Convolutional Neural Networks

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.

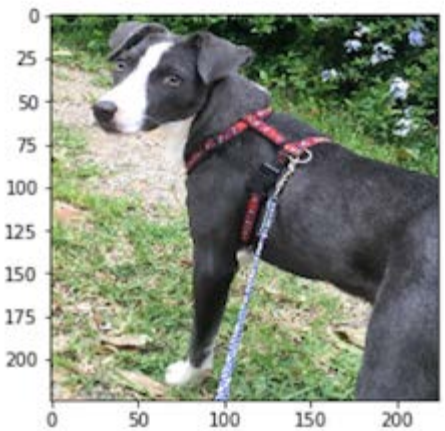
> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. Markdown cells can be edited by double-clicking the cell to enter edit mode.

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.

Why We're Here

In this notebook, you will make the first steps towards developing an algorithm that could be used as part of a mobile or web app. At the end of this project, your code will accept any user-supplied image as input. If a dog is detected in the image, it will provide an estimate of the dog's breed. If a human is detected, it will provide an estimate of the dog breed that is most resembling. The image below displays potential sample output of your finished project (... but we expect that each student's algorithm will behave differently!).

```
hello, dog!
your predicted breed is ...
American Staffordshire terrier
```



In this real-world setting, you will need to piece together a series of models to perform different tasks; for instance, the algorithm that detects humans in an image will be different from the CNN that infers dog breed. There are many points of possible failure, and no perfect algorithm exists. Your imperfect solution will nonetheless create a fun user experience!

The Road Ahead

We break the notebook into separate steps. Feel free to use the links below to navigate the notebook.

Step 0: Import Datasets

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

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

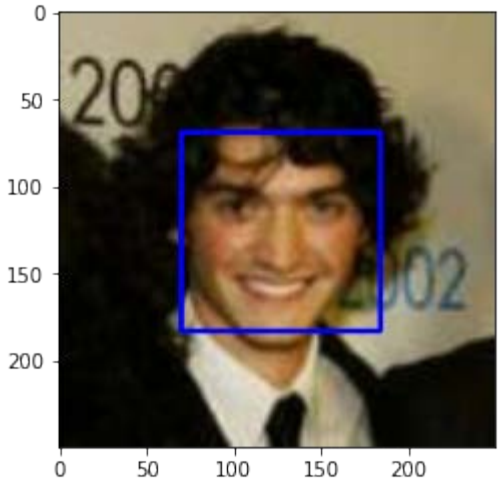
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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[3])
# 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.

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
```

(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)

The percentage of corrected detected human faces is 99.0%

The percentage of corrected detected dog faces is 16.0%

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.

def face_detection_test(files):
    detection_cnt = 0;
    total_cnt = len(files)
    for file in files:
        detection_cnt += face_detector(file)
    return detection_cnt, total_cnt
```

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

In [5]:

```
### (Optional)
```

```
### TODO: Test performance of another face detection algorithm.
### Feel free to use as many code cells as needed.

human_files_test= [face_detector(i) for i in human_files_short]
print("The percentage of corrected detected human faces is
{}%".format(100*sum(human_files_test)/len(human_files_test)))
## on the images in human_files_short and dog_files_short.
dog_files_test= [face_detector(i) for i in dog_files_short]
print("The percentage of corrected detected dog faces is
{}%".format(100*sum(dog_files_test)/len(dog_files_test)))
```

```
The percentage of corrected detected human faces is 99.0%
The percentage of corrected detected dog faces is 16.0%
```

Step 2: Detect Dogs

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

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()

print(VGG16)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
```

```
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

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.

(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]:

```
import os
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_Pretrained(img_path_Pretrained):
    '''
    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
```

```
    '''
    img_path_Pretrained=
os.path.join('data/dog_images/train/001.Affenpinscher/Affenpinscher_00001.jpg')
    img = Image.open(img_path_Pretrained)


    ## 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

    img_loaded = torch.utils.data.DataLoader(img)


    return img.info['jfif'] # predicted class index
```

In [8]:

```
import os
from PIL import Image
img_path_Pretrained =
os.path.join('data/dog_images/train/001.Affenpinscher/Affenpinscher_00001.jpg')
img = Image.open(img_path_Pretrained)
img
```

Out[8]:

In [9]:

```
img_path_Pretrained = os.path.join('data/lfw/Aaron_Peirsol/Aaron_Peirsol_0001.jpg')
VGG16_predict_Pretrained(img_path_Pretrained)
```

Out[9]:

```
257
```

(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 [10]:

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

def load_image(img_path):
    image = Image.open(img_path).convert('RGB')
    # resize to (244, 244) because VGG16 accept this shape
    in_transform = transforms.Compose([
                        transforms.Resize(size=(244, 244)),
                        transforms.ToTensor()]) # normalizaiton parameters from pytorch
doc.

    # discard the transparent, alpha channel (that's the :3) and add the batch dimension
    image = in_transform(image)[:3,:,:].unsqueeze(0)
    return image
```

In [11]:

```
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
    img = load_image(img_path)
    if use_cuda:
        img = img.cuda()
    ret = VGG16(img)
    return torch.max(ret,1)[1].item() # predicted class index
```

In [12]:

```
# predict dog using ImageNet class
VGG16_predict(dog_files_short[0])
```

Out[12]:

```
208
```

In [13]:

```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    idx = VGG16_predict(img_path)
    return idx >= 151 and idx <= 268 # true/false
```

In [14]:

```
print(dog_detector(dog_files_short[0]))
print(dog_detector(human_files_short[0]))
```

```
True
False
```

(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:

The percentage of detect a dog in human_files: 0 / 100

The percentage of detect a dog in dog_files 87 / 100

In [15]:

```
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.

def dog_detector_test(files):
    detection_cnt = 0;
    total_cnt = len(files)
    for file in files:
        detection_cnt += dog_detector(file)
    return detection_cnt, total_cnt
```

In [16]:

```
print("The percentage of detect a dog in human_files: {} /
{}".format(dog_detector_test(human_files_short)[0], dog_detector_test(human_files_short)
[1]))
print("The percentage of detect a dog in dog_files {} /
{}".format(dog_detector_test(dog_files_short)[0], dog_detector_test(dog_files_short)[1]))
```

```
The percentage of detect a dog in human_files: 0 / 100
The percentage of detect a dog in dog files 87 / 100
```

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 [17]:

```
### (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**

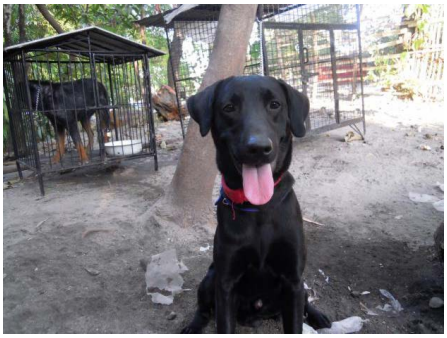

It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).

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** **Black 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!

(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!

In [18]:

```
import os
from torchvision import datasets

from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

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


### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])

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

transform = transforms.Compose([
       transforms.Resize((224,224)),
       transforms.ToTensor(),
       normalize
    ])

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

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

```
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:

the training dataset

I randomly crop and resize all the images to 224*224 pixels.

I randomly flip and rotate images

I normalize the tensors.

validation and test datasets

I just resize all the images into the same size as the training dataset

convert them into tensors, and normalize them.

(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
        ##Applies a 2D convolution over an input signal composed of several input planes.

        ## torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0,
dilation=1, \
        ## groups=1, bias=True, padding_mode='zeros', device=None, dtype=None)

        ## self.conv1 = nn.Conv2d(in_channels=3,  # number of channels in the input (lower
layer)
        ##                        out_channels=16, # number of channels in the output (next
layer)
        ##                         kernel_size=3)  # size of the kernel or receiptive field
        (224,224)
        # Defining a 2D convolution layer
        self.conv1 = nn.Conv2d( 3, 16, 3)
        self.conv2 = nn.Conv2d(16, 32, 3)
```

```
        self.conv3 = nn.Conv2d(32, 64, 3)
        self.conv4 = nn.Conv2d(64, 128, 3)
        self.conv5 = nn.Conv2d(128, 256, 3)

        # max pooling layer
        self.pool = nn.MaxPool2d(2, 2)

        # linear layer (256 * 5* 5 -> 500)
        # apply the fully conected layer

        self.fc1 = nn.Linear( 256 * 5 * 5, 500)
        self.fc2 = nn.Linear(500, 133)


    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))
        x = self.pool(F.relu(self.conv4(x)))
        x = self.pool(F.relu(self.conv5(x)))

        # flatten image input
        #print(x.shape)
        x = x.view(-1, 5 * 5 * 256)
        # add 1st hidden layer, with relu activation function
        x = F.relu(self.fc1(x))
        # add 2nd hidden layer, with relu activation function
        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()
```

In [20]:

```
model_scratch
```

Out[20]:

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=6400, out_features=500, bias=True)
  (fc2): Linear(in_features=500, 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:

1- we'll use five Convolutional layer

The first layer will have in_channels=3, out_channels=16, kernel_size=3 , padding=1

The second layer will have in_channels=16, out_channels=32, kernel_size=3, padding=1 and

The third layer will have in_channels=32, out_channels=64, kernel_size=3 , padding=1 and

The fourth layer will have in_channels=64, out_channels=128, kernel_size=3, padding=1 and

The fifth layer will have in_channels=128, out_channels=256, kernel_size=3, padding=1

final output image size is downsized by factor of 128 and the depth will be 256

2- using Maxpooling layer MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)

will reduce the input size by 2

3- feed our image into two hidden layers and predict the probability

https://pytorch.org/tutorials/beginner/blitz/neural_networks_tutorial.html

https://www.deeplearningwizard.com/deep_learning/practical_pytorch/pytorch_convolutional_neuralnetwork/

(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 [21]:

```
import torch.optim as optim

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

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

(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 [22]:

```
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 #
        ###################
```

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

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


        train_loss = train_loss/len(train_loader.dataset)
        valid_loss = valid_loss/len(valid_loader.dataset)

