dog_app

May 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

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

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

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

Step 1: Detect Humans

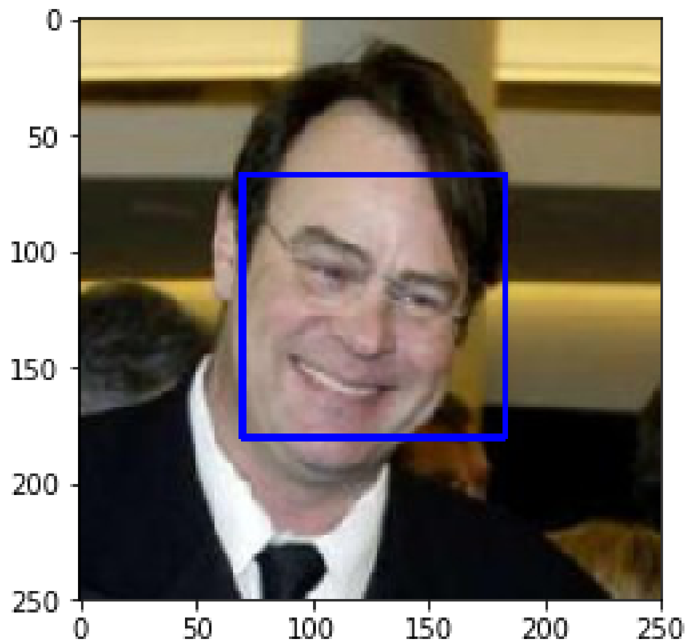
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

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

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

Answer: (You can print out your results and/or write your percentages in this cell)
percentage of the first 100 images in 'human_files_short' have a detected human face: 98.00 %
percentage of the first 100 images in 'dog_files_short' have a detected human face: 17.00 %

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

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

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        human_files_short_human_face_detect = [face_detector(human_files_short[i]) for i in rang
        dog_files_short_human_face_detect = [face_detector(dog_files_short[i]) for i in range(le

In [5]: print("percentage of the first 100 images in 'human_files_short' have a detected human f
        print("percentage of the first 100 images in 'dog_files_short' have a detected human fac
```

```
percentage of the first 100 images in 'human_files_short' have a detected human face: 98.00 %
percentage of the first 100 images in 'dog_files_short' have a detected human face: 17.00 %
```

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

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

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

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

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

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

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 [7]:
```
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
## Return the *index* of the predicted class for that image
image = Image.open(img_path).convert('RGB')
# convert PIL.Image.Image type to 3D tensor
in_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])
])
# refer to Style_Transfer_Exercise.ipynb load_image()
x = in_transform(image)[:3, :, :].unsqueeze(0)

# check if CUDA is available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
x = x.to(device)

# convert output probabilities to predicted class
predictions = VGG16(x)
_, pred = torch.max(predictions, 1)
# convert tensor type to numpy
pred = pred.cpu().numpy()

return pred # 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 [8]: ### 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:
percentage of the images in 'human_files_short' have a detected dog face: 1.00 %
percentage of the images in 'dog_files_short' have a detected dog face: 100.00 %

```
In [9]: ### TODO: Test the performance of the dog_detector function
        ### on the images in human_files_short and dog_files_short.

        # predictions in human_files_short
        human_files_short_dog_face_detect = [dog_detector(human_files_short[i]) for i in range(l
        # predictions in dog_files_short
        dog_files_short_dog_face_detect = [dog_detector(dog_files_short[i]) for i in range(len(d

In [11]: print("percentage of the images in 'human_files_short' have a detected dog face: %.2f %
         print("percentage of the images in 'dog_files_short' have a detected dog face: %.2f %%"

percentage of the images in 'human_files_short' have a detected dog face: 1.00 %
percentage of the images in 'dog_files_short' have a detected dog face: 100.00 %
```

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 [12]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.
         # Load resnet18 pretrained
         resnet50 = models.resnet50(pretrained=True)

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

         # move model to GPU if CUDA is available
         if use_cuda:
             resnet50 = resnet50.cuda()
```

```python
# copy the predict function above, only change the prediction invocation
def resnet50_predict(img_path):
    '''
    Use pre-trained ResNet-50 model to obtain index corresponding to
    predicted ImageNet class for image at specified path

    Args:
        img_path: path to an image

    Returns:
        Index corresponding to VGG-16 model's prediction
    '''
    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image
    image = Image.open(img_path).convert('RGB')
    # convert PIL.Image.Image type to 3D tensor
    in_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])
    ])
    # refer to Style_Transfer_Exercise.ipynb load_image()
    x = in_transform(image)[:3, :, :].unsqueeze(0)

    # check if CUDA is available
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    x = x.to(device)

    # convert output probabilities to predicted class
    predictions = resnet50(x)
    _, pred = torch.max(predictions, 1)
    # convert tensor type to numpy
    pred = pred.cpu().numpy()

    return pred # predicted class index


# copy the dog_detector above
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector_resnet50(img_path):
    ## TODO: Complete the function.
    pred = resnet50_predict(img_path)

    return (pred >= 151 and pred <= 268) # true/false
```

In [13]:
```
### (Optional continue)

# inception predict
# predictions in human_files_short
human_files_short_dog_face_detect_resnet50 = [dog_detector_resnet50(human_files_short[i
# predictions in dog_files_short
dog_files_short_dog_face_detect_resnet50 = [dog_detector_resnet50(dog_files_short[i]) f
```

In [16]:
```
### (Optional continue)

print("using ResNet-50...")
print("percentage of the images in 'human_files_short' have a detected dog face: %.2f %
print("percentage of the images in 'dog_files_short' have a detected dog face: %.2f %%"
```

```
using ResNet-50...
percentage of the images in 'human_files_short' have a detected dog face: 0.00 %
percentage of the images in 'dog_files_short' have a detected dog face: 0.00 %
```

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 [17]:
```
import os
from torchvision import datasets

### 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])
])

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


batch_size = 20
num_workers = 0

train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, shuffle=T
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, shuffle=T
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, shuffle=Tru

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

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

Answer:

- I loaded the training, validation, and test data, and then create 3 DataLoaders for each of them. I resize the images to 256 x 256, then center crop it to 224 x 224 depending on the documentation:

  ```
  All pre-trained models expect input images normalized in the same way, i.e. mini-batches of
  ```

  After converting to tensor, I normalize it to *means = [0.485, 0.456, 0.406]* and *standard deviations = [0.229, 0.224, 0.225]* mentioned in documentation:

  ```
  The images have to be loaded in to a range of [0, 1] and then normalized using mean = [0.48
  ```

  TORCHVISION.MODELS documentation

- No, I didn't add data augmentation, because I would like to see the performance of the original dataset, and I prefer to not add randomness at first.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [19]: import torch.nn as nn
         import torch.nn.functional as F

         # 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
                 # Here, I use the similar architecture as in 'cifar10_cnn_exercise.ipynb' since
                 # convolutional layer 1
                 self.conv1 = nn.Conv2d(3, 8, 3, padding=1)
                 # convolutional layer 2
                 self.conv2 = nn.Conv2d(8, 16, 3, padding=1)
                 # convolutional layer 3
                 self.conv3 = nn.Conv2d(16, 32, 3, padding=1)
                 # convolutional layer 4
                 self.conv4 = nn.Conv2d(32, 64, 3, padding=1)

                 # max pooling layer
                 self.maxpool = nn.MaxPool2d(2, 2)
                 # dropout layer
                 self.dropout = nn.Dropout(p=0.2)
                 # batch norm layer
```

```
            self.batchnorm = nn.BatchNorm1d(num_features=512)

            # fully-connected layer 1
            self.fc1 = nn.Linear(64 * 14 * 14, 512)
            # fully-connected layer 2
            self.fc2 = nn.Linear(512, 133)

        def forward(self, x):
            ## Define forward behavior
            # conv layers
            x = self.maxpool(F.relu(self.conv1(x)))
            x = self.dropout(x)
            x = self.maxpool(F.relu(self.conv2(x)))
            x = self.dropout(x)
            x = self.maxpool(F.relu(self.conv3(x)))
            x = self.dropout(x)
            x = self.maxpool(F.relu(self.conv4(x)))
            x = self.dropout(x)

            # flatten
            x = x.view(-1, 64 * 14 * 14)

            # fc layers
            x = F.relu(self.batchnorm(self.fc1(x)))
            x = self.dropout(x)
            x = self.fc2(x)

            return x

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

    # instantiate the CNN
    model_scratch = Net()

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

    print(model_scratch)
```

```
Net(
  (conv1): Conv2d(3, 8, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(8, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (maxpool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (dropout): Dropout(p=0.2)
  (batchnorm): BatchNorm1d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

```
  (fc1): Linear(in_features=12544, out_features=512, bias=True)
  (fc2): Linear(in_features=512, out_features=133, bias=True)
)
```

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

Answer:

In my scratch CNN model, there are 4 convolutional layers, 1 kind of dropout layers, 2 fully-connected layers. After each convolutional layer and FC layer, ReLU activation function is applied.

In addition, dropout layer is applied to avoid overfitting after each convolutional layer and FC layer. MaxPooling layer will half-size the height and width after each convolutional layer.

At the output layer, there are 133 neurons indicating 133 dog breeds.

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 [20]: import torch.optim as optim

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

         ### TODO: select optimizer
         optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.001, momentum=0.9)
```

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 [21]: 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
         #     valid_loss_min = 3688.127849   # after 5 epochs
         #     valid_loss_min = 3502.294493   # after 10 epochs
         #     valid_loss_min = 3433.308561   # after 15 epochs

             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
    # firstly, clear the gradients
    optimizer.zero_grad()
    # forward pass
    output = model(data)
    # calculate the batch loss
    batch_loss = criterion(output, target)
    # backward pass and update the weights
    batch_loss.backward()
    optimizer.step()

    ## record the average training loss, using something like
    ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
    train_loss += batch_loss.item() * data.size(0)

######################
# validate the model #
######################
model.eval()
for batch_idx, (data, target) in enumerate(loaders['valid']):
    # move to GPU
    if use_cuda:
        data, target = data.cuda(), target.cuda()
    ## update the average validation loss
    # forward pass
    output = model(data)
    # calculate the batch loss
    batch_loss = criterion(output, target)
    # accumulate the average validation error
    valid_loss += batch_loss.item() * data.size(0)


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

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

```
                    valid_loss))
                torch.save(model.state_dict(), save_path)
                # update minimum validation error
                valid_loss_min = valid_loss

        # return trained model
        return model
```

```
In [22]: # train the model
         # model_scratch = train(5, loaders_scratch, model_scratch, optimizer_scratch,
         #                       criterion_scratch, use_cuda, 'model_scratch.pt')

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

Training Record:

Epoch	learning rate	Training Loss	Validation Loss	Test Accuracy
1	0.01	31516.772652	4180.426452	-
2	0.01	29714.745378	4091.309853	-
3	0.01	27824.942403	3789.838214	-
4	0.01	25894.878368	3983.890252	-
5	0.01	23621.665287	3688.127849	5% (45/836)
6	0.005	19132.591491	3502.294493	-
7	0.005	15875.578442	3510.363467	-
8	0.005	12383.409929	3574.413340	-
9	0.005	8644.053274	3684.037652	-
10	0.005	5550.889873	3600.434825	8% (75/836)
11	0.001	14949.858079	3454.024744	-
12	0.001	13830.302112	3433.308561	-
13	0.001	12800.155225	3461.680815	-
14	0.001	11580.932450	3485.916018	-
15	0.001	10580.438592	3483.047397	9% (83/836)
16	0.001	12744.645634	3426.212842	-
17	0.001	11704.069688	3446.241598	-
18	0.001	10577.498126	3458.162595	-
19	0.001	9518.907399	3452.644521	-
20	0.001	8515.197065	3471.823180	11% (93/836)

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

             # monitor test loss and accuracy
```

```
    test_loss = 0.
    correct = 0.
    total = 0.

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

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

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

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

```
Test Loss: 4.049675


Test Accuracy: 11% (93/836)
```

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 [24]: ## TODO: Specify data loaders
         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])
         ])

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

         dataset_transfer = {
             'train': train_data,
             'valid': valid_data,
             'test': test_data
         }

         batch_size = 20
         num_workers = 0

         train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size, shuffle=T
         valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size, shuffle=T
         test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size, shuffle=Tru

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

         ## TODO: Specify model architecture
         model_transfer = models.resnet50(pretrained=True)
         # firstly, freeze parameters in resnet-50
         for param in model_transfer.parameters():
             param.requires_grad = False
         # replace the last fc layer with 2048 -> 133 fc layer
         model_transfer.fc = nn.Linear(2048, 133)
```

```python
model_transfer.fc.requires_grad = True

if use_cuda:
    model_transfer = model_transfer.cuda()

print(model_transfer)
```

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
```

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

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

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

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

Answer:

In transfer learning, I loaded ResNet-50 from torchvision. It is a pretrained model for classify 1000 objects, since originally, the last layer is defined as:

```
(fc): Linear(in_features=2048, out_features=1000, bias=True)
```

But our output layer should have only 133 neurons, therefore, I change the last layer to another fully-connected layer with 133 neurons at the end, so that it fits to our task.

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 [27]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.Adam(model_transfer.fc.parameters(), lr=0.01)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

```
In [28]: # train the model
         # model_transfer = train(5, loaders_transfer, model_transfer, optimizer_transfer, crite

         # save the model
         # torch.save(model_transfer.state_dict(), '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'))
```

Training Record:

Epoch	Learning rate	Training Loss	Validation Loss	Test Accuracy
1	0.01	39096.169847	2883.448672	-
2	0.01	20543.557382	3364.203992	-
3	0.01	20327.140851	3189.229565	-
4	0.01	17101.873147	3135.126466	-
5	0.01	16690.628481	3180.907058	66% (557/836)

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

```
Test Loss: 3.437577


Test Accuracy: 66% (557/836)
```

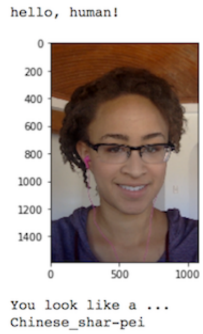
1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

Write a function that takes an image path as input and returns the dog breed (`Affenpinscher`, `Afghan hound`, etc) that is predicted by your model.

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

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

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    img = Image.open(img_path).convert('RGB')
    # convert PIL.Image.Image type to 3D tensor
    in_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])
    ])
    # refer to Style_Transfer_Exercise.ipynb load_image()
    x = in_transform(img)[:3, :, :].unsqueeze(0)

    # check if CUDA is available
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    x = x.to(device)

    if use_cuda:
        x = x.cuda()

    # make prediction
    output = model_transfer(x)
    # get predicted breed class
    _, pred = torch.max(output, 1)
    # convert tensor type to numpy
    pred = pred.cpu().numpy()

    return class_names[pred[0]]
```

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.



Sample Human Output

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

         def show_image(img_path, title=''):
             img = Image.open(img_path)
             plt.title(title)
             plt.imshow(img)
             plt.show()

         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             # check if the image is a human face
             if face_detector(img_path):
                 print('hello, human!')
                 show_image(img_path)
                 print('You look like a ...')
                 breed = predict_breed_transfer(img_path)
                 print(breed)
             elif dog_detector(img_path):
                 print('hello, cani!')
                 show_image(img_path)
                 print('You look like a ...')
                 breed = predict_breed_transfer(img_path)
                 print(breed)
             else:
                 print('Sorry, I could not recognize you...')
                 show_image(img_path)
```

```
        print('But you look like a ...')
        breed = predict_breed_transfer(img_path)
        print(breed)
    print('--------------------------------')
```

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)

- Apply data augmentation to avoid overfitting
- Instead of replacing the last layer of ResNet-50, we may add additional layers to it.
- Tune the hyper-parameters so that the model achieves better performance
- Tune the model using different criterion, like Adam

A few my remaining questions:

1. Question 1:

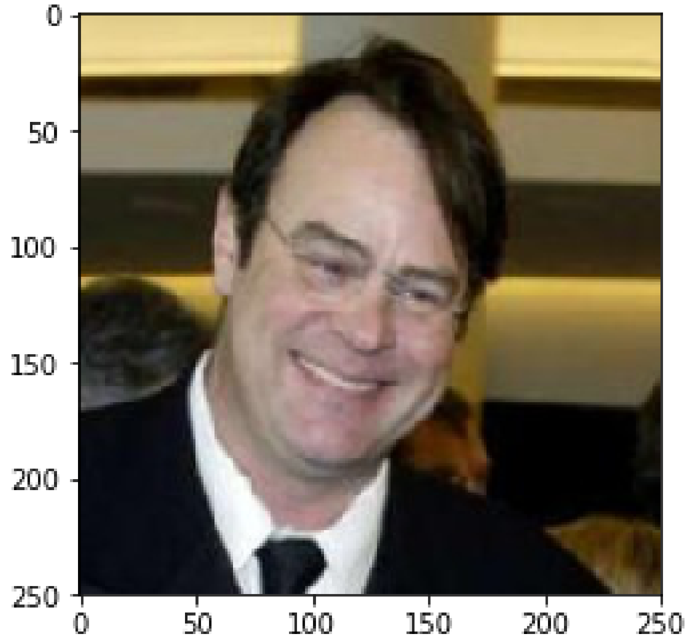
I found BatchNorm1d does better in generalization than dropout layer, I tried to increase dropout probability in the last fully-connected layer in my custom model, but it overfits. Once I change it to BatchNorm1d, it helped a lot. Currently I don't know why, but hopefully I can figure it out later on the lessons.

2. Question 2:

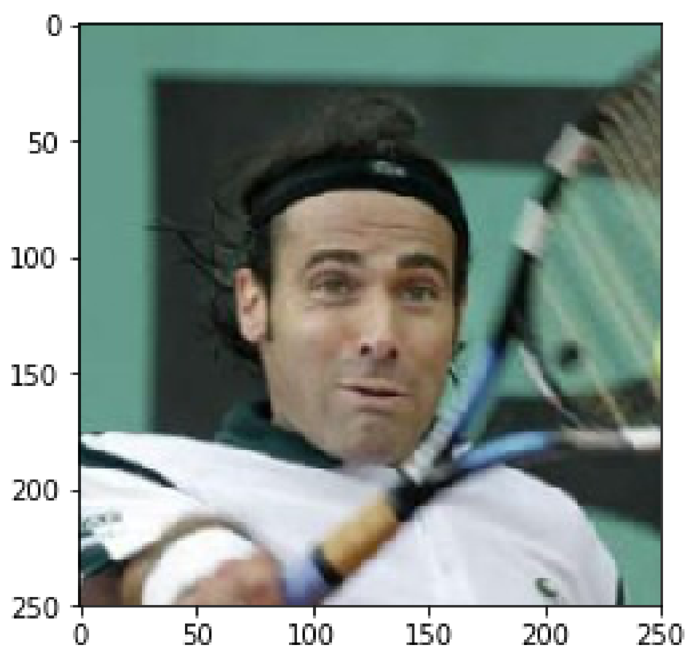
If we compute the loss of our model using `criterion`, why couldn't we optimize the weights using `criterion`. Instead we need to define another term `optimizer` to do the optimization task?

