

# Data Scientist Nanodegree

## Convolutional Neural Networks

### Project: Write an Algorithm for a Dog Identification App

This notebook walks you through one of the most popular Udacity projects across machine learning and artificial intelligence nanodegree programs. The goal is to classify images of dogs according to their breed.

If you are looking for a more guided capstone project related to deep learning and convolutional neural networks, this might be just it. Notice that even if you follow the notebook to creating your classifier, you must still create a blog post or deploy an application to fulfill the requirements of the capstone project.

Also notice, you may be able to use only parts of this notebook (for example certain coding portions or the data) without completing all parts and still meet all requirements of the capstone project.

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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!

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.

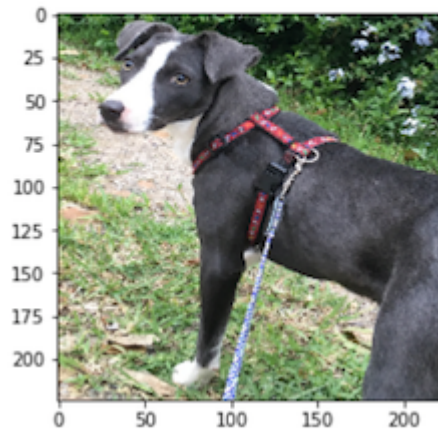
The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this IPython notebook.

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### 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!).

```
hello, dog!  
your predicted breed is ...  
American Staffordshire terrier
```



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](#): Use a CNN to Classify Dog Breeds (using Transfer Learning)
- [Step 5](#): Create a CNN to Classify Dog Breeds (using Transfer Learning)
- [Step 6](#): Write your Algorithm
- [Step 7](#): Test Your Algorithm

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## Step 0: Import Datasets

### Import Dog Dataset

In the code cell below, we import a dataset of dog images. We populate a few variables through the use of the `load_files` function from the scikit-learn library:

- `train_files`, `valid_files`, `test_files` - numpy arrays containing file paths to images
- `train_targets`, `valid_targets`, `test_targets` - numpy arrays containing onehot-encoded classification labels
- `breeds` - list of string-valued dog breed names for translation labels

In [2]:

```
from sklearn.datasets import load_files
from keras.utils import np_utils
import numpy as np
from glob import glob

# define function to load train, test, and validation datasets
def load_dataset(path):
    data = load_files(path)
    dog_files = np.array(data['filenames'])
    dog_targets = np_utils.to_categorical(np.array(data['target']), 133)
    return dog_files, dog_targets

# load train, test, and validation datasets
train_folder = '../.../data/dog_images/train'
valid_folder = '../.../data/dog_images/valid'

train_files, train_targets = load_dataset('../.../data/dog_images/train')
valid_files, valid_targets = load_dataset('../.../data/dog_images/valid')
test_files, test_targets = load_dataset('../.../data/dog_images/test')

# load list of dog names
dog_names = [item.rsplit('/',2)[1] for item in sorted(glob("../.../data/dog_images/train/*/"))]

# print statistics about the dataset
print('There are %d total dog categories.' % len(dog_names))
print('There are %s total dog images.\n' % len(np.hstack([train_files, valid_files, test_files])))
print('There are %d training dog images.' % len(train_files))
print('There are %d validation dog images.' % len(valid_files))
print('There are %d test dog images.' % len(test_files))
```

Using TensorFlow backend.

There are 133 total dog categories.

There are 8351 total dog images.

There are 6680 training dog images.

There are 835 validation dog images.

There are 836 test dog images.

## Import Human Dataset

In the code cell below, we import a dataset of human images, where the file paths are stored in the numpy array `human_files`.

In [3]:

```
import random
random.seed(8675309)

# load filenames in shuffled human dataset
human_files = np.array(glob("../../data/lfw/**/*.jpg"))
random.shuffle(human_files)

# print statistics about the dataset
print('There are %d total human images.' % len(human_files))
```

There are 13233 total human images.

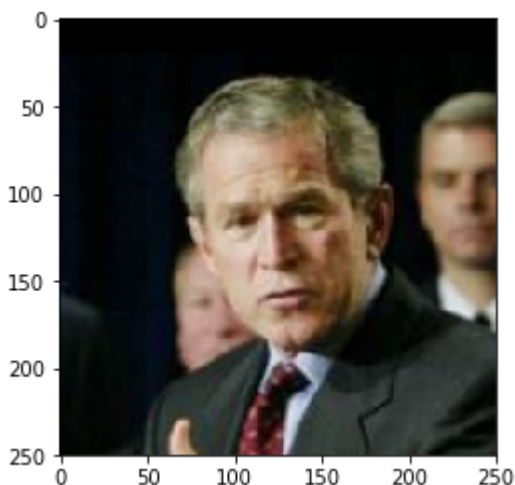
In [4]:

```
from PIL import Image
import matplotlib.pyplot as plt

def show_img(img_file):
    img = Image.open(img_file)
    plt.imshow(img)
```

In [5]:

```
show_img(human_files[4])
```



## Step 1: Detect Humans

We use OpenCV's implementation of [Haar feature-based cascade classifiers](http://docs.opencv.org/trunk/d7/d8b/tutorial_py_face_detection.html) ([http://docs.opencv.org/trunk/d7/d8b/tutorial\\_py\\_face\\_detection.html](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) (<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 [6]:

```
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[4])
# convert BGR image to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

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

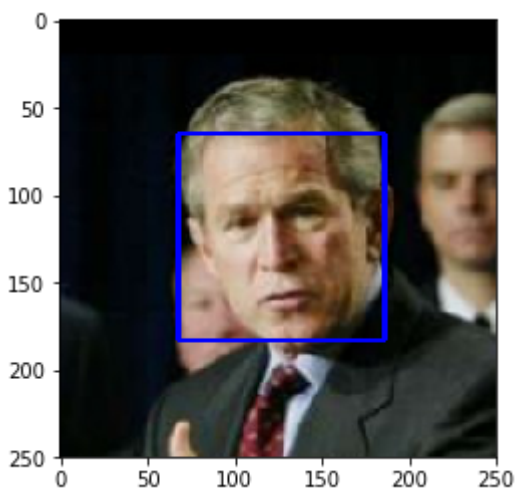
# print number of faces detected in the image
print('Number of faces detected:', len(faces))

# 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 [ ]:

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.

In [7]:

```
# 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:**

In [8]:

```
human_files_short = human_files[:100]
dog_files_short = train_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_detect = np.array([face_detector(h) for h in human_files_short]).sum()
d_detect = np.array([face_detector(d) for d in dog_files_short]).sum()

print(h_detect, '% of the first 100 images in human_files have a detected human face')
print(d_detect, '% of the first 100 images in dog_files have a detected human face')
```

```
100 % of the first 100 images in human_files have a detected human face
11 % of the first 100 images in dog_files have a detected human face
```

In [9]:

```
# dog like human
for d in dog_files_short:
    if face_detector(d):
        print(d)
```

```
../../../../data/dog_images/train/095.Kuvasz/Kuvasz_06442.jpg
../../../../data/dog_images/train/099.Lhasa_apso/Lhasa_apso_06646.jpg
../../../../data/dog_images/train/009.American_water_spaniel/American_water_spaniel_00628.jpg
../../../../data/dog_images/train/057.Dalmatian/Dalmatian_04023.jpg
../../../../data/dog_images/train/096.Labrador_retriever/Labrador_retriever_06474.jpg
../../../../data/dog_images/train/106.Newfoundland/Newfoundland_06989.jpg
../../../../data/dog_images/train/117.Pekingese/Pekingese_07559.jpg
../../../../data/dog_images/train/039.Bull_terrier/Bull_terrier_02805.jpg
../../../../data/dog_images/train/097.Lakeland_terrier/Lakeland_terrier_06516.jpg
../../../../data/dog_images/train/024.Bichon_frise/Bichon_frise_01771.jpg
../../../../data/dog_images/train/084.Icelandic_sheepdog/Icelandic_sheepdog_05705.jpg
```

In [10]:

```
show_img('../.../data/dog_images/train/097.Lakeland_terrier/Lakeland_terrier_06516.jpg')  
# why ?..
```



**Question 2:** This algorithmic choice necessitates that we communicate to the user that we accept human images only when they provide a clear view of a face (otherwise, we risk having unnecessarily frustrated users!). In your opinion, is this a reasonable expectation to pose on the user? If not, can you think of a way to detect humans in images that does not necessitate an image with a clearly presented face?

**Answer:**

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 each of the datasets.

In [11]:

```
## (Optional) TODO: Report the performance of another  
## face detection algorithm on the LFW dataset  
### Feel free to use as many code cells as needed.
```



## Step 2: Detect Dogs

In this section, we use a pre-trained [ResNet-50](https://ethereal.github.io/netscope/#/gist/db945b393d40bfa26006) (<http://ethereal.github.io/netscope/#/gist/db945b393d40bfa26006>) model to detect dogs in images. Our first line of code downloads the ResNet-50 model, along with weights that have been trained on [ImageNet](http://www.image-net.org/) (<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) (<https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a>). Given an image, this pre-trained ResNet-50 model returns a prediction (derived from the available categories in ImageNet) for the object that is contained in the image.

In [12]:

```
from keras.applications.resnet50 import ResNet50

# define ResNet50 model
ResNet50_model = ResNet50(weights='imagenet')
```

```
Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.2/resnet50_weights_tf_dim_ordering_tf_kernels.h5
102858752/102853048 [=====] - 1s 0us/step
```

## Pre-process the Data

When using TensorFlow as backend, Keras CNNs require a 4D array (which we'll also refer to as a 4D tensor) as input, with shape

$$(\text{nb\_samples}, \text{rows}, \text{columns}, \text{channels}),$$

where `nb_samples` corresponds to the total number of images (or samples), and `rows`, `columns`, and `channels` correspond to the number of rows, columns, and channels for each image, respectively.

The `path_to_tensor` function below takes a string-valued file path to a color image as input and returns a 4D tensor suitable for supplying to a Keras CNN. The function first loads the image and resizes it to a square image that is  $224 \times 224$  pixels. Next, the image is converted to an array, which is then resized to a 4D tensor. In this case, since we are working with color images, each image has three channels. Likewise, since we are processing a single image (or sample), the returned tensor will always have shape  $(1, 224, 224, 3)$ .

The `paths_to_tensor` function takes a numpy array of string-valued image paths as input and returns a 4D tensor with shape

$$(\text{nb\_samples}, 224, 224, 3).$$

Here, `nb_samples` is the number of samples, or number of images, in the supplied array of image paths. It is best to think of `nb_samples` as the number of 3D tensors (where each 3D tensor corresponds to a different image) in your dataset!

In [13]:

```
from keras.preprocessing import image
from tqdm import tqdm

def path_to_tensor(img_path):
    # loads RGB image as PIL.Image.Image type
    img = image.load_img(img_path, target_size=(224, 224))
    # convert PIL.Image.Image type to 3D tensor with shape (224, 224, 3)
    x = image.img_to_array(img)
    # convert 3D tensor to 4D tensor with shape (1, 224, 224, 3) and return 4D tensor
    return np.expand_dims(x, axis=0)

def paths_to_tensor(img_paths):
    list_of_tensors = [path_to_tensor(img_path) for img_path in tqdm(img_paths)]
    return np.vstack(list_of_tensors)
```

## Making Predictions with ResNet-50

Getting the 4D tensor ready for ResNet-50, and for any other pre-trained model in Keras, requires some additional processing. First, the RGB image is converted to BGR by reordering the channels. All pre-trained models have the additional normalization step that the mean pixel (expressed in RGB as [103.939, 116.779, 123.68] and calculated from all pixels in all images in ImageNet) must be subtracted from every pixel in each image. This is implemented in the imported function `preprocess_input`. If you're curious, you can check the code for `preprocess_input` [here](https://github.com/fchollet/keras/blob/master/keras/applications/imagenet_utils.py) ([https://github.com/fchollet/keras/blob/master/keras/applications/imagenet\\_utils.py](https://github.com/fchollet/keras/blob/master/keras/applications/imagenet_utils.py)).

Now that we have a way to format our image for supplying to ResNet-50, we are now ready to use the model to extract the predictions. This is accomplished with the `predict` method, which returns an array whose  $i$ -th entry is the model's predicted probability that the image belongs to the  $i$ -th ImageNet category. This is implemented in the `ResNet50_predict_labels` function below.

By taking the argmax of the predicted probability vector, we obtain an integer corresponding to the model's predicted object class, which we can identify with an object category through the use of this [dictionary](https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a) (<https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a>).

In [ ]:

In [14]:

```
from keras.applications.resnet50 import preprocess_input, decode_predictions

def ResNet50_predict_labels(img_path):
    # returns prediction vector for image located at img_path
    img = preprocess_input(path_to_tensor(img_path))
    return np.argmax(ResNet50_model.predict(img))
```

## Write a Dog Detector

While looking at the [dictionary \(https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a\)](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 ResNet-50 model, we need only check if the `ResNet50_predict_labels` function above returns a value between 151 and 268 (inclusive).

We 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 [15]:

```
### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    prediction = ResNet50_predict_labels(img_path)
    return ((prediction <= 268) & (prediction >= 151))
```

## (IMPLEMENTATION) Assess the Dog Detector

**Question 3:** 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:**

In [16]:

```
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
h_detect = np.array([dog_detector(h) for h in tqdm(human_files_short)]).sum()
d_detect = np.array([dog_detector(d) for d in tqdm(dog_files_short)]).sum()

print(h_detect, '% of the first 100 images in human_files have a detected dog')
print(d_detect, '% of the first 100 images in dog_files have a detected dog')
```

```
100%|██████████| 100/100 [00:05<00:00, 17.27it/s]
100%|██████████| 100/100 [00:04<00:00, 24.66it/s]
```

```
0 % of the first 100 images in human_files have a detected dog
100 % of the first 100 images in dog_files have a detected dog
```

---

## 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 1%. In Step 5 of this notebook, you will have the opportunity to use transfer learning to create a CNN that attains greatly improved accuracy.

Be careful with adding too many trainable layers! More parameters means longer training, which means you are more likely to need a GPU to accelerate the training process. Thankfully, Keras provides a handy estimate of the time that each epoch is likely to take; you can extrapolate this estimate to figure out how long it will take for your algorithm to train.

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 great difficulty in distinguishing between a Brittany and a Welsh Springer Spaniel.

**Brittany**



**Welsh Springer Spaniel**

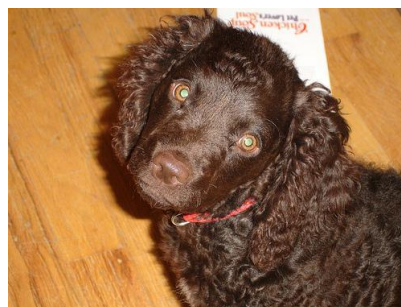


It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).

**Curly-Coated Retriever**



**American Water Spaniel**



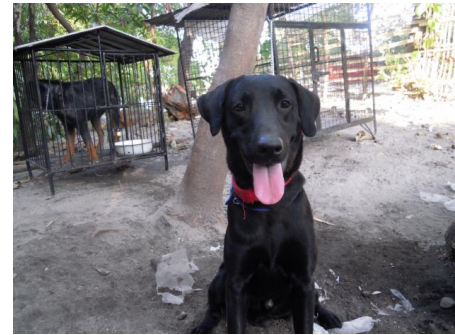
Likewise, recall that labradors come in yellow, chocolate, and black. Your vision-based algorithm will have to conquer this high intra-class variation to determine how to classify all of these different shades as the same breed.

**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 imbalanced, a random guess will provide a correct answer roughly 1 in 133 times, which corresponds to an accuracy of less than 1%.

In [108]:

```
from PIL import ImageFile
from keras.preprocessing.image import ImageDataGenerator
ImageFile.LOAD_TRUNCATED_IMAGES = True

# pre-process the data for Keras
train_tensors = paths_to_tensor(train_files).astype('float32')/255
valid_tensors = paths_to_tensor(valid_files).astype('float32')/255
test_tensors = paths_to_tensor(test_files).astype('float32')/255

# image transform for training data
train_datagen = ImageDataGenerator(rescale=1./255,
    rotation_range=30, horizontal_flip=True, vertical_flip=True)

# just rescale for test/validation data
valid_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    train_folder, target_size=(224, 224), batch_size=32, class_mode='categorical')

validation_generator = valid_datagen.flow_from_directory(
    valid_folder, target_size=(224, 224), batch_size=32, class_mode='categorical')

100% |██████████| 6680/6680 [01:13<00:00, 91.10it/s]
100% |██████████| 835/835 [00:08<00:00, 101.08it/s]
100% |██████████| 836/836 [00:09<00:00, 84.01it/s]
```

Found 6680 images belonging to 133 classes.  
Found 835 images belonging to 133 classes.

In [111]:

Out[111]:

## (IMPLEMENTATION) Model Architecture

Create a CNN to classify dog breed. At the end of your code cell block, summarize the layers of your model by executing the line:

```
model.summary()
```

We have imported some Python modules to get you started, but feel free to import as many modules as you need. If you end up getting stuck, here's a hint that specifies a model that trains relatively fast on CPU and attains >1% test accuracy in 5 epochs:

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 223, 223, 16)	208
max_pooling2d_1 (MaxPooling2D)	(None, 111, 111, 16)	0
conv2d_2 (Conv2D)	(None, 110, 110, 32)	2080
max_pooling2d_2 (MaxPooling2D)	(None, 55, 55, 32)	0
conv2d_3 (Conv2D)	(None, 54, 54, 64)	8256
max_pooling2d_3 (MaxPooling2D)	(None, 27, 27, 64)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 64)	0
dense_1 (Dense)	(None, 133)	8645
Total params: 19,189.0		
Trainable params: 19,189.0		
Non-trainable params: 0.0		



**Question 4:** Outline the steps you took to get to your final CNN architecture and your reasoning at each step. If you chose to use the hinted architecture above, describe why you think that CNN architecture should work well for the image classification task.

**Answer:**



In [131]:

```
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D
from keras.layers import Dropout, Flatten, Dense, Activation
from keras.models import Sequential

model = Sequential()

### TODO: Define your architecture.
model.add(Conv2D(64, (3, 3), activation='relu', input_shape=(224, 224, 3)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(133, activation='softmax'))

model.summary()
```

Layer (type)	Output Shape	Param #
=====		
conv2d_25 (Conv2D)	(None, 222, 222, 64)	1792
conv2d_26 (Conv2D)	(None, 220, 220, 64)	36928
max_pooling2d_18 (MaxPooling)	(None, 110, 110, 64)	0
dropout_28 (Dropout)	(None, 110, 110, 64)	0
conv2d_27 (Conv2D)	(None, 108, 108, 128)	73856
conv2d_28 (Conv2D)	(None, 106, 106, 128)	147584
max_pooling2d_19 (MaxPooling)	(None, 53, 53, 128)	0
dropout_29 (Dropout)	(None, 53, 53, 128)	0
flatten_10 (Flatten)	(None, 359552)	0
dense_32 (Dense)	(None, 256)	92045568
dropout_30 (Dropout)	(None, 256)	0
dense_33 (Dense)	(None, 133)	34181
=====		
Total params: 92,339,909		
Trainable params: 92,339,909		
Non-trainable params: 0		

## Compile the Model

In [132]:

```
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
```

## (IMPLEMENTATION) Train the Model

Train your model in the code cell below. Use model checkpointing to save the model that attains the best validation loss.

You are welcome to [augment the training data \(https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html\)](https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html), but this is not a requirement.



In [133]:

```
from keras.callbacks import ModelCheckpoint

### TODO: specify the number of epochs that you would like to use to train the model.

int(len(train_tensors)/train_generator.batch_size)

epochs = 20

### Do NOT modify the code below this line.

checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.from_scratch.hdf5',
                               verbose=1, save_best_only=True)

model.fit_generator(
    train_generator,
    epochs=5,
    steps_per_epoch=int(len(train_tensors)/train_generator.batch_size),
    validation_data=validation_generator,
    validation_steps=int(len(valid_tensors)/validation_generator.batch_size)
),
    callbacks=[checkpointer], verbose=1, workers=4)

# model.fit_generator(train_tensors, train_targets,
#                     validation_data=(valid_tensors, valid_targets),
#                     epochs=epochs, batch_size=20, callbacks=[checkpointer], verbose=1)
```

```
Epoch 1/5
207/208 [=====>.] - ETA: 0s - loss: 5.0177 -
acc: 0.0082Epoch 00001: val_loss improved from inf to 4.88348, saving
model to saved_models/weights.best.from_scratch.hdf5
208/208 [=====] - 180s 864ms/step - loss:
5.0171 - acc: 0.0081 - val_loss: 4.8835 - val_acc: 0.0108
Epoch 2/5
207/208 [=====>.] - ETA: 0s - loss: 4.8798 -
acc: 0.0090Epoch 00002: val_loss improved from 4.88348 to 4.87410, s
aving model to saved_models/weights.best.from_scratch.hdf5
208/208 [=====] - 175s 841ms/step - loss:
4.8796 - acc: 0.0089 - val_loss: 4.8741 - val_acc: 0.0084
Epoch 3/5
207/208 [=====>.] - ETA: 0s - loss: 4.8860 -
acc: 0.0100Epoch 00003: val_loss improved from 4.87410 to 4.87039, s
aving model to saved_models/weights.best.from_scratch.hdf5
208/208 [=====] - 175s 839ms/step - loss:
4.8859 - acc: 0.0099 - val_loss: 4.8704 - val_acc: 0.0120
Epoch 4/5
207/208 [=====>.] - ETA: 0s - loss: 4.8693 -
acc: 0.0106Epoch 00004: val_loss improved from 4.87039 to 4.86882, s
aving model to saved_models/weights.best.from_scratch.hdf5
208/208 [=====] - 174s 835ms/step - loss:
4.8694 - acc: 0.0105 - val_loss: 4.8688 - val_acc: 0.0108
Epoch 5/5
207/208 [=====>.] - ETA: 0s - loss: 4.8673 -
acc: 0.0106Epoch 00005: val_loss did not improve
208/208 [=====] - 173s 831ms/step - loss:
4.8673 - acc: 0.0105 - val_loss: 4.8693 - val_acc: 0.0108
```

Out[133]:

```
<keras.callbacks.History at 0x7fd68fa835f8>
```

## Load the Model with the Best Validation Loss

In [134]:

```
model.load_weights('saved_models/weights.best.from_scratch.hdf5')
```

## Test the Model

Try out your model on the test dataset of dog images. Ensure that your test accuracy is greater than 1%.

In [135]:

```
# get index of predicted dog breed for each image in test set
dog_breed_predictions = [np.argmax(model.predict(np.expand_dims(tensor, axis=0
))) for tensor in test_tensors]

# report test accuracy
test_accuracy = 100*np.sum(np.array(dog_breed_predictions)==np.argmax(test_targe
ts, axis=1))/len(dog_breed_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
```

Test accuracy: 1.1962%

## Step 4: Use a CNN to Classify Dog Breeds

To reduce training time without sacrificing accuracy, we show you how to train a CNN using transfer learning. In the following step, you will get a chance to use transfer learning to train your own CNN.

In [31]:

```
bottleneck_features = np.load('../data/bottleneck_features/DogVGG16Data.npz')
train_VGG16 = bottleneck_features['train']
valid_VGG16 = bottleneck_features['valid']
test_VGG16 = bottleneck_features['test']
```

### Model Architecture

The model uses the the pre-trained VGG-16 model as a fixed feature extractor, where the last convolutional output of VGG-16 is fed as input to our model. We only add a global average pooling layer and a fully connected layer, where the latter contains one node for each dog category and is equipped with a softmax.

In [74]:

```
VGG16_model = Sequential()
VGG16_model.add(GlobalAveragePooling2D(input_shape=train_VGG16.shape[1:]))
VGG16_model.add(Dense(256, activation='relu'))
VGG16_model.add(Dropout(0.5))
VGG16_model.add(Dense(133, activation='softmax'))

VGG16_model.summary()
```

Layer (type)	Output Shape	Param #
=====		
global_average_pooling2d_9 ( (None, 512)		0
dense_16 (Dense)	(None, 256)	131328
dropout_16 (Dropout)	(None, 256)	0
dense_17 (Dense)	(None, 133)	34181
=====		
Total params: 165,509		
Trainable params: 165,509		
Non-trainable params: 0		

### Compile the Model

In [75]:

```
VGG16_model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
```

## Train the Model

In [76]:

```
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.VGG16.hdf5',  
                               verbose=1, save_best_only=True)  
  
VGG16_model.fit(train_VGG16, train_targets,  
                validation_data=(valid_VGG16, valid_targets),  
                epochs=40, batch_size=20, callbacks=[checkpointer], verbose=0)
```

```
Epoch 00001: val_loss improved from inf to 3.15357, saving model to
saved_models/weights.best.VGG16.hdf5
Epoch 00002: val_loss improved from 3.15357 to 1.96791, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00003: val_loss improved from 1.96791 to 1.45274, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00004: val_loss improved from 1.45274 to 1.28249, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00005: val_loss did not improve
Epoch 00006: val_loss improved from 1.28249 to 1.19157, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00007: val_loss improved from 1.19157 to 1.18020, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00008: val_loss improved from 1.18020 to 1.11512, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00009: val_loss did not improve
Epoch 00010: val_loss did not improve
Epoch 00011: val_loss did not improve
Epoch 00012: val_loss did not improve
Epoch 00013: val_loss improved from 1.11512 to 1.08148, saving model
to saved_models/weights.best.VGG16.hdf5
Epoch 00014: val_loss did not improve
Epoch 00015: val_loss did not improve
Epoch 00016: val_loss did not improve
Epoch 00017: val_loss did not improve
Epoch 00018: val_loss did not improve
Epoch 00019: val_loss did not improve
Epoch 00020: val_loss did not improve
Epoch 00021: val_loss did not improve
Epoch 00022: val_loss did not improve
Epoch 00023: val_loss did not improve
Epoch 00024: val_loss did not improve
Epoch 00025: val_loss did not improve
Epoch 00026: val_loss did not improve
Epoch 00027: val_loss did not improve
Epoch 00028: val_loss did not improve
Epoch 00029: val_loss did not improve
Epoch 00030: val_loss did not improve
Epoch 00031: val_loss did not improve
Epoch 00032: val_loss did not improve
Epoch 00033: val_loss did not improve
Epoch 00034: val_loss did not improve
Epoch 00035: val_loss did not improve
Epoch 00036: val_loss did not improve
Epoch 00037: val_loss did not improve
Epoch 00038: val_loss did not improve
Epoch 00039: val_loss did not improve
Epoch 00040: val_loss did not improve
```

Out[76]:

```
<keras.callbacks.History at 0x7fd6e01702b0>
```

## Load the Model with the Best Validation Loss

In [77]:

```
VGG16_model.load_weights('saved_models/weights.best.VGG16.hdf5')
```

## Test the Model

Now, we can use the CNN to test how well it identifies breed within our test dataset of dog images. We print the test accuracy below.

In [78]:

```
# get index of predicted dog breed for each image in test set
VGG16_predictions = [np.argmax(VGG16_model.predict(np.expand_dims(feature, axis=
0))) for feature in test_VGG16]

# report test accuracy
test_accuracy = 100*np.sum(np.array(VGG16_predictions)==np.argmax(test_targets,
axis=1))/len(VGG16_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
```

Test accuracy: 71.0526%

## Predict Dog Breed with the Model

In [73]:

```
from extract_bottleneck_features import *

def VGG16_predict_breed(img_path):
    # extract bottleneck features
    bottleneck_feature = extract_VGG16(path_to_tensor(img_path))
    # obtain predicted vector
    predicted_vector = VGG16_model.predict(bottleneck_feature)
    # return dog breed that is predicted by the model
    return dog_names[np.argmax(predicted_vector)]
```

---

## Step 5: 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.

In Step 4, we used transfer learning to create a CNN using VGG-16 bottleneck features. In this section, you must use the bottleneck features from a different pre-trained model. To make things easier for you, we have pre-computed the features for all of the networks that are currently available in Keras:

- [VGG-19 \(https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogVGG19Data.npz\)](https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogVGG19Data.npz) bottleneck features
- [ResNet-50 \(https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogResnet50Data.npz\)](https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogResnet50Data.npz) bottleneck features
- [Inception \(https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogInceptionV3Data.npz\)](https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogInceptionV3Data.npz) bottleneck features
- [Xception \(https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogXceptionData.npz\)](https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/DogXceptionData.npz) bottleneck features

The files are encoded as such:

```
Dog{network}Data.npz
```

where `{network}`, in the above filename, can be one of `VGG19`, `Resnet50`, `InceptionV3`, or `Xception`. Pick one of the above architectures, download the corresponding bottleneck features, and store the downloaded file in the `bottleneck_features/` folder in the repository.

### (IMPLEMENTATION) Obtain Bottleneck Features

In the code block below, extract the bottleneck features corresponding to the train, test, and validation sets by running the following:

```
bottleneck_features = np.load('bottleneck_features/Dog{network}Data.npz')
train_{network} = bottleneck_features['train']
valid_{network} = bottleneck_features['valid']
test_{network} = bottleneck_features['test']
```

In [79]:

```
### TODO: Obtain bottleneck features from another pre-trained CNN.
bottleneck_features = np.load('../data/bottleneck_features/DogVGG19Data.npz')
train_VGG19 = bottleneck_features['train']
valid_VGG19 = bottleneck_features['valid']
test_VGG19 = bottleneck_features['test']
```



## (IMPLEMENTATION) Model Architecture

Create a CNN to classify dog breed. At the end of your code cell block, summarize the layers of your model by executing the line:

```
<your model's name>.summary()
```

**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:**

In [80]:

```
VGG19_model = Sequential()
VGG19_model.add(GlobalAveragePooling2D(input_shape=train_VGG19.shape[1:]))
VGG19_model.add(Dense(256, activation='relu'))
VGG19_model.add(Dropout(0.5))
VGG19_model.add(Dense(133, activation='softmax'))

VGG19_model.summary()
```

Layer (type)	Output Shape	Param #
=====		
global_average_pooling2d_10	(None, 512)	0
dense_18 (Dense)	(None, 256)	131328
dropout_17 (Dropout)	(None, 256)	0
dense_19 (Dense)	(None, 133)	34181
=====		
Total params: 165,509		
Trainable params: 165,509		
Non-trainable params: 0		

## (IMPLEMENTATION) Compile the Model

In [81]:

```
### TODO: Compile the model.
VGG19_model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
```

## (IMPLEMENTATION) Train the Model

Train your model in the code cell below. Use model checkpointing to save the model that attains the best validation loss.

You are welcome to [augment the training data \(https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html\)](https://blog.keras.io/building-powerful-image-classification-models-using-very-little-data.html), but this is not a requirement.

In [82]:

```
### TODO: Train the model.
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.VGG19.hdf5',
                               verbose=1, save_best_only=True)

VGG19_model.fit(train_VGG19, train_targets,
                validation_data=(valid_VGG19, valid_targets),
                epochs=60, batch_size=32, callbacks=[checkpointer], verbose=0)
```

Epoch 00001: val\_loss improved from inf to 2.91162, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00002: val\_loss improved from 2.91162 to 1.63376, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00003: val\_loss improved from 1.63376 to 1.28947, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00004: val\_loss improved from 1.28947 to 1.09212, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00005: val\_loss improved from 1.09212 to 1.08261, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00006: val\_loss improved from 1.08261 to 1.05785, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00007: val\_loss improved from 1.05785 to 0.96703, saving model to saved\_models/weights.best.VGG19.hdf5  
Epoch 00008: val\_loss did not improve  
Epoch 00009: val\_loss did not improve  
Epoch 00010: val\_loss did not improve  
Epoch 00011: val\_loss did not improve  
Epoch 00012: val\_loss did not improve  
Epoch 00013: val\_loss did not improve  
Epoch 00014: val\_loss did not improve  
Epoch 00015: val\_loss did not improve  
Epoch 00016: val\_loss did not improve  
Epoch 00017: val\_loss did not improve  
Epoch 00018: val\_loss did not improve  
Epoch 00019: val\_loss did not improve  
Epoch 00020: val\_loss did not improve  
Epoch 00021: val\_loss did not improve  
Epoch 00022: val\_loss did not improve  
Epoch 00023: val\_loss did not improve  
Epoch 00024: val\_loss did not improve  
Epoch 00025: val\_loss did not improve  
Epoch 00026: val\_loss did not improve  
Epoch 00027: val\_loss did not improve  
Epoch 00028: val\_loss did not improve  
Epoch 00029: val\_loss did not improve  
Epoch 00030: val\_loss did not improve  
Epoch 00031: val\_loss did not improve  
Epoch 00032: val\_loss did not improve  
Epoch 00033: val\_loss did not improve  
Epoch 00034: val\_loss did not improve  
Epoch 00035: val\_loss did not improve  
Epoch 00036: val\_loss did not improve  
Epoch 00037: val\_loss did not improve  
Epoch 00038: val\_loss did not improve  
Epoch 00039: val\_loss did not improve  
Epoch 00040: val\_loss did not improve  
Epoch 00041: val\_loss did not improve  
Epoch 00042: val\_loss did not improve  
Epoch 00043: val\_loss did not improve  
Epoch 00044: val\_loss did not improve  
Epoch 00045: val\_loss did not improve  
Epoch 00046: val\_loss did not improve  
Epoch 00047: val\_loss did not improve  
Epoch 00048: val\_loss did not improve  
Epoch 00049: val\_loss did not improve  
Epoch 00050: val\_loss did not improve  
Epoch 00051: val\_loss did not improve  
Epoch 00052: val\_loss did not improve  
Epoch 00053: val\_loss did not improve  
Epoch 00054: val\_loss did not improve

```
Epoch 00055: val_loss did not improve
Epoch 00056: val_loss did not improve
Epoch 00057: val_loss did not improve
Epoch 00058: val_loss did not improve
Epoch 00059: val_loss did not improve
Epoch 00060: val_loss did not improve
```

Out[82]:

```
<keras.callbacks.History at 0x7fd6e0321a20>
```

## (IMPLEMENTATION) Load the Model with the Best Validation Loss

In [83]:

```
### TODO: Load the model weights with the best validation loss.
VGG19_model.load_weights('saved_models/weights.best.VGG19.hdf5')
```

## (IMPLEMENTATION) Test the Model

Try out your model on the test dataset of dog images. Ensure that your test accuracy is greater than 60%.

In [84]:

```
### TODO: Calculate classification accuracy on the test dataset.
# get index of predicted dog breed for each image in test set
VGG19_predictions = [np.argmax(VGG19_model.predict(np.expand_dims(feature, axis=
0))) for feature in test_VGG19]

# report test accuracy
test_accuracy = 100*np.sum(np.array(VGG19_predictions)==np.argmax(test_targets,
axis=1))/len(VGG19_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
```

Test accuracy: 70.6938%

## (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.

Similar to the analogous function in Step 5, your function should have three steps:

1. Extract the bottleneck features corresponding to the chosen CNN model.
2. Supply the bottleneck features as input to the model to return the predicted vector. Note that the `argmax` of this prediction vector gives the index of the predicted dog breed.
3. Use the `dog_names` array defined in Step 0 of this notebook to return the corresponding breed.

The functions to extract the bottleneck features can be found in `extract_bottleneck_features.py` , and they have been imported in an earlier code cell. To obtain the bottleneck features corresponding to your chosen CNN architecture, you need to use the function

```
extract_{network}
```

where `{network}` , in the above filename, should be one of `VGG19` , `Resnet50` , `InceptionV3` , or `Xception` .

In [85]:

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

def VGG19_predict_breed(img_path):
    # extract bottleneck features
    bottleneck_feature = extract_VGG19(path_to_tensor(img_path))
    # obtain predicted vector
    predicted_vector = VGG19_model.predict(bottleneck_feature)
    # return dog breed that is predicted by the model
    return dog_names[np.argmax(predicted_vector)]
```

## Step 6: 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 `dog_detector` functions developed above. You are **required** to use your CNN from Step 5 to predict dog breed.

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



This photo looks like an Afghan Hound.

### (IMPLEMENTATION) Write your Algorithm

In [93]:

```
### TODO: Write your algorithm.
### Feel free to use as many code cells as needed.
def find_dog(img_path):
    if dog_detector(img_path) :
        dog_name = VGG19_predict_breed(img_path)
    elif face_detector(img_path):
        dog_name = 'Emmm, I am not a dog.Maybe I am human.'
    else:
        dog_name = 'Sorry,who are you?'

    print(dog_name)
    show_img(img_path)
```

## Step 7: 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:**

In [94]:

```
## 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.  
  
#find_dog(human_files_short[1])  
find_dog(dog_files_short[0])
```

095.Kuvasz



In [95]:

```
find_dog(dog_files_short[1])
```

057.Dalmatian



In [96]:

```
find_dog(dog_files_short[2])
```

088.Irish\_water\_spaniel

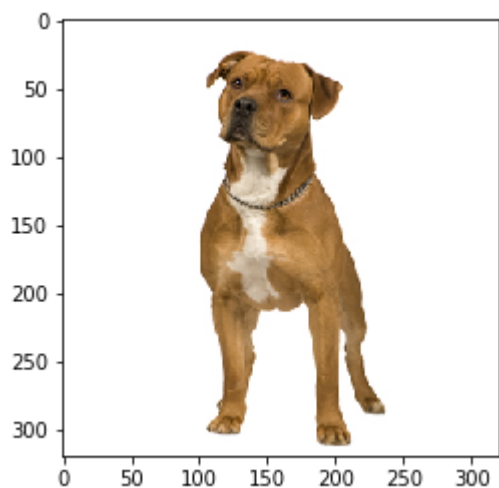




In [97]:

```
find_dog(dog_files_short[3])
```

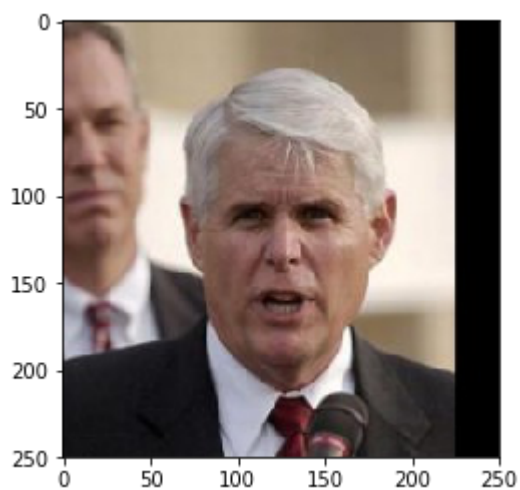
008.American\_staffordshire\_terrier



In [98]:

```
find_dog(human_files_short[0])
```

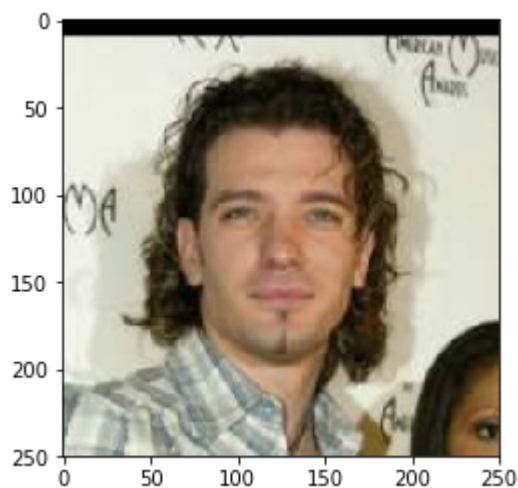
Emmm, I am not a dog.Maybe I am human.



In [99]:

```
find_dog(human_files_short[1])
```

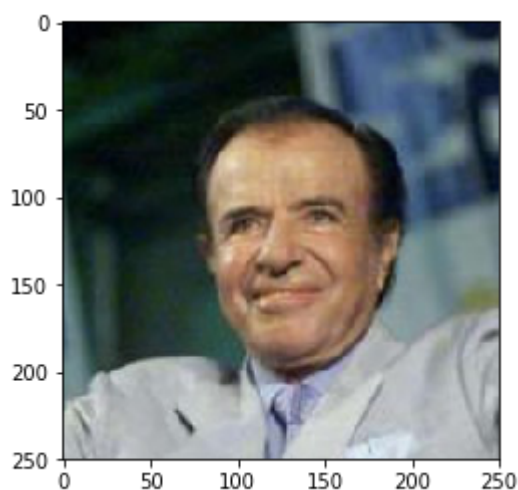
Emmm, I am not a dog.Maybe I am human.



In [100]:

```
find_dog(human_files_short[2])
```

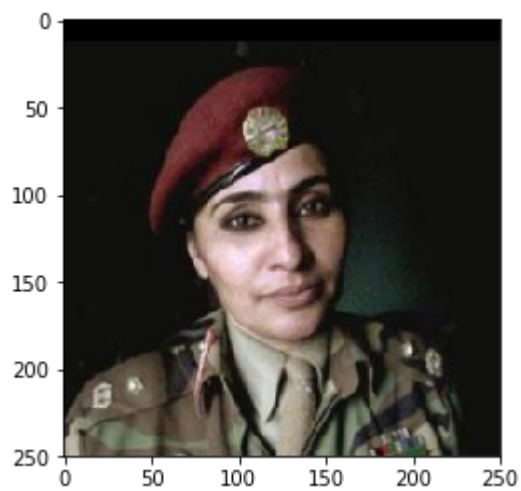
Emmm, I am not a dog.Maybe I am human.



In [101]:

```
find_dog(human_files_short[3])
```

Emmm, I am not a dog.Maybe I am human.



In [ ]: