dog_app

June 7, 2020

1 Convolutional Neural Networks

1.1 Project: Write an Algorithm for a Dog Identification App

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

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

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

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

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

Step 0: Import Datasets

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

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

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

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

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

```
In [0]: #from google.colab import drive
        #drive.mount('/content/drive')
```

```
In [0]: import os
        import shutil

        if not os.path.exists("/content/data/"):
          os.makedirs("/content/data/")
          if not os.path.exists("/content/data/dog_images") and not os.path.exists("/content/dat
            !wget https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip  #&&
            shutil.unpack_archive("/content/dogImages.zip", "/content/data")
            os.rename("/content/data/dogImages", "/content/data/dog_images")
            !rm /content/dogImages.zip
            !wget https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip #-o /conte
            shutil.unpack_archive("/content/lfw.zip", "/content/data")

            !rm /content/lfw.zip
```

```
In [0]: import numpy as np
        from glob import glob


        human_files = np.array(glob("/content/data/lfw/*/*"))
        dog_files = np.array(glob("/content/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.

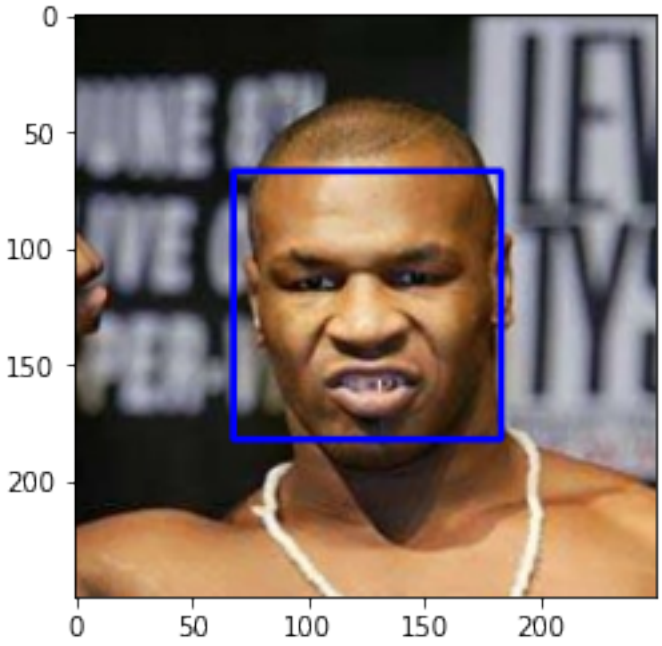
OpenCV provides many pre-trained face detectors, stored as XML files on github. We have downloaded one of these detectors and stored it in the `haarcascades` directory. In the next code cell, we demonstrate how to use this detector to find human faces in a sample image.

In [0]:
```
if not os.path.exists("/content/haarcascades/"):
  os.makedirs("/content/haarcascades/")
!wget https://raw.githubusercontent.com/udacity/deep-learning-v2-pytorch/master/project-
shutil.copy("/content/haarcascade_frontalface_alt.xml", "/content/haarcascades/haarcasca
os.remove("/content/haarcascade_frontalface_alt.xml")
```

```
--2020-06-07 18:51:48--  https://raw.githubusercontent.com/udacity/deep-learning-v2-pytorch/mast
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 151.101.0.133, 151.101.64.133
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|151.101.0.133|:443... connec
HTTP request sent, awaiting response... 200 OK
Length: 676709 (661K) [text/plain]
Saving to: haarcascade_frontalface_alt.xml

haarcascade_frontal 100%[===================>] 660.85K  --.-KB/s    in 0.04s

2020-06-07 18:51:49 (14.8 MB/s) - haarcascade_frontalface_alt.xml saved [676709/676709]
```

In [0]:
```
import cv2
import matplotlib.pyplot as plt
%matplotlib inline
from shutil import copy

