Convolutional Neural Networks

Project: Write an Algorithm for a Dog Identification App

In this notebook, some template code has already been provided for you, and you will need to implement additional functionality to successfully complete this project. You will not need to modify the included code beyond what is requested. Sections that begin with **'(IMPLEMENTATION)'** in the header indicate that the following block of code will require additional functionality which you must provide. Instructions will be provided for each section, and the specifics of the implementation are marked in the code block with a 'TODO' statement. Please be sure to read the instructions carefully!

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the Jupyter Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to **File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question X'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

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

The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this Jupyter notebook.

Why We're Here

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

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

The Road Ahead

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

- Step 0: Import Datasets
- Step 1: Detect Humans
- Step 2: Detect Dogs
- Step 3: Create a CNN to Classify Dog Breeds (from Scratch)
- Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)
- Step 5: Write your Algorithm
- Step 6: Test Your Algorithm

Step 0: Import Datasets

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

Note: if you are using the Udacity workspace, you *DO NOT* need to re-download these - they can be found in the `/data` folder as noted in the cell below.

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

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

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

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

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

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

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

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

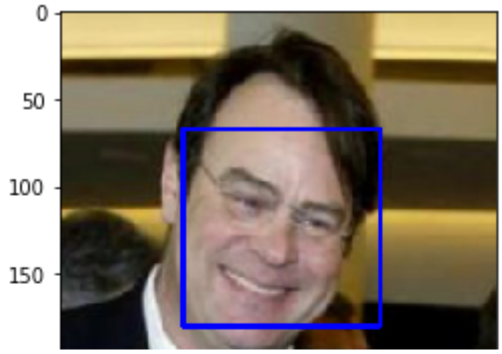
Step 1: Detect Humans

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

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

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

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

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

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

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

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

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

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

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



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

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

Write a Human Face Detector

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

In [3]:

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

(IMPLEMENTATION) Assess the Human Face Detector

Question 1: Use the code cell below to test the performance of the `face_detector` function.

- What percentage of the first 100 images in `human_files` have a detected human face?
- What percentage of the first 100 images in `dog_files` have a detected human face?

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

Answer:

We detected 98 % as humans in the human file

We detected 17 % as humans in the dogs file

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.
counter_human = 0;
counter_dog = 0;
for human in human_files_short:
    if (face_detector(human)):
        counter_human += 1

for dog in dog_files_short:
    if (face_detector(dog)):
        counter_dog += 1
print('We detected',counter_human, '% as humans in the human file')
print('We detected',counter_dog, '% as humans in the dogs file')
```

```
We detected 98 % as humans in the human file
We detected 17 % as humans in the dogs file
```

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

In [5]:

```
### (Optional)
### TODO: Test performance of 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.

Obtain Pre-trained VGG-16 Model

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

In [6]:

```python
import torch
import torchvision.models as models

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

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

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

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

(IMPLEMENTATION) Making Predictions with a Pre-trained Model

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

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

In [7]:

```python
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

    img = Image.open(img_path)
    normalize = transforms.Compose([transforms.Resize((224,224)),transforms
    img=normalize(img)
    #display(img)
    img = img.unsqueeze(0).to('cuda') # unsqueeze to add artificial first d

    return  torch.argmax(VGG16(img))# predicted class index
```

(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.
    prediction = VGG16_predict(img_path)
    return ((prediction <= 268) & (prediction >= 151)) # true/false
```

(IMPLEMENTATION) Assess the Dog Detector

Question 2: Use the code cell below to test the performance of your `dog_detector` function.

- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?

Answer:

We detected 3 % as dogs in the human file

We detected 100 % as dogs in the dogs file

In [9]:
```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
counter_human = 0;
counter_dog = 0;
for human in human_files_short:
    #display(Image.open(human))
    if (dog_detector(human)):
        counter_human += 1

for dog in dog_files_short:
    #display(Image.open(dog))
    if (dog_detector(dog)):
        counter_dog += 1
print('We detected',counter_human, '% as dogs in the human file')
print('We detected',counter_dog, '% as dogs in the dogs file')
```

```
We detected 0 % as dogs in the human file
We detected 100 % as dogs in the dogs file
```

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 [10]:
```
### (Optional)
### TODO: Report the performance of another pre-trained network.
### Feel free to use as many code cells as needed.
```

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

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

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

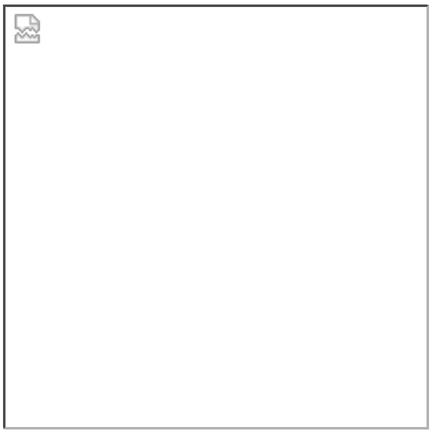
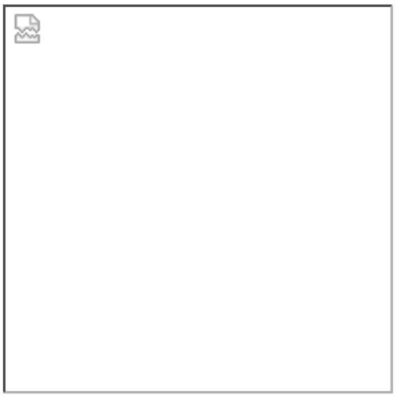
Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador	Black Labrador

Yellow Labrador	Chocolate Labrador	Black Labrador
		

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

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

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `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

In [11]:

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

from torch.utils.data import DataLoader
from torchvision import datasets
from skimage import io

#not sure what the next two lines are doing but they help to avoid error in
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

transformation_train = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(256),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
transformation_validate = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(256),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
transformation_test = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(256),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

dataset_train = datasets.ImageFolder(root='/data/dog_images/train/',transfo
dataset_validate = datasets.ImageFolder(root='/data/dog_images/valid/',tran
dataset_test = datasets.ImageFolder(root='/data/dog_images/test/',transform

data_loader_train = DataLoader(dataset_train,batch_size = 20,shuffle=True)
data_loader_validate = DataLoader(dataset_validate,batch_size = 20)
data_loader_test = DataLoader(dataset_test,batch_size = 20)
```

In [12]:

```
classes = dataset_train.classes
for brew in classes:
    print(brew)
```

```
001.Affenpinscher
002.Afghan_hound
003.Airedale_terrier
004.Akita
005.Alaskan_malamute
006.American_eskimo_dog
007.American_foxhound
008.American_staffordshire_terrier
009.American_water_spaniel
010.Anatolian_shepherd_dog
011.Australian_cattle_dog
012.Australian_shepherd
013.Australian_terrier
014.Basenji
015.Basset_hound
016.Beagle
017.Bearded_collie
018.Beauceron
019.Bedlington_terrier
020.Belgian_malinois
021.Belgian_sheepdog
022.Belgian_tervuren
```

023.Bernese_mountain_dog
024.Bichon_frise
025.Black_and_tan_coonhound
026.Black_russian_terrier
027.Bloodhound
028.Bluetick_coonhound
029.Border_collie
030.Border_terrier
031.Borzoi
032.Boston_terrier
033.Bouvier_des_flandres
034.Boxer
035.Boykin_spaniel
036.Briard
037.Brittany
038.Brussels_griffon
039.Bull_terrier
040.Bulldog
041.Bullmastiff
042.Cairn_terrier
043.Canaan_dog
044.Cane_corso
045.Cardigan_welsh_corgi
046.Cavalier_king_charles_spaniel
047.Chesapeake_bay_retriever
048.Chihuahua
049.Chinese_crested
050.Chinese_shar-pei
051.Chow_chow
052.Clumber_spaniel
053.Cocker_spaniel
054.Collie
055.Curly-coated_retriever
056.Dachshund
057.Dalmatian
058.Dandie_dinmont_terrier
059.Doberman_pinscher
060.Dogue_de_bordeaux
061.English_cocker_spaniel
062.English_setter
063.English_springer_spaniel
064.English_toy_spaniel
065.Entlebucher_mountain_dog
066.Field_spaniel
067.Finnish_spitz
068.Flat-coated_retriever
069.French_bulldog
070.German_pinscher
071.German_shepherd_dog
072.German_shorthaired_pointer
073.German_wirehaired_pointer
074.Giant_schnauzer
075.Glen_of_imaal_terrier
076.Golden_retriever
077.Gordon_setter
078.Great_dane
079.Great_pyrenees
080.Greater_swiss_mountain_dog
081.Greyhound
082.Havanese
083.Ibizan_hound
084.Icelandic_sheepdog
085.Irish_red_and_white_setter
086.Irish_setter
087.Irish_terrier
088.Irish_water_spaniel
089.Irish_wolfhound
090.Italian_greyhound
091.Japanese_chin
092.Keeshond
093.Kerry_blue_terrier
094.Komondor
095.Kuvasz
096.Labrador_retriever
097.Lakeland_terrier
098.Leonberger
099.Lhasa_apso

```
100.Lowchen
101.Maltese
102.Manchester_terrier
103.Mastiff
104.Miniature_schnauzer
105.Neapolitan_mastiff
106.Newfoundland
107.Norfolk_terrier
108.Norwegian_buhund
109.Norwegian_elkhound
110.Norwegian_lundehund
111.Norwich_terrier
112.Nova_scotia_duck_tolling_retriever
113.Old_english_sheepdog
114.Otterhound
115.Papillon
116.Parson_russell_terrier
117.Pekingese
118.Pembroke_welsh_corgi
119.Petit_basset_griffon_vendeen
120.Pharaoh_hound
121.Plott
122.Pointer
123.Pomeranian
124.Poodle
125.Portuguese_water_dog
126.Saint_bernard
127.Silky_terrier
128.Smooth_fox_terrier
129.Tibetan_mastiff
130.Welsh_springer_spaniel
131.Wirehaired_pointing_griffon
132.Xoloitzcuintli
133.Yorkshire_terrier
```

In [ ]:

Question 3: Describe your chosen procedure for preprocessing the data.

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

Answer:

I croped and resized the images to size 256 * 256 and turned it in a tensor in the next step. i decided for 256 = 2^8 to have it nicely scalable in the further steps.

I went for basic augmentation by random rotarion of 10° and random horizontal flip in the training dataset

(IMPLEMENTATION) Model Architecture

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

In [13]:
```
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.conv1 = nn.Conv2d(3,16,3,padding=1)
        self.conv2 = nn.Conv2d(16,32,3,padding=1)
        self.conv3 = nn.Conv2d(32,64,3,padding=1)
        self.conv4 = nn.Conv2d(64,128,3,padding=1)
        #self.conv5 = nn.Conv2d(128,256,3,padding=1)
        self.pool  = nn.MaxPool2d(2,2)

        self.fc1 = nn.Linear(16 * 16 * 128, 2048)
        self.fc2 = nn.Linear(2048,1024)
        self.fc3 = nn.Linear(1024,133)

        self.conv_bn1 = nn.BatchNorm2d(16)
        self.conv_bn2 = nn.BatchNorm2d(32)
        self.conv_bn3 = nn.BatchNorm2d(64)
        self.conv_bn4 = nn.BatchNorm2d(128)
        #self.conv_bn5 = nn.BatchNorm2d(256)

        self.dropout = nn.Dropout(0.2)


    def forward(self, x):
        ## Define forward behavior
        x = self.pool(self.conv_bn1(F.relu(self.conv1(x))))     # 256 * 256
        x = self.pool(self.conv_bn2(F.relu(self.conv2(x))))     # 128 * 128
        x = self.pool(self.conv_bn3(F.relu(self.conv3(x))))     # 64 * 64*
        x = self.pool(self.conv_bn4(F.relu(self.conv4(x))))     # 32 * 32 *
        #x = self.pool(self.conv_bn5(F.relu(self.conv5(x))))     # 16 * 16

        x = x.view(-1,16 * 16 * 128)                  # 7 * 7 * 256 -> 2048
        x = F.relu(self.fc1(x))                       # 2048 -> 1024 brews
        x = self.dropout(x)
        x = F.relu(self.fc2(x))                       # 1024 -> 133 brews
        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()

# 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:

I increased the depth of the layers step by step and ended with a depth of 128. in between all concolutional layers i added a max pooling layer that resuces the area of the 'image' by factor 4. Besides that research in the internet and other classifiers available online pointed me to a batch normalization layer that normalizes the data of each batch as described here. I added a batch normalization layer between all conv and pooling layers to increase the solution quality. After my convolutional layers I added three fully connected layer that reduce the number of features from 32768 ->2048 -> 1024 -> 133 to end up in the brews of the dogs.

(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 [14]:

```
import torch.optim as optim

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

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

(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 [15]:

```
def train(n_epochs, data_loader_train, data_loader_validate, model, optimiz
    """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(data_loader_train):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()

            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output,target)
            loss.backward()
            optimizer.step()
            ## find the loss and update the model parameters accordingly
            ## record the average training loss, using something like
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data -

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(data_loader_validate):
            # 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 = valid_loss + ((1 / (batch_idx + 1)) * (loss.data -

        # print training/validation statistics
        print(f'Epoch: {epoch} \tTraining Loss: {train_loss} \tValidation I

        ## TODO: save the model if validation loss has decreased
        if valid_loss < valid_loss_min:
            print(f'Validation loss decreased from {valid_loss_min} to {val
            torch.save(model.state_dict(),save_path)
            valid_loss_min = valid_loss
    # return trained model
    return model


# train the model
model_scratch = train(20, data_loader_train, data_loader_validate, model_sc
                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1        Training Loss: 4.867491722106934        Validation Loss: 4.
697656154632568
Validation loss decreased from inf to 4.697656154632568.  Saving model ...
Epoch: 2        Training Loss: 4.559758186340332        Validation Loss: 4.
458089828491211
Validation loss decreased from 4.697656154632568 to 4.458089828491211.  Sav
ing model ...
```

```
Epoch: 3 	Training Loss: 4.411094665527344 	Validation Loss: 4.
441132068634033
Validation loss decreased from 4.458089828491211 to 4.441132068634033.  Sav
ing model ...
Epoch: 4 	Training Loss: 4.296548366546631 	Validation Loss: 4.
2024712562561035
Validation loss decreased from 4.441132068634033 to 4.2024712562561035.  Sa
ving model ...
Epoch: 5 	Training Loss: 4.16337776184082 	Validation Loss: 4.
1957879066467285
Validation loss decreased from 4.2024712562561035 to 4.1957879066467285.  S
aving model ...
Epoch: 6 	Training Loss: 4.076774597167969 	Validation Loss: 4.
04243803024292
Validation loss decreased from 4.1957879066467285 to 4.04243803024292.  Sav
ing model ...
Epoch: 7 	Training Loss: 3.964918375015259 	Validation Loss: 4.
003871917724609
Validation loss decreased from 4.04243803024292 to 4.003871917724609.  Savi
ng model ...
Epoch: 8 	Training Loss: 3.871457815170288 	Validation Loss: 3.
9166581630706787
Validation loss decreased from 4.003871917724609 to 3.9166581630706787.  Sa
ving model ...
Epoch: 9 	Training Loss: 3.7667593955993652 	Validation Loss: 3.
8475685119628906
Validation loss decreased from 3.9166581630706787 to 3.8475685119628906.  S
aving model ...
Epoch: 10 	Training Loss: 3.64456844329834 	Validation Loss: 3.
8314199447631836
Validation loss decreased from 3.8475685119628906 to 3.8314199447631836.  S
aving model ...
Epoch: 11 	Training Loss: 3.5162785053253174 	Validation Loss: 3.
8284401893615723
Validation loss decreased from 3.8314199447631836 to 3.8284401893615723.  S
aving model ...
Epoch: 12 	Training Loss: 3.3534352779388428 	Validation Loss: 3.
8643553256988525
Epoch: 13 	Training Loss: 3.2207279205322266 	Validation Loss: 3.
808218240737915
Validation loss decreased from 3.8284401893615723 to 3.808218240737915.  Sa
ving model ...
Epoch: 14 	Training Loss: 3.038426637649536 	Validation Loss: 3.
8191096782684326
Epoch: 15 	Training Loss: 2.912259340286255 	Validation Loss: 3.
747948169708252
Validation loss decreased from 3.808218240737915 to 3.747948169708252.  Sav
ing model ...
Epoch: 16 	Training Loss: 2.7602713108062744 	Validation Loss: 3.
7486391067504883
Epoch: 17 	Training Loss: 2.584132194519043 	Validation Loss: 3.
977067470550537
Epoch: 18 	Training Loss: 2.404409646987915 	Validation Loss: 3.
8101301193237305
Epoch: 19 	Training Loss: 2.231541395187378 	Validation Loss: 3.
881647825241089
Epoch: 20 	Training Loss: 2.0521485805511475 	Validation Loss: 3.
856865644454956
```

In [16]:
```
# load the model that got the best validation accuracy
model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

(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 [17]:

```
def test(data_loader_test, 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(data_loader_test):
        # move to GPU
        if use_cuda:
            data, target = data.cuda(), target.cuda()
        # forward pass: compute predicted outputs by passing inputs to the
        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_
        # 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))).cp
        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(data_loader_test, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.822230


Test Accuracy: 13% (109/836)
```

Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)

You will now use transfer learning to create a CNN that can identify dog breed from images. Your CNN must attain at least 60% accuracy on the test set.

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate [data loaders](http://pytorch.org/docs/master/data.html#torch.utils.data.DataLoader) 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 [18]:

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

from torch.utils.data import DataLoader
from torchvision import datasets
from skimage import io

#not sure what the next two lines are doing but they help to avoid error ir
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

transformation_train = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
transformation_validate = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])
transformation_test = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

dataset_train = datasets.ImageFolder(root='/data/dog_images/train/',transfc
dataset_validate = datasets.ImageFolder(root='/data/dog_images/valid/',trar
dataset_test = datasets.ImageFolder(root='/data/dog_images/test/',transforn

data_loader_train = DataLoader(dataset_train,batch_size = 20,shuffle=True)
data_loader_validate = DataLoader(dataset_validate,batch_size = 20)
data_loader_test = DataLoader(dataset_test,batch_size = 20)
```

(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 [19]:

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

## TODO: Specify model architecture
# vgg16
# resnet18
model_transfer = models.densenet121(pretrained=True)

#print(model_transfer)

#DENSENET121
print(model_transfer.classifier.in_features)
print(model_transfer.classifier.out_features)

#RASNSNET18
#print(model_transfer.fc.in_features)
#print(model_transfer.fc.out_features)


#VGG16
#print(model_transfer.classifier[6].in_features)
#print(model_transfer.classifier[6].out_features)

#for param in model_transfer.features.parameters():
#    param.requires_grad = False
```

```
/opt/conda/lib/python3.6/site-packages/torchvision-0.2.1-py3.6.egg/torchvis
ion/models/densenet.py:212: UserWarning: nn.init.kaiming_normal is now depr
ecated in favor of nn.init.kaiming_normal_.
1024
1000
```

In [20]:

```
print(model_transfer)
```

```
DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3,
3), bias=False)
    (norm0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_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(64, eps=1e-05, momentum=0.1, affine=True, trac
k_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(64, 128, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, trac
k_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(96, 128, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(224, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (transition1): _Transition(
      (norm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
      (relu): ReLU(inplace)
      (conv): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
    )
    (denseblock2): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
```

```
        (conv2): Conv2d(128, 32, 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, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(224, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(288, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer7): _DenseLayer(
        (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(320, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer8): _DenseLayer(
        (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(352, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer9): _DenseLayer(
        (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(384, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer10): _DenseLayer(
        (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(416, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(448, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(480, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (transition2): _Transition(
      (norm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
      (relu): ReLU(inplace)
      (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
    )
    (denseblock3): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(288, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
```

```
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(320, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(352, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, 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, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(384, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(416, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer7): _DenseLayer(
        (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(448, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer8): _DenseLayer(
        (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(480, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer9): _DenseLayer(
        (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer10): _DenseLayer(
        (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(544, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(576, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(608, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer13): _DenseLayer(
        (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(640, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer14): _DenseLayer(
        (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(672, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer15): _DenseLayer(
        (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(704, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer16): _DenseLayer(
        (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(736, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer17): _DenseLayer(
        (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(768, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer18): _DenseLayer(
        (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(800, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer19): _DenseLayer(
        (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer20): _DenseLayer(
        (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(864, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer21): _DenseLayer(
        (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(896, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
```

```
      (denselayer22): _DenseLayer(
        (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(928, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer23): _DenseLayer(
        (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(960, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer24): _DenseLayer(
        (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(992, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (transition3): _Transition(
      (norm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track
_running_stats=True)
      (relu): ReLU(inplace)
      (conv): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=Fal
se)
      (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
    )
    (denseblock4): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(544, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(576, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(608, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(640, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(672, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer7): _DenseLayer(
        (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(704, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer8): _DenseLayer(
        (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(736, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, 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, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(768, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
```

```
      (denselayer10): _DenseLayer(
        (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(800, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(864, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer13): _DenseLayer(
        (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(896, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer14): _DenseLayer(
        (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(928, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer15): _DenseLayer(
        (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(960, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer16): _DenseLayer(
        (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(992, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
```

```
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (norm5): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  )
  (classifier): Linear(in_features=1024, out_features=1000, bias=True)
)
```

In [21]:

```
#densenet
model_transfer.classifier = nn.Linear(1024, 133)
for param in model_transfer.features.parameters():
    param.requires_grad = False



#vgg
#model_transfer.classifier[6] = nn.Linear(512, 133)



use_cuda = torch.cuda.is_available()
if use_cuda:
    model_transfer = model_transfer.cuda()

print(model_transfer)
```

```
DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3,
3), bias=False)
    (norm0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_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(64, eps=1e-05, momentum=0.1, affine=True, trac
k_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(64, 128, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(96, eps=1e-05, momentum=0.1, affine=True, trac
k_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(96, 128, kernel_size=(1, 1), stride=(1, 1), bias=Fa
lse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
```

```
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(192, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(224, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (transition1): _Transition(
      (norm): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
      (relu): ReLU(inplace)
      (conv): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
    )
    (denseblock2): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(128, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(160, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(160, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, 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, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
```

```
        (conv1): Conv2d(192, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(224, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(224, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(288, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer7): _DenseLayer(
        (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(320, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer8): _DenseLayer(
        (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(352, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer9): _DenseLayer(
        (norm1): BatchNorm2d(384, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(384, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
```

```
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer10): _DenseLayer(
        (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(416, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(448, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(480, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (transition2): _Transition(
      (norm): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
      (relu): ReLU(inplace)
      (conv): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
    )
    (denseblock3): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(288, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(288, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(320, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
```

```
        (conv1): Conv2d(320, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(352, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(352, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, 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, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(384, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(416, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(416, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer7): _DenseLayer(
        (norm1): BatchNorm2d(448, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(448, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer8): _DenseLayer(
        (norm1): BatchNorm2d(480, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(480, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer9): _DenseLayer(
        (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
```

```
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer10): _DenseLayer(
        (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(544, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(576, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(608, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer13): _DenseLayer(
        (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(640, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer14): _DenseLayer(
        (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(672, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer15): _DenseLayer(
        (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(704, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer16): _DenseLayer(
        (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(736, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer17): _DenseLayer(
        (norm1): BatchNorm2d(768, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(768, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer18): _DenseLayer(
        (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(800, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer19): _DenseLayer(
        (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer20): _DenseLayer(
        (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(864, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer21): _DenseLayer(
        (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(896, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer22): _DenseLayer(
        (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(928, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer23): _DenseLayer(
        (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(960, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer24): _DenseLayer(
        (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(992, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
    )
    (transition3): _Transition(
      (norm): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track
_running_stats=True)
      (relu): ReLU(inplace)
      (conv): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=Fal
se)
      (pool): AvgPool2d(kernel_size=2, stride=2, padding=0)
    )
    (denseblock4): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer2): _DenseLayer(
        (norm1): BatchNorm2d(544, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(544, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer3): _DenseLayer(
        (norm1): BatchNorm2d(576, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(576, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer4): _DenseLayer(
        (norm1): BatchNorm2d(608, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(608, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer5): _DenseLayer(
        (norm1): BatchNorm2d(640, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(640, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer6): _DenseLayer(
        (norm1): BatchNorm2d(672, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(672, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer7): _DenseLayer(
        (norm1): BatchNorm2d(704, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(704, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer8): _DenseLayer(
        (norm1): BatchNorm2d(736, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(736, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, 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, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(768, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer10): _DenseLayer(
        (norm1): BatchNorm2d(800, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(800, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
```

```
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer11): _DenseLayer(
        (norm1): BatchNorm2d(832, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer12): _DenseLayer(
        (norm1): BatchNorm2d(864, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(864, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer13): _DenseLayer(
        (norm1): BatchNorm2d(896, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(896, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer14): _DenseLayer(
        (norm1): BatchNorm2d(928, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(928, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer15): _DenseLayer(
        (norm1): BatchNorm2d(960, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(960, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
      (denselayer16): _DenseLayer(
        (norm1): BatchNorm2d(992, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu1): ReLU(inplace)
        (conv1): Conv2d(992, 128, kernel_size=(1, 1), stride=(1, 1), bias=F
alse)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (relu2): ReLU(inplace)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding
=(1, 1), bias=False)
      )
```

```
      )
      (norm5): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
    )
    (classifier): Linear(in_features=1024, 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:

I tried around with different pretrained models like vgg, rasnet a but finally ended up with densenet, which acctually performs quite good. I replaced the fully connected layer which initially sorts the data in 1000 classes by a new one that sorts only in 133 classes which represent our dog brews.

(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 [22]:

```
criterion_transfer = nn.CrossEntropyLoss()

#DENSENET121
optimizer_transfer = torch.optim.Adam(model_transfer.classifier.parameters(

#RESNET18
#optimizer_transfer = torch.optim.Adam(model_transfer.fc.parameters(),lr=0.
```

(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 [23]:

```
# train the model

# NOTE, I increased the epochs step by step to get a feeling how the model
# model was trained in 40 epochs.

def train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer, c

    for epoch in range(1, n_epochs+1):

        # keep track of training and validation loss
        train_loss = 0.0

        for batch_i, (data, target) in enumerate(loaders_transfer):
            # move tensors to GPU if CUDA is available
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            # clear the gradients of all optimized variables
            optimizer_transfer.zero_grad()
            # forward pass: compute predicted outputs by passing inputs to
            output = model_transfer(data)
            # calculate the batch loss
            loss = criterion_transfer(output, target)
            # backward pass: compute gradient of the loss with respect to m
            loss.backward()
            # perform a single optimization step (parameter update)
            optimizer_transfer.step()
            # update training loss
            train_loss += loss.item()

        print('Epoch: {} \tBatch: {:.6f} \tTaining Loss: {:.6f}'.format(epo

    torch.save(model_transfer.state_dict(),save_path)
    return model_transfer

model_transfer = train(20, data_loader_train, model_transfer, optimizer_tra


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

```
Epoch: 1 	Batch: 334.000000 	Taining Loss: 795.776187
Epoch: 2 	Batch: 334.000000 	Taining Loss: 289.975165
Epoch: 3 	Batch: 334.000000 	Taining Loss: 199.837618
Epoch: 4 	Batch: 334.000000 	Taining Loss: 160.881858
Epoch: 5 	Batch: 334.000000 	Taining Loss: 132.934374
Epoch: 6 	Batch: 334.000000 	Taining Loss: 117.162692
Epoch: 7 	Batch: 334.000000 	Taining Loss: 103.283296
Epoch: 8 	Batch: 334.000000 	Taining Loss: 91.801418
Epoch: 9 	Batch: 334.000000 	Taining Loss: 88.076197
Epoch: 10 	Batch: 334.000000 	Taining Loss: 74.839251
Epoch: 11 	Batch: 334.000000 	Taining Loss: 68.581057
Epoch: 12 	Batch: 334.000000 	Taining Loss: 68.464725
Epoch: 13 	Batch: 334.000000 	Taining Loss: 59.914117
Epoch: 14 	Batch: 334.000000 	Taining Loss: 59.644717
Epoch: 15 	Batch: 334.000000 	Taining Loss: 57.232594
Epoch: 16 	Batch: 334.000000 	Taining Loss: 51.472112
Epoch: 17 	Batch: 334.000000 	Taining Loss: 46.940801
Epoch: 18 	Batch: 334.000000 	Taining Loss: 52.071123
Epoch: 19 	Batch: 334.000000 	Taining Loss: 46.079554
Epoch: 20 	Batch: 334.000000 	Taining Loss: 46.764298
```

(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 [24]:
```
model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

In [25]:
```
test(data_loader_test, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.593125


Test Accuracy: 83% (695/836)
```

(IMPLEMENTATION) Predict Dog Breed with the Model

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

In [26]:
```
### 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_name
class_names = [item[4:].replace("_", " ") for item in dataset_train.classes

import tensorflow as tf

from PIL import Image

def predict_breed_transfer(img_path, model_transfer=model_transfer):
    image = Image.open(img_path)

    transformation = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

    image = transformation(image)
    image = image[:3,:,:].unsqueeze(0)
    image = image.cuda()

    output = model_transfer(image)

    return class_names[output.cpu().data.numpy().argmax()]


predict_breed_transfer('images/Brittany_02625.jpg', model_transfer)
```

Out[26]:
```
'Brittany'
```

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!

(IMPLEMENTATION) Write your Algorithm

In [27]:

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

def run_app(img_path):
    img = Image.open(img_path)
    display(img)
    human = face_detector(img_path)
    dog = dog_detector(img_path)

    if human:
        human_breed = predict_breed_transfer(img_path)
        print(f'This human looks like a {human_breed}')
    elif dog:
        dog_breed = predict_breed_transfer(img_path)
        print(f'We found a dog here, it is a {dog_breed}')
    else:
        print('Sorry, we could not detect a dog or human on the image...')

    return None

    ## handle cases for a human face, dog, and neither

#run_app('images/Brittany_02625.jpg')
```

Step 6: Test Your Algorithm

In this section, you will take your new algorithm for a spin! What kind of dog does the algorithm think that *you* look like? If you have a dog, does it predict your dog's breed accurately? If you have a cat, does it mistakenly think that your cat is a dog?

(IMPLEMENTATION) Test Your Algorithm on Sample Images!

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

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

Answer: (Three possible points for improvement)

In [28]:

```
## 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)
```

This human looks like a Beagle

This human looks like a Bull terrier

This human looks like a Doberman pinscher

We found a dog here, it is a Mastiff

We found a dog here, it is a Mastiff

```
In [ ]:
```