Convolutional Neural Networks

Project: Write an Algorithm for a Dog Identification App

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

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

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

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

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

Why We're Here

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


Sample Dog Output

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

The Road Ahead

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

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

Step 0: Import Datasets

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

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

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

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

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

```
1 !mkdir data
```

```
!wget https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip -O /content/data/dogImages.zip
!wget https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip -O /content/data/lfw.zip
import zipfile
import os
```

```
--2020-06-03 02:45:52--  https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip
Resolving s3-us-west-1.amazonaws.com (s3-us-west-1.amazonaws.com)... 52.219.120.224
Connecting to s3-us-west-1.amazonaws.com (s3-us-west-1.amazonaws.com)|52.219.120.224|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1132023110 (1.1G) [application/zip]
Saving to: ‘/content/data/dogImages.zip’

/content/data/dogIm 100%[===================>]   1.05G  21.5MB/s    in 51s

2020-06-03 02:46:44 (21.0 MB/s) - ‘/content/data/dogImages.zip’ saved [1132023110/1132023110]

--2020-06-03 02:46:45--  https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip
Resolving s3-us-west-1.amazonaws.com (s3-us-west-1.amazonaws.com)... 52.219.112.96
Connecting to s3-us-west-1.amazonaws.com (s3-us-west-1.amazonaws.com)|52.219.112.96|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 196739509 (188M) [application/zip]
Saving to: ‘/content/data/lfw.zip’

/content/data/lfw.z 100%[===================>] 187.62M  21.2MB/s    in 9.9s

2020-06-03 02:46:56 (19.0 MB/s) - ‘/content/data/lfw.zip’ saved [196739509/196739509]
```

```
# Extract zip
os.chdir('/content/data')
for file in os.listdir():
  zip_ref = zipfile.ZipFile(file, 'r')
  zip_ref.extractall()
  zip_ref.close()
os.chdir('/content')
!rm /content/data/*.zip
```

```
import numpy as np
from glob import glob

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

# 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

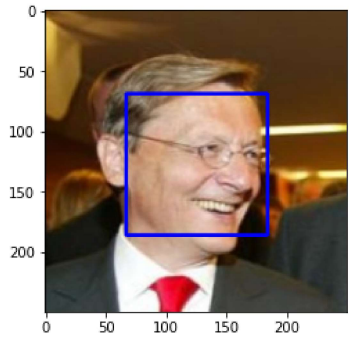
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

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.

```
import cv2
import matplotlib.pyplot as plt
%matplotlib inline

# extract pre-trained face detector
face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades + "haarcascade_frontalface_default.xml")

# load color (BGR) image
img = cv2.imread(human_files[34])
# 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
```

```
    # add bounding box to color image
    cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)

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

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

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



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

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

Write a Human Face Detector

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

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

(IMPLEMENTATION) Assess the Human Face Detector

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

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

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

Answer:

```
from tqdm import tqdm

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

```
really_human_faces = 0
dog_human_faces = 0

for i in tqdm(range(100)):
    really_human_faces += face_detector(human_files_short[i])
    dog_human_faces += face_detector(dog_files_short[i])

print("\n{}% correct human faces and {}% dog classified as human faces" .format(really_human_faces, dog_human_faces))
```

```
100%|██████████| 100/100 [00:39<00:00,  2.56it/s]
99% correct human faces and 52% dog classified as human faces
```

.

Step 2: Detect Dogs

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

Obtain Pre-trained VGG-16 Model

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

```
import torch
import torchvision.models as models

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

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

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.cache/torch/checkpoints/vgg16-397923af.pth
100%                                  528M/528M [00:19<00:00, 29.0MB/s]
```

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

(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.

```
from PIL import Image
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
import torchvision.transforms as transforms

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

    Args:
        img_path: path to an image

    Returns:
        Index corresponding to VGG-16 model's prediction
    '''
    # read image and convert to RGB
    image = Image.open(img_path).convert('RGB')

    # normalize the input
    normalize = transforms.Compose([
                                    transforms.RandomResizedCrop(224),
                                    transforms.ToTensor()
                                    ])
    image = normalize(image).unsqueeze(0)

    # If using cuda, tensor to cuda
```

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

    # run model to predict class
    prediction = VGG16(image)

    # If using cuda, return tensor to cpu
    if use_cuda:
      prediction = prediction.cpu()

    # convert the probabilities to class labels
    # retrieve the most likely result, e.g. highest probability
    label = prediction.data.numpy().argmax()

    return label # predicted class index
```

(IMPLEMENTATION) Write a Dog Detector

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

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

```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):

    return VGG16_predict(img_path) in range(151,268) # true/false
```

(IMPLEMENTATION) Assess the Dog Detector

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

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

Answer:

```
really_dog_faces = 0
human_dog_faces = 0

for i in tqdm(range(100)):
    human_dog_faces += dog_detector(human_files_short[i])
    really_dog_faces += dog_detector(dog_files_short[i])

print("\n{}% of correct classified dog faces and {}% human faces bad classified as dog faces" .format(really_dog_faces, human_dog
```

```
100%|██████████| 100/100 [00:06<00:00, 14.82it/s]
82% of correct classified dog faces and 1% human faces bad classified as dog faces
```

.

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

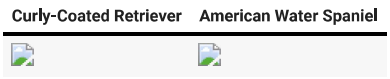
Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning *yet*!), and you must attain a test accuracy of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

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

Brittany	Welsh Springer Spaniel
	

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

Curly-Coated Retriever	American Water Spaniel



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

Yellow Labrador | Chocolate Labrador | Black Labrador

- | - | | |

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

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

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

```
import os
from torchvision import datasets, transforms

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

# number of workers of subprocess to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 20

# convert data to torch.FloatTensor
train_transform = transforms.Compose([
                                transforms.Resize(256),
                                transforms.CenterCrop(224),
                                transforms.RandomHorizontalFlip(),
                                transforms.ToTensor(),
                                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                     std=[0.229, 0.224, 0.225])
                                ])

test_transform = 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])
                                ])

# choose the training, validation and test datasets
img_dir = '/content/data/dogImages/'

data_scratch = {'train': datasets.ImageFolder(img_dir+'train', transform = train_transform),
                'valid': datasets.ImageFolder(img_dir+'valid', transform = test_transform),
                'test' : datasets.ImageFolder(img_dir+'test', transform = test_transform)}

loaders_scratch = {'train': torch.utils.data.DataLoader(data_scratch['train'], batch_size = batch_size, num_workers = num_workers
                   'valid': torch.utils.data.DataLoader(data_scratch['valid'], batch_size = batch_size, num_workers = num_workers
                   'test' : torch.utils.data.DataLoader(data_scratch['test'],  batch_size = batch_size, num_workers = num_workers
```

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've applied Resize, Center Crop, Random Horizontal Flip to training data.

For validation and testing data, I've just applied Resize and Center Crop.

- **Resize**: Resize (256) and Center Crop (224) was important to make it easier to compare performance with pre-trained models.

- **Augmentation**: I've decided to use Data augmentation because it helps to prevent overfitting. I've applied Random Horizontal Flip just to training data.

(IMPLEMENTATION) Model Architecture

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

```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()

        self.conv1 = nn.Conv2d(3, 32, 2, stride = 2)
        self.conv2 = nn.Conv2d(32, 128, 2,  stride = 2)
        self.conv3 = nn.Conv2d(128, 256, 2, padding=1)

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

        self.fc1 = nn.Linear(56 * 56 * 4, 133)

        self.dropout = nn.Dropout(0.8)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = self.pool(F.relu(self.conv3(x)))
        x = x.view(-1, x.shape[1] * x.shape[2] * x.shape[3])
        x = self.dropout(x)
        x = self.fc1(x)

        return x

model_scratch = Net()

if use_cuda:
    model_scratch.cuda()

print(model_scratch)
```

```
Net(
  (conv1): Conv2d(3, 32, kernel_size=(2, 2), stride=(2, 2))
  (conv2): Conv2d(32, 128, kernel_size=(2, 2), stride=(2, 2))
  (conv3): Conv2d(128, 256, kernel_size=(2, 2), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=12544, out_features=133, bias=True)
  (dropout): Dropout(p=0.8, inplace=False)
)
```

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

Answer:

I've started using 3 Conv2d and 2 Linear layers as follows:

- Conv2d(3, 16, 3, padding = 1)
- Conv2d(16, 32, 3, padding = 1)
- Conv2d(32, 64, 3, padding = 1)
- MaxPool2d(2,2) after each of Conv2d layers
- Linear(224 * 224, 1000)
- Linear(1000, 500)
- Linear(500, 133)
- Dropout(p=0.3, inplace=False)

CrossEntropyLoss as Criterion and SGD as Optimizer. Learning Rate of 0.01

After some training, because my loss was not decreasing I've decided to change some hyperparameters like:

- Dropping 2nd Linear layer;
- Trying different learning rates (0.1, 0.01, 0.001, 0.0001);
- Adjusting out-channels in Conv2d layers (from max 64 to 256 in last layer);

- Increasing dropout (0.3, 0.4, 0.5, 0.6, 0.8) because it was overfitting too fast;
- Trying Adam as Optimizer;
- Adjusting kernels in Conv2d layers (from 3 to 2);
- Adjusting stride in Conv2d first layers (from 1 to 2) to reduce dimension;
- Adjusting padding in Conv2d layers (removing 1-padding).
- Dropping one more Linear layer, keeping just one.

(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.

```
import torch.optim as optim

criterion_scratch = nn.CrossEntropyLoss()

optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.003)
```

(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'`.

```
import datetime as dt

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()

            # clear the gradientes of all optimized variables
            optimizer.zero_grad()
            # forward pass: compute predicted outputs by passing inputs to model
            output = model(data)
            # calculate the batch loss
            loss = criterion(output, target)
            # backward pass: compute gradient of the loss with respect to model parameters
            loss.backward()
            # perform a single optimization step (parameter update)
            optimizer.step()
            # update training loss
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))

            if batch_idx % 100 == 0:
                print('Epoch %d, Batch %d loss: %.6f' % (epoch, batch_idx + 1, 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)
            # calculate the batch loss
            loss = criterion(output, target)
            # update the average validation loss
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))
```

```
53
54        # print training/validation statistics
55        print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
56            epoch, train_loss, valid_loss))
57
58        ## TODO: save the model if validation loss has decreased
59        if valid_loss <= valid_loss_min:
60            print(dt.datetime.now())
61            print('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.format(
62                                                              valid_loss_min, valid_loss))
63            torch.save(model.state_dict(), save_path)
64            valid_loss_min = valid_loss
65
66    # return trained model
67    return model
68
69 # train the model
70 model_scratch = train(60, loaders_scratch, model_scratch, optimizer_scratch,
71                       criterion_scratch, use_cuda, '/content/model_scratch.pt')
72
73 # load the model that got the best validation accuracy
74 model_scratch.load_state_dict(torch.load('/content/model_scratch.pt'))
```

```
Epoch 1, Batch 1 loss: 4.985315
Epoch 1, Batch 101 loss: 4.895554
Epoch 1, Batch 201 loss: 4.889157
Epoch 1, Batch 301 loss: 4.886207
Epoch: 1        Training Loss: 4.884841         Validation Loss: 4.847234
2020-06-02 15:13:37.207963
Validation loss decreased (inf --> 4.847234).  Saving model ...
Epoch 2, Batch 1 loss: 4.888307
Epoch 2, Batch 101 loss: 4.846097
Epoch 2, Batch 201 loss: 4.842527
Epoch 2, Batch 301 loss: 4.838199
Epoch: 2        Training Loss: 4.838126         Validation Loss: 4.812659
2020-06-02 15:15:14.622669
Validation loss decreased (4.847234 --> 4.812659).  Saving model ...
Epoch 3, Batch 1 loss: 4.715899
Epoch 3, Batch 101 loss: 4.797911
Epoch 3, Batch 201 loss: 4.785986
Epoch 3, Batch 301 loss: 4.787976
Epoch: 3        Training Loss: 4.786815         Validation Loss: 4.756653
2020-06-02 15:16:51.079031
Validation loss decreased (4.812659 --> 4.756653).  Saving model ...
Epoch 4, Batch 1 loss: 4.746315
Epoch 4, Batch 101 loss: 4.724127
Epoch 4, Batch 201 loss: 4.725090
Epoch 4, Batch 301 loss: 4.713765
Epoch: 4        Training Loss: 4.715325         Validation Loss: 4.681196
2020-06-02 15:18:28.314850
Validation loss decreased (4.756653 --> 4.681196).  Saving model ...
Epoch 5, Batch 1 loss: 4.559677
Epoch 5, Batch 101 loss: 4.614811
Epoch 5, Batch 201 loss: 4.627761
Epoch 5, Batch 301 loss: 4.629848
Epoch: 5        Training Loss: 4.632693         Validation Loss: 4.621498
2020-06-02 15:20:06.001429
Validation loss decreased (4.681196 --> 4.621498).  Saving model ...
Epoch 6, Batch 1 loss: 4.571214
Epoch 6, Batch 101 loss: 4.554010
Epoch 6, Batch 201 loss: 4.562866
Epoch 6, Batch 301 loss: 4.565532
Epoch: 6        Training Loss: 4.567876         Validation Loss: 4.577043
2020-06-02 15:21:43.609185
Validation loss decreased (4.621498 --> 4.577043).  Saving model ...
Epoch 7, Batch 1 loss: 4.563662
Epoch 7, Batch 101 loss: 4.505013
Epoch 7, Batch 201 loss: 4.515303
Epoch 7, Batch 301 loss: 4.514391
Epoch: 7        Training Loss: 4.508681         Validation Loss: 4.532075
2020-06-02 15:23:21.086551
Validation loss decreased (4.577043 --> 4.532075).  Saving model ...
Epoch 8, Batch 1 loss: 4.278951
Epoch 8, Batch 101 loss: 4.456956
Epoch 8, Batch 201 loss: 4.446305
Epoch 8, Batch 301 loss: 4.443437
Epoch: 8        Training Loss: 4.443781         Validation Loss: 4.474672
2020-06-02 15:24:58.503203
Validation loss decreased (4.532075 --> 4.474672).  Saving model ...
Epoch 9, Batch 1 loss: 4.246491
Epoch 9, Batch 101 loss: 4.349432
Epoch 9, Batch 201 loss: 4.363788
Epoch 9, Batch 301 loss: 4.367685
Epoch: 9        Training Loss: 4.366289         Validation Loss: 4.425137
2020-06-02 15:26:36.170895
Validation loss decreased (4.474672 --> 4.425137).  Saving model ...
Epoch 10, Batch 1 loss: 4.214148
Epoch 10, Batch 101 loss: 4.297029
Epoch 10, Batch 201 loss: 4.302025
Epoch 10, Batch 301 loss: 4.302352
Epoch: 10       Training Loss: 4.296602         Validation Loss: 4.377424
2020-06-02 15:28:13.906126
Validation loss decreased (4.425137 --> 4.377424).  Saving model ...
Epoch 11, Batch 1 loss: 3.987419
Epoch 11, Batch 101 loss: 4.264414
Epoch 11, Batch 201 loss: 4.257758
Epoch 11, Batch 301 loss: 4.252130
Epoch: 11       Training Loss: 4.253942         Validation Loss: 4.341602
2020-06-02 15:29:51.502621
Validation loss decreased (4.377424 --> 4.341602).  Saving model ...
Epoch 12, Batch 1 loss: 3.977547
Epoch 12, Batch 101 loss: 4.184776
Epoch 12, Batch 201 loss: 4.184353
Epoch 12, Batch 301 loss: 4.184144
Epoch: 12       Training Loss: 4.186547         Validation Loss: 4.318615
2020-06-02 15:31:29.000990
Validation loss decreased (4.341602 --> 4.318615).  Saving model ...
Epoch 13, Batch 1 loss: 4.554122
Epoch 13, Batch 101 loss: 4.127973
Epoch 13, Batch 201 loss: 4.141908
Epoch 13, Batch 301 loss: 4.140000
Epoch: 13       Training Loss: 4.137816         Validation Loss: 4.299122
```

```
2020-06-02 15:33:06.443227
Validation loss decreased (4.318615 --> 4.299122).  Saving model ...
Epoch 14, Batch 1 loss: 3.867620
Epoch 14, Batch 101 loss: 4.131258
Epoch 14, Batch 201 loss: 4.109872
Epoch 14, Batch 301 loss: 4.109861
Epoch: 14       Training Loss: 4.103307         Validation Loss: 4.281614
2020-06-02 15:34:43.814088
Validation loss decreased (4.299122 --> 4.281614).  Saving model ...
Epoch 15, Batch 1 loss: 4.020345
Epoch 15, Batch 101 loss: 4.056814
Epoch 15, Batch 201 loss: 4.047909
Epoch 15, Batch 301 loss: 4.058424
Epoch: 15       Training Loss: 4.055211         Validation Loss: 4.262178
2020-06-02 15:36:21.245770
Validation loss decreased (4.281614 --> 4.262178).  Saving model ...
Epoch 16, Batch 1 loss: 3.829056
Epoch 16, Batch 101 loss: 3.980830
Epoch 16, Batch 201 loss: 3.994205
Epoch 16, Batch 301 loss: 4.012812
Epoch: 16       Training Loss: 4.013308         Validation Loss: 4.236111
2020-06-02 15:37:58.704893
Validation loss decreased (4.262178 --> 4.236111).  Saving model ...
Epoch 17, Batch 1 loss: 4.377630
Epoch 17, Batch 101 loss: 3.967565
Epoch 17, Batch 201 loss: 3.963082
Epoch 17, Batch 301 loss: 3.966177
Epoch: 17       Training Loss: 3.971371         Validation Loss: 4.226820
2020-06-02 15:39:36.168568
Validation loss decreased (4.236111 --> 4.226820).  Saving model ...
Epoch 18, Batch 1 loss: 4.293939
Epoch 18, Batch 101 loss: 3.916178
Epoch 18, Batch 201 loss: 3.906873
Epoch 18, Batch 301 loss: 3.914640
Epoch: 18       Training Loss: 3.923992         Validation Loss: 4.199404
2020-06-02 15:41:13.603594
Validation loss decreased (4.226820 --> 4.199404).  Saving model ...
Epoch 19, Batch 1 loss: 3.298785
Epoch 19, Batch 101 loss: 3.838221
Epoch 19, Batch 201 loss: 3.849086
Epoch 19, Batch 301 loss: 3.877600
Epoch: 19       Training Loss: 3.878772         Validation Loss: 4.187545
2020-06-02 15:42:51.330547
Validation loss decreased (4.199404 --> 4.187545).  Saving model ...
Epoch 20, Batch 1 loss: 3.530809
Epoch 20, Batch 101 loss: 3.831463
Epoch 20, Batch 201 loss: 3.838648
Epoch 20, Batch 301 loss: 3.836076
Epoch: 20       Training Loss: 3.836796         Validation Loss: 4.171815
2020-06-02 15:44:28.834288
Validation loss decreased (4.187545 --> 4.171815).  Saving model ...
Epoch 21, Batch 1 loss: 3.480233
Epoch 21, Batch 101 loss: 3.781464
Epoch 21, Batch 201 loss: 3.789374
Epoch 21, Batch 301 loss: 3.778076
Epoch: 21       Training Loss: 3.778632         Validation Loss: 4.163908
2020-06-02 15:46:06.530924
Validation loss decreased (4.171815 --> 4.163908).  Saving model ...
Epoch 22, Batch 1 loss: 3.742808
Epoch 22, Batch 101 loss: 3.759482
Epoch 22, Batch 201 loss: 3.755816
Epoch 22, Batch 301 loss: 3.748672
Epoch: 22       Training Loss: 3.753219         Validation Loss: 4.143659
2020-06-02 15:47:44.252382
Validation loss decreased (4.163908 --> 4.143659).  Saving model ...
Epoch 23, Batch 1 loss: 4.260554
Epoch 23, Batch 101 loss: 3.729494
Epoch 23, Batch 201 loss: 3.703620
Epoch 23, Batch 301 loss: 3.714061
Epoch: 23       Training Loss: 3.713829         Validation Loss: 4.136244
2020-06-02 15:49:22.017431
Validation loss decreased (4.143659 --> 4.136244).  Saving model ...
Epoch 24, Batch 1 loss: 3.337513
Epoch 24, Batch 101 loss: 3.632902
Epoch 24, Batch 201 loss: 3.652172
Epoch 24, Batch 301 loss: 3.658002
Epoch: 24       Training Loss: 3.659132         Validation Loss: 4.127567
2020-06-02 15:50:59.269230
Validation loss decreased (4.136244 --> 4.127567).  Saving model ...
Epoch 25, Batch 1 loss: 3.511727
Epoch 25, Batch 101 loss: 3.574825
Epoch 25, Batch 201 loss: 3.608136
Epoch 25, Batch 301 loss: 3.613019
Epoch: 25       Training Loss: 3.615075         Validation Loss: 4.118148
2020-06-02 15:52:35.758878
Validation loss decreased (4.127567 --> 4.118148).  Saving model ...
Epoch 26, Batch 1 loss: 3.285726
Epoch 26, Batch 101 loss: 3.595330
Epoch 26, Batch 201 loss: 3.573340
```

```
Epoch 26, Batch 301 loss: 3.558573
Epoch: 26       Training Loss: 3.566267         Validation Loss: 4.108749
2020-06-02 15:54:10.173460
Validation loss decreased (4.118148 --> 4.108749).  Saving model ...
Epoch 27, Batch 1 loss: 3.429341
Epoch 27, Batch 101 loss: 3.496096
Epoch 27, Batch 201 loss: 3.531896
Epoch 27, Batch 301 loss: 3.516519
Epoch: 27       Training Loss: 3.520737         Validation Loss: 4.096877
2020-06-02 15:55:44.497832
Validation loss decreased (4.108749 --> 4.096877).  Saving model ...
Epoch 28, Batch 1 loss: 3.110164
Epoch 28, Batch 101 loss: 3.418346
Epoch 28, Batch 201 loss: 3.426450
Epoch 28, Batch 301 loss: 3.448282
Epoch: 28       Training Loss: 3.460306         Validation Loss: 4.097501
Epoch 29, Batch 1 loss: 3.545153
Epoch 29, Batch 101 loss: 3.430158
Epoch 29, Batch 201 loss: 3.406110
Epoch 29, Batch 301 loss: 3.415285
Epoch: 29       Training Loss: 3.419601         Validation Loss: 4.104180
Epoch 30, Batch 1 loss: 3.516968
Epoch 30, Batch 101 loss: 3.330854
Epoch 30, Batch 201 loss: 3.351306
Epoch 30, Batch 301 loss: 3.374299
Epoch: 30       Training Loss: 3.378881         Validation Loss: 4.088944
2020-06-02 16:00:28.822117
Validation loss decreased (4.096877 --> 4.088944).  Saving model ...
Epoch 31, Batch 1 loss: 3.039619
Epoch 31, Batch 101 loss: 3.297827
Epoch 31, Batch 201 loss: 3.314181
Epoch 31, Batch 301 loss: 3.331335
Epoch: 31       Training Loss: 3.339298         Validation Loss: 4.079523
2020-06-02 16:02:04.102306
Validation loss decreased (4.088944 --> 4.079523).  Saving model ...
Epoch 32, Batch 1 loss: 2.819317
Epoch 32, Batch 101 loss: 3.261464
Epoch 32, Batch 201 loss: 3.267430
Epoch 32, Batch 301 loss: 3.260022
Epoch: 32       Training Loss: 3.269319         Validation Loss: 4.089709
Epoch 33, Batch 1 loss: 2.997093
Epoch 33, Batch 101 loss: 3.218191
Epoch 33, Batch 201 loss: 3.222209
Epoch 33, Batch 301 loss: 3.234361
Epoch: 33       Training Loss: 3.235718         Validation Loss: 4.078612
2020-06-02 16:05:15.181924
Validation loss decreased (4.079523 --> 4.078612).  Saving model ...
Epoch 34, Batch 1 loss: 2.662524
Epoch 34, Batch 101 loss: 3.178779
Epoch 34, Batch 201 loss: 3.172980
Epoch 34, Batch 301 loss: 3.184120
Epoch: 34       Training Loss: 3.185128         Validation Loss: 4.059879
2020-06-02 16:06:50.693914
Validation loss decreased (4.078612 --> 4.059879).  Saving model ...
Epoch 35, Batch 1 loss: 2.950912
Epoch 35, Batch 101 loss: 3.084563
Epoch 35, Batch 201 loss: 3.105489
Epoch 35, Batch 301 loss: 3.135552
Epoch: 35       Training Loss: 3.150140         Validation Loss: 4.075695
Epoch 36, Batch 1 loss: 3.624819
Epoch 36, Batch 101 loss: 3.058077
Epoch 36, Batch 201 loss: 3.070582
Epoch 36, Batch 301 loss: 3.080901
Epoch: 36       Training Loss: 3.088060         Validation Loss: 4.080075
Epoch 37, Batch 1 loss: 3.320282
Epoch 37, Batch 101 loss: 2.978292
Epoch 37, Batch 201 loss: 3.026520
Epoch 37, Batch 301 loss: 3.025530
Epoch: 37       Training Loss: 3.029251         Validation Loss: 4.077350
Epoch 38, Batch 1 loss: 2.882337
Epoch 38, Batch 101 loss: 2.925730
Epoch 38, Batch 201 loss: 2.949702
Epoch 38, Batch 301 loss: 2.959701
Epoch: 38       Training Loss: 2.969701         Validation Loss: 4.061439
Epoch 39, Batch 1 loss: 2.447482
Epoch 39, Batch 101 loss: 2.876313
Epoch 39, Batch 201 loss: 2.926366
Epoch 39, Batch 301 loss: 2.910908
Epoch: 39       Training Loss: 2.930377         Validation Loss: 4.065003
Epoch 40, Batch 1 loss: 3.151082
Epoch 40, Batch 101 loss: 2.919063
Epoch 40, Batch 201 loss: 2.888525
Epoch 40, Batch 301 loss: 2.903711
Epoch: 40       Training Loss: 2.903639         Validation Loss: 4.089262
Epoch 41, Batch 1 loss: 2.804396
Epoch 41, Batch 101 loss: 2.780061
Epoch 41, Batch 201 loss: 2.816970
Epoch 41, Batch 301 loss: 2.808480
Epoch: 41       Training Loss: 2.822210         Validation Loss: 4.062325
```

```
Epoch 42, Batch 1 loss: 2.435472
Epoch 42, Batch 101 loss: 2.778472
Epoch 42, Batch 201 loss: 2.790959
Epoch 42, Batch 301 loss: 2.792782
Epoch: 42       Training Loss: 2.796916         Validation Loss: 4.073172
Epoch 43, Batch 1 loss: 2.478729
Epoch 43, Batch 101 loss: 2.672075
Epoch 43, Batch 201 loss: 2.695099
Epoch 43, Batch 301 loss: 2.718788
Epoch: 43       Training Loss: 2.726712         Validation Loss: 4.083881
Epoch 44, Batch 1 loss: 2.788377
Epoch 44, Batch 101 loss: 2.679939
Epoch 44, Batch 201 loss: 2.654252
Epoch 44, Batch 301 loss: 2.672819
Epoch: 44       Training Loss: 2.678456         Validation Loss: 4.104927
Epoch 45, Batch 1 loss: 2.573153
Epoch 45, Batch 101 loss: 2.592677
Epoch 45, Batch 201 loss: 2.615326
Epoch 45, Batch 301 loss: 2.653802
Epoch: 45       Training Loss: 2.662523         Validation Loss: 4.103742
Epoch 46, Batch 1 loss: 2.315742
Epoch 46, Batch 101 loss: 2.487746
Epoch 46, Batch 201 loss: 2.548987
Epoch 46, Batch 301 loss: 2.574871
Epoch: 46       Training Loss: 2.576351         Validation Loss: 4.118559
Epoch 47, Batch 1 loss: 2.415347
Epoch 47, Batch 101 loss: 2.533454
Epoch 47, Batch 201 loss: 2.517483
Epoch 47, Batch 301 loss: 2.522407
Epoch: 47       Training Loss: 2.537113         Validation Loss: 4.075542
Epoch 48, Batch 1 loss: 1.970050
Epoch 48, Batch 101 loss: 2.425251
Epoch 48, Batch 201 loss: 2.443509
```

(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%.

```
Epoch 58, Batch 1 loss: 2.203208
```

```
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: 4.020360


Test Accuracy: 10% (88/836)
```

```
Epoch 58, Batch 101 loss: 1.943798
```

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

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

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

Use the code cell below to write three separate [data loaders](http://pytorch.org/docs/master/data.html#torch.utils.data.DataLoader) for the training, validation, and test datasets of dog images (located at `dogImages/train`, `dogImages/valid`, and `dogImages/test`, respectively).

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

```
import os
from torchvision import datasets, transforms

# number of workers of subprocess to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 32

# convert data to torch.FloatTensor
train_transform = transforms.Compose([
                                transforms.Resize(256),
                                transforms.CenterCrop(224),
                                transforms.RandomHorizontalFlip(),
                                transforms.ToTensor(),
                                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                                     std=[0.229, 0.224, 0.225])
                                ])

test_transform = 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])
                                ])

# choose the training, validation and test datasets
img_dir = '/content/data/dogImages/'

data_transfer = {'train': datasets.ImageFolder(img_dir+'train', transform = train_transform),
                 'valid': datasets.ImageFolder(img_dir+'valid', transform = test_transform),
                 'test' : datasets.ImageFolder(img_dir+'test', transform = test_transform)}

loaders_transfer = {'train': torch.utils.data.DataLoader(data_transfer['train'], batch_size = batch_size, num_workers = num_worke
                    'valid': torch.utils.data.DataLoader(data_transfer['valid'], batch_size = batch_size, num_workers = num_worke
                    'test' : torch.utils.data.DataLoader(data_transfer['test'],  batch_size = batch_size, num_workers = num_worke
```

(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`.

```
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.required_grad = False

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

# 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)

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

# move model to GPU if CUDA is available
```

```
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:

I started applying the VGG16 Model to the current problem because It was already been downloaded.

- I've specified de model architecture as VGG16 pre-trained;
- Freeze the pre-trained weights;
- Got the number of inputs the VGG16 last layer;
- Defined the new last Linear layer to the model;
- Replaced original last layer to this new one;
- Applied CrossEntropyLoss as Criterion;
- Applied SGD as Optimizer and learning rate of 0.003.

After these steps, I've decided to train my model for 10 epochs and the accuracy was good enough to reduce to just 5 epochs.

(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.

```
criterion_transfer = nn.CrossEntropyLoss()
optimizer_transfer = optim.SGD(model_transfer.parameters(), lr=0.003)
```

(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'`.

```
import datetime as dt

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()

            # clear the gradientes of all optimized variables
            optimizer.zero_grad()
            # forward pass: compute predicted outputs by passing inputs to model
            output = model(data)
            # calculate the batch loss
            loss = criterion(output, target)
            # backward pass: compute gradient of the loss with respect to model parameters
            loss.backward()
            # perform a single optimization step (parameter update)
            optimizer.step()
            # update training loss
            train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))

            if batch_idx % 100 == 0:
                print('Epoch %d, Batch %d loss: %.6f' % (epoch, batch_idx + 1, 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)
            # calculate the batch loss
            loss = criterion(output, target)
            # update the average validation loss
            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(dt.datetime.now())
            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
```

```
n_epochs = 5

# train the model
model_transfer = train(n_epochs, loaders_transfer, model_transfer, optimizer_transfer,
                       criterion_transfer, use_cuda, '/content/model_transfer.pt')

# load the model that got the best validation accuracy (uncomment the line below)
```

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

```
Epoch 1, Batch 1 loss: 5.011942
Epoch 1, Batch 101 loss: 3.401301
Epoch 1, Batch 201 loss: 2.383790
Epoch: 1        Training Loss: 2.328360         Validation Loss: 0.738288
2020-06-03 02:51:34.011321
Validation loss decreased (inf --> 0.738288).  Saving model ...
Epoch 2, Batch 1 loss: 1.001734
Epoch 2, Batch 101 loss: 0.838221
Epoch 2, Batch 201 loss: 0.775752
Epoch: 2        Training Loss: 0.773284         Validation Loss: 0.572112
2020-06-03 02:54:57.190618
Validation loss decreased (0.738288 --> 0.572112).  Saving model ...
Epoch 3, Batch 1 loss: 0.611176
Epoch 3, Batch 101 loss: 0.580445
Epoch 3, Batch 201 loss: 0.556790
Epoch: 3        Training Loss: 0.555367         Validation Loss: 0.550641
2020-06-03 02:58:20.324023
Validation loss decreased (0.572112 --> 0.550641).  Saving model ...
Epoch 4, Batch 1 loss: 0.382505
Epoch 4, Batch 101 loss: 0.435122
Epoch 4, Batch 201 loss: 0.440844
Epoch: 4        Training Loss: 0.439242         Validation Loss: 0.476754
2020-06-03 03:01:44.009541
Validation loss decreased (0.550641 --> 0.476754).  Saving model ...
Epoch 5, Batch 1 loss: 0.409981
Epoch 5, Batch 101 loss: 0.339705
Epoch 5, Batch 201 loss: 0.350780
Epoch: 5        Training Loss: 0.353507         Validation Loss: 0.445335
2020-06-03 03:05:05.659340
Validation loss decreased (0.476754 --> 0.445335).  Saving model ...
<All keys matched successfully>
```

(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%.

```
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))
```

```
test(loaders_transfer, model_transfer, criterion_transfer, use_cuda)
```

```
Test Loss: 0.430247


Test Accuracy: 86% (727/836)
```

(IMPLEMENTATION) Predict Dog Breed with the Model

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

```
from PIL import Image
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
import torchvision.transforms as transforms

# 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 data_transfer['train'].classes]

def predict_breed_transfer(img_path):
    # load the image and return the predicted breed

    image = Image.open(img_path).convert('RGB')

    normalize = transforms.Compose([
                                    transforms.RandomResizedCrop(224),
                                    transforms.ToTensor()
                                    ])

    image = normalize(image).unsqueeze(0)

    if use_cuda:
      image = image.cuda()

    # run model to predict class
    prediction = model_transfer(image)

    if use_cuda:
      prediction = prediction.cpu()
    # convert the probabilities to class labels
    # retrieve the most likely result, e.g. highest probability
    label = prediction.data.numpy().argmax()

    return class_names[label] # predicted class index
```

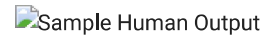
Step 5: Write your Algorithm

Write an algorithm that accepts a file path to an image and first determines whether the image contains a human, dog, or neither. Then,

- if a **dog** is detected in the image, return the predicted breed.
- if a **human** is detected in the image, return the resembling dog breed.
- if **neither** is detected in the image, provide output that indicates an error.

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

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



(IMPLEMENTATION) Write your Algorithm

```
import matplotlib.pyplot as plt

def show_image(img_path):
    img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)
    plt.imshow(img)
    plt.gca().set_xticks([])
    plt.gca().set_yticks([])
    plt.show()
```

```
def run_app(img_path):
    ## handle cases for a human face, dog, and neither

    #if VGG16_predict(img_path) in range(151,268):
    if dog_detector(img_path):
        print('\nHello, dog!')
        show_image(img_path)
        print('\nYour predicted breed is ... \n{}\n'.format(predict_breed_transfer(img_path)))
    elif face_detector(img_path):
        print('Hello human!')
        show_image(img_path)
        print('\nYou look like a ... \n{}\n'.format(predict_breed_transfer(img_path)))
    else:
        show_image(img_path)
```

```
        print('\nNot human nor dog\n')
    print('\n-------------------------------------------------------------\n')
```

Step 6: Test Your Algorithm

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

(IMPLEMENTATION) Test Your Algorithm on Sample Images!

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

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

Answer: The output was as expected. I'm satisfied with the result.

I believe some improvements can be done:

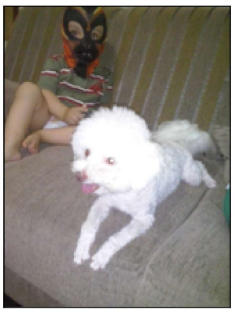
- Change the number of Conv2d layers;
- Change the number of Linear layers;
- Change Dropout layer;
- Change other hyperparameters like learning rate, normalization, resize, crop, augmentation.

```
## 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.

run_app('/content/AvrilLavigne.JPG')
run_app('/content/CapaRevista.jpg')
run_app('/content/Bob.jpg')
run_app('/content/chow_chow-p.jpg')
run_app('/content/DriverNvidia.png')
run_app('/content/IronMaiden_TheFinalFrontier.jpg')

human_pic = np.random.randint(0,len(human_files),2)
dog_pic = np.random.randint(0,len(dog_files),2)

for file in np.hstack((human_files[human_pic], dog_files[dog_pic])):
    run_app(file)
```

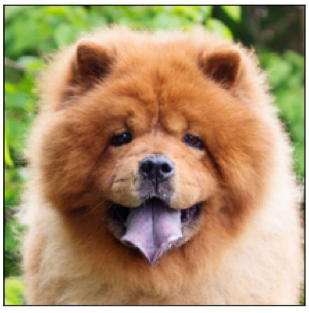
```
Hello human!
```


```
You look like a ...
English toy spaniel


-------------------------------------------------------

Hello human!
```

```
You look like a ...
Chinese crested


-------------------------------------------------------

Hello human!
```



```
You look like a ...
Bichon frise


-------------------------------------------------------


Hello, dog!
```

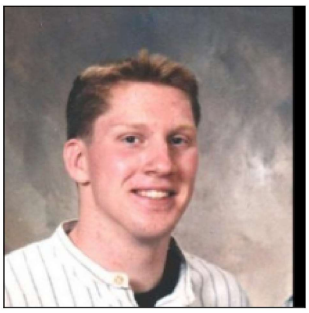


```
Your predicted breed is ...
Chow chow


-------------------------------------------------------
```


```
Not human nor dog
```


```
Not human nor dog
```

```
Hello human!
```



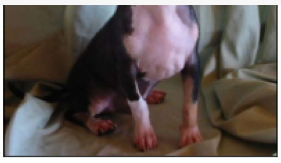
```
You look like a ...
Pharaoh hound
```

```
Hello human!
```

```
You look like a ...
Dogue de bordeaux
```

```
Hello, dog!
```

```
1
```



```
Your predicted breed is ...
Chihuahua


---------------------------------------------------------


Hello, dog!
```