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

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

    # return trained model
```

```
    return model


# train the model
model_scratch = train(30, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')

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

```
Epoch: 1        Training Loss: 0.000729         Validation Loss: 0.005728
Validation loss decreased (inf --> 0.005728).  Saving model ...
Epoch: 2        Training Loss: 0.000701         Validation Loss: 0.005391
Validation loss decreased (0.005728 --> 0.005391).  Saving model ...
Epoch: 3        Training Loss: 0.000674         Validation Loss: 0.005199
Validation loss decreased (0.005391 --> 0.005199).  Saving model ...
Epoch: 4        Training Loss: 0.000656         Validation Loss: 0.005157
Validation loss decreased (0.005199 --> 0.005157).  Saving model ...
Epoch: 5        Training Loss: 0.000639         Validation Loss: 0.005017
Validation loss decreased (0.005157 --> 0.005017).  Saving model ...
Epoch: 6        Training Loss: 0.000628         Validation Loss: 0.004922
Validation loss decreased (0.005017 --> 0.004922).  Saving model ...
Epoch: 7        Training Loss: 0.000618         Validation Loss: 0.004854
Validation loss decreased (0.004922 --> 0.004854).  Saving model ...
Epoch: 8        Training Loss: 0.000604         Validation Loss: 0.004715
Validation loss decreased (0.004854 --> 0.004715).  Saving model ...
Epoch: 9        Training Loss: 0.000596         Validation Loss: 0.004744
Epoch: 10       Training Loss: 0.000585         Validation Loss: 0.004549
Validation loss decreased (0.004715 --> 0.004549).  Saving model ...
Epoch: 11       Training Loss: 0.000574         Validation Loss: 0.004531
Validation loss decreased (0.004549 --> 0.004531).  Saving model ...
Epoch: 12       Training Loss: 0.000564         Validation Loss: 0.004488
Validation loss decreased (0.004531 --> 0.004488).  Saving model ...
Epoch: 13       Training Loss: 0.000557         Validation Loss: 0.004461
Validation loss decreased (0.004488 --> 0.004461).  Saving model ...
Epoch: 14       Training Loss: 0.000541         Validation Loss: 0.004383
Validation loss decreased (0.004461 --> 0.004383).  Saving model ...
Epoch: 15       Training Loss: 0.000537         Validation Loss: 0.004566
Epoch: 16       Training Loss: 0.000524         Validation Loss: 0.004246
Validation loss decreased (0.004383 --> 0.004246).  Saving model ...
Epoch: 17       Training Loss: 0.000520         Validation Loss: 0.004348
Epoch: 18       Training Loss: 0.000508         Validation Loss: 0.004111
Validation loss decreased (0.004246 --> 0.004111).  Saving model ...
Epoch: 19       Training Loss: 0.000505         Validation Loss: 0.004122
Epoch: 20       Training Loss: 0.000494         Validation Loss: 0.004073
Validation loss decreased (0.004111 --> 0.004073).  Saving model ...
Epoch: 21       Training Loss: 0.000492         Validation Loss: 0.004254
Epoch: 22       Training Loss: 0.000481         Validation Loss: 0.004080
Epoch: 23       Training Loss: 0.000479         Validation Loss: 0.004118
Epoch: 24       Training Loss: 0.000475         Validation Loss: 0.004168
Epoch: 25       Training Loss: 0.000469         Validation Loss: 0.004061
Validation loss decreased (0.004073 --> 0.004061).  Saving model ...
Epoch: 26       Training Loss: 0.000469         Validation Loss: 0.004031
Validation loss decreased (0.004061 --> 0.004031).  Saving model ...
Epoch: 27       Training Loss: 0.000461         Validation Loss: 0.004039
Epoch: 28       Training Loss: 0.000453         Validation Loss: 0.003990
Validation loss decreased (0.004031 --> 0.003990).  Saving model ...
Epoch: 29       Training Loss: 0.000450         Validation Loss: 0.003872
Validation loss decreased (0.003990 --> 0.003872).  Saving model ...
Epoch: 30       Training Loss: 0.000450         Validation Loss: 0.003961
```

Out[22]:

```
<All keys matched successfully>
```

plotting the training and validation loss

import matplotlib.pyplot as plt

%matplotlib inline

plt.plot(train_loss2, label='Training loss')

plt.plot(valid_loss2, label='Validation loss')

plt.legend()

plt.show()

(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 [24]:

```
def test(loaders, model, criterion, use_cuda):

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

    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: 3.143888


Test Accuracy: 24% (204/836)
```

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.

(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 [25]:

```
## TODO: Specify data loaders
train_data = datasets.ImageFolder('data/dog_images/train', transform = preprocess)
valid_data = datasets.ImageFolder('data/dog_images/valid', transform = transform)
test_data = datasets.ImageFolder('data/dog_images/test', transform = transform)

train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,shuffle=True,
                                           num_workers=num_workers)
valid_loader = torch.utils.data.DataLoader(valid_data, batch_size=batch_size,shuffle=True,
                                           num_workers=num_workers)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,shuffle=True,
                                           num_workers=num_workers)

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

(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 [26]:

```
import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture
model_transfer = models.resnet18(pretrained=True)

for param in  model_transfer.parameters():
    param.require_grad = False

print(model_transfer)
print(model_transfer.fc)

n_inputs = model_transfer.fc.in_features
last_layer = nn.Linear(n_inputs, 133, bias=True)
model_transfer.fc = last_layer

for param in  model_transfer.fc.parameters():
    param.require_grad = True

# check to see that your last layer produces the expected number of outputs
```

```
print(model_transfer.fc.out_features)
print(model_transfer)

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

```
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=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=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)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=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)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False
)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (downsample): Sequential(
```

```
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      )
    )
    (layer4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (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): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      )
    )
    (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
    (fc): Linear(in_features=512, out_features=1000, bias=True)
)
Linear(in_features=512, out_features=1000, bias=True)
133
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=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=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)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=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)
      )
    )
    (layer2): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False
)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      )
    )
    (layer3): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      )
    )
    (layer4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=Fals
e)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
```

```
e)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (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): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=Fals
e)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=133, bias=True)
)
```

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

Answer:

The steps I took to get to final CNN architecture

I picked ResNet as a transfer model because it performed outstanding on Image Classification.

I looked into the structure and functions of ResNet.

I guess this prevents overfitting when it's training.

I pull out the final Fully-connected layer and replaced with Fully-connected layer with output of 133 Classify Dog Breeds

(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())
```

(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(20, 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: 0.000485         Validation Loss: 0.002040
Validation loss decreased (inf --> 0.002040).  Saving model ...
Epoch: 2        Training Loss: 0.000274         Validation Loss: 0.001458
Validation loss decreased (0.002040 --> 0.001458).  Saving model ...
Epoch: 3        Training Loss: 0.000229         Validation Loss: 0.001230
Validation loss decreased (0.001458 --> 0.001230).  Saving model ...
Epoch: 4        Training Loss: 0.000200         Validation Loss: 0.001201
Validation loss decreased (0.001230 --> 0.001201).  Saving model ...
Epoch: 5        Training Loss: 0.000192         Validation Loss: 0.001059
Validation loss decreased (0.001201 --> 0.001059).  Saving model ...
Epoch: 6        Training Loss: 0.000183         Validation Loss: 0.001055
Validation loss decreased (0.001059 --> 0.001055).  Saving model ...
Epoch: 7        Training Loss: 0.000176         Validation Loss: 0.001014
Validation loss decreased (0.001055 --> 0.001014).  Saving model ...
Epoch: 8        Training Loss: 0.000174         Validation Loss: 0.001035
Epoch: 9        Training Loss: 0.000166         Validation Loss: 0.000987
Validation loss decreased (0.001014 --> 0.000987).  Saving model ...
Epoch: 10       Training Loss: 0.000162         Validation Loss: 0.001009
Epoch: 11       Training Loss: 0.000158         Validation Loss: 0.000998
Epoch: 12       Training Loss: 0.000161         Validation Loss: 0.000923
Validation loss decreased (0.000987 --> 0.000923).  Saving model ...
Epoch: 13       Training Loss: 0.000154         Validation Loss: 0.000956
Epoch: 14       Training Loss: 0.000157         Validation Loss: 0.000995
Epoch: 15       Training Loss: 0.000149         Validation Loss: 0.001022
Epoch: 16       Training Loss: 0.000149         Validation Loss: 0.000945
Epoch: 17       Training Loss: 0.000148         Validation Loss: 0.001009
Epoch: 18       Training Loss: 0.000148         Validation Loss: 0.000970
Epoch: 19       Training Loss: 0.000148         Validation Loss: 0.001004
Epoch: 20       Training Loss: 0.000147         Validation Loss: 0.001064
```

Out[28]:

```
<All keys matched successfully>
```

plotting the training and validation loss

```
import matplotlib.pyplot as plt

%matplotlib inline

plt.plot(train_loss, label='Training loss')

plt.plot(valid_loss, label='Validation loss')

plt.legend()

plt.show()
```

(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 [55]:

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

```
Test Loss: 0.796304


Test Accuracy: 76% (636/836)
```

(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 [56]:

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

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

data_transfer = loaders_transfer.copy()

# 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_transfer['train'].dataset.classes]

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

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    image = Image.open(img_path)
    transformations = transforms.Compose([transforms.Resize(size=(224, 224)),
                                          transforms.ToTensor(),
                                          normalize])

# discard the transparent, alpha channel (that's the :3) and add the batch dimensio
    transformed_image = transformations(image)[:3,:,:].unsqueeze(0)

## Load and pre-process an image from the given img_path
## Return the *class_names* of the predicted class for that image
    if use_cuda:
        transformed_image = transformed_image.cuda()

    predict_breed_class = model_transfer(transformed_image)

    index = torch.max(predict_breed_class,1)[1].item()
    return class_names[index] # predicted class name
```

Step 5: Write your Algorithm

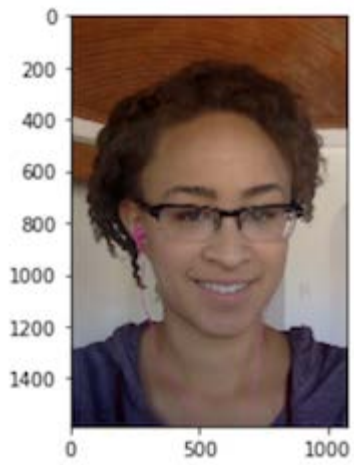
Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then,

- 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!

```
hello, human!
```




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

(IMPLEMENTATION) Write your Algorithm

In [66]:

```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.
def load_image(img_path):
    image = Image.open(img_path)
    plt.imshow(image)
    plt.show()

def run_app(img_path):
    ## handle cases for a human face, dog, and neither

    if face_detector(img_path):
        print ("Hello Human!")
        predicted_breed = predict_breed_transfer(img_path)
        print("You Look Like a","dog_breed: ",predicted_breed)
        load_image(img_path)

    elif predict_breed_transfer(img_path):
        print ("Hello Dog!")
        predicted_breed = predict_breed_transfer(img_path)
        print("You Look Like a" ,predicted_breed)
        load_image(img_path)

    else:
        print ("no humans or dogs in the picture")
```

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?

(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 picked six images three with human faces, and three images with dogs and the both outside the tranined pic The program can not detect it when there is neither dogs or humans in the images. Among dogs or humans, even my Test Accuracy: 74% (626/836) but the program cannot really distinguish between different breeds or differet looks. This is not as good as what I expect.

three possible points of improvement for your algorithm

- change the hyperparamter to have better accurate models
- change the weight initializings
- change the learning rates
- change the batch_sizes
- add more data for tranning

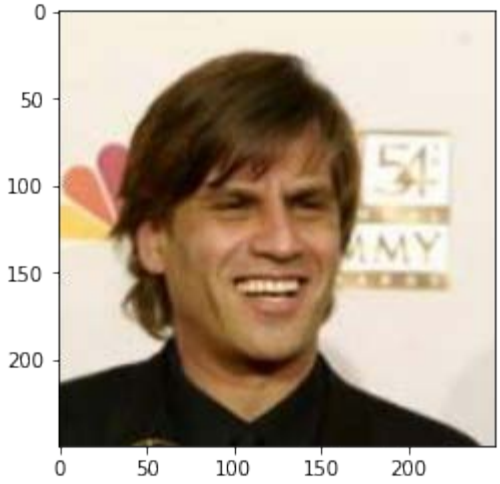
In [67]:

```
# load filenames for test app images

my_dog_files = np.array(glob('data/my_dog_files/*'))
my_human_files = np.array(glob('data/my_human_files/*'))
```

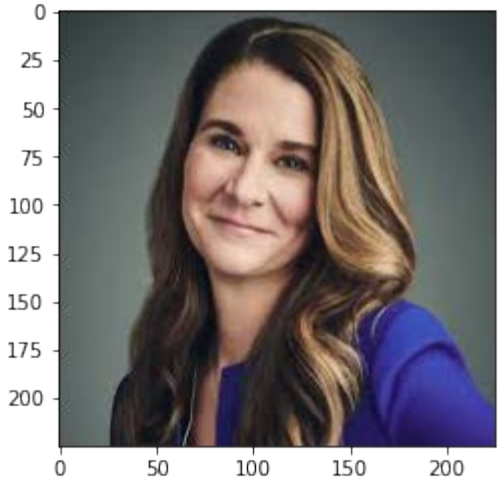
In [68]:

```
## 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((my_human_files[:3], my_dog_files[:3])):
    run_app(file)
```

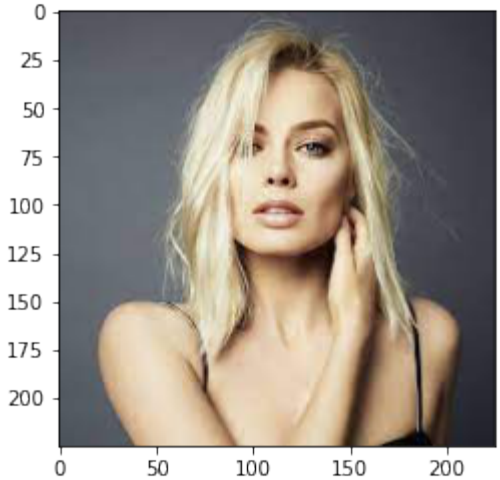
```
Hello Human!
You Look Like a dog breed:  Afghan hound
```



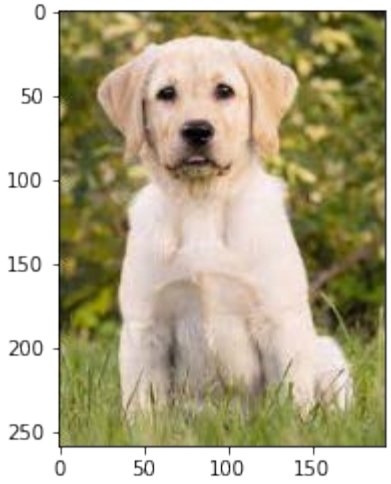
```
Hello Human!
You Look Like a dog breed:  Afghan hound
```



```
Hello Human!
You Look Like a dog breed:  Afghan hound
```

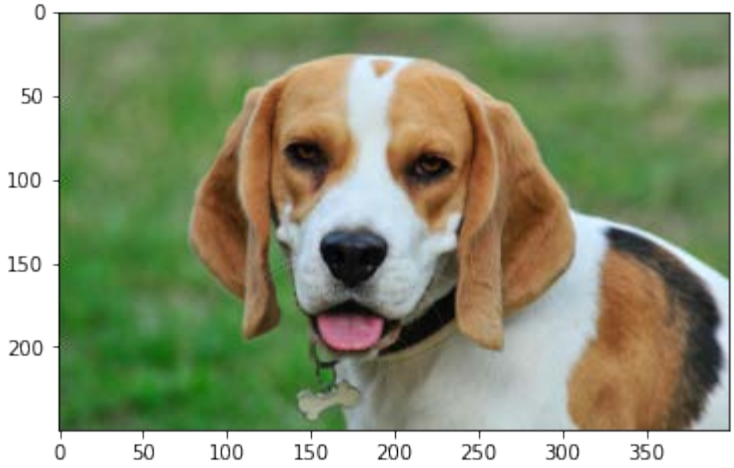


```
Hello Dog!
You Look Like a Afghan hound
```



```
Hello Human!
You Look Like a dog breed:  Afghan hound
```

```
Hello Dog!
You Look Like a Afghan hound
```



In [ ]:

```
!jupyter nbconvert dog_app.ipynb - -to html
```