dog_app

September 23, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

Step 0: Import Datasets

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`.

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

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

# 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.

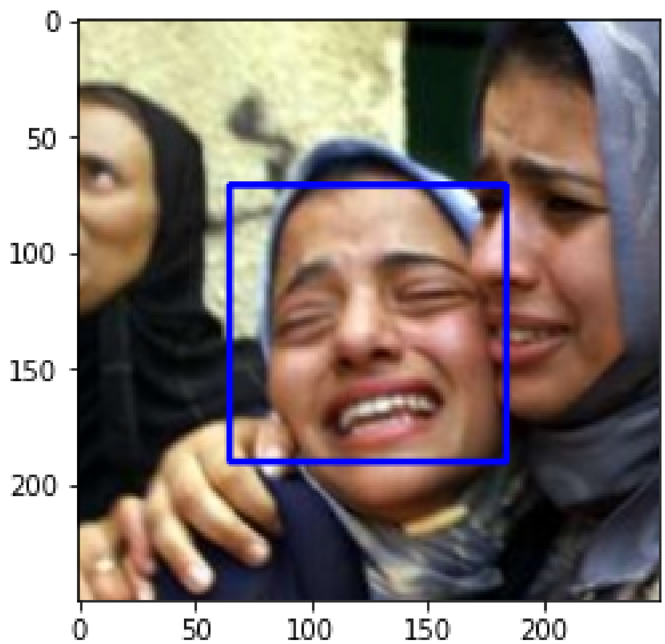
[2]:
```
import cv2
import matplotlib.pyplot as plt
%matplotlib inline

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

```python
# 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()
```

```
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The text.latex.preview rcparam was deprecated in Matplotlib 3.3 and will be
removed two minor releases later.
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The mathtext.fallback_to_cm rcparam was deprecated in Matplotlib 3.3 and will be
removed two minor releases later.
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle: Support for setting the
'mathtext.fallback_to_cm' rcParam is deprecated since 3.3 and will be removed
two minor releases later; use 'mathtext.fallback : 'cm' instead.
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The validate_bool_maybe_none function was deprecated in Matplotlib 3.3 and will
be removed two minor releases later.
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The savefig.jpeg_quality rcparam was deprecated in Matplotlib 3.3 and will be
removed two minor releases later.
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The keymap.all_axes rcparam was deprecated in Matplotlib 3.3 and will be removed
two minor releases later.
```

```
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The animation.avconv_path rcparam was deprecated in Matplotlib 3.3 and will be
removed two minor releases later.
In /home/user21st/.local/lib/python3.6/site-packages/matplotlib/mpl-
data/stylelib/_classic_test.mplstyle:
The animation.avconv_args rcparam was deprecated in Matplotlib 3.3 and will be
removed two minor releases later.
```

```
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.

[3]:
```python
# 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`.

[33]:
```python
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.
count1 = 0
for img in human_files_short:
    count1 += face_detector(img)
print(f'{count1/len(human_files_short)*100:.1f}%, Total {count1} human faces␣
 ↪found in {len(human_files_short)} human images')
print('This is the accuracy\n')

count2 = 0
for img in dog_files_short:
    count2 += face_detector(img)
print(f'{count2/len(dog_files_short)*100:.1f}%, Total {count2} human faces␣
 ↪found in {len(dog_files_short)} dog images')
print('This is the error rate\n')
```

```
100.0%, Total 100 human faces found in 100 human images
This is the accuracy

16.0%, Total 16 human faces found in 100 dog images
This is the error rate
```

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`.

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

Step 2: Detect Dogs

In this section, we use a pre-trained model to detect dogs in images.

1.1.3 Obtain Pre-trained VGG-16 Model

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

[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()
```

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.

[7]:

```python
from PIL import Image
import torchvision.transforms as transforms

# Set PIL to be tolerant of image files that are truncated.
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

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
    img = Image.open(img_path)

    ## Normalize
    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.
↪224, 0.225])
    ## Transform
    # resize to default input image size of 224x224, below we resize and crop
    transform = transforms.Compose([transforms.Resize(256), transforms.
↪CenterCrop(224), transforms.ToTensor(), normalize])
    img_tensor = transform(img).unsqueeze_(0)

    # Load tensor on GPU if available
    if use_cuda:
        img_tensor = img_tensor.cuda()

    # For inference
    VGG16.eval()

    # Disabling gradient calculation is useful for inference, saves memory␣
↪consumption
    with torch.no_grad():
        classes = VGG16(img_tensor)

    ## Return the *index* of the predicted class for that image
    return classes.argmax() # 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).

[8]:
```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    index = VGG16_predict(img_path)
    return True if 151 <= index and index <= 268 else False  # 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:

[9]:
```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
count1 = 0
for img_path in dog_files_short:
    count1 += dog_detector(img_path)
print(f'{count1/len(dog_files_short)*100:.1f}%, Total {count1} dog faces found␣
 ↪in {len(dog_files_short)} dog images')
print('This is the accuracy\n')

count2 = 0
for img_path in human_files_short:
    count2 += dog_detector(img_path)
print(f'{count2/len(human_files_short)*100:.1f}%, Total {count2} dog faces␣
 ↪found in {len(human_files_short)} human images')
print('This is the error rate\n')
```

```
100.0%, Total 100 dog faces found in 100 dog images
This is the accuracy

0.0%, Total 0 dog faces found in 100 human images
This is the error rate
```

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`.

