dog_app

January 1, 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 [49]: 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

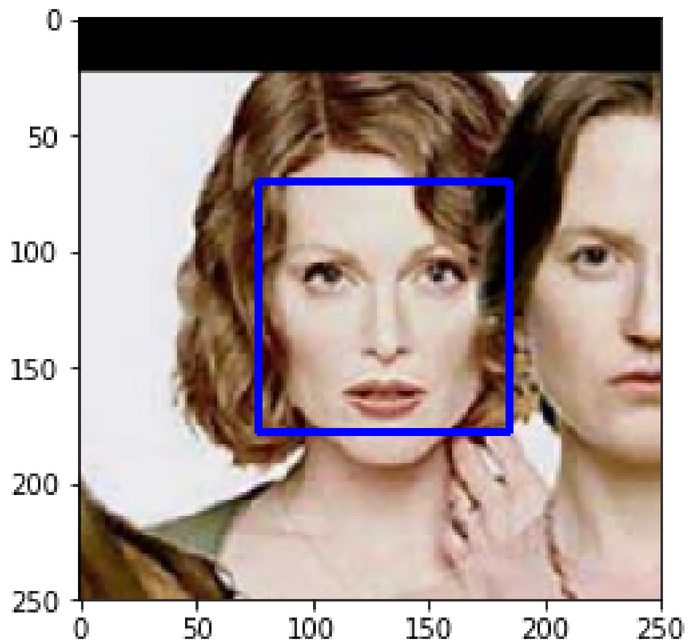
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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[40])
        # 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))
```

```python
# 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: There are 98.0% images of the first 100 human_files that have a detected human face. There are 17.0% images of the first 100 dog_files that have a detected dog face.

```
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_faces = [face_detector(human_file) for human_file in human_files_short]
        percentage_human = 100 * (np.sum(human_faces) / len(human_faces))

        dog_faces = [face_detector(dog_file) for dog_file in dog_files_short]
        percentage_dog = 100 * (np.sum(dog_faces) / len(dog_faces))

        print("There are %.1f%% images of the first 100 human_files that have a detected human f
        print("There are %.1f%% images of the first 100 dog_files that have a detected dog face.
```

```
There are 98.0% images of the first 100 human_files that have a detected human face.
There are 17.0% images of the first 100 dog_files that have a detected dog face.
```

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

```
In [ ]: ### (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 [5]: import torch
        import torchvision.models as models

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

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

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:08<00:00, 68633416.87it/s]
```

```
In [6]: dir(models)
```

```
Out[6]: ['AlexNet',
         'DenseNet',
         'Inception3',
         'ResNet',
         'SqueezeNet',
         'VGG',
         '__builtins__',
         '__cached__',
         '__doc__',
         '__file__',
```

```
 '__loader__',
 '__name__',
 '__package__',
 '__path__',
 '__spec__',
 'alexnet',
 'densenet',
 'densenet121',
 'densenet161',
 'densenet169',
 'densenet201',
 'inception',
 'inception_v3',
 'resnet',
 'resnet101',
 'resnet152',
 'resnet18',
 'resnet34',
 'resnet50',
 'squeezenet',
 'squeezenet1_0',
 'squeezenet1_1',
 'vgg',
 'vgg11',
 'vgg11_bn',
 'vgg13',
 'vgg13_bn',
 'vgg16',
 'vgg16_bn',
 'vgg19',
 'vgg19_bn']
```

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.

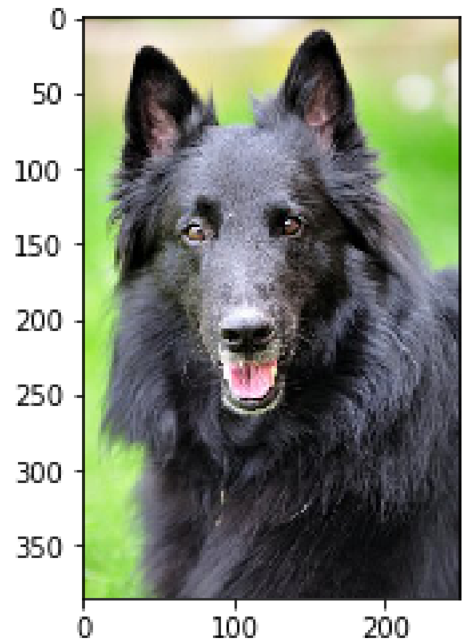
```
In [6]: from PIL import Image
        import torchvision.transforms as transforms

        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

    # step1: load image from provided file path
    img = Image.open(img_path)
    # step2: define transform
    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])
    transform = transforms.Compose([transforms.Resize(256),
                                     transforms.CenterCrop(224),
                                     transforms.ToTensor(),
                                     normalize])

    if show_image:
        plt.imshow(img)

    img_t = transform(img)
    batch_t = torch.unsqueeze(img_t, 0)

    # step3: put model in eval mode
    VGG16.eval()

    if use_cuda:
        batch_t = batch_t.cuda()

    # step4: carry out inference
    out = VGG16(batch_t)
    _, index = torch.max(out, 1)


    return index.item() # predicted class index
```

