dog_app

February 20, 2019

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

- Download the human dataset. Unzip the folder and place it in the home directory, at location `/lfw`.

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

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

```
In [1]: # write all imports here
        import os
        import torch
        from torchvision import datasets, transforms, models

        import torch.nn as nn
        import torch.nn.functional as F
        import torch.optim as optim

        import numpy as np
        from glob import glob

        import cv2
        import matplotlib.pyplot as plt
        %matplotlib inline

        from tqdm import tqdm

        from PIL import Image, ImageFile
        ImageFile.LOAD_TRUNCATED_IMAGES = True
```

```
In [2]: # 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

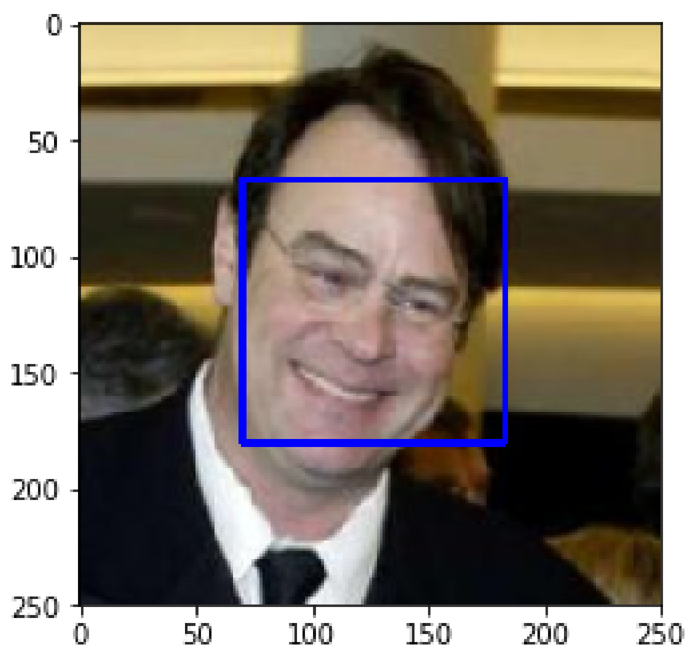
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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

         # load color (BGR) image
         img = cv2.imread(human_files[0])
```

```python
# convert BGR image to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

```
In [22]: # returns "True" if face is detected in image stored at img_path
         def face_detector(img_path):
             #read the image
             img = cv2.imread(img_path)
             #convert the BGR image to gray scale
             gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
             #detect face
             faces = face_cascade.detectMultiScale(gray)
             #return True if human face exists
             return len(faces) > 0
```

```
In [23]: face_detector('test/me.jpeg')
```

```
Out[23]: True
```

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:

98% of first 100 images in `human_files` have detected human face

17% of first 100 images in `dog_files` have detected human face

```
In [5]: human_files_short = human_files[:100]
        dog_files_short = dog_files[:100]

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

        ## TODO: Test the performance of the face_detector algorithm
        ## on the images in human_files_short and dog_files_short.
        found_1 = 0
        for img_path in human_files_short:
```

```
            if(face_detector(img_path)):
                found_1+=1

        found_2 = 0
        for img_path in dog_files_short:
            if(face_detector(img_path)):
                found_2+=1

        print('Human face detected in human files: {:.2f}%'.format(found_1/len(human_files_short
        print('Human face detected in dog files: {:.2f}%'.format(found_2/len(dog_files_short)*10
```

```
Human face detected in human files: 98.00%
Human face detected in dog files: 17.00%
```

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

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

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

```
In [3]: # check if CUDA is available
        use_cuda = torch.cuda.is_available()
```

```
In [19]: # define VGG16 model
         VGG16 = models.vgg16(pretrained=True)

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:08<00:00, 62576331.10it/s]
```

Given an image, this pre-trained VGG-16 model returns a prediction (derived from the 1000 possible categories in ImageNet) for the object that is contained in the image.

1.1.4 (IMPLEMENTATION) Making Predictions with a Pre-trained Model

In the next code cell, you will write a function that accepts a path to an image (such as `'dogImages/train/001.Affenpinscher/Affenpinscher_00001.jpg'`) as input and returns the index corresponding to the ImageNet class that is predicted by the pre-trained VGG-16 model. The output should always be an integer between 0 and 999, inclusive.

Before writing the function, make sure that you take the time to learn how to appropriately pre-process tensors for pre-trained models in the PyTorch documentation.

```
In [17]: 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
             '''

             # display the image
             img = cv2.imread(img_path)
             # 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)

             ## 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
             pil_img = Image.open(img_path)
             loader = transforms.Compose([
                 transforms.RandomResizedCrop(224),
                 transforms.ToTensor()
             ])
             img = loader(pil_img)
             img.unsqueeze_(0)
             if(use_cuda):
                 img = img.cuda()
             output = VGG16(img)
             _, preds = torch.max(output,1)


             return preds # predicted class index
```

1.1.5 (IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary, you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all categories from `'Chihuahua'` to `'Mexican hairless'`. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

Use these ideas to complete the `dog_detector` function below, which returns `True` if a dog is detected in an image (and `False` if not).

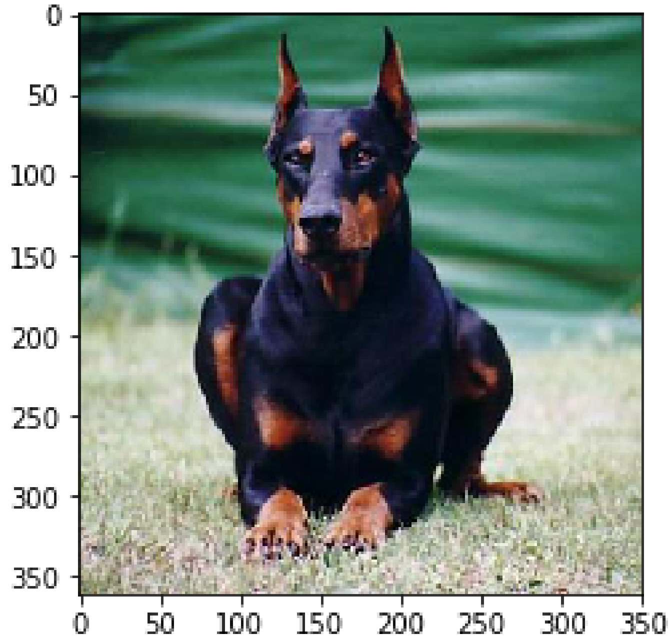
```
In [24]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             ## TODO: Complete the function.
             pred_idx = VGG16_predict(img_path)
             #print('VGG16 predicted class index',pred_idx)
             if(pred_idx>=151 and pred_idx<=268):
                 return True
             else:
                 return False
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your `dog_detector` function.
- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?

Answer:
0% of first 100 images in `human_files` have detected dog face
76% of first 100 images in `dog_files` have detected dog face

```
In [11]: ### 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]

         found_1 = 0
         for img_path in human_files_short:
             if(dog_detector(img_path)):
                 found_1+=1

         found_2 = 0
         for img_path in dog_files_short:
             if(dog_detector(img_path)):
                 found_2+=1

         print('Dog face detected in human files: {:.2f}%'.format(found_1/len(human_files_short)
         print('Dog face detected in dog files: {:.2f}%'.format(found_2/len(dog_files_short)*100

Dog face detected in human files: 1.00%
Dog face detected in dog files: 83.00%
```



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

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

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)
Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of at least 10%. In Step 4 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

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

Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador

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

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

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

In [5]:
```
### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
batch_size = 32

data_root = {
    'train': '/data/dog_images/train',
    'valid': '/data/dog_images/valid',
    'test': '/data/dog_images/test'
}


data_transforms = {
    'train': transforms.Compose([
        transforms.RandomRotation(45),
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0.224, 0.225])
      ]),
    'valid': transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
```

```
            transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0.224, 0.225])
        ]),
        'test': transforms.Compose([
            transforms.RandomResizedCrop(224),
            transforms.ToTensor(),
            transforms.Normalize([0.485, 0.456, 0.406],[0.229, 0.224, 0.225])
        ])
    }

    img_datasets = {x: datasets.ImageFolder(data_root[x], data_transforms[x]) for x in ['tra

    data_loaders = {x: torch.utils.data.DataLoader(img_datasets[x],batch_size=batch_size,shu

    dataset_sizes = {x: len(img_datasets[x]) for x in ['train','valid','test']}
    classes = img_datasets['train'].classes
```

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:

1) I have cropped the image to size 224x224 by using `RandomResizedCrop()` for train dataloader and for valid dataloader I decided to use a `CenterCrop()`. Most of the pretrained models take 224x224 size images as input so I kept it the same way for CNN from scratch part and also normalization as is required by pretrained models.