[10]:
```
### (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 `dogImages/train`, `dogImages/valid`, and `dogImages/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!

[11]:
```
import torch
```

[12]:
```
import os
from torchvision import datasets

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

# parameters
batch_size = 32
num_workers = 0

# Set data paths
path_to_data = 'dogImages/'
folders = {'train': 'train', 'valid': 'valid', 'test': 'test'}
dict_keys = ['train', 'valid', 'test']

# create normalizer
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,␣
↪0.225])

# Set transforms
trans = {'train': transforms.Compose([transforms.Resize(256), transforms.
↪RandomHorizontalFlip(), transforms.RandomRotation(5),transforms.
↪CenterCrop(224), transforms.ToTensor(), normalize]),
         'valid': transforms.Compose([transforms.Resize(256), transforms.
↪RandomHorizontalFlip(), transforms.RandomRotation(5),transforms.
↪CenterCrop(224), transforms.ToTensor(), normalize]),
         'test': transforms.Compose([transforms.Resize(256), transforms.
↪CenterCrop(224), transforms.ToTensor(), normalize])}

# create dataset
data= {}
for key in dict_keys:
    data.update({key : datasets.ImageFolder(path_to_data+folders[key],␣
↪transform=trans[key])})

# create data loaders
loaders_scratch = {}
```

```
for key in dict_keys:
    loaders_scratch .update({key : torch.utils.data.DataLoader(data[key],␣
↪batch_size=batch_size, shuffle=True, num_workers=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?

The pre-processing steps involve first resizing the image to 256x256 and then performing random-filp and/or rotation up to 5 degrees. After which a center crop is performed to the desired image size of 224x224. This allows for the essential features to be centered, and it is also important to augment the image before cropping. Finally, the image is converted to a tensor and normalized. The input image size was chosen to be 224x224 becuase the network I built is inspired by VGG16 and hence I went with the same input image size.

- Did you decide to augment the dataset? If so, how (through translations, flips, rotations, etc)? If not, why not?

  I did choose to augment the dataset. There are two augment operations, Random-Flip and Rotaion of up to 5 degrees. This allows for the network to generalize better as it learns that all the variations of the same image result in the same label.

1.1.8 (IMPLEMENTATION) Model Architecture

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

[13]:
```
import torch.nn as nn
import torch.nn.functional as F

num_classes = 133

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=64, kernel_size=3,␣
↪stride=1, padding=1)
        self.conv2 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3,␣
↪stride=1, padding=1)
        self.conv3 = nn.Conv2d(in_channels=128, out_channels=256,␣
↪kernel_size=3, stride=1, padding=1)
        self.conv4 = nn.Conv2d(in_channels=256, out_channels=512,␣
↪kernel_size=3, stride=1, padding=1)
        self.conv5 = nn.Conv2d(in_channels=512, out_channels=512,␣
↪kernel_size=3, stride=1, padding=1)
```

```
        # pool
        self.pool = nn.MaxPool2d(2, 2)

        # fully-connected
        self.fc1 = nn.Linear(7*7*512, 512) #25088
        #self.fc2 = nn.Linear(512, 512)
        self.fc2 = nn.Linear(512, num_classes)

        # Normalization
        self.dropout = nn.Dropout(0.5)

    def forward(self, x):
        ## Define forward behavior
        # Conv layers - Feature detection
        x = F.relu(self.conv1(x))
        x = self.pool(x)
        x = F.relu(self.conv2(x))
        x = self.pool(x)
        x = F.relu(self.conv3(x))
        x = self.pool(x)
        x = F.relu(self.conv4(x))
        x = self.pool(x)
        x = F.relu(self.conv5(x))
        x = self.pool(x)
        # Flatten
        x = x.view(-1, 7*7*512) #25088
        # Fully connected - Classifier
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = self.fc2(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()
```

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

The CNN architecture that I ended up with was inspired from VGG16. The convolution layers were chosen from column A architecture. But I didn't choose to repeat each convolution layer before pooling. This is because I thought the complexity of the problem

I am trying to solve here is relatively easy compared to the 1000 different categories. Hence there are fewer features to be detected. Next, the output of the convolution or feature detection portion of the network was flattened to be fed into the fully connected network or the classifier portion of the network. I chose two fully connected layers; the first FC layer starts with the total pixels at the end of convolution layers, which is 7 * 7 * 512 to 512, and the next one is 512->133, which is the number of labels. In between the two FC layers, I used a dropout layer, and this is to avoid overfitting to training data.

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.

[14]:
```
import torch.optim as optim

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

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

1.1.10 (IMPLEMENTATION) Train and Validate the Model

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

[16]:
```
# the following import is required for training to be robust to truncated images
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

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

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

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
```

```
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            # clear gradients of all optimized variables
            optimizer.zero_grad()
            # forwarward pass
            output = model(data)
            # calculate batch loss
            loss = criterion(output, target)
            # backward pass
            loss.backward()
            # perform optimization step
            optimizer.step()
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data -␣
↪train_loss))
            train_loss += ((1 / (batch_idx + 1)) * (loss.data - train_loss))

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):

            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss
            with torch.no_grad():
                output = model(data)
            loss = criterion(output, target)
            valid_loss += ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