In [7]:
```
# Tests for VGG16_predict
import random

show_image = True
```

```
dog_files_test = dog_files
random_number = random.randint(0, len(dog_files_test))
file = dog_files_test[random_number]
print(file)
print(VGG16_predict(file))
```

```
/data/dog_images/train/021.Belgian_sheepdog/Belgian_sheepdog_01527.jpg
224
```



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.

            dog_detected = False
            index = VGG16_predict(img_path)
```

```
            if index in range(151, 268 + 1):
                dog_detected = True
            return dog_detected # true/false
```

In [9]:
```
# dog detector tests
show_image = True
dog_files_test = np.concatenate((human_files, dog_files), axis=0)
random_number = random.randint(0, len(dog_files_test))
file = dog_files_test[random_number]
print(file)
print(VGG16_predict(file))
dog_detector(file)
```

```
/data/dog_images/train/062.English_setter/English_setter_04392.jpg
212
```

Out[9]: True

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: Dogs in human files: 0.0% Dogs in dog files: 100.0%

```
In [10]: ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         from tqdm import tqdm

         show_image = False

         def percentage_dogs(file_list):
             dogs_found = 0

             for file in tqdm(file_list):
                 if dog_detector(file) is True:
                     dogs_found += 1

             percentage_dogs_found = (dogs_found / len(file_list)) * 100

             return percentage_dogs_found

         dogs_in_human_files = percentage_dogs(human_files_short)
         dogs_in_dogs_files = percentage_dogs(dog_files_short)

         print("Dogs in human files: {}%".format(dogs_in_human_files))
         print("Dogs in dog files: {}%".format(dogs_in_dogs_files))
```

```
100%|| 100/100 [00:03<00:00, 30.81it/s]
100%|| 100/100 [00:04<00:00, 22.28it/s]

Dogs in human files: 0.0%
Dogs in dog files: 100.0%
```

We suggest VGG-16 as a potential network to detect dog images in your algorithm, but you are free to explore other pre-trained networks (such as Inception-v3, ResNet-50, etc). Please use the code cell below to test other pre-trained PyTorch models. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

```
In [11]: ### (Optional)
         ### TODO: Report the performance of another pre-trained network.
         ### Feel free to use as many code cells as needed.
         import torch
         import torchvision.models as models
         from PIL import Image
         import torchvision.transforms as transforms
         from torch.autograd import Variable
         from tqdm import tqdm

         # define model
         model_resnet = models.resnet50(pretrained = True)
```

```
Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /root/.torch/models/
100%|| 102502400/102502400 [00:01<00:00, 90392950.14it/s]
```

```
In [12]: def predict_breed(img_path, model):

             ## 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 = Image.open(img_path) # Load the image from provided path

             normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                              std=[0.229, 0.224, 0.225])
             preprocess = transforms.Compose([transforms.Resize(224),
                                              transforms.CenterCrop(224),
                                              transforms.ToTensor(),
                                              normalize])
             img_tensor = preprocess(img).float()
             img_tensor.unsqueeze_(0)  # Insert the new axis at index 0 i.e. in front of the oth
             img_tensor = Variable(img_tensor) #The input to the network needs to be an autograd
             #if use_cuda:
                 #img_tensor = Variable(img_tensor.cuda())

             model_resnet.eval()
             output = model(img_tensor) # Returns a Tensor of shape (batch, num class labels)
             output = output.cpu()
             predict_index = output.data.numpy().argmax() # Our prediction will be the index of

             return predict_index
```

```
In [13]: def dog_detector_general(img_path, model):
             ## TODO: Complete the function.
             prediction = predict_breed(img_path, model)
             return ((prediction <= 268) & (prediction >= 151)) # true/false

         ### TODO: Test the performance of the dog_detector function
         ### on the images in human_files_short and dog_files_short.
         human_files_short = human_files[:100]
         dog_files_short = dog_files[:100]

         human_detections = np.sum([dog_detector_general(img, model_resnet) for img in tqdm(huma
         dog_detections = np.sum([dog_detector_general(img, model_resnet) for img in tqdm(dog_fi

         print('dog detection in human image set = {}%'.format(human_detections))
         print('dog detection in dog image set = {}%'.format(dog_detections))
```

```
100%|| 100/100 [00:26<00:00,  3.81it/s]
100%|| 100/100 [00:28<00:00,  3.68it/s]
```

```
dog detection in human image set = 0%
dog detection in dog image set = 100%
```

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

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

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

Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador

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

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

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

```
In [14]: import os
         import numpy
         import time
         import copy
         from glob import glob

         import torch
         import torchvision
         import matplotlib.pyplot as plt
         import torch.nn as nn
         import torch.nn.functional as F
         import torch.optim as optim
         from torch.optim import lr_scheduler
         from torchvision import datasets, models
         import torchvision.transforms as transforms
         from torch.utils.data.sampler import SubsetRandomSampler
         from PIL import Image
         from torch.autograd import Variable
         import random

