

dog_app

October 31, 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 [3]: 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 [4]: import cv2
        import matplotlib.pyplot as plt
        %matplotlib inline

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

        # load color (BGR) image
        img = cv2.imread(human_files[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 [5]: # 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: - 98% images correctly classified in `human_files_short` - 17% images classified wrong as human face in `dog_files_short`

```
In [6]: 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.
humanTrue = 0
humanFalse = 0
dogTrue = 0
dogFalse = 0
for img_path in human_files_short:
    if face_detector(img_path):
        humanTrue += 1
    else:
        humanFalse += 1
print("Human : True-" + str(humanTrue) + "\tFalse-" + str(humanFalse))
for img_path in dog_files_short:
    if face_detector(img_path):
        dogTrue += 1
    else:
```

```

        dogFalse += 1
    print("Dog : True-"+ str(dogTrue) + "\tFalse-"+ str(dogFalse))

Human : True-98      False-2
Dog : True-17       False-83

```

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

```

In [ ]: ### (Optional)
        ### TODO: Test performance of another face 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 [17]: 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 [18]: from PIL import Image
import torchvision.transforms as transforms
from torch.autograd import Variable
VGG16.eval()

def transfrom(image_path):
    img =Image.open(image_path)

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
    ## Normalize the data according to the needs of the models
    transform_img = transforms.Compose([
        transforms.Resize(size=(224,224)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406],
                              std=[0.229, 0.224, 0.225])
    ])

    img = Image.open(img_path)
    img = transform_img(img)

    # PyTorch pretrained models expect the Tensor dims to be (num input imgs, num color
    # Currently however, we have (num color channels, height, width); let's fix this by
    img = img.unsqueeze(0) # Insert the new axis at index 0 i.e. in front of the other

    # Now that we have preprocessed our img, we need to convert it into a
    # Variable; PyTorch models expect inputs to be Variables. A PyTorch Variable is a
    # wrapper around a PyTorch Tensor.
    img = Variable(img)
```

```

prediction = VGG16(img.cuda()) # Returns a Tensor of shape (batch, num class labels)
prediction = prediction.cpu().data.numpy().argmax() # Our prediction will be the index of the max value

return prediction # predicted class index

```

```

In [19]: from PIL import Image
import glob
image = Image.open(human_files[0])
# summarize some details about the image
print(image.format)
print(image.mode)
print(image.size)
# show the image
image.show()

```

```

JPEG
RGB
(250, 250)

```

```

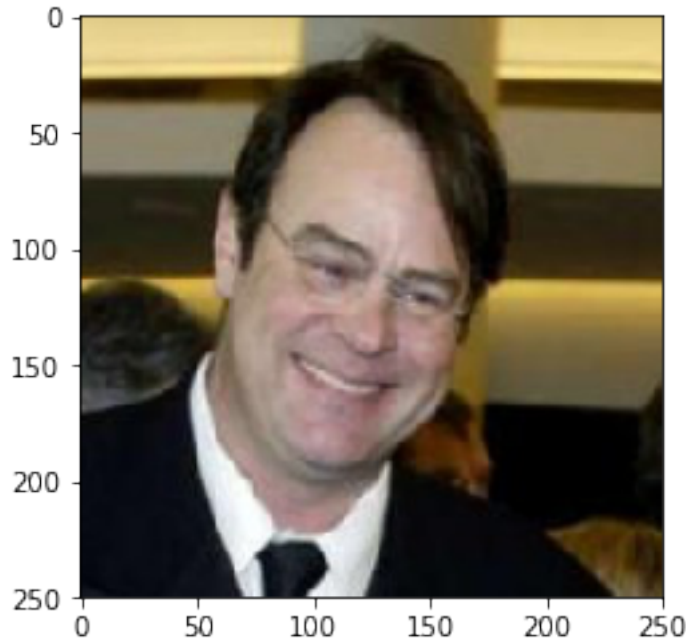
In [20]: # load and display an image with Matplotlib
from matplotlib import image
from matplotlib import pyplot
# load image as pixel array
data = image.imread(human_files[0])
# summarize shape of the pixel array
print(data.dtype)
print(data.shape)
# display the array of pixels as an image
pyplot.imshow(data)
pyplot.show()

```

```

uint8
(250, 250, 3)

```



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 [21]: ### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    pred=VGG16_predict(img_path)
    if pred >= 151 and pred <= 268:
        return True
    else:
        return False

#return None # 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: - dogs detected in human_files_short = 0% - dogs detected in dog_files_short = 100%

```
In [22]: from tqdm import tqdm
        ### TODO: Test the performance of the dog_detector function
        ### on the images in human_files_short and dog_files_short.
        human_files_short = human_files[:100]
        dog_files_short = dog_files[:100]

        counter_human = 0
        counter_dog = 0

        for human_file in tqdm(human_files_short):
            if(dog_detector(human_file)):
                counter_human +=1
        for dog_file in tqdm(dog_files_short):
            if(dog_detector(dog_file)):
                counter_dog +=1
        print("Detected dogs in human files ", counter_human, "%")
        print("Detected dogs in dogs files ", counter_dog, "%")

100%|| 100/100 [00:03<00:00, 30.10it/s]
100%|| 100/100 [00:04<00:00, 25.89it/s]

Detected dogs in human files  0 %
Detected dogs in dogs files  100 %
```

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

```
In [ ]: ### (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 imbalanced, 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 [26]: import os
import torch
from torchvision import datasets
import torchvision.transforms as transforms

### TODO: Write data loaders for training, validation, and test sets
## Specify appropriate transforms, and batch_sizes
data_dir = "/data/dog_images"
num_workers = 0
batch_size = 10
data_transforms = {
    'train' : transforms.Compose([
        transforms.Resize(256),
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(), # randomly flip and rotate
        transforms.RandomRotation(15),
```

```

transforms.ToTensor(),
transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
]),
# no need of image augmentation for the validation test set
'valid' : transforms.Compose([
transforms.Resize(256),
transforms.CenterCrop(224),
transforms.ToTensor(),
transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
]),
# test dataset flips can be found out in fast.ai
'test' : transforms.Compose([
transforms.Resize(256),
transforms.CenterCrop(224),
transforms.ToTensor(),
transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
]),
}

train_dir = data_dir + '/train'
valid_dir = data_dir + '/valid'
test_dir = data_dir + '/test'

image_datasets = {
    'train' : datasets.ImageFolder(root=train_dir,transform=data_transforms['train']),
    'valid' : datasets.ImageFolder(root=valid_dir,transform=data_transforms['valid']),
    'test' : datasets.ImageFolder(root=test_dir,transform=data_transforms['test'])
}

# Loading Dataset
loaders_scratch = {
    'train' : torch.utils.data.DataLoader(image_datasets['train'],batch_size = batch_size),
    'valid' : torch.utils.data.DataLoader(image_datasets['valid'],batch_size = batch_size),
    'test' : torch.utils.data.DataLoader(image_datasets['test'],batch_size = batch_size)
}

```

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?

```
In [39]: from matplotlib import image
         image.imread(human_files[0]).shape
```

```
Out[39]: (250, 250, 3)
```

Answer: - Previous size of image was (250, 250, 3). We stretch it to 256 and then randomly center crop it to (224, 224, 3). We cropped it to (224, 224, 3) because VGG16 model expect it in that way. - Yes we augment the data from horizontal flip, Random center crop, random rotation.

1.1.8 (IMPLEMENTATION) Model Architecture

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

```
In [27]: 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__()
        ## Follow the architecture of VGG-16
        self.conv1 = nn.Conv2d(3, 16, 3)
        self.conv2 = nn.Conv2d(16, 32, 3)
        self.conv3 = nn.Conv2d(32, 64, 3)
        self.conv4 = nn.Conv2d(64, 128, 3)
        self.conv5 = nn.Conv2d(128, 256, 3)

        self.fc1 = nn.Linear(256 * 6 * 6, 133)
        self.max_pool = nn.MaxPool2d(2, 2, ceil_mode=True)

        self.dropout = nn.Dropout(0.20)

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

    def forward(self, x):
        ## Define forward behavior
        x = F.relu(self.conv1(x))
        x = self.max_pool(x)
        x = self.conv_bn2(x)

        x = F.relu(self.conv2(x))
        x = self.max_pool(x)
        x = self.conv_bn3(x)

        x = F.relu(self.conv3(x))
        x = self.max_pool(x)
        x = self.conv_bn4(x)

        x = F.relu(self.conv4(x))
        x = self.max_pool(x)
        x = self.conv_bn5(x)
```

```

        x = F.relu(self.conv5(x))
        x = self.max_pool(x)
        x = self.conv_bn6(x)

        x = x.view(-1, 256 * 6 * 6)

        x = self.dropout(x)
        x = self.fc1(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()

```

In [40]: model_scratch

```

Out[40]: Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1))
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1))
  (conv5): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1))
  (fc1): Linear(in_features=9216, out_features=133, bias=True)
  (max_pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=True)
  (dropout): Dropout(p=0.2)
  (conv_bn1): BatchNorm2d(224, eps=3, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn2): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn5): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv_bn6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
)

```

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

Answer: It is generally a good idea to start with small and then keep on increasing. I've Drop Out to add some regularization followed by sequence of BatchNorm.

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 [28]: import torch.optim as optim
```

```

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

### TODO: select optimizer
optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.005)

```

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 [29]: import numpy as np
         from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         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_loss))
                     optimizer.zero_grad()
                     # forward pass
                     output = model(data)
                     # Loss
                     loss = criterion(output, target)
                     # backward pass
                     loss.backward()
                     # Optimization
                     optimizer.step()
                     # update training loss
                     # train_loss += loss.item()*data.size(0)
                     train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))

```

```

#####
# validate the model #
#####
model.eval()
for batch_idx, (data, target) in enumerate(loaders['valid']):
    # move to GPU
    if use_cuda:
        data, target = data.cuda(), target.cuda()

    output = model(data)
    loss = criterion(output, target)
    # update average validation loss
    valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

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

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

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

# return trained model
return model

# train the model
model_scratch = train(20, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')

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

```

```

Epoch: 1      Training Loss: 0.000706      Validation Loss: 0.005241
Validation loss decreased (inf --> 0.005241). Saving model ...
Epoch: 2      Training Loss: 0.000675      Validation Loss: 0.005088
Validation loss decreased (0.005241 --> 0.005088). Saving model ...
Epoch: 3      Training Loss: 0.000656      Validation Loss: 0.004938
Validation loss decreased (0.005088 --> 0.004938). Saving model ...
Epoch: 4      Training Loss: 0.000639      Validation Loss: 0.004827
Validation loss decreased (0.004938 --> 0.004827). Saving model ...
Epoch: 5      Training Loss: 0.000626      Validation Loss: 0.004866
Epoch: 6      Training Loss: 0.000609      Validation Loss: 0.004778
Validation loss decreased (0.004827 --> 0.004778). Saving model ...
Epoch: 7      Training Loss: 0.000601      Validation Loss: 0.004569
Validation loss decreased (0.004778 --> 0.004569). Saving model ...
Epoch: 8      Training Loss: 0.000587      Validation Loss: 0.004580
Epoch: 9      Training Loss: 0.000582      Validation Loss: 0.004444
Validation loss decreased (0.004569 --> 0.004444). Saving model ...
Epoch: 10     Training Loss: 0.000571      Validation Loss: 0.004439
Validation loss decreased (0.004444 --> 0.004439). Saving model ...
Epoch: 11     Training Loss: 0.000562      Validation Loss: 0.004507
Epoch: 12     Training Loss: 0.000559      Validation Loss: 0.004340
Validation loss decreased (0.004439 --> 0.004340). Saving model ...
Epoch: 13     Training Loss: 0.000545      Validation Loss: 0.004231
Validation loss decreased (0.004340 --> 0.004231). Saving model ...
Epoch: 14     Training Loss: 0.000543      Validation Loss: 0.004255
Epoch: 15     Training Loss: 0.000534      Validation Loss: 0.004168
Validation loss decreased (0.004231 --> 0.004168). Saving model ...
Epoch: 16     Training Loss: 0.000529      Validation Loss: 0.004161
Validation loss decreased (0.004168 --> 0.004161). Saving model ...
Epoch: 17     Training Loss: 0.000521      Validation Loss: 0.004149
Validation loss decreased (0.004161 --> 0.004149). Saving model ...
Epoch: 18     Training Loss: 0.000516      Validation Loss: 0.004131
Validation loss decreased (0.004149 --> 0.004131). Saving model ...
Epoch: 19     Training Loss: 0.000510      Validation Loss: 0.004151
Epoch: 20     Training Loss: 0.000504      Validation Loss: 0.004000
Validation loss decreased (0.004131 --> 0.004000). Saving model ...

```

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 [30]: 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: 3.261792

Test Accuracy: 19% (166/836)

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 [31]: ## TODO: Specify data loaders
         from torchvision import datasets
         import torchvision.transforms as transforms

```

```

data_dir = "/data/dog_images"
num_workers = 0
batch_size = 10
data_transforms = {
    'train' : transforms.Compose([
        transforms.Resize(256),
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(), # randomly flip and rotate
        transforms.RandomRotation(15),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    # no need of image augmentation for the validation test set
    'valid' : transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
    # test dataset flips can be found out in fast.ai
    'test' : transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ]),
}

train_dir = data_dir + '/train'
valid_dir = data_dir + '/valid'
test_dir = data_dir + '/test'

image_datasets = {
    'train' : datasets.ImageFolder(root=train_dir,transform=data_transforms['train']),
    'valid' : datasets.ImageFolder(root=valid_dir,transform=data_transforms['valid']),
    'test' : datasets.ImageFolder(root=test_dir,transform=data_transforms['test'])
}

class_names = image_datasets['train'].classes
# Loading Dataset
loaders_transfer= {
    'train' : torch.utils.data.DataLoader(image_datasets['train'],batch_size = batch_size),
    'valid' : torch.utils.data.DataLoader(image_datasets['valid'],batch_size = batch_size),
    'test' : torch.utils.data.DataLoader(image_datasets['test'],batch_size = batch_size)
}

import torchvision.utils as torchutil
import matplotlib.pyplot as plt

```

```

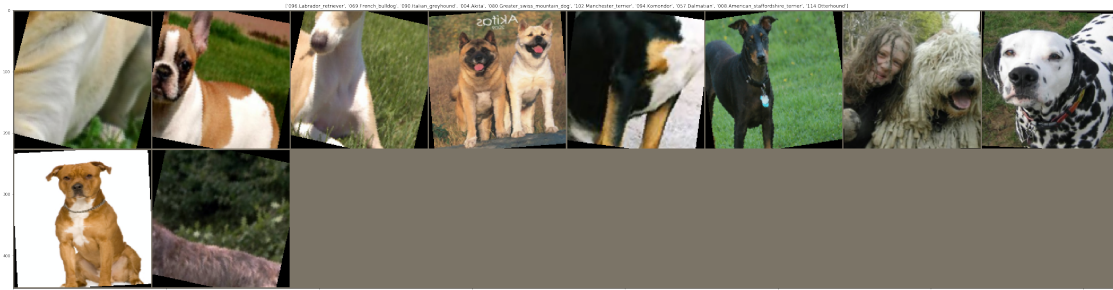
plt.ion()
def imshow(inp, title=None):
    """Imshow for Tensor."""
    inp = inp.numpy().transpose((1, 2, 0))
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    inp = std * inp + mean
    inp = np.clip(inp, 0, 1)
    fig = plt.figure(figsize=(50, 25))
    plt.imshow(inp)
    if title is not None:
        plt.title(title)
    plt.pause(0.001) # pause a bit so that plots are updated

# Get a batch of training data
inputs, classes = next(iter(loaders_transfer['train']))

# Make a grid from batch
out = torchutil.make_grid(inputs)

imshow(out, title=[class_names[x] for x in classes])

```



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 [32]: import torchvision.models as models
import torch.nn as nn

## TODO: Specify model architecture
model_transfer = models.vgg16(pretrained=True)
# Freeze the pre-trained weights
for param in model_transfer.features.parameters():
    param.requires_grad = False

```

```

# Get the input of the last layer of VGG-16
n_inputs = model_transfer.classifier[6].in_features

# Create a new layer(n_inputs -> 133)
# The new layer's requires_grad will be automatically True.
last_layer = nn.Linear(n_inputs, 133)

# Change the last layer to the new layer.
model_transfer.classifier[6] = last_layer

# Print the model.
print(model_transfer)

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)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace)
    (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)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace)
    (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)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace)
    (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)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace)
    (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)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  )
)

```

```

(27): ReLU(inplace)
(28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
(29): ReLU(inplace)
(30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
)
(classifier): Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace)
  (2): Dropout(p=0.5)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace)
  (5): Dropout(p=0.5)
  (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: After many hit and trial I've come with this architecture. This type usually works well in Image classification task. Conv -> Relu -> Conv -> Relu -> Maxpool it often a standard architecture. Using DropOut give some regularisation and prevent Overfitting.

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 [33]: criterion_transfer = nn.CrossEntropyLoss()
optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr=0.001, momentum=0.9)

```

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 [34]: import numpy as np
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
# train the model
n_epochs = 5

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_loss))
    optimizer.zero_grad()
    # forward pass
    output = model(data)
    # Loss
    loss = criterion(output, target)
    # backward pass
    loss.backward()
    # Optimization
    optimizer.step()
    # update training loss
    # train_loss += loss.item()*data.size(0)
    train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))

#####
# validate the model #
#####
model.eval()
for batch_idx, (data, target) in enumerate(loaders['valid']):
    # move to GPU
    if use_cuda:
        data, target = data.cuda(), target.cuda()

    output = model(data)
    loss = criterion(output, target)
    # update average validation loss
    valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))

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

```

```

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

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

    # return trained model
    return model

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: 0.000352          Validation Loss: 0.000946
Validation loss decreased (inf --> 0.000946). Saving model ...
Epoch: 2          Training Loss: 0.000241          Validation Loss: 0.000897
Validation loss decreased (0.000946 --> 0.000897). Saving model ...
Epoch: 3          Training Loss: 0.000227          Validation Loss: 0.000844
Validation loss decreased (0.000897 --> 0.000844). Saving model ...
Epoch: 4          Training Loss: 0.000218          Validation Loss: 0.000847
Epoch: 5          Training Loss: 0.000214          Validation Loss: 0.000849

```

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

```
Test Loss: 0.764405
```

```
Test Accuracy: 78% (658/836)
```

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

         # list of class names by index, i.e. a name can be accessed like class_names[0]
         class_names = [item[4:].replace("_", " ") for item in image_datasets['train'].classes]
         # Load the trained model 'model_transfer.pt'
         model_transfer.load_state_dict(torch.load('model_transfer.pt', map_location='cpu'))
         def predict_breed_transfer(img_path):
             # load the image and return the predicted breed
             image = Image.open(img_path).convert('RGB')
             prediction_transform = transforms.Compose([transforms.Resize(size=(224, 224)),
                                                         transforms.ToTensor(),
                                                         transforms.Normalize(mean=[0.485, 0.456, 0.406], s

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

             model_transfer.eval()
             idx = torch.argmax(model_transfer(image))
             return class_names[idx]
```

Step 5: Write your Algorithm

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

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

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

1.1.18 (IMPLEMENTATION) Write your Algorithm

```
In [37]: ### TODO: Write your algorithm.
         ### Feel free to use as many code cells as needed.
         from PIL import Image
         def run_app(img_path):
             ## handle cases for a human face, dog, and neither
             img = Image.open(img_path)
```




Sample Human Output

```
plt.imshow(img)
plt.show()

if dog_detector(img_path) is True:
    prediction = predict_breed_transfer(img_path)
    print("A dog has been detected which most likely to be {0} breed".format(prediction))
elif face_detector(img_path) > 0:
    prediction = predict_breed_transfer(img_path)
    print("This is a Human who looks like a {0}".format(prediction))
else:
    print("Neither Human nor Dog")
```

Step 6: Test Your Algorithm

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

1.1.19 (IMPLEMENTATION) Test Your Algorithm on Sample Images!

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

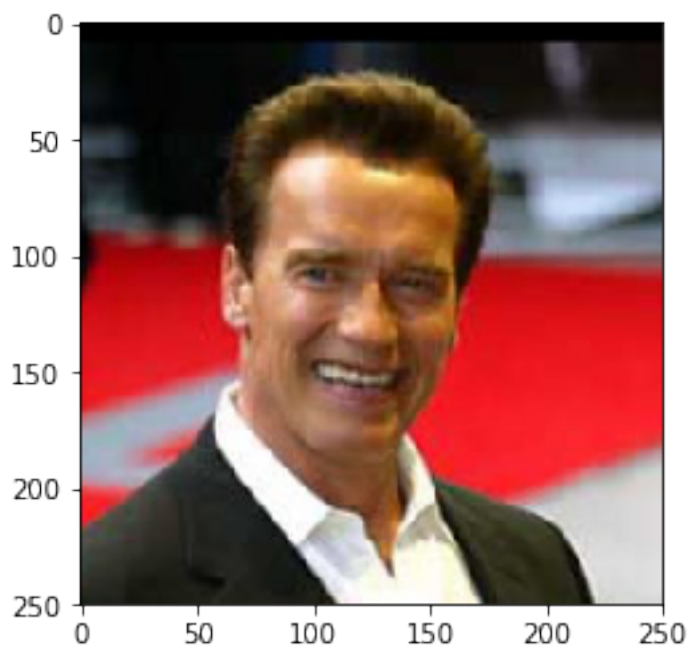
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.

Answer: - Output accuracy lies in expected range. it neither perform best nor worst. while predicting dog breed for dog image it does it job nicely. but for predicting dog breed for human image, can be improved. - passing images after cropping the image to center of face can improve the accuracy. - image with multiple faces or zero faces often confuses the predictor, which can be improved.

```
In [43]: ## 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[799], dog_files[799])):  
    run_app(file)
```



This is a Human who looks like a Dachshund



A dog has been detected which most likely to be Bluetick coonhound breed

In []: