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 (https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip). Unzip the folder and place it in this project's home directory, at the location `/dog_images` .
- Download the human dataset (https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/lfw.zip). 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 (http://www.7-zip.org/) to extract the folder.

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

In [1]:

```
import numpy as np
from glob import glob
import os
import torch
import torchvision
from torchvision import datasets
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision.models as models

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

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

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

In [2]:

```
!pip install pytorch-model-summary
```

```
Collecting pytorch-model-summary
  Downloading https://files.pythonhosted.org/packages/a0/de/f3548f3081045c
fc4020fc297cc9db74839a6849da8a41b89c48a3307da7/pytorch_model_summary-0.1.1
-py3-none-any.whl
Requirement already satisfied: torch in /opt/conda/lib/python3.6/site-pack
ages (from pytorch-model-summary) (0.4.0)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.6/site-packa
ges (from pytorch-model-summary) (4.11.2)
Requirement already satisfied: numpy in /opt/conda/lib/python3.6/site-pack
ages (from pytorch-model-summary) (1.12.1)
Installing collected packages: pytorch-model-summary
Successfully installed pytorch-model-summary-0.1.1
```

In [2]:

```python
import os
import random
import requests
import time
import ast
import numpy as np
from glob import glob
import cv2
from tqdm import tqdm
from PIL import Image, ImageFile

import matplotlib.pyplot as plt
%matplotlib inline


ImageFile.LOAD_TRUNCATED_IMAGES = True

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

Step 1: Detect Humans

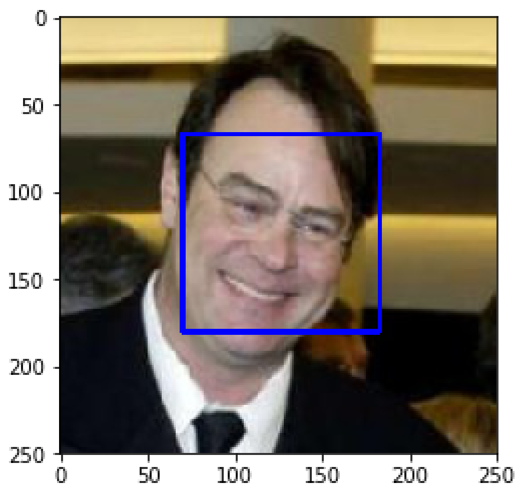
In this section, we use OpenCV's implementation of Haar feature-based cascade classifiers (http://docs.opencv.org/trunk/d7/d8b/tutorial_py_face_detection.html) to detect human faces in images.

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

In [47]:

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

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

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

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

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

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

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

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

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



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

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

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

In [48]:

```
# 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:

Detected human faces (LBP): 98 Detected human faces (LBP): 98%

Detected faces in dogs(LBP): 17 Detected faces in dogs(LBP): 17%

In [49]:

```
# 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.
detected_faces_in_humans = 0
detected_faces_in_dogs = 0

for ii in range(100):
    if face_detector(human_files_short[ii]):
        detected_faces_in_humans += 1
    if face_detector(dog_files_short[ii]):
        detected_faces_in_dogs +=1

print (f"Detected human faces (LBP): {detected_faces_in_humans}\t",f"Detected human fac
es (LBP): {detected_faces_in_humans}%")
print (f"Detected faces in dogs(LBP): {detected_faces_in_dogs}\t",f"Detected faces in d
ogs(LBP): {detected_faces_in_dogs}%\n")
```

```
Detected human faces (LBP): 98   Detected human faces (LBP): 98%
Detected faces in dogs(LBP): 17  Detected faces in dogs(LBP): 17%
```

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

In [7]:

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

Step 2: Detect Dogs

In this section, we use a pre-trained model (http://pytorch.org/docs/master/torchvision/models.html) 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 (http://www.image-net.org/), 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 (https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a).

In [50]:

```
import torch
import torchvision.models as models

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

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

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

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth" to /
root/.torch/models/vgg16-397923af.pth
100%|██████████| 553433881/553433881 [00:23<00:00, 23151245.82it/s]
```

In [51]:

```
def image_to_tensor(img_path):
    img = Image.open(img_path).convert('RGB')
    transformations = transforms.Compose([transforms.Resize(size=224),
                                          transforms.CenterCrop((224,224)),
                                         transforms.ToTensor(),
                                         transforms.Normalize(mean=[0.485, 0.456, 0.406
],
                                                                     std=[0.229, 0.224, 0.225
])])
    image_tensor = transformations(img)[:3,:,:].unsqueeze(0)
    return image_tensor