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

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

```python
            valid_loss_min = valid_loss
            torch.save(model.state_dict(), save_path)


    # return trained model
    return model


# train the model
model_scratch = train(25, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1        Training Loss: 4.888966         Validation Loss: 4.871403
Validation loss decreased (inf --> 4.871403).  Saving model …
Epoch: 2        Training Loss: 4.838046         Validation Loss: 4.682314
Validation loss decreased (4.871403 --> 4.682314).  Saving model …
Epoch: 3        Training Loss: 4.501217         Validation Loss: 4.422232
Validation loss decreased (4.682314 --> 4.422232).  Saving model …
Epoch: 4        Training Loss: 4.278875         Validation Loss: 4.182371
Validation loss decreased (4.422232 --> 4.182371).  Saving model …
Epoch: 5        Training Loss: 4.119110         Validation Loss: 4.077655
Validation loss decreased (4.182371 --> 4.077655).  Saving model …
Epoch: 6        Training Loss: 3.956884         Validation Loss: 3.923495
Validation loss decreased (4.077655 --> 3.923495).  Saving model …
Epoch: 7        Training Loss: 3.791081         Validation Loss: 3.857402
Validation loss decreased (3.923495 --> 3.857402).  Saving model …
Epoch: 8        Training Loss: 3.660864         Validation Loss: 3.823748
Validation loss decreased (3.857402 --> 3.823748).  Saving model …
Epoch: 9        Training Loss: 3.529158         Validation Loss: 3.698552
Validation loss decreased (3.823748 --> 3.698552).  Saving model …
Epoch: 10       Training Loss: 3.386931         Validation Loss: 3.680907
Validation loss decreased (3.698552 --> 3.680907).  Saving model …
Epoch: 11       Training Loss: 3.233665         Validation Loss: 3.737078
Epoch: 12       Training Loss: 3.100406         Validation Loss: 3.636933
Validation loss decreased (3.680907 --> 3.636933).  Saving model …
Epoch: 13       Training Loss: 2.957784         Validation Loss: 3.617869
Validation loss decreased (3.636933 --> 3.617869).  Saving model …
Epoch: 14       Training Loss: 2.827422         Validation Loss: 3.564928
Validation loss decreased (3.617869 --> 3.564928).  Saving model …
Epoch: 15       Training Loss: 2.691028         Validation Loss: 3.570630
Epoch: 16       Training Loss: 2.541063         Validation Loss: 3.596966
Epoch: 17       Training Loss: 2.390352         Validation Loss: 3.648751
Epoch: 18       Training Loss: 2.255760         Validation Loss: 3.734132
Epoch: 19       Training Loss: 2.169391         Validation Loss: 3.664026
Epoch: 20       Training Loss: 2.039843         Validation Loss: 3.874290
Epoch: 21       Training Loss: 1.896063         Validation Loss: 3.876294
Epoch: 22       Training Loss: 1.833193         Validation Loss: 3.984812
```

```
Epoch: 23       Training Loss: 1.720141         Validation Loss: 3.976660
Epoch: 24       Training Loss: 1.655990         Validation Loss: 3.973254
Epoch: 25       Training Loss: 1.530332         Validation Loss: 4.290498
```

[17]:
```
# load the model that got the best validation accuracy
model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

[17]:
```
<All keys matched successfully>
```

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%.

[19]:
```
def test(loaders, model, criterion, use_cuda):

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

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

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

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

# call test function
```

```
test(loaders_scratch, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.561034


Test Accuracy: 18% (154/836)
```

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.

[20]:
```
## TODO: Specify data loaders
loaders_transfer = loaders_scratch
```

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`.

[21]:
```
use_cuda = torch.cuda.is_available()
```

[22]:
```
import torchvision.models as models
import torch.nn as nn

# Specify model architecture
# Bas model selected as RESNET50
model_transfer = models.resnet50(pretrained=True)
# Freeze the weights of feature detection layer
for param in model_transfer.parameters():
    param.requires_grad = False
# we now need to build the fully connected classifier portion
model_transfer.fc = nn.Linear(2048, num_classes, bias=True)
# we now ensure that weights of FC layers are updated, usually set to true by␣
 ↪defalut
for param in model_transfer.fc.parameters():
    param.requires_grad = True
```

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

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.

> For transfer learning, I chose to start with ResNet50 base model and then freeze the network's weights of feature detection portion. Next, I created a FC layer and attached it to the output of the feature detection layer. I set the weights of the classifier layer to update during training. The reason to choose ResNet 50 as my base model is because it is a classic neural network used as a backbone for many computer vision tasks. Also, since its a deep neural network, meaning it has 50 layers, which allow for more features to be detected. This could allow the model to pick up the subtle feature difference between various breeds of dogs.

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.

[23]:
```
import torch.optim as optim
```

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

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

[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']):
```

```
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            # clear gradients of all optimized variables
            optimizer.zero_grad()
            # forwarward pass
            output = model(data)
            # calculate batch loss
            loss = criterion(output, target)
            # backward pass
            loss.backward()
            # perform optimization step
            optimizer.step()
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data -␣
↪train_loss))
            train_loss += ((1 / (batch_idx + 1)) * (loss.data - train_loss))

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):

            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss
            with torch.no_grad():
                output = model(data)
            loss = criterion(output, target)
            valid_loss += ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

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

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

```
            valid_loss_min = valid_loss
            torch.save(model.state_dict(), save_path)


    # return trained model
    return model
```

[26]:
```
# train the model
model_transfer = train(100, 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: 4.861074         Validation Loss: 4.741574
Validation loss decreased (inf --> 4.741574).  Saving model …
Epoch: 2        Training Loss: 4.649438         Validation Loss: 4.512198
Validation loss decreased (4.741574 --> 4.512198).  Saving model …
Epoch: 3        Training Loss: 4.462958         Validation Loss: 4.343228
Validation loss decreased (4.512198 --> 4.343228).  Saving model …
Epoch: 4        Training Loss: 4.286045         Validation Loss: 4.165967
Validation loss decreased (4.343228 --> 4.165967).  Saving model …
Epoch: 5        Training Loss: 4.119147         Validation Loss: 4.001207
Validation loss decreased (4.165967 --> 4.001207).  Saving model …
Epoch: 6        Training Loss: 3.953655         Validation Loss: 3.820854
Validation loss decreased (4.001207 --> 3.820854).  Saving model …
Epoch: 7        Training Loss: 3.800119         Validation Loss: 3.649893
Validation loss decreased (3.820854 --> 3.649893).  Saving model …
Epoch: 8        Training Loss: 3.649270         Validation Loss: 3.526798
Validation loss decreased (3.649893 --> 3.526798).  Saving model …
Epoch: 9        Training Loss: 3.501874         Validation Loss: 3.369722
Validation loss decreased (3.526798 --> 3.369722).  Saving model …
Epoch: 10       Training Loss: 3.360759         Validation Loss: 3.224309
Validation loss decreased (3.369722 --> 3.224309).  Saving model …
Epoch: 11       Training Loss: 3.234702         Validation Loss: 3.126889
Validation loss decreased (3.224309 --> 3.126889).  Saving model …
Epoch: 12       Training Loss: 3.108602         Validation Loss: 2.963945
Validation loss decreased (3.126889 --> 2.963945).  Saving model …
Epoch: 13       Training Loss: 2.983377         Validation Loss: 2.829194
Validation loss decreased (2.963945 --> 2.829194).  Saving model …
Epoch: 14       Training Loss: 2.876716         Validation Loss: 2.720563
Validation loss decreased (2.829194 --> 2.720563).  Saving model …
Epoch: 15       Training Loss: 2.769311         Validation Loss: 2.635584
Validation loss decreased (2.720563 --> 2.635584).  Saving model …
Epoch: 16       Training Loss: 2.671262         Validation Loss: 2.526525
Validation loss decreased (2.635584 --> 2.526525).  Saving model …
```

```
Epoch: 17       Training Loss: 2.574443         Validation Loss: 2.449710
Validation loss decreased (2.526525 --> 2.449710).  Saving model …
Epoch: 18       Training Loss: 2.486816         Validation Loss: 2.359264
Validation loss decreased (2.449710 --> 2.359264).  Saving model …
Epoch: 19       Training Loss: 2.398007         Validation Loss: 2.265009
Validation loss decreased (2.359264 --> 2.265009).  Saving model …
Epoch: 20       Training Loss: 2.322216         Validation Loss: 2.207319
Validation loss decreased (2.265009 --> 2.207319).  Saving model …
Epoch: 21       Training Loss: 2.252200         Validation Loss: 2.138244
Validation loss decreased (2.207319 --> 2.138244).  Saving model …
Epoch: 22       Training Loss: 2.180997         Validation Loss: 2.081569
Validation loss decreased (2.138244 --> 2.081569).  Saving model …
Epoch: 23       Training Loss: 2.107383         Validation Loss: 1.950685
Validation loss decreased (2.081569 --> 1.950685).  Saving model …
Epoch: 24       Training Loss: 2.046895         Validation Loss: 1.923798
Validation loss decreased (1.950685 --> 1.923798).  Saving model …
Epoch: 25       Training Loss: 1.977793         Validation Loss: 1.833797
Validation loss decreased (1.923798 --> 1.833797).  Saving model …
Epoch: 26       Training Loss: 1.932164         Validation Loss: 1.824086
Validation loss decreased (1.833797 --> 1.824086).  Saving model …
Epoch: 27       Training Loss: 1.867011         Validation Loss: 1.783223
Validation loss decreased (1.824086 --> 1.783223).  Saving model …
Epoch: 28       Training Loss: 1.817760         Validation Loss: 1.701579
Validation loss decreased (1.783223 --> 1.701579).  Saving model …
Epoch: 29       Training Loss: 1.772650         Validation Loss: 1.658042
Validation loss decreased (1.701579 --> 1.658042).  Saving model …
Epoch: 30       Training Loss: 1.732828         Validation Loss: 1.650875
Validation loss decreased (1.658042 --> 1.650875).  Saving model …
Epoch: 31       Training Loss: 1.685686         Validation Loss: 1.572746
Validation loss decreased (1.650875 --> 1.572746).  Saving model …
Epoch: 32       Training Loss: 1.646210         Validation Loss: 1.534486
Validation loss decreased (1.572746 --> 1.534486).  Saving model …
Epoch: 33       Training Loss: 1.605691         Validation Loss: 1.482776
Validation loss decreased (1.534486 --> 1.482776).  Saving model …
Epoch: 34       Training Loss: 1.571698         Validation Loss: 1.478265
Validation loss decreased (1.482776 --> 1.478265).  Saving model …
Epoch: 35       Training Loss: 1.530386         Validation Loss: 1.465091
Validation loss decreased (1.478265 --> 1.465091).  Saving model …
Epoch: 36       Training Loss: 1.503598         Validation Loss: 1.387476
Validation loss decreased (1.465091 --> 1.387476).  Saving model …
Epoch: 37       Training Loss: 1.462626         Validation Loss: 1.364170
Validation loss decreased (1.387476 --> 1.364170).  Saving model …
Epoch: 38       Training Loss: 1.440783         Validation Loss: 1.363916
Validation loss decreased (1.364170 --> 1.363916).  Saving model …
Epoch: 39       Training Loss: 1.412455         Validation Loss: 1.327295
Validation loss decreased (1.363916 --> 1.327295).  Saving model …
Epoch: 40       Training Loss: 1.389763         Validation Loss: 1.287943
Validation loss decreased (1.327295 --> 1.287943).  Saving model …
```

```
Epoch: 41       Training Loss: 1.352471         Validation Loss: 1.262640
Validation loss decreased (1.287943 --> 1.262640).  Saving model …
Epoch: 42       Training Loss: 1.331324         Validation Loss: 1.255759
Validation loss decreased (1.262640 --> 1.255759).  Saving model …
Epoch: 43       Training Loss: 1.303917         Validation Loss: 1.205993
Validation loss decreased (1.255759 --> 1.205993).  Saving model …
Epoch: 44       Training Loss: 1.282093         Validation Loss: 1.223682
Epoch: 45       Training Loss: 1.253937         Validation Loss: 1.244893
Epoch: 46       Training Loss: 1.237588         Validation Loss: 1.162869
Validation loss decreased (1.205993 --> 1.162869).  Saving model …
Epoch: 47       Training Loss: 1.214630         Validation Loss: 1.158660
Validation loss decreased (1.162869 --> 1.158660).  Saving model …
Epoch: 48       Training Loss: 1.198045         Validation Loss: 1.132278
Validation loss decreased (1.158660 --> 1.132278).  Saving model …
Epoch: 49       Training Loss: 1.185991         Validation Loss: 1.134612
Epoch: 50       Training Loss: 1.160899         Validation Loss: 1.158857
Epoch: 51       Training Loss: 1.146287         Validation Loss: 1.087095
Validation loss decreased (1.132278 --> 1.087095).  Saving model …
Epoch: 52       Training Loss: 1.125291         Validation Loss: 1.067611
Validation loss decreased (1.087095 --> 1.067611).  Saving model …
Epoch: 53       Training Loss: 1.110537         Validation Loss: 1.055646
Validation loss decreased (1.067611 --> 1.055646).  Saving model …
Epoch: 54       Training Loss: 1.089388         Validation Loss: 1.038809
Validation loss decreased (1.055646 --> 1.038809).  Saving model …
Epoch: 55       Training Loss: 1.082572         Validation Loss: 1.055686
Epoch: 56       Training Loss: 1.061018         Validation Loss: 1.025884
Validation loss decreased (1.038809 --> 1.025884).  Saving model …
Epoch: 57       Training Loss: 1.051227         Validation Loss: 0.988089
Validation loss decreased (1.025884 --> 0.988089).  Saving model …
Epoch: 58       Training Loss: 1.035744         Validation Loss: 1.007999
Epoch: 59       Training Loss: 1.027504         Validation Loss: 0.968183
Validation loss decreased (0.988089 --> 0.968183).  Saving model …
Epoch: 60       Training Loss: 1.013815         Validation Loss: 0.975320
Epoch: 61       Training Loss: 0.997134         Validation Loss: 0.959102
Validation loss decreased (0.968183 --> 0.959102).  Saving model …
Epoch: 62       Training Loss: 0.985381         Validation Loss: 0.970575
Epoch: 63       Training Loss: 0.972179         Validation Loss: 0.938378
Validation loss decreased (0.959102 --> 0.938378).  Saving model …
Epoch: 64       Training Loss: 0.957414         Validation Loss: 0.938996
Epoch: 65       Training Loss: 0.955240         Validation Loss: 0.916841
Validation loss decreased (0.938378 --> 0.916841).  Saving model …
Epoch: 66       Training Loss: 0.946350         Validation Loss: 0.893197
Validation loss decreased (0.916841 --> 0.893197).  Saving model …
Epoch: 67       Training Loss: 0.940556         Validation Loss: 0.901186
Epoch: 68       Training Loss: 0.914434         Validation Loss: 0.894415
Epoch: 69       Training Loss: 0.918203         Validation Loss: 0.902498
Epoch: 70       Training Loss: 0.906517         Validation Loss: 0.865387
Validation loss decreased (0.893197 --> 0.865387).  Saving model …
```

```
Epoch: 71       Training Loss: 0.896847         Validation Loss: 0.883316
Epoch: 72       Training Loss: 0.884279         Validation Loss: 0.882106
Epoch: 73       Training Loss: 0.872245         Validation Loss: 0.849521
Validation loss decreased (0.865387 --> 0.849521).  Saving model …
Epoch: 74       Training Loss: 0.863293         Validation Loss: 0.848786
Validation loss decreased (0.849521 --> 0.848786).  Saving model …
Epoch: 75       Training Loss: 0.862378         Validation Loss: 0.829902
Validation loss decreased (0.848786 --> 0.829902).  Saving model …
Epoch: 76       Training Loss: 0.853409         Validation Loss: 0.812134
Validation loss decreased (0.829902 --> 0.812134).  Saving model …
Epoch: 77       Training Loss: 0.844563         Validation Loss: 0.840715
Epoch: 78       Training Loss: 0.837397         Validation Loss: 0.817218
Epoch: 79       Training Loss: 0.831824         Validation Loss: 0.819612
Epoch: 80       Training Loss: 0.820295         Validation Loss: 0.829215
Epoch: 81       Training Loss: 0.806467         Validation Loss: 0.810572
Validation loss decreased (0.812134 --> 0.810572).  Saving model …
Epoch: 82       Training Loss: 0.803974         Validation Loss: 0.813242
Epoch: 83       Training Loss: 0.797611         Validation Loss: 0.805883
Validation loss decreased (0.810572 --> 0.805883).  Saving model …
Epoch: 84       Training Loss: 0.796228         Validation Loss: 0.827766
Epoch: 85       Training Loss: 0.788148         Validation Loss: 0.785465
Validation loss decreased (0.805883 --> 0.785465).  Saving model …
Epoch: 86       Training Loss: 0.783593         Validation Loss: 0.774304
Validation loss decreased (0.785465 --> 0.774304).  Saving model …
Epoch: 87       Training Loss: 0.770042         Validation Loss: 0.766459
Validation loss decreased (0.774304 --> 0.766459).  Saving model …
Epoch: 88       Training Loss: 0.767047         Validation Loss: 0.756995
Validation loss decreased (0.766459 --> 0.756995).  Saving model …
Epoch: 89       Training Loss: 0.757137         Validation Loss: 0.721440
Validation loss decreased (0.756995 --> 0.721440).  Saving model …
Epoch: 90       Training Loss: 0.751720         Validation Loss: 0.762249
Epoch: 91       Training Loss: 0.755747         Validation Loss: 0.764819
Epoch: 92       Training Loss: 0.737752         Validation Loss: 0.793308
Epoch: 93       Training Loss: 0.735784         Validation Loss: 0.735440
Epoch: 94       Training Loss: 0.736081         Validation Loss: 0.754412
Epoch: 95       Training Loss: 0.730870         Validation Loss: 0.766856
Epoch: 96       Training Loss: 0.716373         Validation Loss: 0.745343
Epoch: 97       Training Loss: 0.720706         Validation Loss: 0.709383
Validation loss decreased (0.721440 --> 0.709383).  Saving model …
Epoch: 98       Training Loss: 0.719775         Validation Loss: 0.722219
Epoch: 99       Training Loss: 0.708850         Validation Loss: 0.730780
Epoch: 100      Training Loss: 0.704674         Validation Loss: 0.711720
```

```
[26]: <All keys matched successfully>
```

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%.

[27]:
```
test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.715865


Test Accuracy: 86% (720/836)
```

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.

[28]:
```
### TODO: Write a function that takes a path to an image as input
### and returns the dog breed that is predicted by the model.

# list of class names by index, i.e. a name can be accessed like class_names[0]
class_names = [item[4:].replace("_", " ") for item in data['train'].classes]

def predict_breed_transfer(img_path):
     ## Load and pre-process an image from the given img_path
    img = Image.open(img_path)

    ## Normalize
    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.
 ↪224, 0.225])
    ## Transform
    # resize to default input image size of 224x224, below we resize and crop
    transform = transforms.Compose([transforms.Resize(256), transforms.
 ↪CenterCrop(224), transforms.ToTensor(), normalize])
    img_tensor = transform(img).unsqueeze_(0)

    # Load tensor on GPU if available
    if use_cuda:
        img_tensor = img_tensor.cuda()

    # For inference
    model_transfer.eval()

    # Disabling gradient calculation is useful for inference, saves memory␣
 ↪consumption
    with torch.no_grad():
        classes = model_transfer(img_tensor)
```

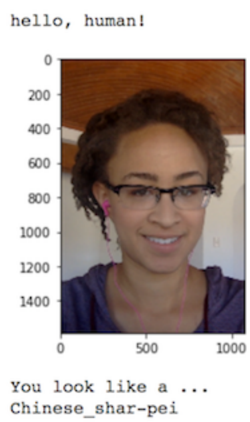
```
    ## Return the breed
    return class_names[classes.argmax()] # predicted class index
```

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 `dog_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

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

def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    img = Image.open(img_path)
    plt.imshow(img)
    plt.show()
    # Now test various models against the image
    if face_detector(img_path):
        print('Hello, Human!')
        dog_breed = predict_breed_transfer(img_path)
        print(f'You look like a {dog_breed}')
    elif dog_detector(img_path):
```

```
        print('Dog Detected!')
        dog_breed = predict_breed_transfer(img_path)
        print(f'Detected Dog is a {dog_breed}')
    else:
        print('ERROR: Nothing detected!')

    print('\n--------------------------------\n')
```

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!

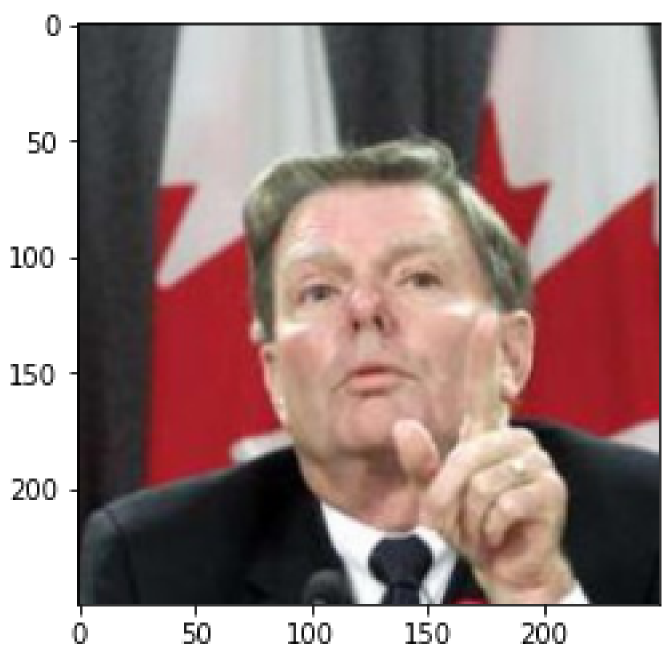
Test your algorithm at least six images on your computer. Feel free to use any images you like. Use at least two human and two dog images.

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

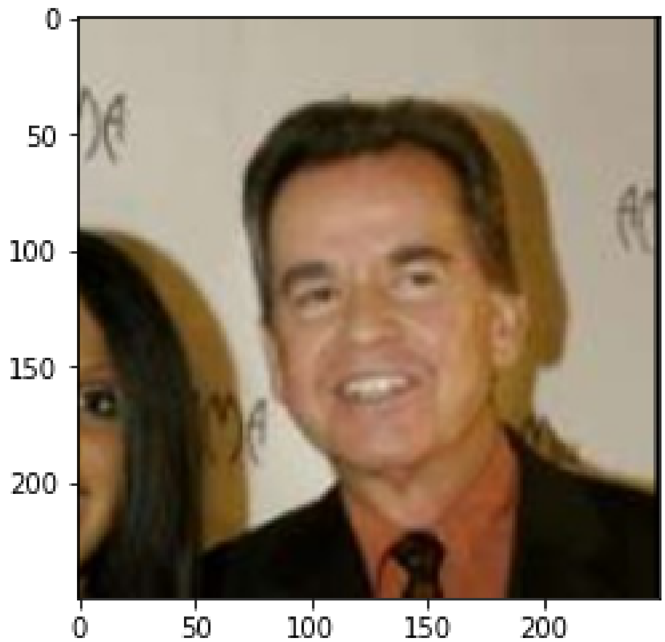
> I tested the algorithm on images of my own dog, and some acquired from the internet. For the most part, it did a great job at detecting human faces, but when it came to dog breeds, it seemed to struggle. For example, my dog is a Golden Doodle, but it was categorized as Havanese. Here are a few possible improvements to the application: - Adding more augmentations to the training data as well as increasing the overall size of training data. This would allow the model to generalize better, which will result in better accuracy on data its never seen before. - I observed that the algorithm struggled when the image was not cropped to the dog area. That is, the dog was not centered in the image. Again I think this can be improved by augmentation and varying input data. This could also be solved by adding a Region Proposal Network (RPN) to first narrow down the area where the dog is in the image and then crop to that region and classify it. - In terms of the overall application, a possible improvement would be to use multiple models and use the best of three results.

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

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

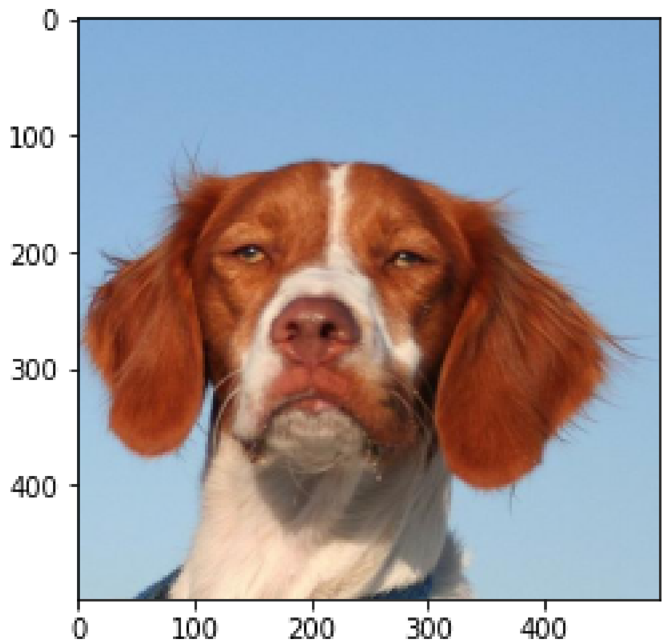

```
Hello, Human!
You look like a Dogue de bordeaux

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



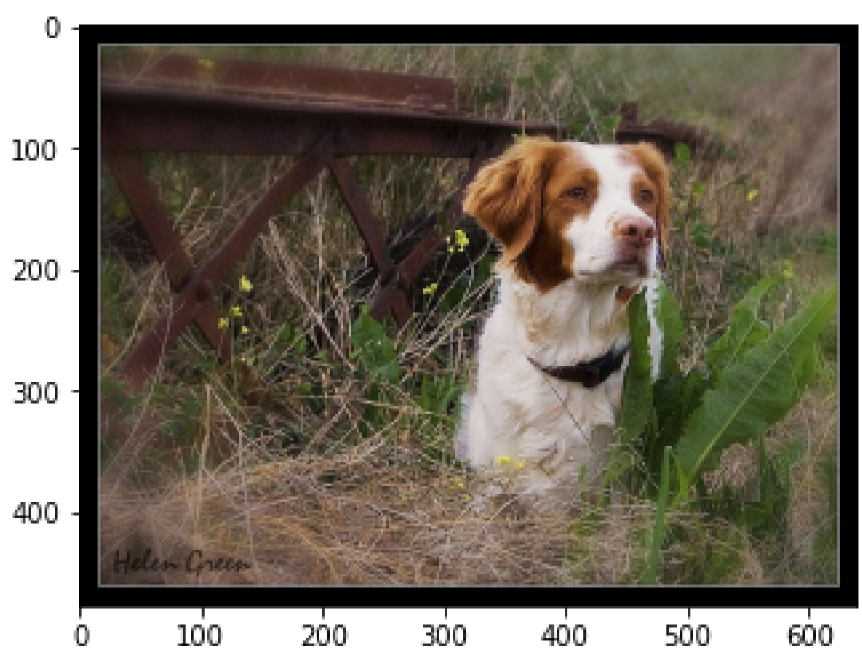
```
Hello, Human!
You look like a Dogue de bordeaux

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



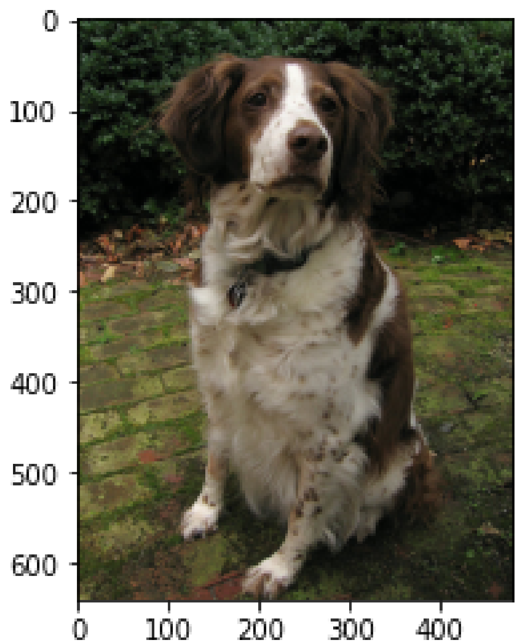
```
Hello, Human!
You look like a Dachshund

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




```
Dog Detected!
Detected Dog is a Brittany

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



```
Dog Detected!
Detected Dog is a Brittany

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

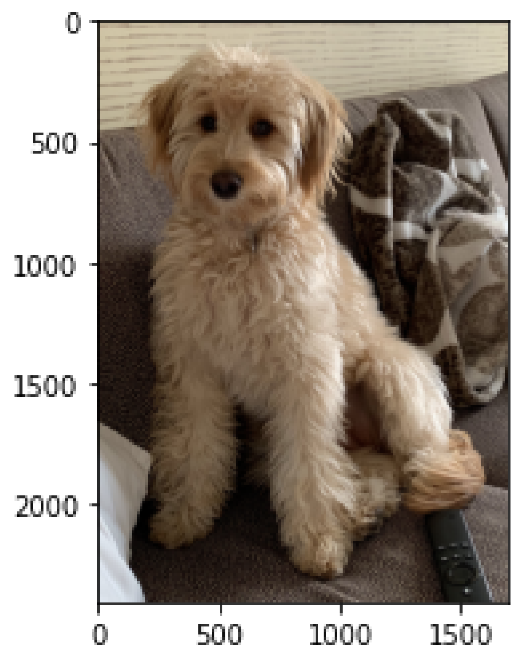



```
Hello, Human!
You look like a English springer spaniel

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

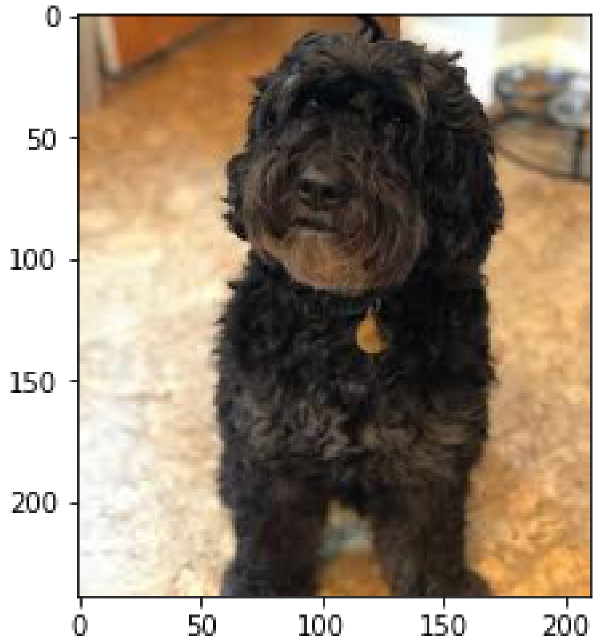
[31]:
```
import glob
new_dog_images = np.array(glob.glob('images/dog*'))
new_human_faces = np.array(glob.glob('images/face*'))
new_images_path = np.concatenate((new_dog_images,new_human_faces), axis = 0)
```

[32]:
```
for img_path in new_images_path:
    run_app(img_path)
```

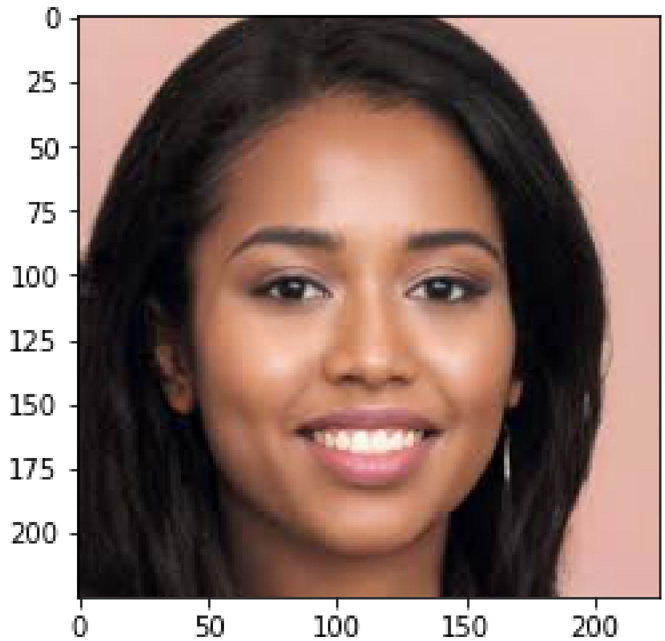

```
Dog Detected!
Detected Dog is a Bichon frise

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



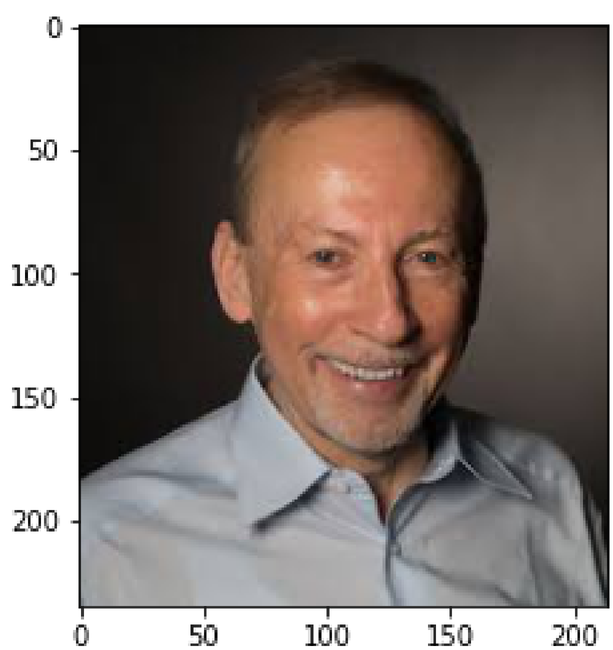
```
Dog Detected!
Detected Dog is a Havanese

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



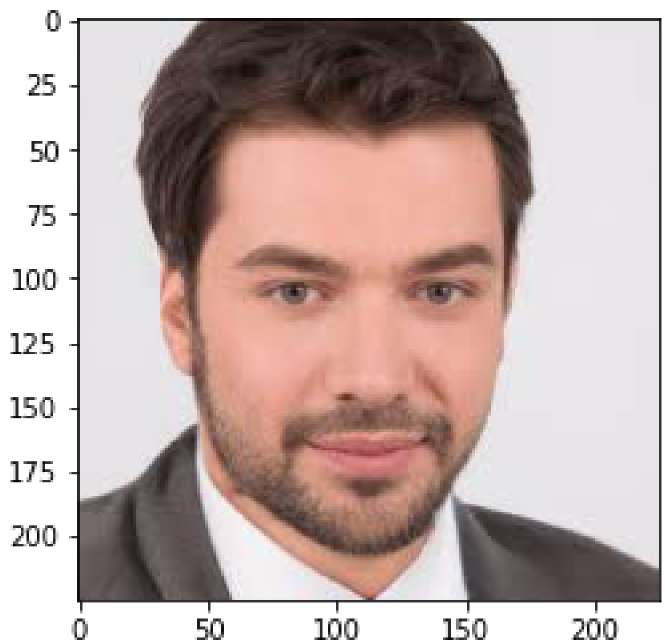
```
Dog Detected!
Detected Dog is a Portuguese water dog

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




```
Hello, Human!
You look like a English toy spaniel

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



```
Hello, Human!
You look like a Dachshund

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




```
Hello, Human!
You look like a Dachshund

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

[ ]: