       Validation Loss: 3.375037
```

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

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 [15]: def test(loaders, model, criterion, use_cuda):

             # monitor test loss and accuracy
             test_loss = 0.
             correct = 0.
             total = 0.

             model.eval()
             for batch_idx, (data, target) in enumerate(loaders['test']):
                 # move to GPU
                 if use_cuda:
                     data, target = data.cuda(), target.cuda()
                 # forward pass: compute predicted outputs by passing inputs to the model
                 output = model(data)
                 # calculate the loss
                 loss = criterion(output, target)
                 # update average test loss
                 test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
                 # convert output probabilities to predicted class
                 pred = output.data.max(1, keepdim=True)[1]
                 # compare predictions to true label
                 correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
                 total += data.size(0)

             print('Test Loss: {:.6f}'.format(test_loss))

             print('Test Accuracy: %2d%% (%2d/%2d)' % (
                 100. * correct / total, correct, total))
```

```
        # call test function
        test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.256747
Test Accuracy: 21% (180/836)
```

## 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 [20]: ## TODO: Specify data loaders
         loaders_transfer = {'train': train_loader, 'valid': valid_loader, 'test': test_loader}
```

1.1.13 (IMPLEMENTATION) Model Architecture

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

```
In [21]: ## TODO: Specify model architecture
         model_transfer = models.resnet50(pretrained=True)
         print(model_transfer.fc)
```

```
Linear(in_features=2048, out_features=1000, 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:

I used the resnet50 model as suggested above.
By looking at the structure of the model, we can see that the last layer is a fully connected layer that outputs 1000 features. For the dog breed classification problem, we only need to classify 133 outputs. Therefore, I will change the fully connected layer.

```
In [22]: model_transfer.fc = nn.Linear(2048, 133)
         print(model_transfer.fc)
         if use_cuda:
             model_transfer = model_transfer.cuda()
```

```
Linear(in_features=2048, out_features=133, bias=True)
```

1.1.14 (IMPLEMENTATION) Specify Loss Function and Optimizer

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

```
In [23]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adam(model_transfer.fc.parameters(), lr=0.001)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

```
In [24]: n_epochs = 15
         # train the model
         model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,
                                criterion_transfer, use_cuda, 'model_transfer.pt')
```

```
Epoch: 1 	Training Loss: 2.258341 	Validation Loss: 0.852894
Validation loss decreased (inf --> 0.852894).  Saving model ...
Epoch: 2 	Training Loss: 0.904291 	Validation Loss: 0.643187
Validation loss decreased (0.852894 --> 0.643187).  Saving model ...
Epoch: 3 	Training Loss: 0.728750 	Validation Loss: 0.617624
Validation loss decreased (0.643187 --> 0.617624).  Saving model ...
Epoch: 4 	Training Loss: 0.631235 	Validation Loss: 0.517142
Validation loss decreased (0.617624 --> 0.517142).  Saving model ...
Epoch: 5 	Training Loss: 0.575184 	Validation Loss: 0.597033
Epoch: 6 	Training Loss: 0.538891 	Validation Loss: 0.534641
Epoch: 7 	Training Loss: 0.485832 	Validation Loss: 0.491377
Validation loss decreased (0.517142 --> 0.491377).  Saving model ...
Epoch: 8 	Training Loss: 0.479076 	Validation Loss: 0.504963
Epoch: 9 	Training Loss: 0.444034 	Validation Loss: 0.639487
Epoch: 10 	Training Loss: 0.434617 	Validation Loss: 0.575493
Epoch: 11 	Training Loss: 0.417515 	Validation Loss: 0.605072
Epoch: 12 	Training Loss: 0.419660 	Validation Loss: 0.547591
Epoch: 13 	Training Loss: 0.376053 	Validation Loss: 0.634738
Epoch: 14 	Training Loss: 0.397752 	Validation Loss: 0.576669
Epoch: 15 	Training Loss: 0.392880 	Validation Loss: 0.586920
```

```
In [25]: # load the model that got the best validation accuracy (uncomment the line below)
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

1.1.16 (IMPLEMENTATION) Test the Model

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

```
In [27]: def test(loaders, model, criterion, use_cuda):
```

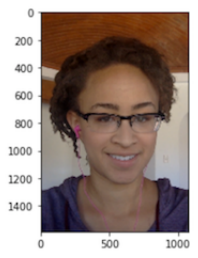
```
            # monitor test loss and accuracy
            test_loss = 0.
            correct = 0.
            total = 0.

            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}'.format(test_loss))

            print('Test Accuracy: %2d%% (%2d/%2d)' % (
                100. * correct / total, correct, total))

        test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.480169
Test Accuracy: 86% (719/836)
```

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 [39]: ### 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 loaders_transfer['train'].dataset

         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             img = Image.open(img_path).convert('RGB')
             transform = transforms.Compose([
hello, human!
```



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

Sample Human Output

```
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406],
                             std=[0.229, 0.224, 0.225])
])
img = transform(img).unsqueeze(0)

if use_cuda:
    img = img.cuda()

# get output
output = model_transfer(img)
# convert output probabilities to predicted class
_, preds_tensor = torch.max(output, 1)
# predicted class index
preds = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tens

return class_names[preds]
```

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

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             if face_detector(img_path):
                 predicted_breed = predict_breed_transfer(img_path)
                 plt.imshow(Image.open(img_path))
                 plt.show()
                 print('Hello, Human!')
                 print('You look like a ...\n' + predicted_breed + '\n\n')
             elif dog_detector(img_path):
                 predicted_breed = predict_breed_transfer(img_path)
                 plt.imshow(Image.open(img_path))
                 plt.show()
                 print('dog!')
                 print('Detected dog looks like a ...\n' + predicted_breed + '\n\n')
             else:
                 predicted_breed = predict_breed_transfer(img_path)
                 plt.imshow(Image.open(img_path))
                 plt.show()
                 print('Error! You are neither a human nor a dog.\n But, you look like a ' + pre
```

## 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.

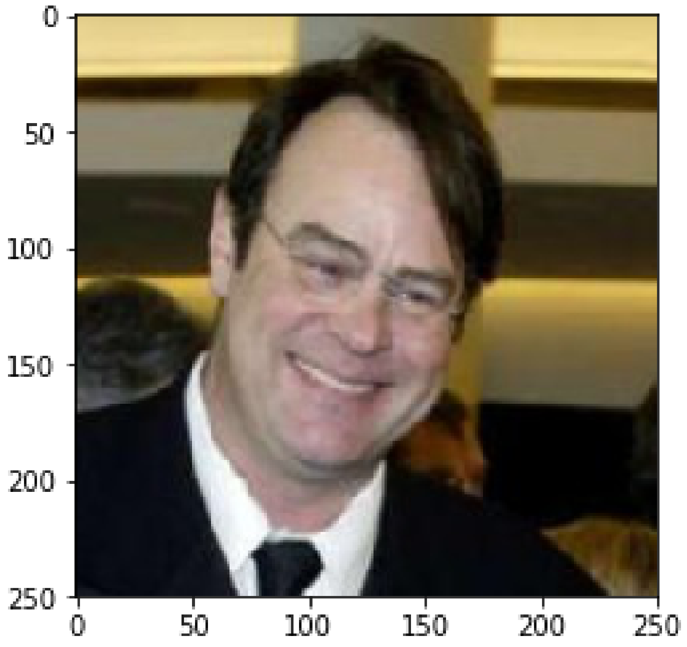
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement)
- Instead of center-croping, croping the images around the face of the dog or human can improve the detection of new images that do not have the face centered.

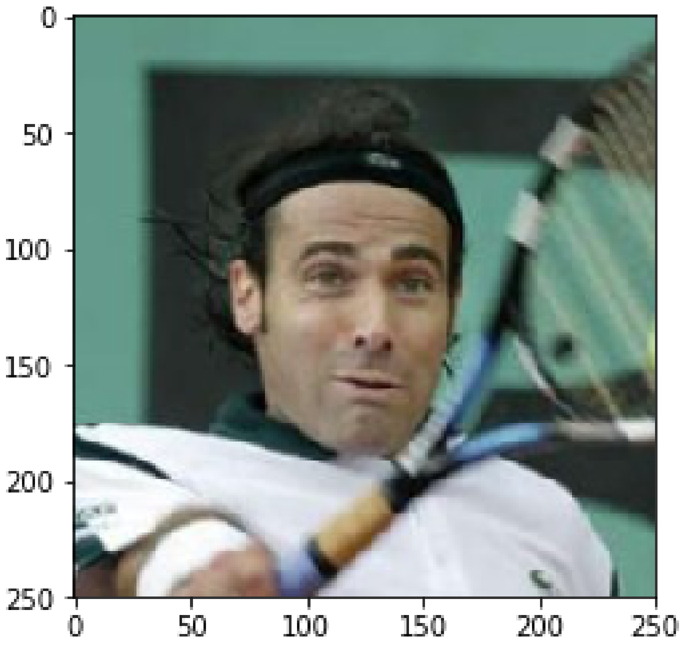
- Having more data is always better. The dataset has 8351 dog images, roughly 62 images per dog breed.
- Having a more complex architecture for the network can improve the results but would take longer time to train.

```
In [65]: ## TODO: Execute your algorithm from Step 6 on
         ## at least 6 images on your computer.
```

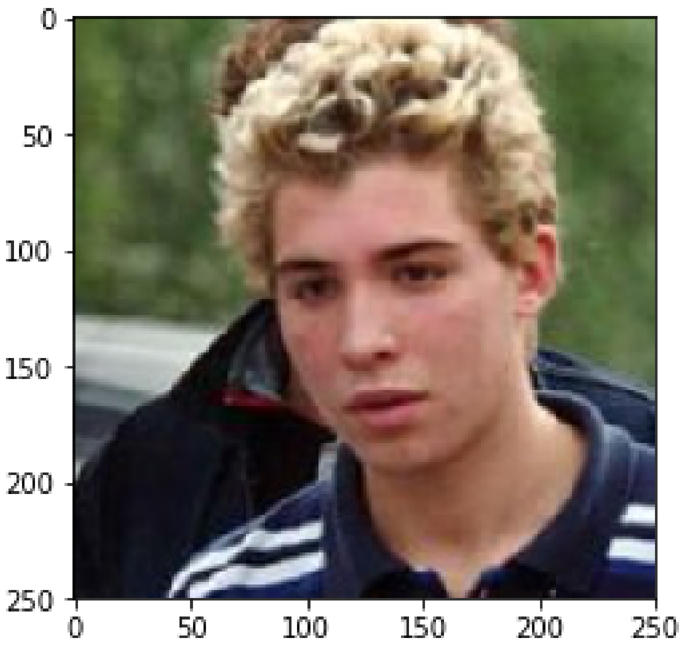
```python
## Feel free to use as many code cells as needed.

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



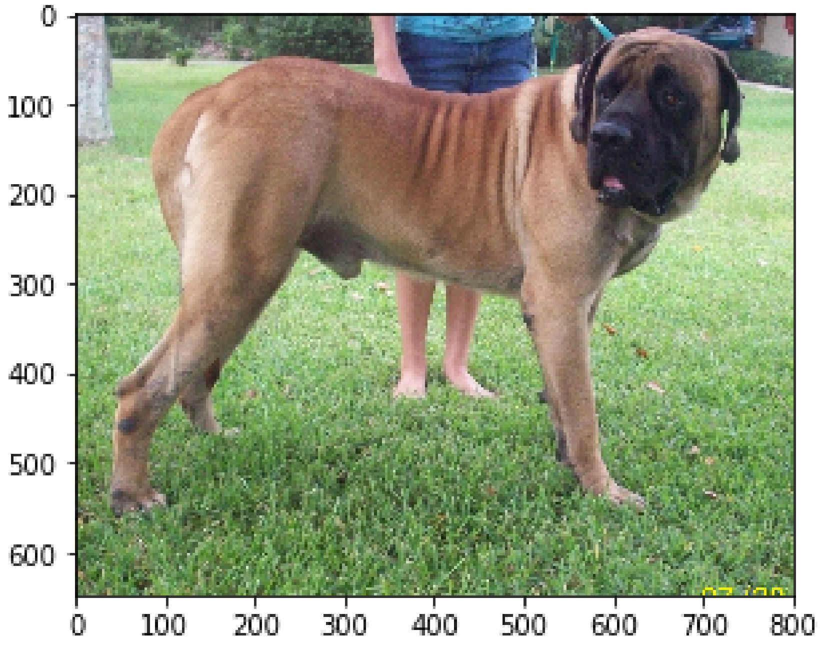
```
Hello, Human!
You look like a ...
Norfolk terrier
```



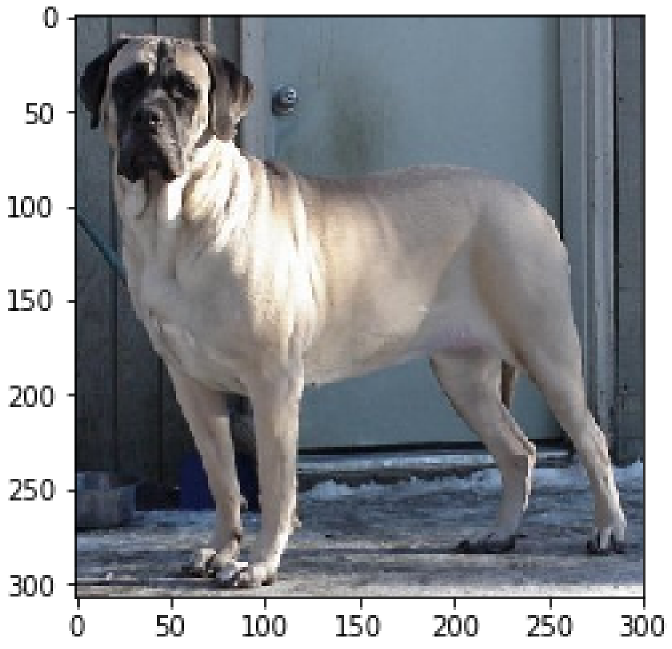
```
Hello, Human!
You look like a ...
Chihuahua
```



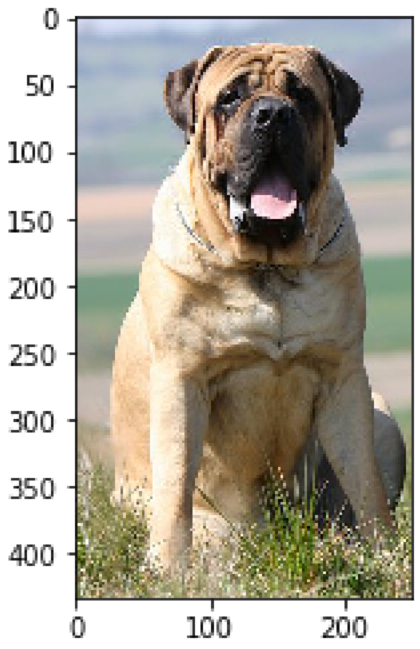
```
Hello, Human!
You look like a ...
American water spaniel
```



```
dog!
Detected dog looks like a ...
Mastiff
```

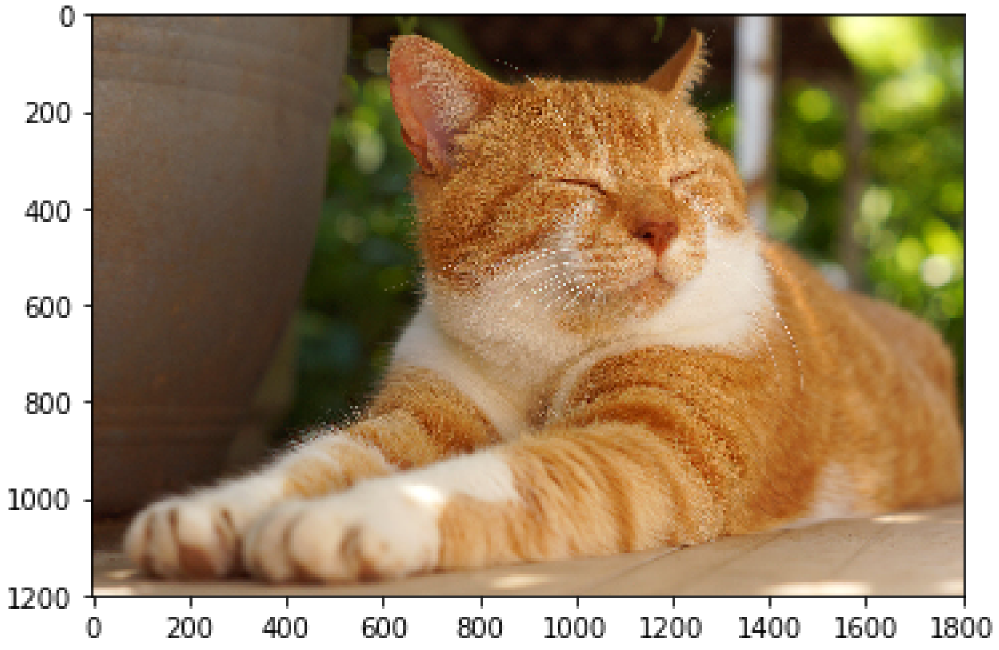


```
dog!
Detected dog looks like a ...
Mastiff
```

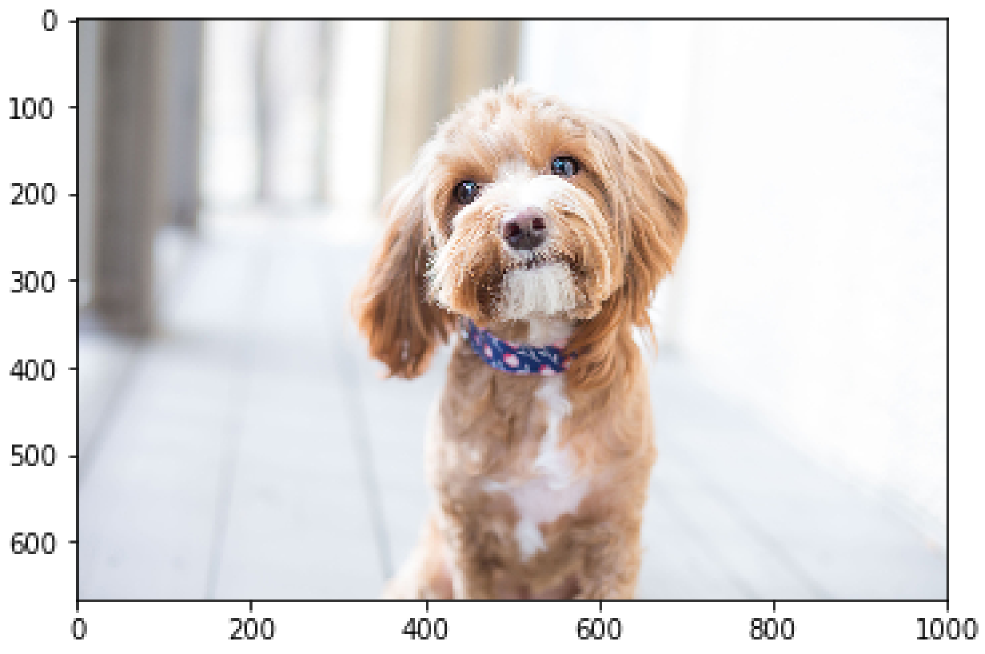


```
dog!
Detected dog looks like a ...
Bullmastiff
```

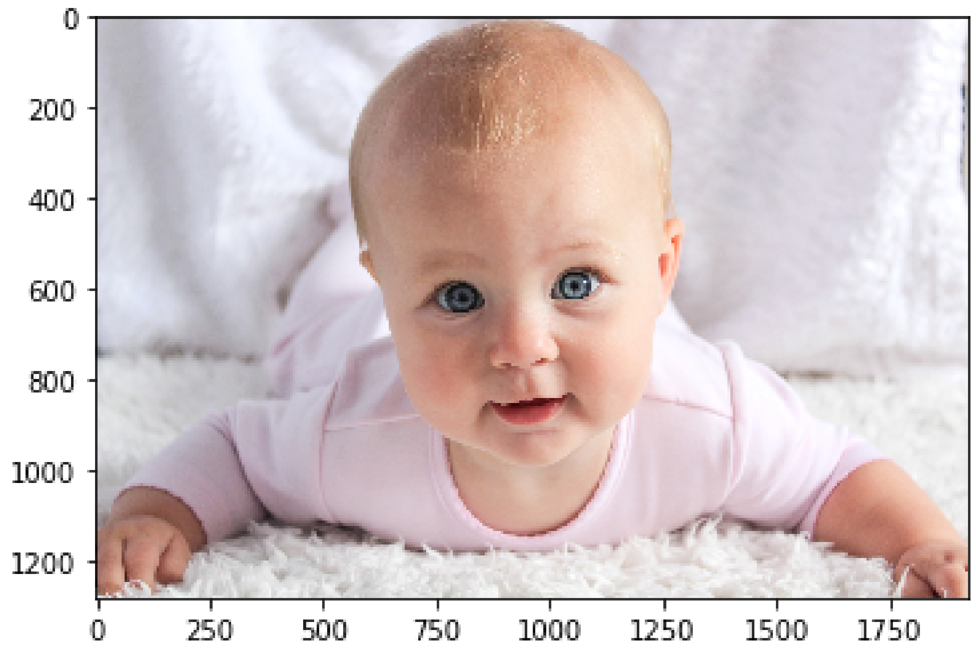
```
In [64]: pics = [os.path.join('./test_pics/', pic) for pic in os.listdir('./test_pics/')]
         for pic in pics:
             run_app(pic)
```



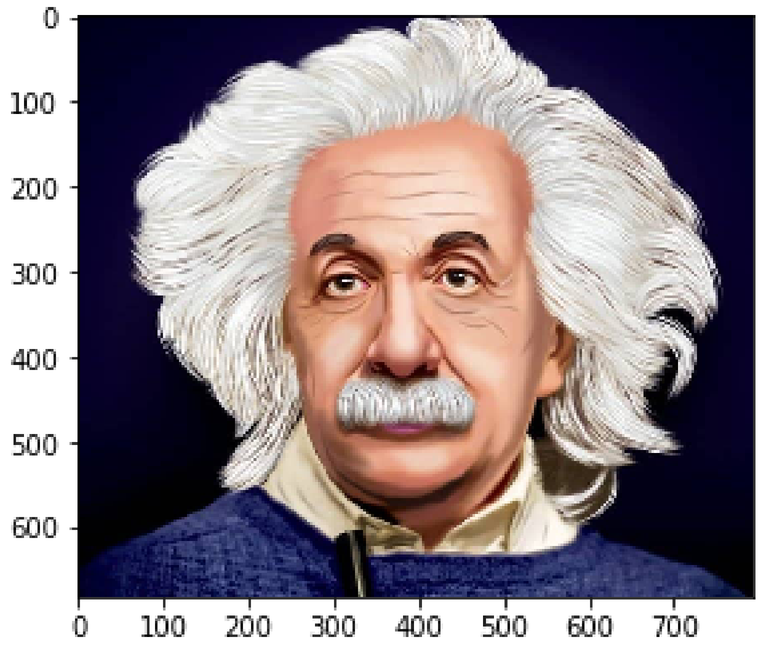
```
Error! You are neither a human nor a dog.
 But, you look like a Nova scotia duck tolling retriever
```



```
dog!
Detected dog looks like a ...
Silky terrier
```

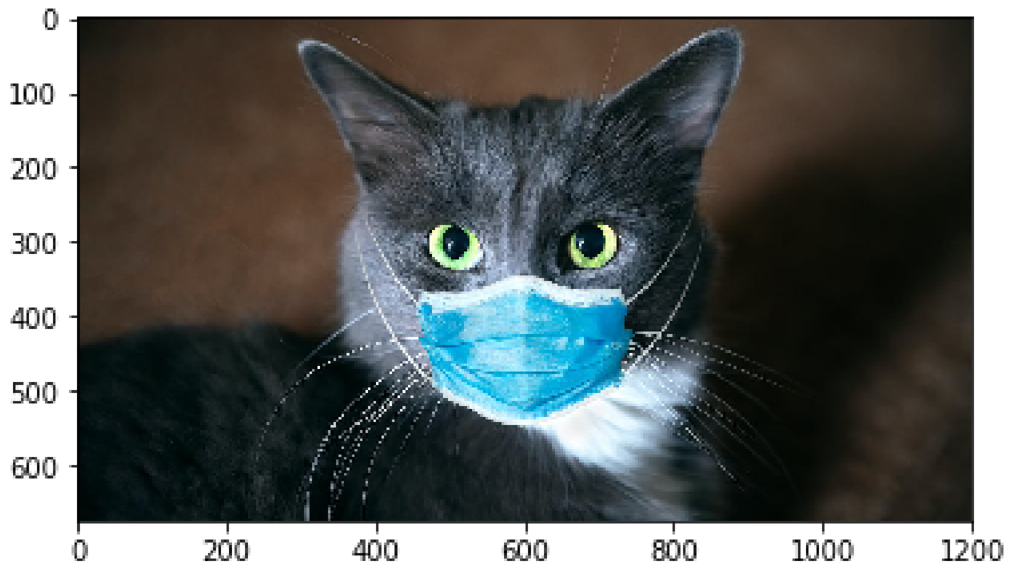


```
Hello, Human!
You look like a ...
Maltese
```



```
Hello, Human!
You look like a ...
Chinese crested
```

```
dog!
Detected dog looks like a ...
Pomeranian
```



```
Error! You are neither a human nor a dog.
 But, you look like a Pomeranian
```

```
In [ ]:
```