# helper function for un-normalizing an image  - from STYLE TRANSFER exercise
# and converting it from a Tensor image to a NumPy image for display
def im_convert(tensor):
    """ Display a tensor as an image. """

    image = tensor.to("cpu").clone().detach()
    image = image.numpy().squeeze()
    image = image.transpose(1,2,0)
    image = image * np.array((0.229, 0.224, 0.225)) + np.array((0.485, 0.456, 0.406))
    image = image.clip(0, 1)

    return image
```

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 (http://pytorch.org/docs/stable/torchvision/models.html).

In [52]:

```
from PIL import Image
import torchvision.transforms as transforms

def VGG16_predict(img_path):

    image_tensor = image_to_tensor(img_path)

    # move model inputs to cuda, if GPU available
    if use_cuda:
        image_tensor = image_tensor.cuda()

    # get sample outputs
    output = VGG16(image_tensor)
    # convert output probabilities to predicted class
    _, preds_tensor = torch.max(output, 1)
    pred = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tenso
r.cpu().numpy())
    return int(pred)

def get_human_readable_label_for_class_id(class_id):
    labels = ast.literal_eval(requests.get(LABELS_MAP_URL).text)
#     print(f"Label:{labels[class_id]}")
    return labels[class_id]



LABELS_MAP_URL = "https://gist.githubusercontent.com/yrevar/942d3a0ac09ec9e5eb3a/raw/c2
c91c8e767d04621020c30ed31192724b863041/imagenet1000_clsid_to_human.txt"
data=sorted(glob("/data/dog_images/test/*/*"))
for i in data[100:]:
    test_prediction = VGG16_predict(i)
    pred_class = int(test_prediction)
    print(f"\n\n NAME: {i[:-10]}",f"Predicted class id: {pred_class}")
    class_description = get_human_readable_label_for_class_id(pred_class)
    break
#     print(f"Predicted class for image is *** {class_description.upper()} ***\n\n")
# test_prediction = VGG16_predict('/data/dog_images/train/001.Affenpinscher/Affenpinsch
er_00001.jpg')
# pred_class = int(test_prediction)
# print(f"\n\n NAME: {i[:-10]}",f"Predicted class id: {pred_class}")
# class_description = get_human_readable_label_for_class_id(pred_class)
```

```
 NAME: /data/dog_images/test/014.Basenji/Basenji Predicted class id: 253
```

In [53]:

```
test_prediction = VGG16_predict('/data/dog_images/train/001.Affenpinscher/Affenpinscher
_00001.jpg')
pred_class = int(test_prediction)
print(f"Predicted class id: {pred_class}")
class_description = get_human_readable_label_for_class_id(pred_class)
print(class_description)
```

```
Predicted class id: 252
affenpinscher, monkey pinscher, monkey dog
```

(IMPLEMENTATION) Write a Dog Detector

While looking at the dictionary (https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a), you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all categories from `'Chihuahua'` to `'Mexican hairless'`. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

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

In [54]:

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

    prediction = VGG16_predict(img_path)
    return ((prediction >= 151) & (prediction <=268))
```

(IMPLEMENTATION) Assess the Dog Detector

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

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

Answer:

Percentage of the images in human_files_short that have a detected dog: 0% Percentage of the images in dog_files_short that have a detected dog: 100%

In [55]:

```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.

detected_dogs_in_humans = 0
detected_dogs_in_dogs = 0

for ii in range(100):
    if dog_detector(human_files_short[ii]):
        detected_dogs_in_humans += 1
        print(f"This human ({ii}) looks like a dog")
#          human_dog_image = Image.open(human_files_short[ii])
#          plt.imshow(human_dog_image)
#          plt.show()
    if dog_detector(dog_files_short[ii]):
        detected_dogs_in_dogs +=1

print (f"Percentage of the images in human_files_short that have a detected dog: {detec
ted_dogs_in_humans}%")
print (f"Percentage of the images in dog_files_short that have a detected dog: {detecte
d_dogs_in_dogs}%")
```

```
Percentage of the images in human_files_short that have a detected dog: 0%
Percentage of the images in dog_files_short that have a detected dog: 100%
```

We suggest VGG-16 as a potential network to detect dog images in your algorithm, but you are free to explore other pre-trained networks (such as [Inception-v3 (http://pytorch.org/docs/master/torchvision/models.html#inception-v3)](http://pytorch.org/docs/master/torchvision/models.html#inception-v3), [ResNet-50 (http://pytorch.org/docs/master/torchvision/models.html#id3)](http://pytorch.org/docs/master/torchvision/models.html#id3), etc). Please use the code cell below to test other pre-trained PyTorch models. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short` .

