dog_app

July 9, 2020

1 Convolutional Neural Networks

1.1 Project: Algorithm for a Dog Identification App

In this project, you will follow along on how to make dog breed classifier

1.1.1 The Road Ahead

- Section ??: Import Datasets
- Section ??: Detect Humans
- Section ??: Detect Dogs
- Section ??: Create a CNN to Classify Dog Breeds (from Scratch)
- Section ??: Create a CNN to Classify Dog Breeds (using Transfer Learning)
- Section ??: Write your Algorithm
- Section ??: Test Your Algorithm

Step 0: Import Datasets

In [2]:
```
import numpy as np
from glob import glob


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


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

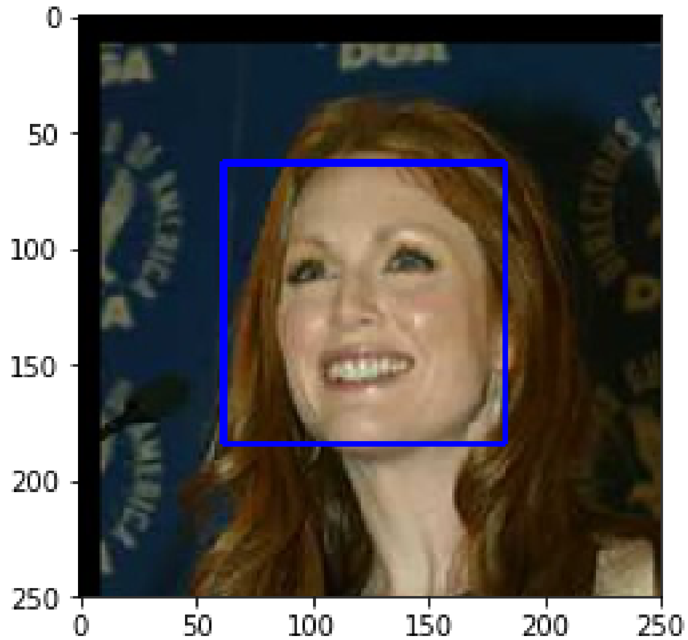
In this section, I'll use OpenCV's implementation of Haar feature-based cascade classifiers to detect human faces in images.

Sample Dog Output

In [3]:
```
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[52])
# 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
```



```
In [4]: # 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 Assess the Human Face Detector

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

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

Answer:

98% of human faces are detected.

17% of dogs are detected.

```
In [5]: 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.

h_counter = 0
d_counter = 0  # Initialize both a counter of human and dogs.

list_h = []
list_d = []
for i in range(len(human_files_short)):
    if face_detector(human_files_short[i]) == True: h_counter += 1 # Counter the number
    else: list_h.append(human_files_short[i])                                          #

for i in range(len(dog_files_short)):
    if face_detector(dog_files_short[i]) == True: d_counter += 1 # Counter the number of
    else: list_d.append(dog_files_short[i])                                          # thi

print(h_counter)
print(d_counter)
```

```
98
17
```

Now just for curiosity, I'll do some investigation about the undeducted faces, also the detected faces in the dog photos.

First the undeducted faces:

In [6]:
```
def face_print(z):
    # method to print the photos, same as the one above
    fig=plt.figure(figsize=(14, 14))
    columns = 5
    rows = 4

    for i, mg in enumerate(z):
        i += 1
        img = cv2.imread(mg)
        # 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)
                fig.add_subplot(rows, columns, i)
            # convert BGR image to RGB for plotting
            cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
            plt.imshow(cv_rgb)

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

```
In [7]: list_d = np.array(list_d)
        list_h = np.array(list_h)
```

```
In [8]: face_print(list_h)
```

1.1.3 It's very strange that the algorithm did not pick up on the faces in the images.

Now I'll take a look at the undeducted images of dogs

```
In [9]: face_print(list_d)
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/cbook/deprecation.py:106: MatplotlibDeprecatio
  warnings.warn(message, mplDeprecation, stacklevel=1)
```

1.1.4 Some images have faces in it, so I wouldn't really consider them failures, others are just failuers.

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

1.1.5 Obtain Pre-trained VGG-16 Model

```
In [10]: 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()
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /root/.torch/models/vgg
100%|| 553433881/553433881 [00:06<00:00, 81888608.70it/s]
```

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

1.1.6 Making Predictions with a Pre-trained Model

In the next code cell, I'll 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.

```
In [1]: from PIL import Image
        import torchvision.transforms as transforms

        def VGG16_predict(img_path):
            img = Image.open(img_path)
            transform = transforms.Compose([transforms.CenterCrop(224),
                                            transforms.ToTensor(),
                                            transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                            std=[0.229, 0.224, 0.225])
                                            ])
            img = transform(img)
            img = torch.unsqueeze(img,0)
            output = VGG16(img)
            _, pred = torch.max(output, 1)

            return pred
```

1.1.7 Write a Dog Detector

```
In [13]: ### returns "True" if a dog is detected in the image stored at img_path
         def dog_detector(img_path):
             ## TODO: Complete the function.
             pred_class = VGG16_predict(img_path)
             if pred_class >= 151 and pred_class <= 268:
                 return True
             else:
                 return False
```

1.1.8 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:
90 % of dogs images are detected as dogs
1 % of humen images are detected as dogs

In [14]:
```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
d_counter = 0
h_counter = 0
for i in dog_files_short:
    if dog_detector(i) == True: d_counter += 1
for i in human_files_short:
    if dog_detector(i) == True: h_counter += 1

print(d_counter,"% of dogs images are detected as dogs")
print(h_counter,"% of humen images are detected as dogs")
```

```
90 % of dogs images are detected as dogs
1 % of humen images are detected as dogs
```

Step 3: Create a CNN to Classify Dog Breeds (from Scratch)
In this step I will create CNN to classify dog Breeds from scratch

In [17]:
```
import os
from torchvision import datasets
## TODO: Specify data loaders
import numpy as np
import torch
import torchvision
import torchvision.transforms as transforms
import torch.optim as optim
from torchvision import datasets

use_cuda = torch.cuda.is_available()
num_workers = 0
batch_size = 20
transform ={'train': transforms.Compose([transforms.RandomResizedCrop(224),
                                 transforms.RandomRotation(25),
                                transforms.ToTensor(),
                                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                std=[0.229, 0.224, 0.225]),
                                ]),
                              'valid':transforms.Compose([transforms.CenterCrop(224),
                                transforms.ToTensor(),
                                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                std=[0.229, 0.224, 0.225])
                                ]),
```

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

dog_train = datasets.ImageFolder(root='/data/dog_images/train',transform=transform['tra
dog_valid = datasets.ImageFolder(root='/data/dog_images/valid',transform=transform['val
dog_test = datasets.ImageFolder(root='/data/dog_images/test',transform=transform['test'



train_loader = torch.utils.data.DataLoader(dog_train, batch_size=batch_size, num_worker
valid_loader = torch.utils.data.DataLoader(dog_valid, batch_size=batch_size, num_worker
test_loader = torch.utils.data.DataLoader(dog_test, batch_size=batch_size, num_workers=

loaders = {'train':train_loader,
           'valid': valid_loader,
           'test': test_loader}
```

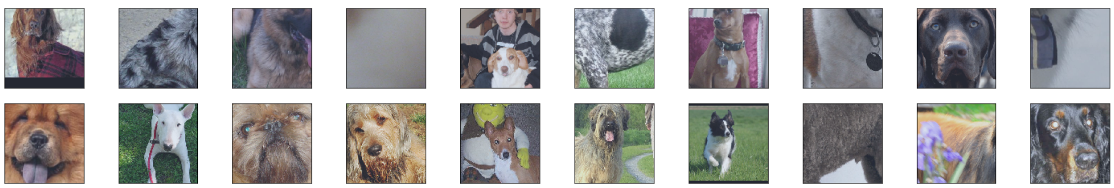
1.1.9 Display some of the images from the loader.

In [24]:
```
import matplotlib.pyplot as plt
%matplotlib inline

# helper function to un-normalize and display an image
def imshow(img):
    img = (1/(2*3)) * img + 0.5  # unnormalize
    plt.imshow(np.transpose(img, (1, 2, 0)))  # convert from Tensor image
```

In [25]:
```
# obtain one batch of training images
dataiter = iter(train_loader)
images, labels = dataiter.next()
images = images.numpy()
# convert images to numpy for display

# plot the images in the batch, along with the corresponding labels
fig = plt.figure(figsize=(25, 4))
# display 20 images
for idx in np.arange(20):
    ax = fig.add_subplot(2, 20/2, idx+1, xticks=[], yticks=[])
    imshow(images[idx])
```

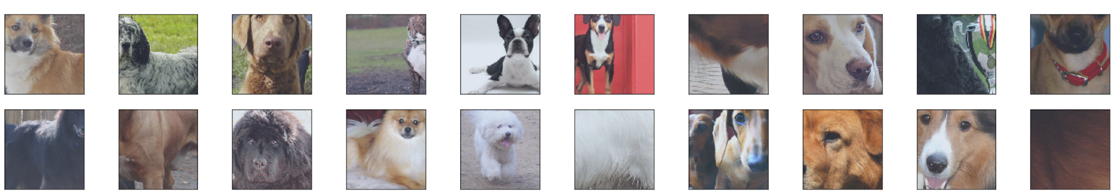
In [26]:

```
# obtain one batch of training images
dataiter = iter(valid_loader)
images, labels = dataiter.next()
images = images.numpy()
# convert images to numpy for display

# plot the images in the batch, along with the corresponding labels
fig = plt.figure(figsize=(25, 4))
# display 20 images
for idx in np.arange(20):
    ax = fig.add_subplot(2, 20/2, idx+1, xticks=[], yticks=[])
    imshow(images[idx])
```



In [27]:

```
# obtain one batch of training images
dataiter = iter(test_loader)
images, labels = dataiter.next()
images = images.numpy()
# convert images to numpy for display

# plot the images in the batch, along with the corresponding labels
fig = plt.figure(figsize=(25, 4))
# display 20 images
for idx in np.arange(20):
    ax = fig.add_subplot(2, 20/2, idx+1, xticks=[], yticks=[])
    imshow(images[idx])
```



In [28]:

```
print(len(train_loader))
print(len(valid_loader))
```

```
334
42
```

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 did a random resize chop to size 224, also I normalize it to fit VGG because I am planning to use it for prediction. - I did a random chop and rotation to help the NN accuracy, because image data augmentation proved to help the training.

1.1.10 Model Architecture

Create a CNN to classify dog breed.

```
In [2]: # define the CNN architecture3
        import torch
        import torch.nn as nn
        import torch.nn.functional as F
        class Net(nn.Module):
            ### TODO: choose an architecture, and complete the class
            def __init__(self):
                super(Net, self).__init__()

                ## Define layers of a CNN
                # input: 224*224*3
                self.conv1 = nn.Conv2d(3, 16, 3, padding = 1 ) #224*224*16
                self.pool = nn.MaxPool2d(2, 2)
                #pool: 112*112*16
                self.conv2 = nn.Conv2d(16, 32, 3, padding = 1) #112*112*32
                #pool: 56*56*16
                self.conv3 = nn.Conv2d(32, 64, 3, padding = 1) #56*56*64
                #pool: 32*32*64
                self.conv4 = nn.Conv2d(64, 128, 3, padding = 1) #28*28*128
                #pool: 14*14*128

                #FCL
                self.fc1 = nn.Linear(14*14*128, 133)

            def forward(self, x):
                ## Define forward behavior
                # add sequence of convolutional and max pooling layers
                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 = self.pool(F.relu(self.conv4(x)))

            # flatten image input
            x = x.view(-1, 14*14*128)
            # add dropout layer
            # add second hidden layer
            x = self.fc1(x)

            return x



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

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

```
Net(
  (conv1): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv4): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (fc1): Linear(in_features=25088, out_features=133, bias=True)
)
```

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

Answer: I started with 4 conventional layers and maxpooling layer after each layer, and 1 fully-connected layer to predect one of the 133 classes

1.1.11 Specify Loss Function and Optimizer

in the next cell, I'll specify a loss function and optimizer.

```
In [3]: import torch.optim as optim


        criterion_scratch = nn.CrossEntropyLoss()


        optimizer_scratch = optim.SGD(model_scratch.parameters(), lr=0.025)
```

```
In [31]: loaders = {'train':train_loader,
                    'valid': valid_loader,
                    'test': test_loader}
```

1.1.12 Train and Validate the Model

```
In [32]: from PIL import ImageFile
         ImageFile.LOAD_TRUNCATED_IMAGES = True

         def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):

             # 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.to('cuda'), target.to('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_lo

                     # clear the gradients of all optimized variables
                     optimizer.zero_grad()
                     # forward pass: compute predicted outputs by passing inputs to the model
                     output = model(data)
                     # calculate the batch loss
                     loss = criterion(output, target)
                     # backward pass: compute gradient of the loss with respect to model paramet
                     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)

                 ######################
                 # validate the model #
                 ######################
                 model.eval()
```

```
            for batch_idx, (data, target) in enumerate(loaders['valid']):
                # move to GPU
                if use_cuda:
                    data, target = data.to('cuda'), target.to('cuda')
                ## update the average validation loss
                # forward pass: compute predicted outputs by passing inputs to the model
                output = model(data)
                # calculate the batch loss
                loss = criterion(output, target)
                # update 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('Validation loss decreased ({:.6f} --> {:.6f}).  Saving model ...'.fo
                valid_loss_min,
                valid_loss))
                torch.save(model.state_dict(), save_path)
                valid_loss_min = valid_loss

        # return trained model
        return model
```

In [314]:
```
# train the model
model_scratch = train(21, loaders, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'mode1l_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: 3.817332        Validation Loss: 3.994675
Validation loss decreased (inf --> 3.994675).  Saving model ...
Epoch: 2         Training Loss: 3.767670        Validation Loss: 4.002237
Epoch: 3         Training Loss: 3.691598        Validation Loss: 4.006469
Epoch: 4         Training Loss: 3.652674        Validation Loss: 4.114274
Epoch: 5         Training Loss: 3.585432        Validation Loss: 4.027638
Epoch: 6         Training Loss: 3.527893        Validation Loss: 4.073727
Epoch: 7         Training Loss: 3.482253        Validation Loss: 4.027990
Epoch: 8         Training Loss: 3.416155        Validation Loss: 4.055351
Epoch: 9         Training Loss: 3.377621        Validation Loss: 3.963725
```

```
Validation loss decreased (3.994675 --> 3.963725).  Saving model ...
Epoch: 10 	Training Loss: 3.324858 	Validation Loss: 4.006460
Epoch: 11 	Training Loss: 3.275381 	Validation Loss: 4.033025
Epoch: 12 	Training Loss: 3.233689 	Validation Loss: 4.005313
Epoch: 13 	Training Loss: 3.190840 	Validation Loss: 4.095656
Epoch: 14 	Training Loss: 3.157285 	Validation Loss: 4.290526
Epoch: 15 	Training Loss: 3.136892 	Validation Loss: 4.028389
Epoch: 16 	Training Loss: 3.065481 	Validation Loss: 4.106514
Epoch: 17 	Training Loss: 3.014201 	Validation Loss: 4.225411
Epoch: 18 	Training Loss: 2.967736 	Validation Loss: 4.007470
Epoch: 19 	Training Loss: 2.947862 	Validation Loss: 4.100077
Epoch: 20 	Training Loss: 2.930635 	Validation Loss: 4.169955
Epoch: 21 	Training Loss: 2.857903 	Validation Loss: 4.058319
```

```
In [33]: model_scratch.load_state_dict(torch.load('model_scratch.pt'))
```

1.1.13 Test the Model

```
In [315]: def test(loaders, model, criterion, use_cuda):

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

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

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

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

In [316]:
```
# call test function
test(loaders, model_scratch, criterion_scratch, use_cuda)
```

```
Test Loss: 3.990614


Test Accuracy: 13% (117/836)
```

Step 4: Create a CNN to Classify Dog Breeds (using Transfer Learning)
Create CNN to predict dog breeds but this time using transfer learning

In [35]:
```
import numpy as np
import torch
import torchvision
import torchvision.transforms as transforms
import torch.optim as optim
from torchvision import datasets

use_cuda = torch.cuda.is_available()
num_workers = 0
batch_size = 20
transform ={'train': transforms.Compose([transforms.RandomResizedCrop(224),
                                  transforms.RandomRotation(25),
                                 transforms.ToTensor(),
                                 transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225]),
                                 ]),
                                'valid':transforms.Compose([transforms.CenterCrop(224),
                                 transforms.ToTensor(),
                                 transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
                                 ]),
                                'test':transforms.Compose([transforms.CenterCrop(224),
                                 transforms.ToTensor(),
                                 transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
                                 ])}

dog_train = datasets.ImageFolder(root='/data/dog_images/train',transform=transform['tra
dog_valid = datasets.ImageFolder(root='/data/dog_images/valid',transform=transform['val
dog_test = datasets.ImageFolder(root='/data/dog_images/test',transform=transform['test'



train_loader = torch.utils.data.DataLoader(dog_train, batch_size=batch_size, num_worker
valid_loader = torch.utils.data.DataLoader(dog_valid, batch_size=batch_size, num_worker
```

```
test_loader = torch.utils.data.DataLoader(dog_test, batch_size=batch_size, num_workers=

loaders = {'train':train_loader,
           'valid': valid_loader,
           'test': test_loader}
```

1.1.14 (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 [36]: import torchvision.models as models
         import torch.nn as nn


         model_transfer = models.vgg19(pretrained=True) # load the model pretrained to save time
```

```
Downloading: "https://download.pytorch.org/models/vgg19-dcbb9e9d.pth" to /root/.torch/models/vgg
100%|| 574673361/574673361 [00:12<00:00, 44288126.06it/s]
```

```
In [37]: print(model_transfer.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=1000, bias=True)
)
```

```
In [38]: for x in model_transfer.features.parameters():
             x.requires_grad = False #stop the training from changing the weights of the feature
```

```
In [39]: # remove the last layer in the classifier
         model_transfer.classifier = nn.Sequential(*list(model_transfer.classifier.children())[:
```

```
In [40]: model_transfer.classifier
```

```
Out[40]: 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)
         )
```

```
In [41]: model_transfer.classifier.add_module("6", nn.Linear(4096,133)) # add new last layer wit
```

```
In [42]: model_transfer
```

```
Out[42]: 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): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (17): ReLU(inplace)
             (18): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
             (19): Conv2d(256, 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): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (24): ReLU(inplace)
             (25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (26): ReLU(inplace)
             (27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
             (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (29): ReLU(inplace)
             (30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (31): ReLU(inplace)
             (32): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (33): ReLU(inplace)
             (34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
             (35): ReLU(inplace)
             (36): 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: I choose VGG19 to do the dog's breed image classification, I stopped the grads from changing in the feature level, and I change the last fully-connected layer to predict 133 class instead of 1000 class.

1.1.15 Specify Loss Function and Optimizer

```
In [43]: criterion_transfer = nn.CrossEntropyLoss()
         optimizer_transfer = optim.SGD(model_transfer.classifier.parameters(), lr= 0.0025)
```

1.1.16 Train and Validate the Model

```
In [44]: if use_cuda:
             model_transfer = model_transfer.to('cuda')
         print(use_cuda)
```

```
True
```

```
In [ ]: # train the model
        model_transfer =  train(25, loaders, model_transfer, optimizer_transfer, criterion_trans

        # 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: 3.556074         Validation Loss: 1.790756
Validation loss decreased (inf --> 1.790756).  Saving model ...
Epoch: 2         Training Loss: 1.952480         Validation Loss: 1.182509
Validation loss decreased (1.790756 --> 1.182509).  Saving model ...
Epoch: 3         Training Loss: 1.585505         Validation Loss: 1.038430
Validation loss decreased (1.182509 --> 1.038430).  Saving model ...
Epoch: 4         Training Loss: 1.459008         Validation Loss: 0.964366
Validation loss decreased (1.038430 --> 0.964366).  Saving model ...
Epoch: 5         Training Loss: 1.351333         Validation Loss: 0.935441
Validation loss decreased (0.964366 --> 0.935441).  Saving model ...
Epoch: 6         Training Loss: 1.319573         Validation Loss: 0.901578
Validation loss decreased (0.935441 --> 0.901578).  Saving model ...
Epoch: 7         Training Loss: 1.275779         Validation Loss: 0.888911
Validation loss decreased (0.901578 --> 0.888911).  Saving model ...
Epoch: 8         Training Loss: 1.219185         Validation Loss: 0.879810
Validation loss decreased (0.888911 --> 0.879810).  Saving model ...
```

```
Epoch: 9        Training Loss: 1.195473        Validation Loss: 0.865470
Validation loss decreased (0.879810 --> 0.865470).  Saving model ...
```

1.1.17 Test the Model

```
In [45]: model_transfer.load_state_dict(torch.load('model_transfer.pt'))
```

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

```
Test Loss: 0.915118


Test Accuracy: 74% (626/836)
```

```
In [296]: # 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 dog_train.classes]

          def predict_breed_transfer(img_path):
              img = Image.open(img_path)
              transform = transforms.Compose([transforms.CenterCrop(224),
                                             transforms.ToTensor(),
                                             transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                             std=[0.229, 0.224, 0.225])
                                             ])
              img = transform(img)
              img = torch.unsqueeze(img,0)
              if use_cuda:
                              img = img.to('cuda')
              output = model_transfer(img)
              _, pred = torch.max(output, 1)
              output = class_names[pred]


              return print(output.replace("'",""), end=" ")
```

Step 5: Write your Algorithm
Write algorithm that's return the following:

- 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.

1.1.18 Write your Algorithm

```
In [4]: def run_app(img_path):
            img = Image.open(img_path)
```

```
    plt.figure(figsize=(4,4))
    plt.imshow(img)
    plt.show()
    if face_detector(img_path) == True:
        print  ("A human face dedected, and it's looks like a",end=" "),predict_breed_tr
    elif dog_detector(img_path) == True:

        print("A dog dedected in the image and, it's breed is", end=" " ), predict_breed

    else:
        return print('The image has no human or dog in it.')
```

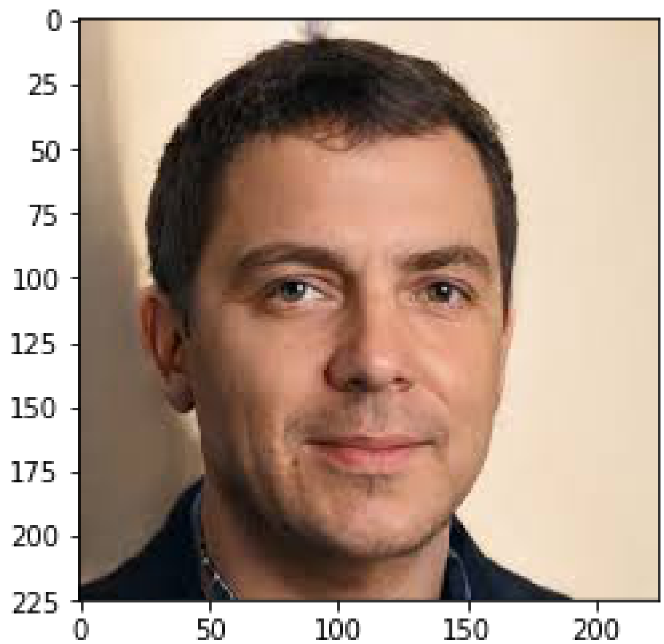
Step 6: Test Your Algorithm

1.1.19 Test Your Algorithm on Sample Images!

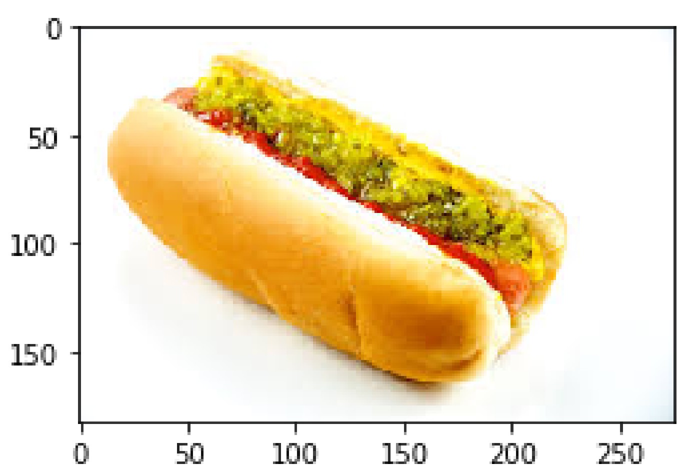
Question 6: Is the output better than you expected :) ? Or worse :(? Provide at least three possible points of improvement for your algorithm.
Answer:

- The training time is very short, I would train it more if I want a better result
- I need more images of dogs and human to improve the accuracy, what I have know is very small dataset.
- Test other models and compare the accuracy and pick the best one for this task.

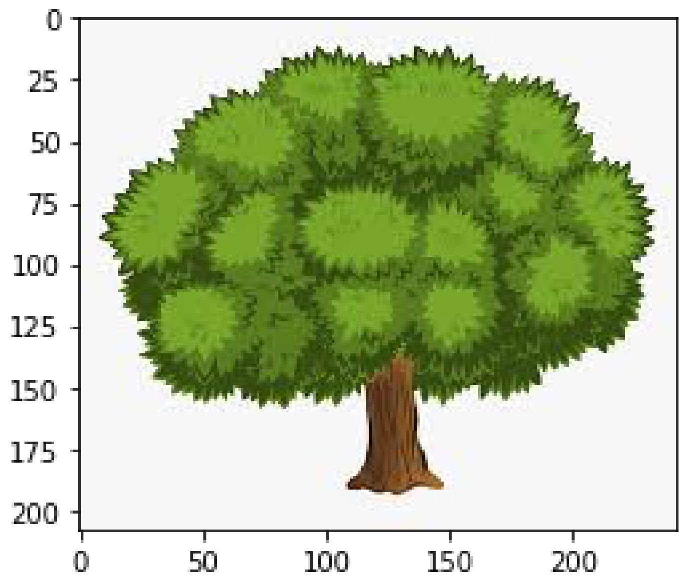
```
In [313]: image_dir = 'test_images/'
          image_path = os.listdir(test_image_dir)
          for file in image_path:
              file_path = image_dir + file
              run_app(file_path)
```



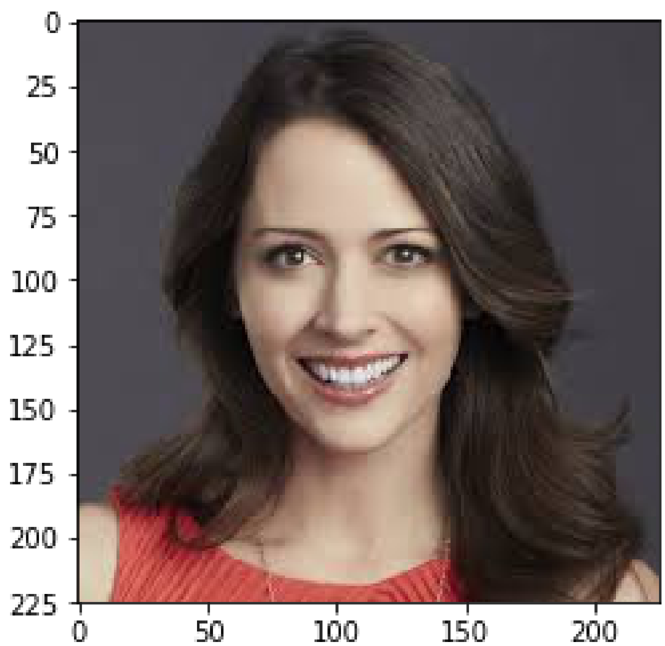
```
A human face dedected, and it's looks like a Basenji dog
```



```
The image has no human or dog in it.
```

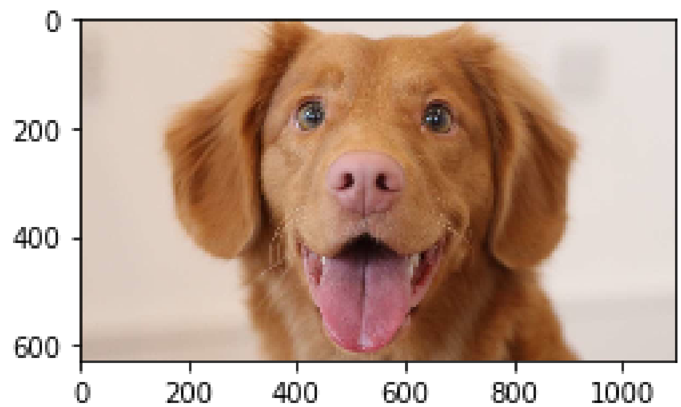



```
The image has no human or dog in it.
```




```
A human face dedected, and it's looks like a Papillon dog
```


```
A dog dedected in the image and, it's breed is Pomeranian
```




```
A human face dedected, and it's looks like a Nova scotia duck tolling retriever dog
```