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

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

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

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

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

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

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

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



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

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

1.1.1 Write a Human Face Detector

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

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

1.1.2 (IMPLEMENTATION) Assess the Human Face Detector

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

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

Answer: (You can print out your results and/or write your percentages in this cell)

```
In [0]: 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.
        faces_detected_in_human_files = 0
        faces_detected_in_dog_files = 0

        for i in range(len(human_files_short)):
            if face_detector(human_files_short[i]):
                faces_detected_in_human_files += 1
            if face_detector(dog_files_short[i]):
                faces_detected_in_dog_files += 1
        print("Percentage of faces detected in human files: {:.2f}%\n".format(faces_detected_in_
              "Percentage of faces detected in dog files: {:.2f}%".format(faces_detected_in_dog_


Percentage of faces detected in human files: 99.00%
Percentage of faces detected in dog files: 10.00%
```

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

```
In [0]: ### (Optional)
        ### TODO: Test performance of anotherface detection algorithm.
        ### Feel free to use as many code cells as needed.
```

Step 2: Detect Dogs

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

1.1.3 Obtain Pre-trained VGG-16 Model

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

```
In [0]: import torch
        import torchvision.models as models

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

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

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

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

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

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

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

```
In [0]: from PIL import Image
        import torchvision.transforms as transforms
        from torchvision import datasets
        from torch.autograd import Variable
        from PIL import ImageFile
        ImageFile.LOAD_TRUNCATED_IMAGES = True

        def VGG16_predict(img_path):
            '''
            Use pre-trained VGG-16 model to obtain index corresponding to
            predicted ImageNet class for image at specified path

            Args:
                img_path: path to an image

            Returns:
                Index corresponding to VGG-16 model's prediction
```

```
    '''
    normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225])
    image_transform = transforms.Compose([
            transforms.ToTensor(),
            normalize])
    image = Image.open(img_path)
#     plt.imshow(image)
#     plt.show()
    image_tensor = image_transform(image)
    image_tensor.unsqueeze_(0)

    model_input = Variable(image_tensor)
    if use_cuda:
      model_input=model_input.cuda()

    output = VGG16(model_input)
    _, pred_tensor = torch.max(output, 1)
    pred = np.squeeze(pred_tensor.numpy()) if not use_cuda else np.squeeze(pred_tensor.c
    ## 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
    return pred # predicted class index
#Test run with dog image from the list
print(VGG16_predict(dog_files_short[47]))
```

```
195
```

1.1.5 (IMPLEMENTATION) Write a Dog Detector

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

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

```
In [0]: ### returns "True" if a dog is detected in the image stored at img_path
        def dog_detector(img_path):
            ## TODO: Complete the function.
            pred_index = VGG16_predict(img_path)
            return  pred_index>150 and pred_index<269  # true/false
```

1.1.6 (IMPLEMENTATION) Assess the Dog Detector

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

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

Answer:

- Percentage of dog detected in dog files short: 97.00%
- Percentage of dog detected in human files short: 1.00%

```
In [0]: ### TODO: Test the performance of the dog_detector function
        ### on the images in human_files_short and dog_files_short.
        dog_detected_in_human_files =0
        dog_detected_in_dog_files = 0
        for i in range(len(dog_files_short)):
            if dog_detector(dog_files_short[i]):
                dog_detected_in_dog_files +=1;
            if dog_detector(human_files_short[i]):
                dog_detected_in_human_files +=1;
        print("Percentage of dog detected in dog files short: {:.2f}%\n".format(dog_detected_in_
              +"Percentage of dog detected in human files short: {:.2f}%".format(dog_detected_in
```

```
Percentage of dog detected in dog files short: 98.00%
Percentage of dog detected in human files short: 1.00%
```

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

```
In [0]: ### (Optional)
        ### TODO: Report the performance of another pre-trained network.
        ### Feel free to use as many code cells as needed.
```

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

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

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

Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador

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

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

1.1.7 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

```
In [0]: import os
        from torchvision import datasets
        from shutil import copy
        import random

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



        # normalize = transforms.Normalize(mean=[0.5, 0.5, 0.5],
                                        #  std=[0.5, 0.5, 0.5])
        train_transform = transforms.Compose([transforms.RandomRotation(30),
                                        transforms.RandomResizedCrop(224),
                                        transforms.RandomHorizontalFlip(),
                                        transforms.ToTensor(), normalize])

        test_transform = transforms.Compose([transforms.Resize(256), transforms.CenterCrop(224),

        train_path = "/content/data/dog_images/train"
        valid_path = "/content/data/dog_images/valid"
```

```
        test_path = "/content/data/dog_images/test"
        train_dataset = datasets.ImageFolder(train_path, transform=train_transform)
        valid_dataset = datasets.ImageFolder(valid_path, transform=test_transform)
        test_dataset = datasets.ImageFolder(test_path, transform=test_transform)

        no_classes = len(next(os.walk(train_path))[1])
        print("numbers of breeds in folders: {}".format( no_classes))

        batch_size = 32
        num_worker = 0
        train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size, num_wor
        valid_loader = torch.utils.data.DataLoader(valid_dataset, batch_size=batch_size, num_wor
        test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size, num_worke

numbers of breeds in folders: 133
```

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 resized the images to 224 which will help keep the input tensor uniform during training so as to avoid disparity between input images.
- Yes the dataset were augmented. The augmentation applied includes randomly rotating it 30 degree and also fliping it horizontally (left and right). This will help it get variety of images to train on that will match with real world scenario.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [0]: 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)
                self.bn1_2 = nn.BatchNorm2d(16)
                self.conv2 = nn.Conv2d(16, 32, 3)
                self.bn2_3 = nn.BatchNorm2d(32)
                self.conv3 = nn.Conv2d(32, 64, 3)
                self.bn3_4 = nn.BatchNorm2d(64)
                self.conv4 = nn.Conv2d(64, 128, 3)
```

```
                self.bn4 = nn.BatchNorm2d(128)

                self.pool = nn.MaxPool2d(2, 2)

                self.fc1 = nn.Linear(128 * 12 * 12, 1024)
                self.fc_out = nn.Linear(1024, no_classes)
                self.dropout = nn.Dropout(p=0.2)



            def forward(self, x):
                ## Define forward behavior
                x = self.bn1_2(self.pool(F.relu(self.conv1(x))))
                x = self.bn2_3(self.pool(F.relu(self.conv2(x))))
                x = self.bn3_4(self.pool(F.relu(self.conv3(x))))
                x = self.bn4(self.pool(F.relu(self.conv4(x))))
                # print(x.shape)
                x = F.relu(self.fc1(self.dropout(x.view(-1,128 * 12 * 12))))
                x = self.fc_out(x)
                return x

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

        # instantiate the CNN
        model_scratch = Net()

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1))
  (bn1_2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1))
  (bn2_3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1))
  (bn3_4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1))
  (bn4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=18432, out_features=1024, bias=True)
  (fc_out): Linear(in_features=1024, out_features=133, bias=True)
  (dropout): Dropout(p=0.2, inplace=False)
)
```

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

Answer:

1. Four convolutional layers were added to the network with Max Pooling layers in between them to reduce the size of the input. This layers are used to extract the feautures in the images.
2. The output of each of this resized layers are normalized using Batch Normalization.
3. Two fully connected layers were added to help classify the images.

1.1.9 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_scratch`, and the optimizer as `optimizer_scratch` below.

```
In [0]: import torch.optim as optim

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

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

1.1.10 (IMPLEMENTATION) Train and Validate the Model

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

```
In [0]: def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
            """returns trained model"""
            # initialize tracker for minimum validation loss
            valid_loss_min = np.Inf

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

                ###################
                # train the model #
                ###################
                model.train()
                for batch_idx, (data, target) in enumerate(loaders['train']):
                    # move to GPU
                    if use_cuda:
                        data, target = data.cuda(), target.cuda()
                    ## find the loss and update the model parameters accordingly
                    ## record the average training loss, using something like
                    ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_los
                    optimizer.zero_grad()
                    output = model(data)
```

```
            loss = criterion(output, target)
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))
            loss.backward()
            optimizer.step()

        ######################
        # validate the model #
        ######################
        model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):
            # move to GPU
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## update the average validation loss
            output = model(data)
            loss = criterion(output, target)
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))


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

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

    # return trained model
    return model

loaders_scratch ={'train':train_loader,
                  'valid':valid_loader,
                  'test':test_loader}
# train the model
model_scratch = train(50, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')

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

```
Epoch: 1         Training Loss: 6.629701         Validation Loss: 4.790613
```

```
Validation loss has decreased FROM inf To 4.790613.  Saving model ...
Epoch: 2         Training Loss: 4.697094         Validation Loss: 4.522999
Validation loss has decreased FROM 4.790613 To 4.522999.  Saving model ...
Epoch: 3         Training Loss: 4.540474         Validation Loss: 4.299630
Validation loss has decreased FROM 4.522999 To 4.299630.  Saving model ...
Epoch: 4         Training Loss: 4.440723         Validation Loss: 4.284299
Validation loss has decreased FROM 4.299630 To 4.284299.  Saving model ...
Epoch: 5         Training Loss: 4.364151         Validation Loss: 4.236231
Validation loss has decreased FROM 4.284299 To 4.236231.  Saving model ...
Epoch: 6         Training Loss: 4.291152         Validation Loss: 4.170027
Validation loss has decreased FROM 4.236231 To 4.170027.  Saving model ...
Epoch: 7         Training Loss: 4.236381         Validation Loss: 4.168479
Validation loss has decreased FROM 4.170027 To 4.168479.  Saving model ...
Epoch: 8         Training Loss: 4.153550         Validation Loss: 3.888469
Validation loss has decreased FROM 4.168479 To 3.888469.  Saving model ...
Epoch: 9         Training Loss: 4.104774         Validation Loss: 3.869721
Validation loss has decreased FROM 3.888469 To 3.869721.  Saving model ...
Epoch: 10         Training Loss: 4.048058         Validation Loss: 3.977080
Epoch: 11         Training Loss: 3.988475         Validation Loss: 3.719526
Validation loss has decreased FROM 3.869721 To 3.719526.  Saving model ...
Epoch: 12         Training Loss: 3.932464         Validation Loss: 3.726465
Epoch: 13         Training Loss: 3.878364         Validation Loss: 3.647441
Validation loss has decreased FROM 3.719526 To 3.647441.  Saving model ...
Epoch: 14         Training Loss: 3.814190         Validation Loss: 3.692593
Epoch: 15         Training Loss: 3.794463         Validation Loss: 3.639379
Validation loss has decreased FROM 3.647441 To 3.639379.  Saving model ...
Epoch: 16         Training Loss: 3.694455         Validation Loss: 3.452593
Validation loss has decreased FROM 3.639379 To 3.452593.  Saving model ...
Epoch: 17         Training Loss: 3.691112         Validation Loss: 3.486204
Epoch: 18         Training Loss: 3.628769         Validation Loss: 3.322242
Validation loss has decreased FROM 3.452593 To 3.322242.  Saving model ...
Epoch: 19         Training Loss: 3.583717         Validation Loss: 3.365583
Epoch: 20         Training Loss: 3.564640         Validation Loss: 3.341337
Epoch: 21         Training Loss: 3.540216         Validation Loss: 3.225154
Validation loss has decreased FROM 3.322242 To 3.225154.  Saving model ...
Epoch: 22         Training Loss: 3.449183         Validation Loss: 3.224923
Validation loss has decreased FROM 3.225154 To 3.224923.  Saving model ...
Epoch: 23         Training Loss: 3.433574         Validation Loss: 3.176670
Validation loss has decreased FROM 3.224923 To 3.176670.  Saving model ...
Epoch: 24         Training Loss: 3.429693         Validation Loss: 3.239021
Epoch: 25         Training Loss: 3.369601         Validation Loss: 3.169491
Validation loss has decreased FROM 3.176670 To 3.169491.  Saving model ...
Epoch: 26         Training Loss: 3.367813         Validation Loss: 3.183253
Epoch: 27         Training Loss: 3.287535         Validation Loss: 3.054049
Validation loss has decreased FROM 3.169491 To 3.054049.  Saving model ...
Epoch: 28         Training Loss: 3.308252         Validation Loss: 3.049331
Validation loss has decreased FROM 3.054049 To 3.049331.  Saving model ...
Epoch: 29         Training Loss: 3.273991         Validation Loss: 3.037584
```

```
Validation loss has decreased FROM 3.049331 To 3.037584.  Saving model ...
Epoch: 30         Training Loss: 3.234268         Validation Loss: 2.997297
Validation loss has decreased FROM 3.037584 To 2.997297.  Saving model ...
Epoch: 31         Training Loss: 3.191875         Validation Loss: 3.115773
Epoch: 32         Training Loss: 3.177372         Validation Loss: 2.932702
Validation loss has decreased FROM 2.997297 To 2.932702.  Saving model ...
Epoch: 33         Training Loss: 3.151655         Validation Loss: 2.876754
Validation loss has decreased FROM 2.932702 To 2.876754.  Saving model ...
Epoch: 34         Training Loss: 3.121633         Validation Loss: 2.881234
Epoch: 35         Training Loss: 3.080214         Validation Loss: 2.981074
Epoch: 36         Training Loss: 3.069890         Validation Loss: 2.907768
Epoch: 37         Training Loss: 3.076109         Validation Loss: 2.912707
Epoch: 38         Training Loss: 3.028234         Validation Loss: 2.909400
Epoch: 39         Training Loss: 2.974410         Validation Loss: 3.004783
Epoch: 40         Training Loss: 2.986123         Validation Loss: 2.907861
Epoch: 41         Training Loss: 2.964571         Validation Loss: 2.882069
Epoch: 42         Training Loss: 3.006709         Validation Loss: 2.825088
Validation loss has decreased FROM 2.876754 To 2.825088.  Saving model ...
Epoch: 43         Training Loss: 2.932766         Validation Loss: 2.769774
Validation loss has decreased FROM 2.825088 To 2.769774.  Saving model ...
Epoch: 44         Training Loss: 2.899696         Validation Loss: 2.832141
Epoch: 45         Training Loss: 2.896025         Validation Loss: 2.942693
Epoch: 46         Training Loss: 2.838781         Validation Loss: 2.776588
Epoch: 47         Training Loss: 2.869505         Validation Loss: 2.786551
Epoch: 48         Training Loss: 2.817445         Validation Loss: 2.722183
Validation loss has decreased FROM 2.769774 To 2.722183.  Saving model ...
Epoch: 49         Training Loss: 2.802245         Validation Loss: 2.717546
Validation loss has decreased FROM 2.722183 To 2.717546.  Saving model ...
Epoch: 50         Training Loss: 2.806018         Validation Loss: 2.692484
Validation loss has decreased FROM 2.717546 To 2.692484.  Saving model ...
```

```
Out[0]: <All keys matched successfully>
```

1.1.11 (IMPLEMENTATION) Test the Model

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

```
In [0]: def test(loaders, model, criterion, use_cuda):

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

            model.eval()
            for batch_idx, (data, target) in enumerate(loaders['test']):
```

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

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

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

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

```
Test Loss: 2.618895


Test Accuracy: 31% (265/836)
```

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

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

1.1.12 (IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate data loaders for the training, validation, and test datasets of dog images (located at `dogImages/train`, `dogImages/valid`, and `dogImages/test`, respectively).

If you like, **you are welcome to use the same data loaders from the previous step**, when you created a CNN from scratch.

```
In [0]: ## TODO: Specify data loaders
        train_loader_transfer = train_loader
        valid_loader_transfer = valid_loader
        test_loader_transfer = test_loader
        loaders_transfer = {
            "train":train_loader_transfer,
```

```
        "valid":valid_loader_transfer,
        "test":test_loader_transfer,
    }
```

1.1.13 (IMPLEMENTATION) Model Architecture

Use transfer learning to create a CNN to classify dog breed. Use the code cell below, and save your initialized model as the variable `model_transfer`.

```
In [0]: import torchvision.models as models
        import torch.nn as nn

        ## TODO: Specify model architecture
        model_transfer = models.vgg16(pretrained=True)
        # print(model_transfer)
        for params in model_transfer.features.parameters():
          params.requires_grad = False
        in_feature = model_transfer.classifier[6].in_features
        model_transfer.classifier[6] = nn.Linear(in_feature, no_classes)
        print(model_transfer)
        # for param in models_tranfer.
        if use_cuda:
            model_transfer = model_transfer.cuda()
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

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

1. VGG16 was selected due to the fact that amongst its dataset it was trained on earlier, includes dog breeds which makes it closer to our intended use case.
2. Since it was trained on the dataset that is similar or the same as our dataset, I decided to freeze the feature extractor and only update the weights of the classifier
3. To ensure that the output matches the numbers of classes I would want to predict on, I modified the last fully connected layer of the pretrained VGG16

1.1.14 (IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function and optimizer. Save the chosen loss function as `criterion_transfer`, and the optimizer as `optimizer_transfer` below.

```
In [0]: criterion_transfer = nn.CrossEntropyLoss()
        optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr =0.001)
```

1.1.15 (IMPLEMENTATION) Train and Validate the Model

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

```
In [48]: # train the model
         n_epochs = 40
```

```
        model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,

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

```
Epoch: 1         Training Loss: 4.572328         Validation Loss: 3.721711
Validation loss has decreased FROM inf To 3.721711.  Saving model ...
Epoch: 2         Training Loss: 3.568750         Validation Loss: 2.361459
Validation loss has decreased FROM 3.721711 To 2.361459.  Saving model ...
Epoch: 3         Training Loss: 2.639437         Validation Loss: 1.429182
Validation loss has decreased FROM 2.361459 To 1.429182.  Saving model ...
Epoch: 4         Training Loss: 2.036240         Validation Loss: 0.952843
Validation loss has decreased FROM 1.429182 To 0.952843.  Saving model ...
Epoch: 5         Training Loss: 1.743719         Validation Loss: 0.750006
Validation loss has decreased FROM 0.952843 To 0.750006.  Saving model ...
Epoch: 6         Training Loss: 1.555732         Validation Loss: 0.665869
Validation loss has decreased FROM 0.750006 To 0.665869.  Saving model ...
Epoch: 7         Training Loss: 1.474554         Validation Loss: 0.599523
Validation loss has decreased FROM 0.665869 To 0.599523.  Saving model ...
Epoch: 8         Training Loss: 1.340686         Validation Loss: 0.533392
Validation loss has decreased FROM 0.599523 To 0.533392.  Saving model ...
Epoch: 9         Training Loss: 1.285666         Validation Loss: 0.489526
Validation loss has decreased FROM 0.533392 To 0.489526.  Saving model ...
Epoch: 10         Training Loss: 1.224947         Validation Loss: 0.478271
Validation loss has decreased FROM 0.489526 To 0.478271.  Saving model ...
Epoch: 11         Training Loss: 1.205785         Validation Loss: 0.503817
Epoch: 12         Training Loss: 1.155072         Validation Loss: 0.445435
Validation loss has decreased FROM 0.478271 To 0.445435.  Saving model ...
Epoch: 13         Training Loss: 1.140359         Validation Loss: 0.427713
Validation loss has decreased FROM 0.445435 To 0.427713.  Saving model ...
Epoch: 14         Training Loss: 1.091177         Validation Loss: 0.429827
Epoch: 15         Training Loss: 1.090073         Validation Loss: 0.417918
Validation loss has decreased FROM 0.427713 To 0.417918.  Saving model ...
Epoch: 16         Training Loss: 1.089339         Validation Loss: 0.410772
Validation loss has decreased FROM 0.417918 To 0.410772.  Saving model ...
Epoch: 17         Training Loss: 1.047442         Validation Loss: 0.402365
Validation loss has decreased FROM 0.410772 To 0.402365.  Saving model ...
Epoch: 18         Training Loss: 1.040881         Validation Loss: 0.386101
Validation loss has decreased FROM 0.402365 To 0.386101.  Saving model ...
Epoch: 19         Training Loss: 1.024881         Validation Loss: 0.391511
Epoch: 20         Training Loss: 0.993292         Validation Loss: 0.395210
Epoch: 21         Training Loss: 0.984791         Validation Loss: 0.373235
Validation loss has decreased FROM 0.386101 To 0.373235.  Saving model ...
Epoch: 22         Training Loss: 0.985479         Validation Loss: 0.364193
Validation loss has decreased FROM 0.373235 To 0.364193.  Saving model ...
Epoch: 23         Training Loss: 0.986921         Validation Loss: 0.361617
Validation loss has decreased FROM 0.364193 To 0.361617.  Saving model ...
Epoch: 24         Training Loss: 0.966003         Validation Loss: 0.410155
```

```
Epoch: 25         Training Loss: 0.951377         Validation Loss: 0.355599
Validation loss has decreased FROM 0.361617 To 0.355599.  Saving model ...
Epoch: 26         Training Loss: 0.938547         Validation Loss: 0.364134
Epoch: 27         Training Loss: 0.932959         Validation Loss: 0.355440
Validation loss has decreased FROM 0.355599 To 0.355440.  Saving model ...
Epoch: 28         Training Loss: 0.935327         Validation Loss: 0.345651
Validation loss has decreased FROM 0.355440 To 0.345651.  Saving model ...
Epoch: 29         Training Loss: 0.904990         Validation Loss: 0.356180
Epoch: 30         Training Loss: 0.910272         Validation Loss: 0.362729
Epoch: 31         Training Loss: 0.886665         Validation Loss: 0.352708
Epoch: 32         Training Loss: 0.912784         Validation Loss: 0.373474
Epoch: 33         Training Loss: 0.911292         Validation Loss: 0.348481
Epoch: 34         Training Loss: 0.900077         Validation Loss: 0.340252
Validation loss has decreased FROM 0.345651 To 0.340252.  Saving model ...
Epoch: 35         Training Loss: 0.874569         Validation Loss: 0.339875
Validation loss has decreased FROM 0.340252 To 0.339875.  Saving model ...
Epoch: 36         Training Loss: 0.900249         Validation Loss: 0.340921
Epoch: 37         Training Loss: 0.898671         Validation Loss: 0.363179
Epoch: 38         Training Loss: 0.872281         Validation Loss: 0.346127
Epoch: 39         Training Loss: 0.873108         Validation Loss: 0.337731
Validation loss has decreased FROM 0.339875 To 0.337731.  Saving model ...
Epoch: 40         Training Loss: 0.848455         Validation Loss: 0.326925
Validation loss has decreased FROM 0.337731 To 0.326925.  Saving model ...
```

```
Out[48]: <All keys matched successfully>
```

1.1.16 (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Use the code cell below to calculate and print the test loss and accuracy. Ensure that your test accuracy is greater than 60%.

```
In [49]: test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.397213


Test Accuracy: 86% (726/836)
```

1.1.17 (IMPLEMENTATION) Predict Dog Breed with the Model

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

```
In [50]: ### TODO: Write a function that takes a path to an image as input
         ### and returns the dog breed that is predicted by the model.

         # list of class names by index, i.e. a name can be accessed like class_names[0]
```