2) First I did not apply data augmentation and built my CNN from scratch and tried training but I never got accuracy above 1% even after changing other parameters like learning rate. After applying augmentation my accuracy increased. I have rotated images by 45deg and also applied horizontal flip. I choose 45deg because I wanted the images to be slightly titled, neither too much nor too little like by 20deg.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [5]: # define the CNN architecture
        class Net(nn.Module):
            ### TODO: choose an architecture, and complete the class
            def __init__(self):
                super(Net, self).__init__()
                ## Define layers of a CNN
                ## convolutional layer sees 224x224x3 image tensor
                self.conv1 = nn.Conv2d(3,16,3,padding=1)
                ## convolutional layer sees 112x112x3 image tensor
                self.conv2 = nn.Conv2d(16,32,3,padding=1)
                ## convolutional layer sees  56X56x3 image tensor
                self.conv3 = nn.Conv2d(32,64,3,padding=1)
```

```
        ## convolutional layer sees  28X28x3 image tensor
        self.conv4 = nn.Conv2d(64,128,3,padding=1)
        ## convolutional layer sees  14X14x3 image tensor
        self.conv5 = nn.Conv2d(128,256,3,padding=1)
        # max pooling layer
        self.pool = nn.MaxPool2d(2,2)

        self.bn1 = nn.BatchNorm2d(16)
        self.bn2 = nn.BatchNorm2d(32)
        self.bn3 = nn.BatchNorm2d(64)
        self.bn4 = nn.BatchNorm2d(128)
        self.bn5 = nn.BatchNorm2d(256)

        self.fc1 = nn.Linear(7*7*256,4096)
        self.fc2 = nn.Linear(4096,512)
        self.fc3 = nn.Linear(512,133)
        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        ## Define forward behavior
        x = self.pool(F.relu(self.bn1(self.conv1(x))))
        x = self.pool(F.relu(self.bn2(self.conv2(x))))
        x = self.pool(F.relu(self.bn3(self.conv3(x))))
        x = self.pool(F.relu(self.bn4(self.conv4(x))))
        x = self.pool(F.relu(self.bn5(self.conv5(x))))

        #print(x.shape)
        #flatten the image input
        x = x.view(-1, 7*7*256)

        #add a dropout layer
        x = F.relu(self.fc1(x))
        x = self.dropout(x)
        x = F.relu(self.fc2(x))
        x = self.dropout(x)
        x = self.fc3(x)

        return x

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

# instantiate the CNN
model_scratch = Net()
print(model_scratch)

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (bn1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (bn2): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (bn3): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (bn4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (bn5): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (fc1): Linear(in_features=12544, out_features=4096, bias=True)
  (fc2): Linear(in_features=4096, out_features=512, bias=True)
  (fc3): Linear(in_features=512, out_features=133, bias=True)
  (dropout): Dropout(p=0.2)
)
```

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

Answer: 1) 2 conv layer + 1 linear layer. Very bad accuarcy. Like no decrease in training loss at all

2) Increase conv layers and added max pooling layer after each conv layer. Tried with 3 conv + 2 fc layer.
3) Then again added one more conv layer and fc layer. But accuracy was not high enough to cross 10%
4) Since I had increased the numbers of layers in network. I also added dropout of 0.25 to try and improve accuracy

Till here I had not applied image augmentation. Now I applied image augmentation and also read about batch normalization.

5) With same arch in Step 4) + image augmentation + batch normalization. The accuarcy reached 18% with 35 epcohs
6) Training for 50 epochs the accurcy reached 28%

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

        ### TODO: select optimizer
        optimizer_scratch = optim.SGD(model_scratch.parameters(),lr=0.03,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 [6]:
```
def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
    """returns trained model"""
    # initialize tracker for minimum validation loss
    valid_loss_min = np.Inf

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

        ###################
        # train the model #
        ###################
        model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly

            # 1.clear all gradients
            optimizer.zero_grad()
            # 2.Forward Pass
            output = model(data)
            # 3.Calculate Loss
            loss = criterion(output,target)
            # 4.Backward pass
            loss.backward()
            # 5.Optimization step
            optimizer.step()
            ## record the average training loss, using something like
            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
            output = model(data)
            loss = criterion(output,target)
```

```
                valid_loss += ((1 / (batch_idx + 1)) * (loss.data - valid_loss))


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

            ## TODO: save the model if validation loss has decreased
            if valid_loss < valid_loss_min:
                print('SAVE MODEL \n Validation Loss Decreased{:.6f}->{:.6f}'.format(valid_l
                torch.save(model.state_dict(),save_path)
                valid_loss_min = valid_loss
        # return trained model
        return model
```

```
In [9]: n_epochs = 50
        # train the model
        model_scratch = train(n_epochs, data_loaders, model_scratch, optimizer_scratch,
                              criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1 	Training Loss: 4.807864 	Validation Loss: 4.570700
SAVE MODEL 
 Validation Loss Decreasedinf->4.570700
Epoch: 2 	Training Loss: 4.682255 	Validation Loss: 4.687647
Epoch: 3 	Training Loss: 4.608634 	Validation Loss: 4.462261
SAVE MODEL 
 Validation Loss Decreased4.570700->4.462261
Epoch: 4 	Training Loss: 4.551040 	Validation Loss: 4.688740
Epoch: 5 	Training Loss: 4.467935 	Validation Loss: 4.367352
SAVE MODEL 
 Validation Loss Decreased4.462261->4.367352
Epoch: 6 	Training Loss: 4.387055 	Validation Loss: 4.254793
SAVE MODEL 
 Validation Loss Decreased4.367352->4.254793
Epoch: 7 	Training Loss: 4.331546 	Validation Loss: 4.141040
SAVE MODEL 
 Validation Loss Decreased4.254793->4.141040
Epoch: 8 	Training Loss: 4.267070 	Validation Loss: 4.010479
SAVE MODEL 
 Validation Loss Decreased4.141040->4.010479
Epoch: 9 	Training Loss: 4.223013 	Validation Loss: 3.988127
SAVE MODEL 
 Validation Loss Decreased4.010479->3.988127
Epoch: 10 	Training Loss: 4.173136 	Validation Loss: 4.025090
Epoch: 11 	Training Loss: 4.122323 	Validation Loss: 4.014546
```

```
Epoch: 12         Training Loss: 4.077969        Validation Loss: 3.935348
SAVE MODEL
 Validation Loss Decreased3.988127->3.935348
Epoch: 13         Training Loss: 4.042255        Validation Loss: 3.938178
Epoch: 14         Training Loss: 3.994144        Validation Loss: 3.817835
SAVE MODEL
 Validation Loss Decreased3.935348->3.817835
Epoch: 15         Training Loss: 3.945725        Validation Loss: 3.784928
SAVE MODEL
 Validation Loss Decreased3.817835->3.784928
Epoch: 16         Training Loss: 3.895559        Validation Loss: 4.001422
Epoch: 17         Training Loss: 3.835678        Validation Loss: 3.929674
Epoch: 18         Training Loss: 3.807669        Validation Loss: 3.534925
SAVE MODEL
 Validation Loss Decreased3.784928->3.534925
Epoch: 19         Training Loss: 3.745853        Validation Loss: 3.596328
Epoch: 20         Training Loss: 3.691704        Validation Loss: 3.478845
SAVE MODEL
 Validation Loss Decreased3.534925->3.478845
Epoch: 21         Training Loss: 3.652713        Validation Loss: 3.520856
Epoch: 22         Training Loss: 3.608290        Validation Loss: 3.791255
Epoch: 23         Training Loss: 3.588705        Validation Loss: 3.757257
Epoch: 24         Training Loss: 3.521772        Validation Loss: 3.351794
SAVE MODEL
 Validation Loss Decreased3.478845->3.351794
Epoch: 25         Training Loss: 3.486180        Validation Loss: 3.233312
SAVE MODEL
 Validation Loss Decreased3.351794->3.233312
Epoch: 26         Training Loss: 3.454849        Validation Loss: 3.381733
Epoch: 27         Training Loss: 3.411398        Validation Loss: 3.139597
SAVE MODEL
 Validation Loss Decreased3.233312->3.139597
Epoch: 28         Training Loss: 3.372507        Validation Loss: 3.305145
Epoch: 29         Training Loss: 3.335486        Validation Loss: 3.073500
SAVE MODEL
 Validation Loss Decreased3.139597->3.073500
Epoch: 30         Training Loss: 3.288126        Validation Loss: 3.259075
Epoch: 31         Training Loss: 3.299250        Validation Loss: 3.113655
Epoch: 32         Training Loss: 3.211797        Validation Loss: 3.240150
Epoch: 33         Training Loss: 3.206977        Validation Loss: 3.423803
Epoch: 34         Training Loss: 3.162702        Validation Loss: 3.169557
Epoch: 35         Training Loss: 3.126074        Validation Loss: 3.030885
SAVE MODEL
 Validation Loss Decreased3.073500->3.030885
Epoch: 36         Training Loss: 3.126993        Validation Loss: 2.845523
SAVE MODEL
 Validation Loss Decreased3.030885->2.845523
Epoch: 37         Training Loss: 3.048069        Validation Loss: 2.696229
```

```
SAVE MODEL
 Validation Loss Decreased2.845523->2.696229
Epoch: 38       Training Loss: 3.055345       Validation Loss: 3.011873
Epoch: 39       Training Loss: 3.020714       Validation Loss: 2.933620
Epoch: 40       Training Loss: 2.995264       Validation Loss: 3.057419
Epoch: 41       Training Loss: 2.959730       Validation Loss: 2.788172
Epoch: 42       Training Loss: 2.953582       Validation Loss: 2.824506
Epoch: 43       Training Loss: 2.860500       Validation Loss: 2.575108
SAVE MODEL
 Validation Loss Decreased2.696229->2.575108
Epoch: 44       Training Loss: 2.885045       Validation Loss: 2.679615
Epoch: 45       Training Loss: 2.850555       Validation Loss: 3.458832
Epoch: 46       Training Loss: 2.824334       Validation Loss: 2.595512
Epoch: 47       Training Loss: 2.795360       Validation Loss: 2.377294
SAVE MODEL
 Validation Loss Decreased2.575108->2.377294
Epoch: 48       Training Loss: 2.731642       Validation Loss: 2.527838
Epoch: 49       Training Loss: 2.768501       Validation Loss: 2.507193
Epoch: 50       Training Loss: 2.695214       Validation Loss: 2.418853
```

```
In [12]: # load the model that got the best validation accuracy
         model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

1.1.11 (IMPLEMENTATION) Test the Model

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

```
In [7]: 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))
```

```
In [13]: # call test function
         test(data_loaders, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 2.907567


Test Accuracy: 28% (236/836)
```

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 [ ]: # USING THE SAME DATA LOADERS AS ABOVE
```

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 [8]: ## TODO: Specify model architecture
        model_transfer = models.densenet161(pretrained=True)
        for param in model_transfer.parameters():
            param.requires_grad_(False)

        model_transfer.classifier = nn.Linear(2208,133)
        print(model_transfer)

        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 [00:04<00:00, 27051387.00it/s]


DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 96, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (norm0): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True)
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(144, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
        (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer6): _DenseLayer(
      (norm1): BatchNorm2d(336, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition1): _Transition(
    (norm): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(240, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(336, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(432, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer7): _DenseLayer(
    (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer8): _DenseLayer(
    (norm1): BatchNorm2d(528, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer10): _DenseLayer(
    (norm1): BatchNorm2d(624, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer11): _DenseLayer(
      (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(720, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
  )
  (transition2): _Transition(
    (norm): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (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_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer2): _DenseLayer(
      (norm1): BatchNorm2d(432, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer4): _DenseLayer(
    (norm1): BatchNorm2d(528, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer5): _DenseLayer(
    (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer6): _DenseLayer(
    (norm1): BatchNorm2d(624, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer7): _DenseLayer(
    (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer8): _DenseLayer(
    (norm1): BatchNorm2d(720, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
    (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer10): _DenseLayer(
      (norm1): BatchNorm2d(816, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer11): _DenseLayer(
      (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer12): _DenseLayer(
      (norm1): BatchNorm2d(912, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer13): _DenseLayer(
      (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer14): _DenseLayer(
      (norm1): BatchNorm2d(1008, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer15): _DenseLayer(
      (norm1): BatchNorm2d(1056, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer16): _DenseLayer(
      (norm1): BatchNorm2d(1104, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer17): _DenseLayer(
      (norm1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer18): _DenseLayer(
      (norm1): BatchNorm2d(1200, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer19): _DenseLayer(
      (norm1): BatchNorm2d(1248, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer20): _DenseLayer(
      (norm1): BatchNorm2d(1296, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer21): _DenseLayer(
      (norm1): BatchNorm2d(1344, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer22): _DenseLayer(
    (norm1): BatchNorm2d(1392, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer23): _DenseLayer(
    (norm1): BatchNorm2d(1440, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer24): _DenseLayer(
    (norm1): BatchNorm2d(1488, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer25): _DenseLayer(
    (norm1): BatchNorm2d(1536, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer26): _DenseLayer(
    (norm1): BatchNorm2d(1584, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer27): _DenseLayer(
    (norm1): BatchNorm2d(1632, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer28): _DenseLayer(
      (norm1): BatchNorm2d(1680, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer29): _DenseLayer(
      (norm1): BatchNorm2d(1728, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer30): _DenseLayer(
      (norm1): BatchNorm2d(1776, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer31): _DenseLayer(
      (norm1): BatchNorm2d(1824, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer32): _DenseLayer(
      (norm1): BatchNorm2d(1872, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer33): _DenseLayer(
      (norm1): BatchNorm2d(1920, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
          (relu2): ReLU(inplace)
          (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        )
        (denselayer34): _DenseLayer(
          (norm1): BatchNorm2d(1968, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
          (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_stats=True
          (relu2): ReLU(inplace)
          (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        )
        (denselayer35): _DenseLayer(
          (norm1): BatchNorm2d(2016, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
          (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_stats=True
          (relu2): ReLU(inplace)
          (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        )
        (denselayer36): _DenseLayer(
          (norm1): BatchNorm2d(2064, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
          (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_stats=True
          (relu2): ReLU(inplace)
          (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        )
      )
      (transition3): _Transition(
        (norm): BatchNorm2d(2112, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (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_stats=Tru
          (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_stats=True
          (relu2): ReLU(inplace)
          (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        )
        (denselayer2): _DenseLayer(
          (norm1): BatchNorm2d(1104, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
          (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer3): _DenseLayer(
      (norm1): BatchNorm2d(1152, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer4): _DenseLayer(
      (norm1): BatchNorm2d(1200, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer5): _DenseLayer(
      (norm1): BatchNorm2d(1248, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer6): _DenseLayer(
      (norm1): BatchNorm2d(1296, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer7): _DenseLayer(
      (norm1): BatchNorm2d(1344, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer8): _DenseLayer(
      (norm1): BatchNorm2d(1392, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer9): _DenseLayer(
    (norm1): BatchNorm2d(1440, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer10): _DenseLayer(
    (norm1): BatchNorm2d(1488, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer11): _DenseLayer(
    (norm1): BatchNorm2d(1536, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer12): _DenseLayer(
    (norm1): BatchNorm2d(1584, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer13): _DenseLayer(
    (norm1): BatchNorm2d(1632, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
    (relu2): ReLU(inplace)
    (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
  )
  (denselayer14): _DenseLayer(
    (norm1): BatchNorm2d(1680, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
    (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer15): _DenseLayer(
      (norm1): BatchNorm2d(1728, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer16): _DenseLayer(
      (norm1): BatchNorm2d(1776, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer17): _DenseLayer(
      (norm1): BatchNorm2d(1824, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer18): _DenseLayer(
      (norm1): BatchNorm2d(1872, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer19): _DenseLayer(
      (norm1): BatchNorm2d(1920, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
      (relu2): ReLU(inplace)
      (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    )
    (denselayer20): _DenseLayer(
      (norm1): BatchNorm2d(1968, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
      (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer21): _DenseLayer(
        (norm1): BatchNorm2d(2016, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer22): _DenseLayer(
        (norm1): BatchNorm2d(2064, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer23): _DenseLayer(
        (norm1): BatchNorm2d(2112, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
      (denselayer24): _DenseLayer(
        (norm1): BatchNorm2d(2160, eps=1e-05, momentum=0.1, affine=True, track_running_stats=Tru
        (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_stats=True
        (relu2): ReLU(inplace)
        (conv2): Conv2d(192, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
    )
    (norm5): BatchNorm2d(2208, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (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: First I chose Resnet152 because it had the least Top-1 error as mentioned in pytorch docs . Also I simply just changed the last fully connected layer to have 133 output classes. The accuracy reached around 75% with only 10 epochs. After training for 5 more epochs the accuracy still remained the same.

So i decided to explore another pretrained model Densenet161, which I wanted to try since Phase 1.So after training the network for 15 epochs I was able to achieve a accuracy of 79%

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 [9]: criterion_transfer = nn.CrossEntropyLoss()
        optimizer_transfer = optim.Adam(model_transfer.classifier.parameters(),lr=0.001)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

```
In [10]: # train the model
         n_epochs = 15
         model_transfer = train(n_epochs, data_loaders, model_transfer, optimizer_transfer, crit
```

```
Epoch: 1          Training Loss: 2.751493         Validation Loss: 1.106280
SAVE MODEL
 Validation Loss Decreasedinf->1.106280
Epoch: 2          Training Loss: 1.256064         Validation Loss: 0.661089
SAVE MODEL
 Validation Loss Decreased1.106280->0.661089
Epoch: 3          Training Loss: 1.001512         Validation Loss: 0.535759
SAVE MODEL
 Validation Loss Decreased0.661089->0.535759
Epoch: 4          Training Loss: 0.865054         Validation Loss: 0.485332
SAVE MODEL
 Validation Loss Decreased0.535759->0.485332
Epoch: 5          Training Loss: 0.806639         Validation Loss: 0.482317
SAVE MODEL
 Validation Loss Decreased0.485332->0.482317
Epoch: 6          Training Loss: 0.726245         Validation Loss: 0.387564
SAVE MODEL
 Validation Loss Decreased0.482317->0.387564
Epoch: 7          Training Loss: 0.688502         Validation Loss: 0.339233
SAVE MODEL
 Validation Loss Decreased0.387564->0.339233
Epoch: 8          Training Loss: 0.673879         Validation Loss: 0.373056
Epoch: 9          Training Loss: 0.657730         Validation Loss: 0.343404
Epoch: 10          Training Loss: 0.643821         Validation Loss: 0.367252
Epoch: 11          Training Loss: 0.631555         Validation Loss: 0.332464
SAVE MODEL
 Validation Loss Decreased0.339233->0.332464
Epoch: 12          Training Loss: 0.619025         Validation Loss: 0.361401
```

```
Epoch: 13        Training Loss: 0.607118        Validation Loss: 0.362836
Epoch: 14        Training Loss: 0.587798        Validation Loss: 0.353061
Epoch: 15        Training Loss: 0.579581        Validation Loss: 0.334276
```

```
In [27]: # 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 [11]: test(data_loaders, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.728400


Test Accuracy: 79% (667/836)
```

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 [12]: for idx,item in enumerate(classes[:10]):
             print(idx,item[4:])
```

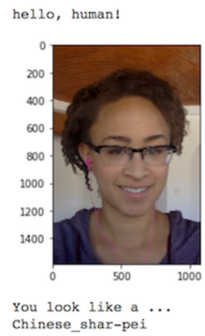
```
0 Affenpinscher
1 Afghan_hound
2 Airedale_terrier
3 Akita
4 Alaskan_malamute
5 American_eskimo_dog
6 American_foxhound
7 American_staffordshire_terrier
8 American_water_spaniel
9 Anatolian_shepherd_dog
```

```
In [13]: ### 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 classes]

         def predict_breed_transfer(img_path):
```

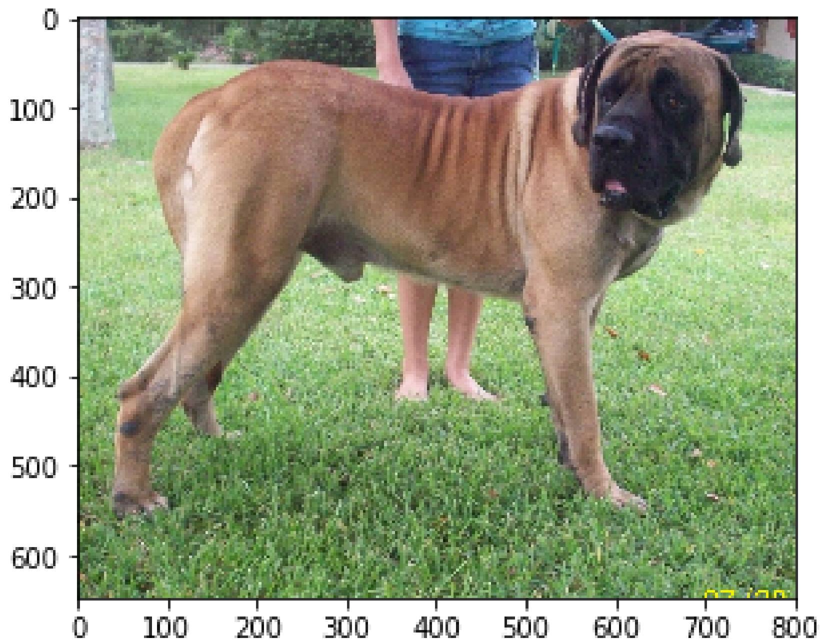
```
        # display the image
        img = cv2.imread(img_path)
        # convert BGR image to RGB for plotting
        cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

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

        # load the image and return the predicted breed
        pil_img = Image.open(img_path).convert('RGB')
        loader = transforms.Compose([
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor()
        ])
        img = loader(pil_img)
        # add batch dimension
        img = img.unsqueeze_(0)

        model_transfer.eval()
        model_transfer.cpu()

        output = model_transfer(img)
        _, pred = torch.max(output,1)

        return class_names[pred.item()]
```

In [14]:
```
predict_breed_transfer(dog_files[0])
```

Out[14]: 'Mastiff'



Sample Human Output



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 [15]:
```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.

def run_app(img_path):
    ## handle cases for a human face, dog, and neither
    pred_class = predict_breed_transfer(img_path)
    print('Image Path:',img_path)
    #print('Dog',dog_detector(img_path))
    #print('Human',face_detector(img_path))
    if(dog_detector(img_path)):
        print('Hello, {}'.format(pred_class))
    elif(face_detector(img_path)):
        print('Hello human')
        print('You look like {}'.format(pred_class))
    else:
        print('Oops!! Couldn\'t detect anything')
```

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.

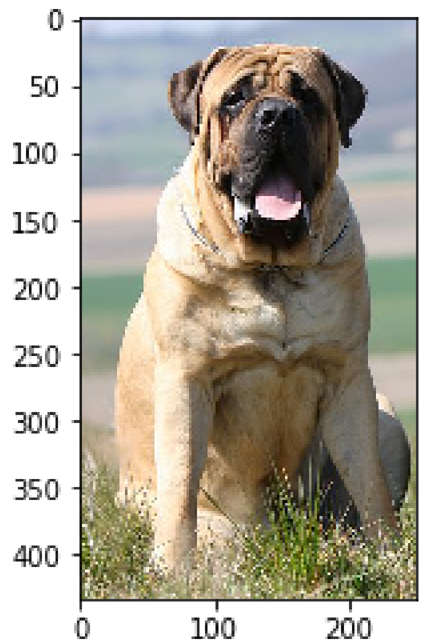
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: (Three possible points for improvement) 1. Fine Tuning the model: I have not performed it here, as I did in phase 1 of scholarship because I had to devote a lot of time to CNN from scratch part. Fine tuning would further improve the accuracy by 2-4% 2. Reducing the batch_size to 16 I think would increase the accuracy 3.

In [25]:
```
## 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)
```

```
Image Path: /data/lfw/Dan_Ackroyd/Dan_Ackroyd_0001.jpg
Hello human
You look like Great dane
Image Path: /data/lfw/Alex_Corretja/Alex_Corretja_0001.jpg
```

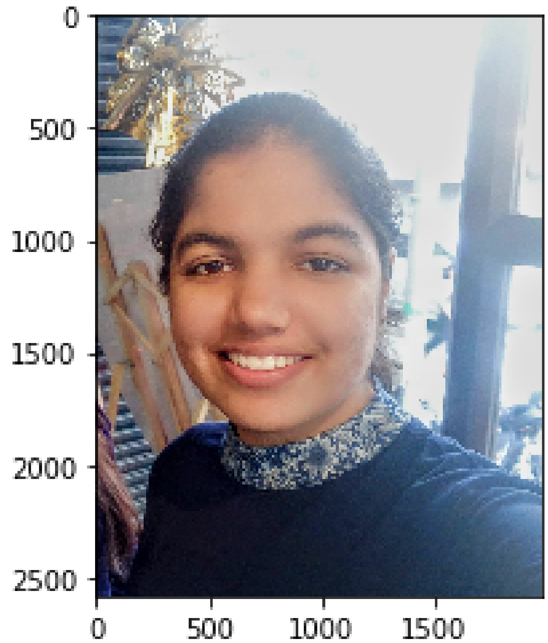
```
Hello human
You look like American foxhound
Image Path: /data/lfw/Daniele_Bergamin/Daniele_Bergamin_0001.jpg
Hello human
You look like Poodle
Image Path: /data/dog_images/train/103.Mastiff/Mastiff_06833.jpg
Hello, Mastiff
Image Path: /data/dog_images/train/103.Mastiff/Mastiff_06826.jpg
Hello, Mastiff
Image Path: /data/dog_images/train/103.Mastiff/Mastiff_06871.jpg
Hello, Mastiff
```




```
In [27]: for file in os.listdir('test'):
             run_app('test/'+file)
```

```
Image Path: test/tony_stark.jpg
Hello human
You look like Doberman pinscher
Image Path: test/Mastiff.jpg
Hello, Mastiff
Image Path: test/Yellow Labrador.jpg
Hello, Labrador retriever
Image Path: test/silky terrier.png
Hello, Silky terrier
Image Path: test/me.jpeg
```

```
Hello human
You look like Poodle
```




```
In [ ]:
```