In [34]:
```
## 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)
```

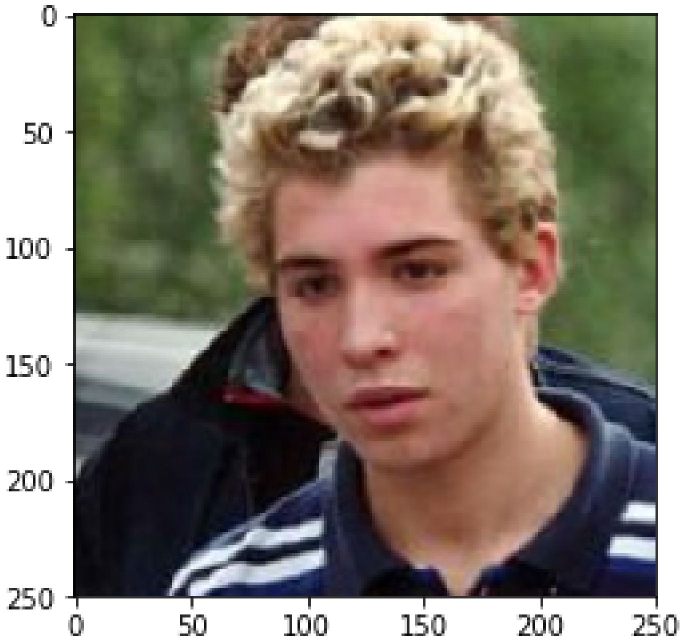
```
hello, human!
```



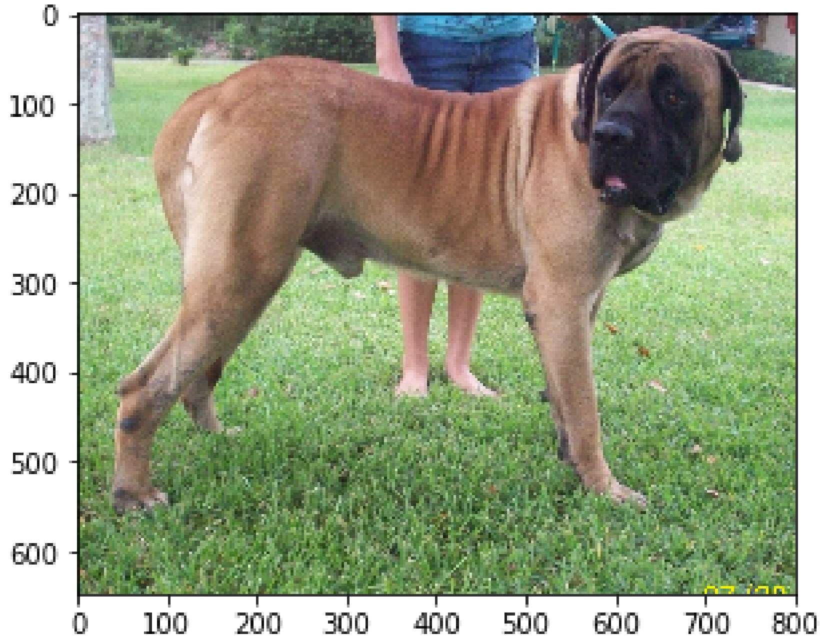

```
You look like a ...
Dachshund
---------------------------------
hello, human!
```



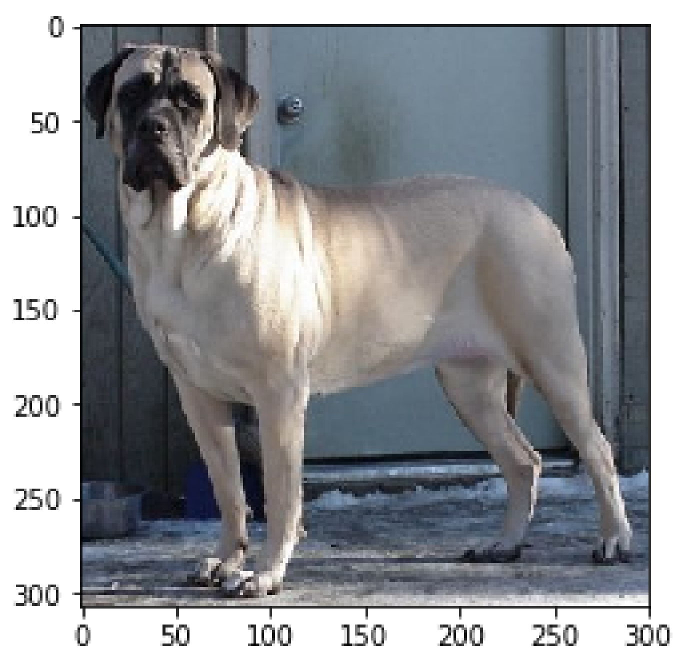
```
You look like a ...
Bullmastiff
--------------------------------
hello, human!
```



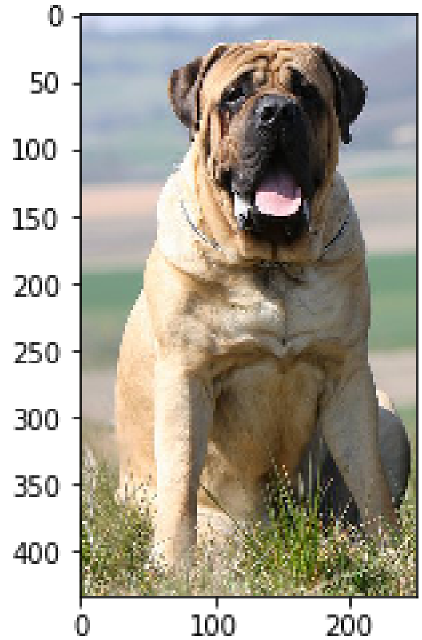

```
You look like a ...
American water spaniel
--------------------------------
hello, cani!
```



```
You look like a ...
Mastiff
---------------------------------
hello, cani!
```



```
You look like a ...
Mastiff
--------------------------------
hello, cani!
```




```
You look like a ...
Bullmastiff
--------------------------------
```