         # Fix for cuda error resulting from truncated images
         # https://stackoverflow.com/a/23575424/7434289
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         plt.ion() # interactive mode
         %matplotlib inline
```

```
In [15]: ### TODO: Write data loaders for training, validation, and test sets
         ## Specify appropriate transforms, and batch_sizes

         # All images are resized to 224x224 and normalized
         # Only training images receive further augmentation

         normalize = transforms.Normalize(mean=[0.485, 0.465, 0.406],
                                          std=[0.229, 0.224, 0.225])
         data_transforms = {
             'train': transforms.Compose([
                 transforms.RandomResizedCrop(224),
                 transforms.RandomHorizontalFlip(),
                 transforms.RandomRotation(10),
                 transforms.ToTensor(),
                 normalize
             ]),
             'valid': transforms.Compose([
```

```
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            normalize
        ]),
        'test': transforms.Compose([
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            normalize
        ])
    }

    data_dir = '/data/dog_images'
```

```
In [18]: # number of subprocesses to use for data loading
         num_workers = 0
         # number of samples per batch to load
         batch_size = 20
```

```
In [19]: image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x), data_transforms[x]
                          for x in ['train', 'valid', 'test']}

         loaders_data = {x: torch.utils.data.DataLoader(image_datasets[x], batch_size = batch_si
                                                        shuffle = True, num_workers = num_workers
                        for x in ['train', 'valid', 'test']}
         dataset_sizes = {x: len(image_datasets[x]) for x in ['train', 'valid', 'test']}
         class_names = image_datasets['train'].classes
         n_classes = len(class_names)
```

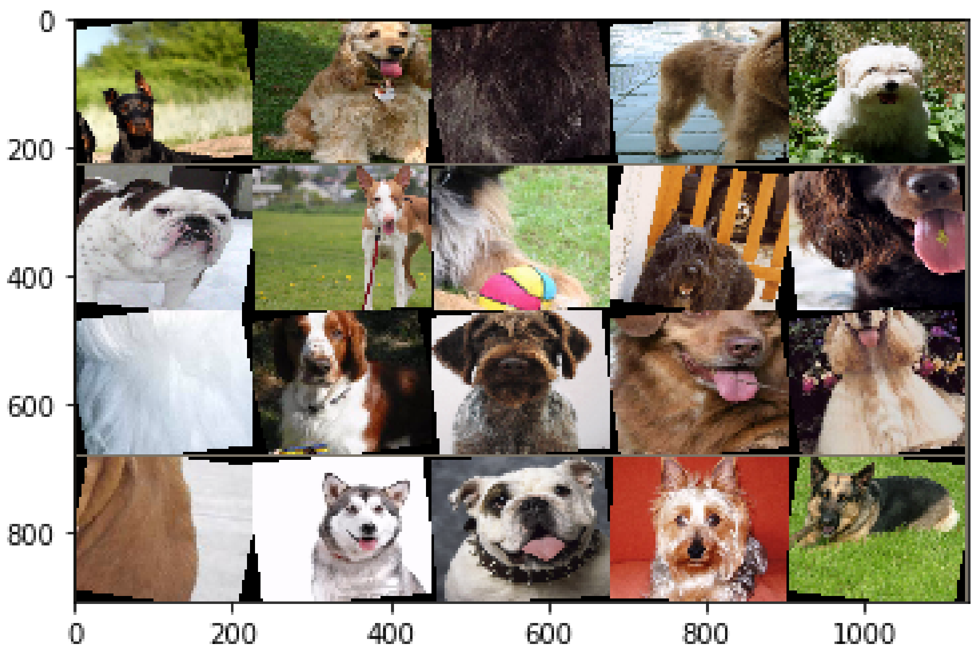
```
In [20]: print(f"No. of Training Records: {dataset_sizes['train']}")
         print(f"No. of Validation Records: {dataset_sizes['valid']}")
         print(f"No. of Testing Records: {dataset_sizes['test']}")
         print(f"No. of Classes: {n_classes}")

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

```
No. of Training Records: 6680
No. of Validation Records: 835
No. of Testing Records: 836
No. of Classes: 133
```

```
In [21]: def imshow(image):
             """ Helper function to un_normalize and display an image.
             """
             image = image.numpy().transpose((1, 2, 0))
             mean = np.array([0.485, 0.456, 0.406])
```

```
    std = np.array([0.229, 0.224, 0.225])
    image = std * image + mean
    image = np.clip(image, 0, 1)
    plt.imshow(image, aspect='auto') #convert from Tensor image
```

```
In [22]: # loader
         from torchvision import utils

         images, labels = next(iter(loaders_data['train']))
         # images, labels = next(iter(loaders['valid']))
         # images, labels = next(iter(loaders['test']))

         # Make a frid from batch
         grid = utils.make_grid(images, nrow=5)

         # show images
         imshow(grid)
```



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: - All images are resized and used all color channel to 224x224x3 and normalized. All pre-trained models expect input images normalized in the same way, i.e. mini-batches of 3-channel RGB images of shape (3 x H x W), where H and W are expected to be at least 224. - Only training images receive further augmentation by flipping the images horizontally and 10 degree of rotation. These augmentations should help our model generalize and reduce overfitting.

Overfitting is a general problem in our experiment. Some methods used to preprocessing our data to improve the effect of model training and alleviate the effect of overfitting are: 1. Crop: Random Cropping is a common method in augmentation, which is to randomly sample a section from the original image and resize it to its original image size. In our experiment, we randomly extract a 224 Œ 224 pixels section from 256 Œ 256 pixels. 2. Flip: Each image can be flipped horizontally and vertically. In our task, images are flipped horizontally. 3. Rotation: Each image can be rotated. In our task, images are rotated to 10 degrees.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [23]: 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
                 self.input_size = 224
                 self.input_dept = 3

                 # convolution layer sees (self.inpuet_size x self.input_size x 3 image tensor)
                 # convolutional layer (sees 224x224x3 image tensor)
                 self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
                 # convolutional layer (sees 112x112x16 image tensor)
                 self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
                 # convolutional layer (sees 56x56x32 image tensor)
                 self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
                 # convolutional layer (sees 28x28x64 image tensor)
                 self.conv4 = nn.Conv2d(64, 128, 3, padding=1)
                 # convolutional layer (sees 14x14x128 image tensor)
                 self.conv5 = nn.Conv2d(128, 256, 3, padding=1)

                 # max pooling layer
                 self.pool = nn.MaxPool2d(2, 2)
                 # dropout layer
                 self.dropout = nn.Dropout(0.2)

                 self.conv_bn1 = nn.BatchNorm2d(224, 3)
                 self.conv_bn2 = nn.BatchNorm2d(16)
                 self.conv_bn3 = nn.BatchNorm2d(32)
                 self.conv_bn4 = nn.BatchNorm2d(64)
                 self.conv_bn5 = nn.BatchNorm2d(128)
                 self.conv_bn6 = nn.BatchNorm2d(256)
```

```python
        # linear layer (256 * 5 * 5 -> 500)
        self.fc1 = nn.Linear(256 * 7 * 7, 512)
        self.fc2 = nn.Linear(512, n_classes)

    def forward(self, x):
        # add sequence of conv and maxpool layers
        x = self.pool(F.relu(self.conv1(x)))
        x = self.conv_bn2(x)
        x = self.pool(F.relu(self.conv2(x)))
        x = self.conv_bn3(x)
        x = self.pool(F.relu(self.conv3(x)))
        x = self.conv_bn4(x)
        x = self.pool(F.relu(self.conv4(x)))
        x = self.conv_bn5(x)
        x = self.pool(F.relu(self.conv5(x)))
        x = self.conv_bn6(x)

        # flatten image input
        x = x.view(-1, 256 * 7 * 7)
        # add dropout layer
        x = self.dropout(x)
        # add 1st hidden layer with relu activation function
        x = F.relu(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()
```

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

Answer:

- Five convolution layers are used with all the convolutions of size=3, stride=1 and padding=1. The five layers are defined with 16,32,64,128 and 256 filters respectively. And they are each followed by a max pooling layer.
- Also, two connected linear layers at the end are used.
- Relu activations are used after each layers except the last one
- Max pooling layers of 2x2 are applied.
- Batch normalization are applied after each maxpooling
- Dropout is applied with a probability of 0.2

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 [24]: 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 [27]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
             """returns trained model"""
             # initialize tracker for minimum validation loss
             valid_loss_min = np.Inf

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

                 ###################
                 # train the model #
                 ###################
                 model.train()
                 for batch_idx, (data, target) in enumerate(loaders['train']):
                     # move to GPU
                     if use_cuda:
                         data, target = data.cuda(), target.cuda()
                     ## record the average training loss, using something like
                     ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo

                     # clear the gradients of all optimized variables
                     optimizer.zero_grad()
                     # forward pass
                     output = model(data)
                     # find the loss and update the model parameters accordingly
                     loss = criterion(output, target)
                     # backward pass: compute gradient of the loss with respect to model paramet
                     loss.backward()
                     # perform the optimization step for the purpose of gradient descent(paramte
                     optimizer.step()
```

```
                ## record the average training loss
                #train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss
                train_loss = train_loss + (1 / (batch_idx + 1)) * (loss.data - train_loss)

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

            # calculate average losses
            train_loss = train_loss/len(loaders['train'].dataset)
            valid_loss = valid_loss/len(loaders['valid'].dataset)


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

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

        # return trained model
        return model
```

In [25]:
```
model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

In [26]:
```
# train the model
n_epochs = 25
loaders_scratch = loaders_data
#model_scratch = train(n_epochs, loaders_scratch, model_scratch, optimizer_scratch,
#                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

1.1.11 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 10%.

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

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

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

             print('Test Loss: {:.6f}\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: 2.277245


Test Accuracy: 39% (333/836)
```

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 [ ]: ## TODO: Specify data loaders
```

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 [96]: # import torchvision.models as models
         # import torch.nn as nn

         ## TODO: Specify model architecture
         # model_resnet50 = models.resnet50(pretrained=True)

         # Freeze training for all "features" layers
         # for param in model_resnet50.parameters():
             # param.requires_grad = False

         #num_features = model_transfer.fc.in_features
         #model_transfer.classifier = nn.Linear(num_features, n_classes)

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

```
In [97]: print(model_resnet50)
```

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

```
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
  )
)
(layer2): Sequential(
  (0): Bottleneck(
    (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
    (downsample): Sequential(
      (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace)
  )
  (2): Bottleneck(
    (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
```

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

```
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
```

```
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace)
      )
      (2): Bottleneck(
        (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace)
      )
    )
    (avgpool): AvgPool2d(kernel_size=7, stride=1, padding=0)
    (fc): Linear(in_features=2048, out_features=1000, bias=True)
  )
```

In [27]:
```
import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture
model_transfer = models.densenet161(pretrained=True)

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

num_features = model_transfer.classifier.in_features
model_transfer.classifier = nn.Linear(num_features, n_classes)

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

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvision/models/densenet.p
Downloading: "https://download.pytorch.org/models/densenet161-8d451a50.pth" to /root/.torch/mode
100%|| 115730790/115730790 [00:01<00:00, 90085012.09it/s]
```

In [95]:
```
model_transfer
```

Out[95]:
```
DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 96, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=Fals
    (norm0): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_stats=
    (relu0): ReLU(inplace)
    (pool0): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
    (denseblock1): _DenseBlock(
      (denselayer1): _DenseLayer(
```

```
      (norm1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_st
      (relu1): ReLU(inplace)
      (conv1): Conv2d(96, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(144, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(192, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(240, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer5): _DenseLayer(
      (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(288, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer6): _DenseLayer(
      (norm1): BatchNorm2d(336, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(336, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
  )
```

```
(transition1): _Transition(
  (norm): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  (relu): ReLU(inplace)
  (conv): Conv2d(384, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
)
(denseblock2): _DenseBlock(
  (denselayer1): _DenseLayer(
    (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu1): ReLU(inplace)
    (conv1): Conv2d(192, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer2): _DenseLayer(
    (norm1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu1): ReLU(inplace)
    (conv1): Conv2d(240, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer3): _DenseLayer(
    (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu1): ReLU(inplace)
    (conv1): Conv2d(288, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(336, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu1): ReLU(inplace)
    (conv1): Conv2d(336, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu1): ReLU(inplace)
    (conv1): Conv2d(384, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer6): _DenseLayer(
```

```
      (norm1): BatchNorm2d(432, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(432, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer7): _DenseLayer(
      (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(480, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer8): _DenseLayer(
      (norm1): BatchNorm2d(528, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(528, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer9): _DenseLayer(
      (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(576, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer10): _DenseLayer(
      (norm1): BatchNorm2d(624, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(624, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer11): _DenseLayer(
      (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(672, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer12): _DenseLayer(
```

```
      (norm1): BatchNorm2d(720, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(720, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
  )
  (transition2): _Transition(
    (norm): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stat
    (relu): ReLU(inplace)
    (conv): Conv2d(768, 384, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
  )
  (denseblock3): _DenseBlock(
    (denselayer1): _DenseLayer(
      (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(384, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(432, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(432, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(480, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(528, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(528, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer5): _DenseLayer(
```

```
  (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu1): ReLU(inplace)
  (conv1): Conv2d(576, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer6): _DenseLayer(
  (norm1): BatchNorm2d(624, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu1): ReLU(inplace)
  (conv1): Conv2d(624, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer7): _DenseLayer(
  (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu1): ReLU(inplace)
  (conv1): Conv2d(672, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer8): _DenseLayer(
  (norm1): BatchNorm2d(720, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu1): ReLU(inplace)
  (conv1): Conv2d(720, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer9): _DenseLayer(
  (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu1): ReLU(inplace)
  (conv1): Conv2d(768, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer10): _DenseLayer(
  (norm1): BatchNorm2d(816, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu1): ReLU(inplace)
  (conv1): Conv2d(816, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer11): _DenseLayer(
```

```
      (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(864, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(912, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(912, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer13): _DenseLayer(
      (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu1): ReLU(inplace)
      (conv1): Conv2d(960, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer14): _DenseLayer(
      (norm1): BatchNorm2d(1008, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1008, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer15): _DenseLayer(
      (norm1): BatchNorm2d(1056, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1056, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer16): _DenseLayer(
      (norm1): BatchNorm2d(1104, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1104, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer17): _DenseLayer(
```

```
      (norm1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer18): _DenseLayer(
      (norm1): BatchNorm2d(1200, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1200, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer19): _DenseLayer(
      (norm1): BatchNorm2d(1248, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1248, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer20): _DenseLayer(
      (norm1): BatchNorm2d(1296, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1296, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer21): _DenseLayer(
      (norm1): BatchNorm2d(1344, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1344, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer22): _DenseLayer(
      (norm1): BatchNorm2d(1392, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1392, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer23): _DenseLayer(
```

```
  (norm1): BatchNorm2d(1440, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1440, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer24): _DenseLayer(
  (norm1): BatchNorm2d(1488, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1488, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer25): _DenseLayer(
  (norm1): BatchNorm2d(1536, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1536, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer26): _DenseLayer(
  (norm1): BatchNorm2d(1584, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1584, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer27): _DenseLayer(
  (norm1): BatchNorm2d(1632, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1632, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer28): _DenseLayer(
  (norm1): BatchNorm2d(1680, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1680, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer29): _DenseLayer(
```

```
    (norm1): BatchNorm2d(1728, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1728, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer30): _DenseLayer(
    (norm1): BatchNorm2d(1776, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1776, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer31): _DenseLayer(
    (norm1): BatchNorm2d(1824, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1824, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer32): _DenseLayer(
    (norm1): BatchNorm2d(1872, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1872, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer33): _DenseLayer(
    (norm1): BatchNorm2d(1920, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1920, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer34): _DenseLayer(
    (norm1): BatchNorm2d(1968, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1968, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer35): _DenseLayer(
```

```
      (norm1): BatchNorm2d(2016, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(2016, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer36): _DenseLayer(
      (norm1): BatchNorm2d(2064, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(2064, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
  )
  (transition3): _Transition(
    (norm): BatchNorm2d(2112, eps=1e-05, momentum=0.1, affine=True, track_running_sta
    (relu): ReLU(inplace)
    (conv): Conv2d(2112, 1056, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
  )
  (denseblock4): _DenseBlock(
    (denselayer1): _DenseLayer(
      (norm1): BatchNorm2d(1056, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1056, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(1104, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1104, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True, track_running_
      (relu1): ReLU(inplace)
      (conv1): Conv2d(1152, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
    )
    (denselayer4): _DenseLayer(
```

```
  (norm1): BatchNorm2d(1200, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1200, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer5): _DenseLayer(
  (norm1): BatchNorm2d(1248, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1248, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer6): _DenseLayer(
  (norm1): BatchNorm2d(1296, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1296, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer7): _DenseLayer(
  (norm1): BatchNorm2d(1344, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1344, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer8): _DenseLayer(
  (norm1): BatchNorm2d(1392, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1392, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer9): _DenseLayer(
  (norm1): BatchNorm2d(1440, eps=1e-05, momentum=0.1, affine=True, track_running_
  (relu1): ReLU(inplace)
  (conv1): Conv2d(1440, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
  (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
  (relu2): ReLU(inplace)
  (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
)
(denselayer10): _DenseLayer(
```

```
    (norm1): BatchNorm2d(1488, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1488, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer11): _DenseLayer(
    (norm1): BatchNorm2d(1536, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1536, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer12): _DenseLayer(
    (norm1): BatchNorm2d(1584, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1584, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer13): _DenseLayer(
    (norm1): BatchNorm2d(1632, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1632, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer14): _DenseLayer(
    (norm1): BatchNorm2d(1680, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1680, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer15): _DenseLayer(
    (norm1): BatchNorm2d(1728, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1728, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer16): _DenseLayer(
```

```
    (norm1): BatchNorm2d(1776, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1776, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer17): _DenseLayer(
    (norm1): BatchNorm2d(1824, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1824, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer18): _DenseLayer(
    (norm1): BatchNorm2d(1872, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1872, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer19): _DenseLayer(
    (norm1): BatchNorm2d(1920, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1920, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer20): _DenseLayer(
    (norm1): BatchNorm2d(1968, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(1968, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer21): _DenseLayer(
    (norm1): BatchNorm2d(2016, eps=1e-05, momentum=0.1, affine=True, track_running_
    (relu1): ReLU(inplace)
    (conv1): Conv2d(2016, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
  )
  (denselayer22): _DenseLayer(
```

```
        (norm1): BatchNorm2d(2064, eps=1e-05, momentum=0.1, affine=True, track_running_
        (relu1): ReLU(inplace)
        (conv1): Conv2d(2064, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
      )
      (denselayer23): _DenseLayer(
        (norm1): BatchNorm2d(2112, eps=1e-05, momentum=0.1, affine=True, track_running_
        (relu1): ReLU(inplace)
        (conv1): Conv2d(2112, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
      )
      (denselayer24): _DenseLayer(
        (norm1): BatchNorm2d(2160, eps=1e-05, momentum=0.1, affine=True, track_running_
        (relu1): ReLU(inplace)
        (conv1): Conv2d(2160, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (norm2): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_s
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bia
      )
    )
    (norm5): BatchNorm2d(2208, eps=1e-05, momentum=0.1, affine=True, track_running_stat
  )
  (classifier): Linear(in_features=2208, 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:

- Transfer learning involves taking a pre-trained neural network and adapting the neural network to a new, different data set. Depending on the size of the new data set, and the similarity of the new data set to the original data set.

- Since our data set is small CONVNET AS FIXED FEATURE EXTRACTOR method are used (https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html):

1. slice off the end of the neural network
2. freeze all the network except the final layer. We need to set requires_grad == False to freeze the parameters so that the gradients are not computed in backward().
3. add a new fully connected layer that matches the number of classes in the new data set
4. randomize the weights of the new fully connected layer; freeze all the weights from the pre-trained network
5. train the network to update the weights of the new fully connected layer

- In our task, we need to classify 133 breeds of dogs from only approximatly 6600 images. We do not have sufficient training data to train a new and complex model that can perform well on testing dataset. Thus, we directly download different models ,such as ResNet18, VGG16, and DenseNet161 from Pytorch which we use as our framework. But the weights on the last layer of each model are exactly random and the number of categories in outputs of each model is different from 133 that we need. In order to fix it, we freeze all layer but the last. Freezing is to make the layer weights invariant during training. We also add one fully connected layers to replace the last layer of each pre-trained model.

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 [29]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr=0.001, moment
```

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
         n_epochs = 25
         loaders_transfer = loaders_data
         #model_transfer = train(n_epochs, loaders_transfer, model_transfer,
         #                       optimizer_transfer, criterion_transfer,
         #                       use_cuda, 'model_transfer.pt')
         # load the model that got the best validation accuracy (uncomment the line below)
         model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

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 [31]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)

Test Loss: 0.384374


Test Accuracy: 89% (746/836)
```

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 [38]: ### 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 image_datasets['train'].classes]

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed
    img = Image.open(img_path) # Load the image from provided path

    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])
    transform = transforms.Compose([
        transforms.Resize(224),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        normalize])

    img_tensor = transform(img)
    img_tensor.unsqueeze_(0) #Insert the new axis at the index 0 i.e in front of the ot

    if use_cuda:
        img_tensor = img_tensor.cuda()
    model_transfer.eval()
    output = model_transfer(img_tensor)
    _, prediction = torch.max(output.data, 1)
    breed = class_names[prediction]

    return breed
```

In [ ]:

Step 5: Write your Algorithm

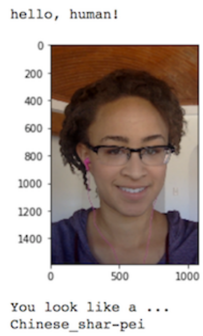
Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then, - if a **dog** is detected in the image, return the predicted breed. - if a **human** is detected in the image, return the resembling dog breed. - if **neither** is detected in the image, provide output that indicates an error.

You are welcome to write your own functions for detecting humans and dogs in images, but feel free to use the `face_detector` and `human_detector` functions developed above. You are **required** to use your CNN from Step 4 to predict dog breed.

Some sample output for our algorithm is provided below, but feel free to design your own user experience!

1.1.18 (IMPLEMENTATION) Write your Algorithm

In [52]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.

def run_app(img_path):
```



Sample Human Output

```
## handle cases for a human face, dog, and neither
if dog_detector(img_path) == True:
    pred = "Looks like a dog. The breed of dog is "
    pred = pred + predict_breed_transfer(img_path)
    print (pred)
elif face_detector(img_path) == True:
    pred = "Looks like a human. If it were a dog, it would be  "
    pred = pred + predict_breed_transfer(img_path)
    print (pred)
else:
    warn = "no dogs or humans in the picture"
    print (warn)
```

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)

1. Do more data augmentation
2. Fine tune more layers and not just the last linear layers
3. Go for different architecture model with layers

```
In [53]: ## 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.
```

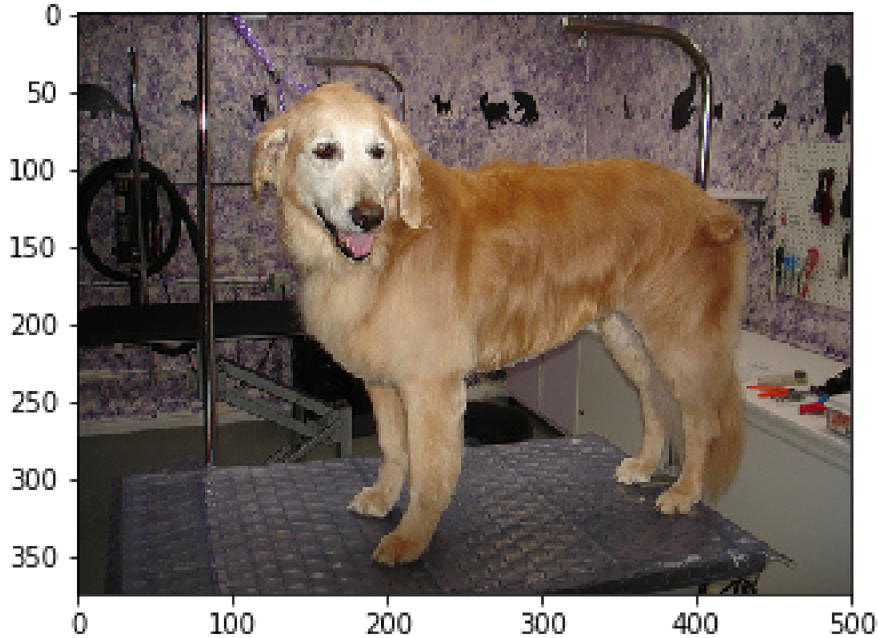
```
    ## suggested code, below
    for file in np.hstack((human_files[:3], dog_files[:3])):
        run_app(file)
```

```
Looks like a human. If it were a dog, it would be  Great dane
Looks like a human. If it were a dog, it would be  Dachshund
Looks like a human. If it were a dog, it would be  American water spaniel
Looks like a dog. The breed of dog is Mastiff
Looks like a dog. The breed of dog is Mastiff
Looks like a dog. The breed of dog is Bullmastiff
```

```
In [ ]: fig = plt.figure()
        file = "D:/Programming/hello/taqdees.jpg"
        pred = run_app(file)
        img=np.asarray(Image.open(file))
        plt.imshow(img)

        print('\n{}. '.format(pred))
```

```
In [56]: show_image = True
         dog_files_test = np.concatenate((human_files, dog_files), axis=0)
         random_number = random.randint(0, len(dog_files_test))
         file = dog_files_test[random_number]
         print(file)
         pred = run_app(file)
         img=np.asarray(Image.open(file))
         plt.imshow(img)

         print('\n{}. '.format(pred))
```

```
/data/dog_images/train/076.Golden_retriever/Golden_retriever_05209.jpg
Looks like a dog. The breed of dog is Golden retriever

None.
```

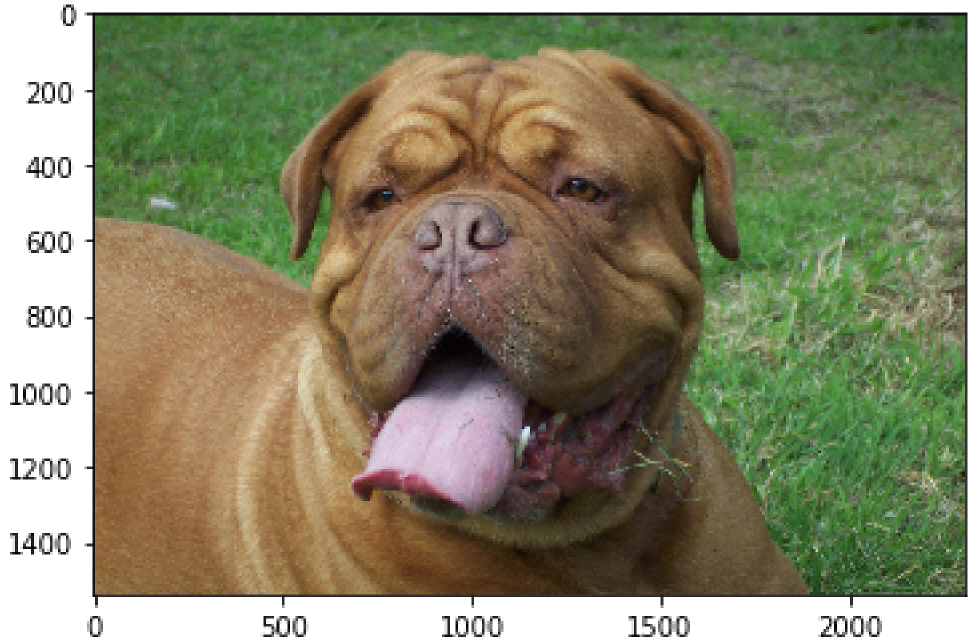



```
In [57]: show_image = True
         dog_files_test = np.concatenate((human_files, dog_files), axis=0)
         random_number = random.randint(0, len(dog_files_test))
         file = dog_files_test[random_number]
         print(file)
         pred = run_app(file)
         img=np.asarray(Image.open(file))
         plt.imshow(img)

         print('\n{}. '.format(pred))
```

```
/data/dog_images/test/047.Chesapeake_bay_retriever/Chesapeake_bay_retriever_03386.jpg
Looks like a dog. The breed of dog is Chesapeake bay retriever

None.
```

In [58]:
```
show_image = True
dog_files_test = np.concatenate((human_files, dog_files), axis=0)
random_number = random.randint(0, len(dog_files_test))
file = dog_files_test[random_number]
print(file)
pred = run_app(file)
img=np.asarray(Image.open(file))
plt.imshow(img)

print('\n{}. '.format(pred))
```

```
/data/dog_images/test/060.Dogue_de_bordeaux/Dogue_de_bordeaux_04216.jpg
Looks like a dog. The breed of dog is Dogue de bordeaux

None.
```



```
In [ ]:
```