In [14]:

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

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

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

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

Brittany	Welsh Springer Spaniel

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

Curly-Coated Retriever	American Water Spaniel

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

Yellow Labrador	Chocolate Labrador	Black Labrador

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 (http://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader) 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 (http://pytorch.org/docs/stable/torchvision/datasets.html) to be a useful resource. If you are interested in augmenting your training and/or validation data, check out the wide variety of transforms (http://pytorch.org/docs/stable/torchvision/transforms.html?highlight=transform)!

In [10]:

```
import os
import torch
import torchvision
from torchvision import datasets
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision.models as models

import matplotlib.pyplot as plt
%matplotlib inline

ImageFile.LOAD_TRUNCATED_IMAGES = True

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

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

batch_size = 8

num_workers = 1

transform = transforms.Compose([transforms.Resize(size=224),
                                transforms.CenterCrop((224,224)),
                                transforms.RandomHorizontalFlip(), # randomly flip and
 rotate
                                transforms.RandomRotation(10),
                                transforms.ToTensor(),
                                transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[
0.229, 0.224, 0.225])])

data_dir = '/data/dog_images/'

image_datasets = {x: datasets.ImageFolder(os.path.join(data_dir, x), transform)
                  for x in ['train', 'valid', 'test']}
loaders_scratch = {
    x: torch.utils.data.DataLoader(image_datasets[x], shuffle=True, batch_size=batch_si
ze, num_workers=num_workers)
    for x in ['train', 'valid', 'test']}
```

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:

Data loaded into the training, test and validation data

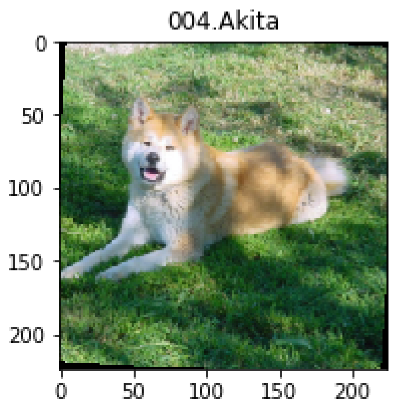
Resized all image to 320 x 320 and center cropped

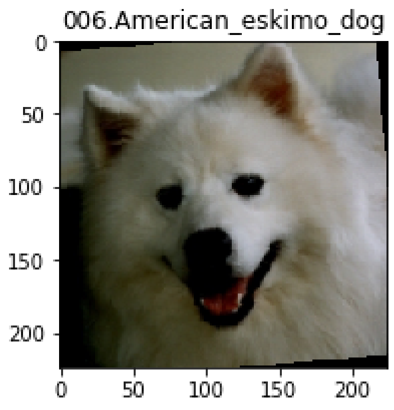
(320, 320, 3) images in this tesing so the inputs are larger than usual dataset.

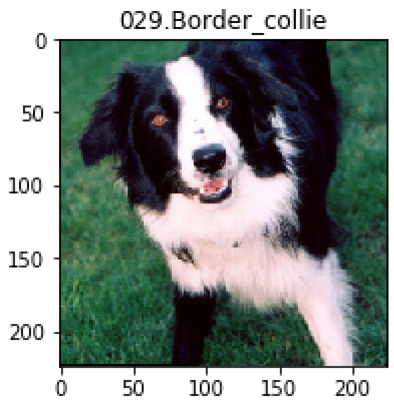
Each color channel was normalized separately, the means are [0.485, 0.456, 0.406] and the standard deviations are [0.229, 0.224, 0.225].

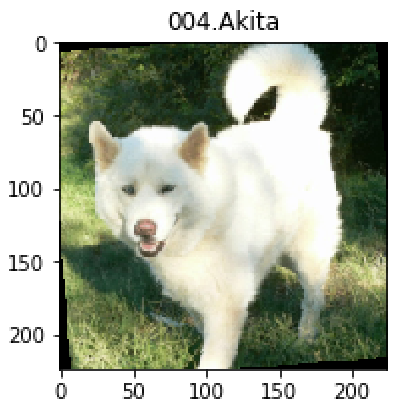
In [38]:

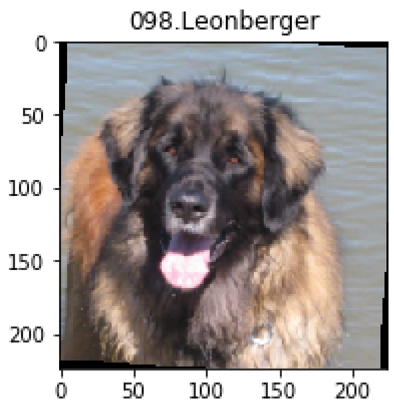
```
class_names = image_datasets['train'].classes
nb_classes = len(class_names)
inputs, classes = next(iter(loaders_scratch['train']))

for image, label in zip(inputs, classes):
    image = image.to("cpu").clone().detach()
    image = image.numpy().squeeze()
    image = image.transpose(1,2,0)
    image = image * np.array((0.229, 0.224, 0.225)) + np.array((0.485, 0.456, 0.406))
    image = image.clip(0, 1)

    fig = plt.figure(figsize=(12,3))
    plt.imshow(image)
    plt.title(class_names[label])
```

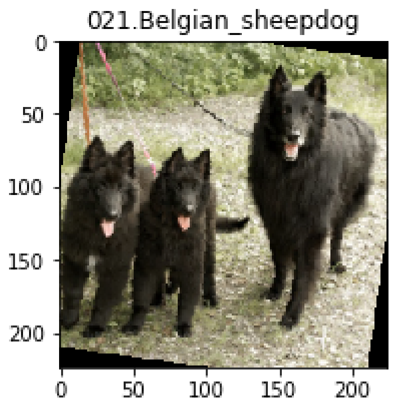

004.Akita
0
50
100
150
200
0
50
100
150
200

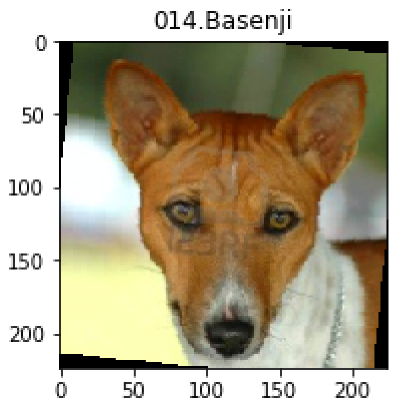

006.American_eskimo_dog
0
50
100
150
200
0
50
100
150
200

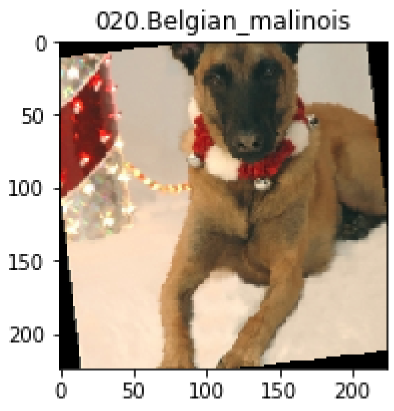

029.Border_collie
0
50
100
150
200
0
50
100
150
200


004.Akita
0
50
100
150
200
0
50
100
150
200









(IMPLEMENTATION) Model Architecture

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

In [21]:

```
import torch.nn as nn
import torch.nn.functional as F
# from pytorch_model_summary import summary

# define the CNN architecture
class Net(nn.Module):
    ### TODO: choose an architecture, and complete the class
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(3, 16, 3, padding=1)
        self.conv2 = nn.Conv2d(16, 32, 3, padding=1)
        self.conv3 = nn.Conv2d(32, 64, 3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.fc1 = nn.Linear(64*28*28, 500)
        self.fc2 = nn.Linear(500, 133)
        self.dropout = nn.Dropout(0.33)
        self.batch_norm = nn.BatchNorm1d(num_features=500)


    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.dropout(x)

        x = self.pool(F.relu(self.conv2(x)))
        x = self.dropout(x)

        x = self.pool(F.relu(self.conv3(x)))
        x = self.dropout(x)

        x = x.view(x.size(0), -1)

        x = F.relu(self.batch_norm(self.fc1(x)))
        x = self.dropout(x)
        x = self.fc2(x)

        return x

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

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

# print(summary(Net(), torch.zeros((320, 320,3)), show_input=True))

# 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))
  (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))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_m
ode=False)
  (fc1): Linear(in_features=50176, out_features=500, bias=True)
  (fc2): Linear(in_features=500, out_features=133, bias=True)
  (dropout): Dropout(p=0.33)
  (batch_norm): BatchNorm1d(500, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
)
```

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

Answer:

First layer has input shape of (320, 320, 3) and last layer should output 133 classes.

Convolutional layers (stack of filtered images) and Maxpooling layers(reduce the x-y size of an input, keeping only the most active pixels from the previous layer) as well as the usual Linear + Dropout layers to avoid overfitting and produce a 133-dim output.

MaxPooling2D seems to be a common choice to downsample in these type of classification problems and that is why I chose it.

To filter to jump 1 pixel at a time.

nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0)

Then, to construct this convolutional layer, I would use the following line of code: self.conv2 = nn.Conv2d(3, 32, 3, padding=1)

Pool layer that takes in a kernel_size and a stride after every convolution layer. This will down-sample the input's x-y dimensions, by a factor of 2:

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

I am adding a fully connected Linear Layer to produce a 133-dim output. As well as a Dropout layer to avoid overfitting.

Forward pass would give:

torch.Size([16, 3, 320, 320]) torch.Size([16, 16, 160, 160]) torch.Size([16, 32, 80, 80]) torch.Size([16, 64, 40, 40]) torch.Size([16, 50176]) torch.Size([16, 500]) torch.Size([16, 133])

(IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a [loss function (http://pytorch.org/docs/stable/nn.html#loss-functions)](http://pytorch.org/docs/stable/nn.html#loss-functions) and [optimizer (http://pytorch.org/docs/stable/optim.html)](http://pytorch.org/docs/stable/optim.html). Save the chosen loss function as `criterion_scratch` , and the optimizer as `optimizer_scratch` below.

In [22]:

```
import torch.optim as optim

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

### TODO: select optimizer
optimizer_scratch = optim.SGD(model_scratch.parameters(), lr = 0.05)
```

(IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters (http://pytorch.org/docs/master/notes/serialization.html) at filepath `'model_scratch.pt'` .

In [23]:

```
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
#             print(batch_idx)
            if use_cuda:
                data, target = data.cuda(), target.cuda()
            ## find the loss and update the model parameters accordingly
            ## record the average training loss, using something like
            ## train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_lo
ss))

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


        # 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

    # return trained model
    return model


# train the model
model_scratch = train(1, loaders_scratch, model_scratch, optimizer_scratch,
                      criterion_scratch, use_cuda, 'model_scratch.pt')
```

```
Epoch: 1        Training Loss: 0.000000         Validation Loss: 0.000000
```

In [24]:

```
# model_scratch.load_state_dict(torch.load('./model_scratch.pt'))
torch.save(model_scratch.state_dict(), 'model_scratch.pt')
```

In [27]:

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

(IMPLEMENTATION) Test the Model

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

In [28]:

```
def test(loaders, model, criterion, use_cuda):

    # monitor test loss and accuracy
    test_loss = 0.0
    correct = 0.0
    total = 0.0

    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: 4.890775


Test Accuracy:  1% (10/836)
```

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

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

(IMPLEMENTATION) Specify Data Loaders for the Dog Dataset

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

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

In [29]:

```
## TODO: Specify data loaders
loaders_transfer = loaders_scratch
print(loaders_transfer)
```

```
{'train': <torch.utils.data.dataloader.DataLoader object at 0x7f87bd24e358
>, 'valid': <torch.utils.data.dataloader.DataLoader object at 0x7f87bd264c
50>, 'test': <torch.utils.data.dataloader.DataLoader object at 0x7f87bd665
6d8>}
```

(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 [30]:

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

## TODO: Specify model architecture
model_transfer = models.resnet50(pretrained=True)
# Freeze parameters so we don't backprop through them
for param in model_transfer.parameters():
    param.requires_grad = False
# Replace the last fully connected layer with a Linnear layer with 133 out features
model_transfer.fc = nn.Linear(2048, 133)
if use_cuda:
    model_transfer = model_transfer.cuda()
```

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:

ResNet as a transfer model because it performed outstanding on Image Classification. ResNet have perfect layer structure with convolution and activation function to extract features gradually. just need to transfer final output layer for required no outputs as 133 dog breeds.

(fc): Linear(in_features=2048, out_features=133, bias=True)

(IMPLEMENTATION) Specify Loss Function and Optimizer

Use the next code cell to specify a loss function (http://pytorch.org/docs/master/nn.html#loss-functions) and optimizer (http://pytorch.org/docs/master/optim.html). Save the chosen loss function as `criterion_transfer` , and the optimizer as `optimizer_transfer` below.

In [34]:

```
criterion_transfer = nn.CrossEntropyLoss()
optimizer_transfer = optim.Adam(model_transfer.fc.parameters(), lr=0.005)
```

(IMPLEMENTATION) Train and Validate the Model

Train and validate your model in the code cell below. Save the final model parameters (http://pytorch.org/docs/master/notes/serialization.html) at filepath `'model_transfer.pt'` .

In [35]:

```
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()

            # initialize weights to zero
            optimizer.zero_grad()

            output = model(data)

            # calculate loss
            loss = criterion(output, target)

            # back prop
            loss.backward()

            # grad
            optimizer.step()

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


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

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

    # return trained model
    return model
```

In [36]:

```
# train the model
# train the model
model_transfer =  train(2, loaders_transfer, model_transfer, optimizer_transfer, criter
ion_transfer, use_cuda, 'model_transfer.pt')
```

```
Epoch 1, Batch 1 loss: 4.944936
Epoch 1, Batch 101 loss: 5.052818
Epoch 1, Batch 201 loss: 4.031952
Epoch 1, Batch 301 loss: 3.440007
Epoch 1, Batch 401 loss: 3.062503
Epoch 1, Batch 501 loss: 2.795802
Epoch 1, Batch 601 loss: 2.600297
Epoch 1, Batch 701 loss: 2.441255
Epoch 1, Batch 801 loss: 2.305764
Epoch: 1        Training Loss: 2.272491         Validation Loss: 0.836627
Validation loss decreased (inf --> 0.836627).  Saving model ...
Epoch 2, Batch 1 loss: 0.958345
Epoch 2, Batch 101 loss: 1.011053
Epoch 2, Batch 201 loss: 1.028527
Epoch 2, Batch 301 loss: 1.069919
Epoch 2, Batch 401 loss: 1.105675
Epoch 2, Batch 501 loss: 1.101217
Epoch 2, Batch 601 loss: 1.077997
Epoch 2, Batch 701 loss: 1.080276
Epoch 2, Batch 801 loss: 1.075158
Epoch: 2        Training Loss: 1.077895         Validation Loss: 0.739235
Validation loss decreased (0.836627 --> 0.739235).  Saving model ...
```

(IMPLEMENTATION) Test the Model

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

In [37]:

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

```
Test Loss: 0.773312


Test Accuracy: 77% (649/836)
```

In [59]:

```
torch.save(model_transfer.state_dict(), 'model_Trnsfer_Learning.pt')
```

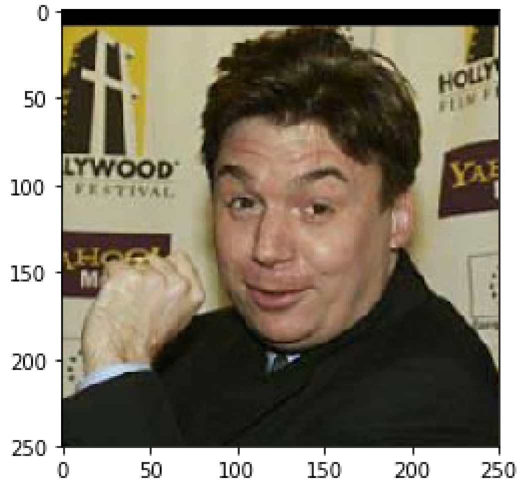
(IMPLEMENTATION) Predict Dog Breed with the Model

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

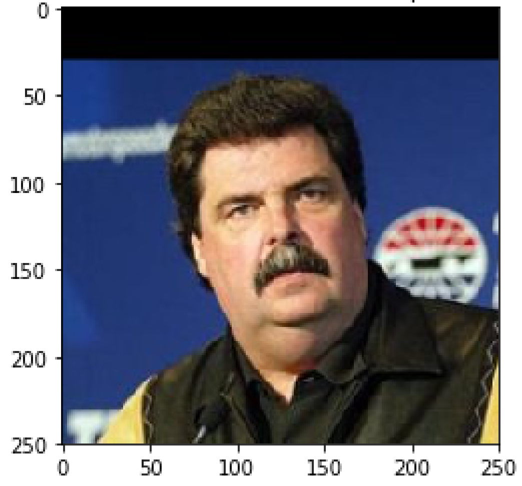
In [41]:

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

# list of class names by index, i.e. a name can be accessed like class_names[0]
class_names = [item[4:].replace("_", " ") for item in  image_datasets['train'].classes]

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

    # move model inputs to cuda, if GPU available
    if use_cuda:
        image_tensor = image_tensor.cuda()

    # get sample outputs
    output = model_transfer(image_tensor)
    # convert output probabilities to predicted class
    _, preds_tensor = torch.max(output, 1)
    pred = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tenso
r.cpu().numpy())

    return class_names[pred]

def display_image(img_path, title="Title"):
    image = Image.open(img_path)
    plt.title(title)
    plt.imshow(image)
    plt.show()

import random

# Try out the function
for image in random.sample(list(human_files_short), 4):
    predicted_breed = predict_breed_transfer(image)
    display_image(image, title=f"Predicted:{predicted_breed}")
```

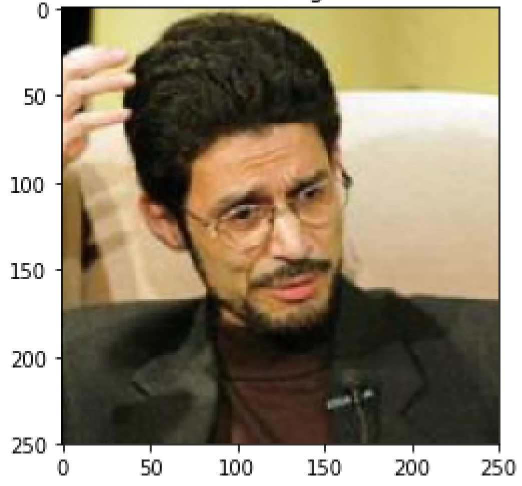
Predicted:Chinese crested

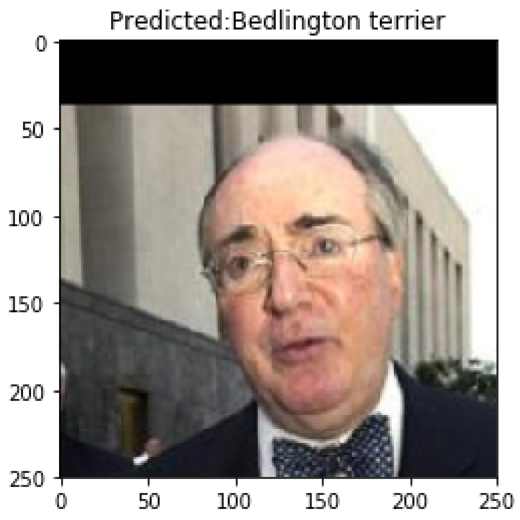


Predicted:American water spaniel



Predicted:Bedlington terrier





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!

Sample Human Output

(IMPLEMENTATION) Write your Algorithm

In [56]:

```
### Feel free to use as many code cells as needed.

def run_app(img_path):
    # check if image has juman faces:
    if (face_detector(img_path)):
        print("Hello Human!")
        predicted_breed = predict_breed_transfer(img_path)
        display_image(img_path, title=f"Predicted:{predicted_breed}")

        print("You look like a ...")
        print(predicted_breed.upper())
    # check if image has dogs:
    elif dog_detector(img_path):
        print("Hello Doggie!")
        predicted_breed = predict_breed_transfer(img_path)
        display_image(img_path, title=f"Predicted:{predicted_breed}")

        print("Your breed is most likley ...")
        print(predicted_breed.upper())
    else:
        print("Oh, we're sorry! We couldn't detect any dog or human face in the image."
)
        display_image(img_path, title="...")
        print("Try another!")
    print("\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: (Three possible points for improvement)

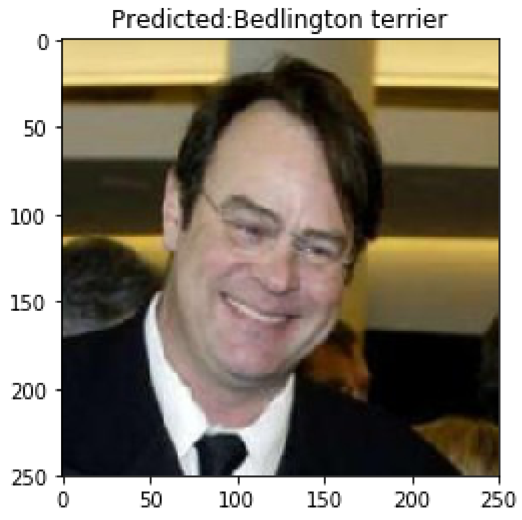
Some improvements:

1.Fine tune the model to give a better accuracy. 2.Serve this function as an API (Flask, AWS, etc.) 3.Try with different models, opimizers and loss functions, as well as different input image sizes. 4.Must increase no of epochs to get better accuraccy.

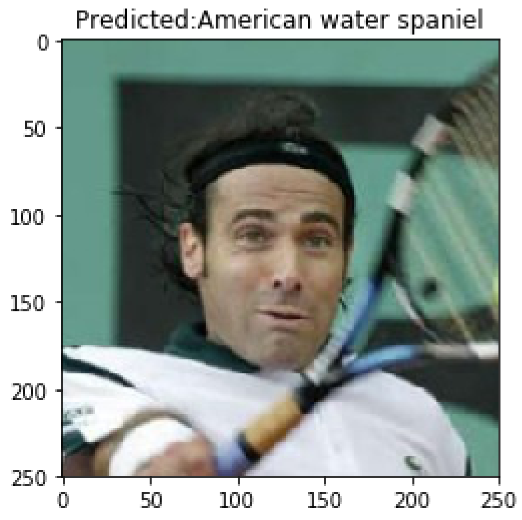
In [57]:

```
## TODO: Execute your algorithm from Step 6 on
## at least 6 images on your computer.
## Feel free to use as many code cells as needed.

## suggested code, below
for file in np.hstack((human_files[:3], dog_files[:3])):
    run_app(file)
```

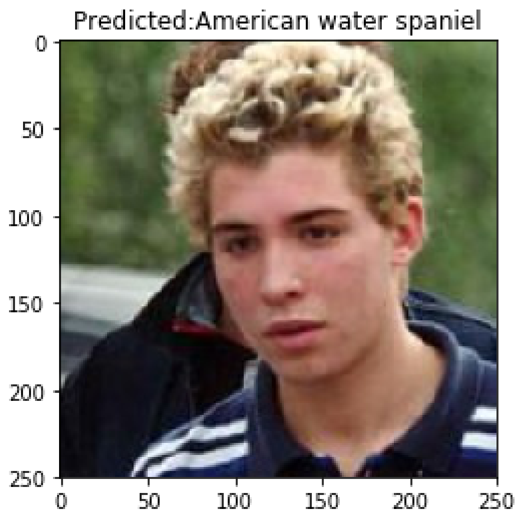
```
Hello Human!
```



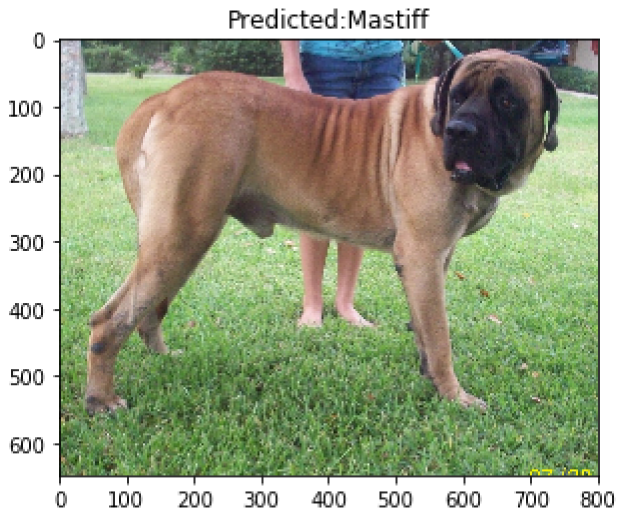
```
You look like a ...
BEDLINGTON TERRIER


Hello Human!
```



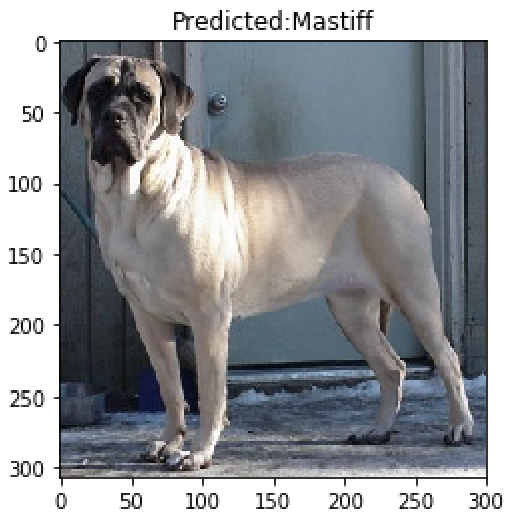
```
You look like a ...
AMERICAN WATER SPANIEL


Hello Human!
```



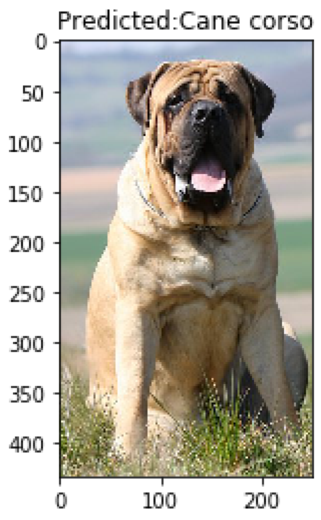
```
You look like a ...
AMERICAN WATER SPANIEL


Hello Doggie!
```



```
Your breed is most likley ...
MASTIFF


Hello Doggie!
```



```
Your breed is most likley ...
MASTIFF


Hello Doggie!
```



```
Your breed is most likley ...
CANE CORSO
```

In [ ]:

```

```