

# Artificial Intelligence Nanodegree

## Convolutional Neural Networks

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

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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!

**Note:** Once you have completed all of the code implementations, you need to finalize your work by exporting the iPython 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 "\n", "**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.

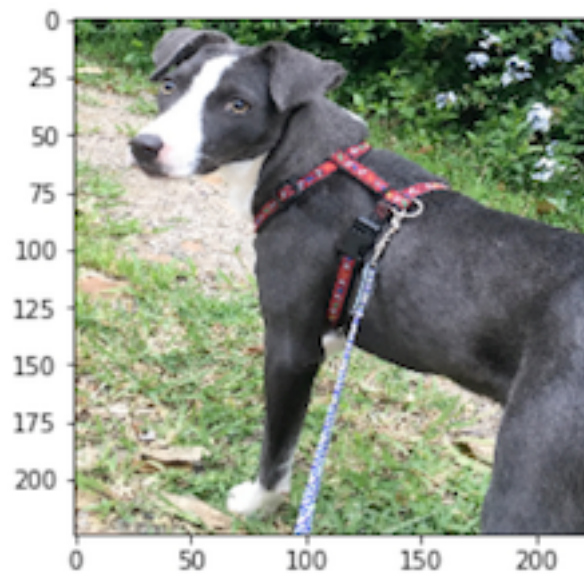
The rubric contains *optional* "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. If you decide to pursue the "Stand Out Suggestions", you should include the code in this IPython notebook.

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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
- `dog_names` - list of string-valued dog breed names for translating labels

In [1]:

```
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_files, train_targets = load_dataset('dogImages/train')
valid_files, valid_targets = load_dataset('dogImages/valid')
test_files, test_targets = load_dataset('dogImages/test')

# load list of dog names
dog_names = [item[20:-1] for item in sorted(glob("dogImages/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 [2]:

```
import random
random.seed(8675309)

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

## 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)) 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 [3]:

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

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

# load color (BGR) image
img = cv2.imread(human_files[1])
# convert BGR image to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

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

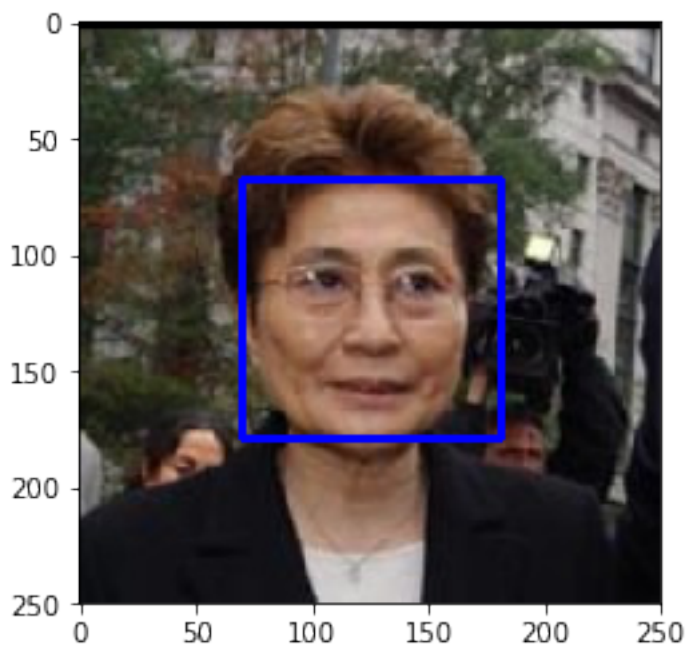
# print number of faces detected in the image
print('Number of faces detected:', len(faces))

# 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 [84]:

```
human_files[1]
```

Out[84]:

```
'lfw/Yoko_Ono/Yoko_Ono_0001.jpg'
```

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 [4]:

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

## (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:**

- What percentage of the first 100 images in `human_files` have a detected human face? >>> 98%
- What percentage of the first 100 images in `dog_files` have a detected human face? >>> 11%

In [5]:

```
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.

def face_detector_file_name(file_name):
    img = cv2.imread(file_name)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    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()

    #def face_bounding_box(file_name):

    return len(faces) > 0

count = 0
for picture in human_files_short:
    if face_detector_file_name(picture)== True:
        count += 1
print('human file detect', count/100*100)

count = 0
for picture in dog_files_short:
    if face_detector_file_name(picture)== True:
        count += 1
print('dog file detect', count/100*100)
```

```
human file detect 98.0
dog file detect 11.0
```

**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:** I need to show to users a short notice before users use this application. The example is ' Caution , the human face should be the center of picture and the face shoulde face the front '. Otherwise this algorithm can't detect properly and this causes a bad user experience.

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 [ ]:

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

### I will implement the human face detector by CNN with transter learning.
```

## Step 2: Detect Dogs

In this section, we use a pre-trained ResNet-50 (<http://ethereon.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/>), 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>). 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 [6]:

```
from keras.applications.resnet50 import ResNet50

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

## 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

(nb\_samples, rows, columns, 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

$(nb\_samples, 224, 224, 3)$ .

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 [7]:

```
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)
```

In [81]:

```
a = path_to_tensor('dogImages/test/004.Akita/Akita_00262.jpg')
a.shape
```

Out[81]:

$(1, 224, 224, 3)$

## 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 [8]:

```
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 [9]:

```
### 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:**

- What percentage of the images in `human_files_short` have a detected dog? 1%
- What percentage of the images in `dog_files_short` have a detected dog? 100%

In [10]:

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

```
def data_to_tensor(img_data):
    # loads RGB image as PIL.Image.Image type
    img = image.load_img(img_data, 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 te
    return np.expand_dims(x, axis=0)
```

```
#list_to_tensor(human_files_short[0])
```

```
#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))
```

```
def dog_detector_data(picture):
    img = preprocess_input(data_to_tensor(picture))
    prediction = np.argmax(ResNet50_model.predict(img))
    #prediction = ResNet50_predict_labels(img_path)
    return ((prediction <= 268) & (prediction >= 151))
```

```
def show_picture(picture):
    img = cv2.imread(picture)
    # 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()
    return
```

```
#show_picture(human_files_short[3])
```

```
count = 0
for picture in human_files_short:
    if dog_detector_data(picture) == True:
        count += 1
    # show_picture(picture)
print('human detected by dog detector ResNet50', count/100*100)
```

```
count = 0
for picture in dog_files_short:
    if dog_detector_data(picture) == True:
        count += 1
    # show_picture(picture)
print('dog detect ResNet50', count/100*100)
```

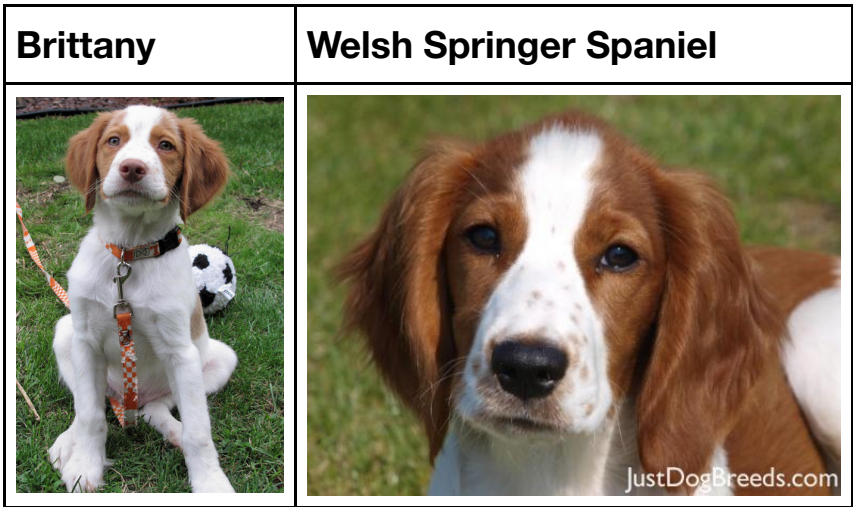
```
human detected by dog detector ResNet50 1.0
dog detect ResNet50 100.0
```

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

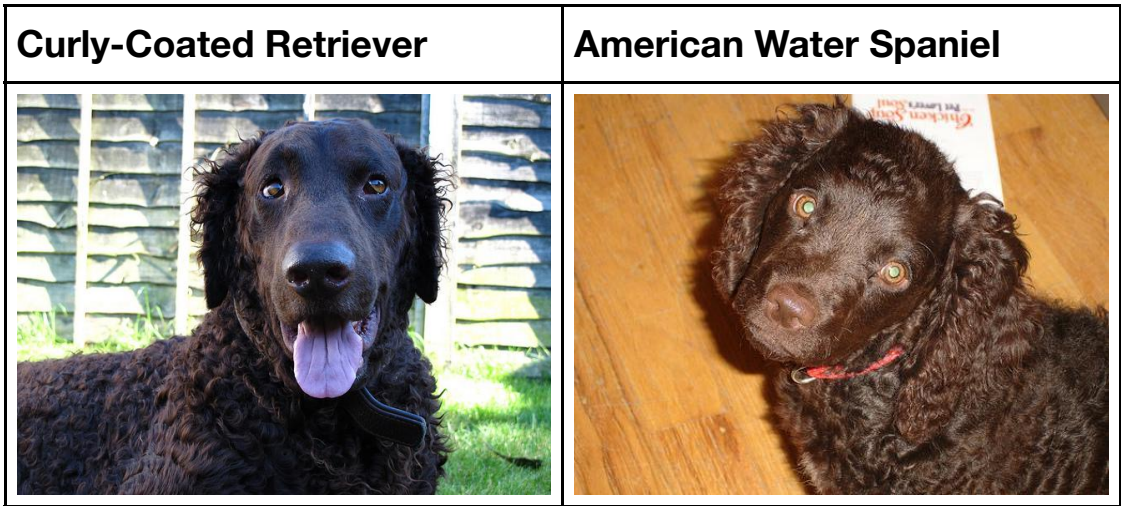
Now that we have functions for detecting humans and dogs in images, we need a way to predict breed from images. In this step, you will create a CNN that classifies dog breeds. You must create your CNN *from scratch* (so, you can't use transfer learning yet!), and you must attain a test accuracy of at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

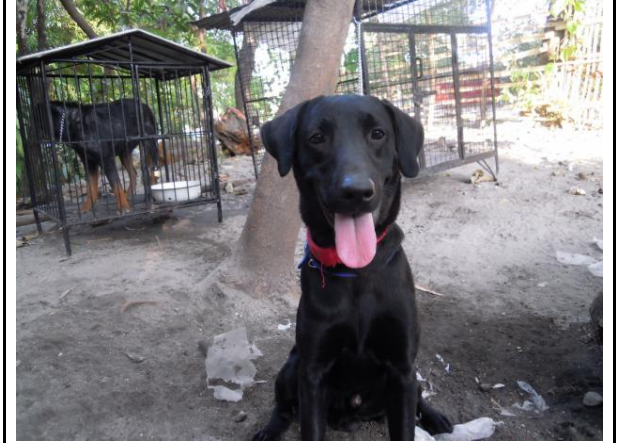


It is not difficult to find other dog breed pairs with minimal inter-class variation (for instance, Curly-Coated Retrievers and American Water Spaniels).



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%.

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!

## Pre-process the Data

We rescale the images by dividing every pixel in every image by 255.

In [11]:

```
from PIL import ImageFile
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
```

```
100%|██████████| 6680/6680 [03:28<00:00, 32.08it/s]
100%|██████████| 835/835 [00:24<00:00, 34.67it/s]
100%|██████████| 836/836 [00:23<00:00, 35.81it/s]
```

In [27]:

```
train_tensors[10].shape
```

Out[27]:

```
(224, 224, 3)
```

## (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 (MaxPooling2)	(None, 111, 111, 16)	0
conv2d_2 (Conv2D)	(None, 110, 110, 32)	2080
max_pooling2d_2 (MaxPooling2)	(None, 55, 55, 32)	0
conv2d_3 (Conv2D)	(None, 54, 54, 64)	8256
max_pooling2d_3 (MaxPooling2)	(None, 27, 27, 64)	0
global_average_pooling2d_1 (	(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:** The first convolution layer detects the simple patterns like horizontal line, vertical line, 45 deg line. The second convolution layer detects more complicated patterns like coner, wave, circle. The third layer detects more complicated patterns related for each dog breeds. The third layer has 64 depth which represent features. Each convolution layers are followed maxpooling, maxpooling layers reduce the spatial dimension from 224 to 28 totally. The next Gloval Average Pooling layer averages processed data with 28\*28 filer for each 64 features. The resulting 64 features are connected to 133 fully connected layer(Dense layer). This layer are activated by softmax function, then we get the percentage of each dog breed.

In [30]:

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

model = Sequential()

### TODO: Define your architecture.
model.add(Conv2D(filters=16, kernel_size=2, padding='same', activation='relu',
                 input_shape=(224, 224, 3)))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=32, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=64, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
#model.add(Dropout(0.3))
model.add(GlobalAveragePooling2D(data_format=None))
model.add(Dense(133, activation='softmax'))

model.summary()
```

Layer (type)	Output Shape	Param #
=====		
conv2d_19 (Conv2D)	(None, 224, 224, 16)	208
<hr/>		
max_pooling2d_20 (MaxPooling)	(None, 112, 112, 16)	0
<hr/>		
conv2d_20 (Conv2D)	(None, 112, 112, 32)	2080
<hr/>		
max_pooling2d_21 (MaxPooling)	(None, 56, 56, 32)	0
<hr/>		
conv2d_21 (Conv2D)	(None, 56, 56, 64)	8256
<hr/>		
max_pooling2d_22 (MaxPooling)	(None, 28, 28, 64)	0
<hr/>		
global_average_pooling2d_5 (GlobalAveragePooling2D)	(None, 64)	0
<hr/>		
dense_6 (Dense)	(None, 133)	8645
=====		
Total params: 19,189.0		
Trainable params: 19,189.0		
Non-trainable params: 0.0		
<hr/>		

## Compile the Model

In [31]:

```
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['acc
```

## (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 [32]:

```
from keras.callbacks import ModelCheckpoint

### TODO: specify the number of epochs that you would like to use to train the model
epochs = 10

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

Train on 6680 samples, validate on 835 samples

Epoch 1/10

```
6660/6680 [=====>.] - ETA: 1s - loss: 4.8842
- acc: 0.0096      Epoch 00000: val_loss improved from inf to 4.870
28, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 484s - loss: 4.8842 - a
cc: 0.0096 - val_loss: 4.8703 - val_acc: 0.0132
```

Epoch 2/10

```
6660/6680 [=====>.] - ETA: 1s - loss: 4.8690
- acc: 0.0098      Epoch 00001: val_loss improved from 4.87028 to 4.
86168, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 575s - loss: 4.8691 - a
cc: 0.0097 - val_loss: 4.8617 - val_acc: 0.0180
```

Epoch 3/10

```
6660/6680 [=====>.] - ETA: 3s - loss: 4.8486
- acc: 0.0155      Epoch 00002: val_loss improved from 4.86168 to 4.
83413, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 1303s - loss: 4.8489 -
acc: 0.0154 - val_loss: 4.8341 - val_acc: 0.0192
```

Epoch 4/10

```
6660/6680 [=====>.] - ETA: 1s - loss: 4.8018
- acc: 0.0194      Epoch 00003: val_loss improved from 4.83413 to 4.
79949, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 432s - loss: 4.8013 - a
cc: 0.0193 - val_loss: 4.7995 - val_acc: 0.0192
```

Epoch 5/10

```
6660/6680 [=====>.] - ETA: 65s - loss: 4.7662
- acc: 0.0216      Epoch 00004: val_loss improved from 4.79949 to 4.7
7141, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 21993s - loss: 4.7665 -
acc: 0.0216 - val_loss: 4.7714 - val_acc: 0.0168
```

Epoch 6/10

```
6660/6680 [=====>.] - ETA: 9s - loss: 4.7392
- acc: 0.0207      Epoch 00005: val_loss improved from 4.77141 to 4.76
```



```
986, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 3081s - loss: 4.7392 -
acc: 0.0207 - val_loss: 4.7699 - val_acc: 0.0180
Epoch 7/10
6660/6680 [=====>.] - ETA: 6s - loss: 4.7103
- acc: 0.0243 Epoch 00006: val_loss improved from 4.76986 to 4.738
98, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 2228s - loss: 4.7102 -
acc: 0.0243 - val_loss: 4.7390 - val_acc: 0.0216
Epoch 8/10
6660/6680 [=====>.] - ETA: 1s - loss: 4.6841
- acc: 0.0285 Epoch 00007: val_loss improved from 4.73898 to 4.
73377, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 418s - loss: 4.6841 - a
cc: 0.0284 - val_loss: 4.7338 - val_acc: 0.0287
Epoch 9/10
6660/6680 [=====>.] - ETA: 3s - loss: 4.6556
- acc: 0.0327 Epoch 00008: val_loss improved from 4.73377 to 4.704
78, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 1044s - loss: 4.6558 -
acc: 0.0326 - val_loss: 4.7048 - val_acc: 0.0251
Epoch 10/10
6660/6680 [=====>.] - ETA: 1s - loss: 4.6284
- acc: 0.0375 Epoch 00009: val_loss did not improve
6680/6680 [=====] - 592s - loss: 4.6274 - a
cc: 0.0376 - val_loss: 4.7260 - val_acc: 0.0371
```

Out[32]:

```
<keras.callbacks.History at 0x127a277f0>
```

## Load the Model with the Best Validation Loss

In [33]:

```
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 [34]:

```
# 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)))]

# report test accuracy
test_accuracy = 100*np.sum(np.array(dog_breed_predictions)==np.argmax(test_target
print('Test accuracy: %.4f%%' % test_accuracy)
```

Test accuracy: 3.4689%

# 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.

## Obtain Bottleneck Features

In [35]:

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

In [50]:

```
test_VGG16[0].shape
```

Out[50]:

(7, 7, 512)

## 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 [36]:

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

VGG16_model.summary()
```

Layer (type)	Output Shape	Param #
=====		
global_average_pooling2d_6 (	(None, 512)	0
=====		
dense_7 (Dense)	(None, 133)	68229
=====		
Total params: 68,229.0		
Trainable params: 68,229.0		
Non-trainable params: 0.0		
=====		

## Compile the Model

In [37]:

```
VGG16_model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics
```

## Train the Model

In [39]:

```
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=20, batch_size=20, callbacks=[checkpointer], verbose=1)
```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

```
6620/6680 [=====>.] - ETA: 0s - loss: 12.0596  
- acc: 0.1285 Epoch 00000: val_loss improved from inf to 10.422  
00, saving model to saved_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 6s - loss: 12.0432 - ac  
c: 0.1293 - val_loss: 10.4220 - val_acc: 0.2251
```

Epoch 2/20

```
6560/6680 [=====>.] - ETA: 0s - loss: 9.6615  
- acc: 0.3040 Epoch 00001: val_loss improved from 10.42200 to 9.6564  
7, saving model to saved_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 9.6495 - acc  
: 0.3051 - val_loss: 9.6565 - val_acc: 0.3054
```

Epoch 3/20

```
6540/6680 [=====>.] - ETA: 0s - loss: 9.0719  
- acc: 0.3708 Epoch 00002: val_loss improved from 9.65647 to 9.36057  
, saving model to saved_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 9.0915 - acc  
: 0.3698 - val_loss: 9.3606 - val_acc: 0.3413
```

Epoch 4/20

```
6500/6680 [=====>.] - ETA: 0s - loss: 8.7879  
- acc: 0.4086 Epoch 00003: val_loss improved from 9.36057 to 9.27877,  
saving model to saved_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 8.8032 - acc  
: 0.4078 - val_loss: 9.2788 - val_acc: 0.3485
```

Epoch 5/20

```
6560/6680 [=====>.] - ETA: 0s - loss: 8.5916  
- acc: 0.4305 Epoch 00004: val_loss improved from 9.27877 to 8.97543,  
saving model to saved_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 8.5918 - acc  
: 0.4305 - val_loss: 8.9754 - val_acc: 0.3760
```

Epoch 6/20

```
6600/6680 [=====>.] - ETA: 0s - loss: 8.3426  
- acc: 0.4509 Epoch 00005: val_loss improved from 8.97543 to 8.82585,  
saving model to saved_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 8.3301 - acc  
: 0.4515 - val_loss: 8.8258 - val_acc: 0.3808
```

Epoch 7/20

```
6660/6680 [=====>.] - ETA: 0s - loss: 8.0835  
- acc: 0.4734 Epoch 00006: val_loss improved from 8.82585 to 8.72444,
```

saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 8.0932 - acc  
: 0.4729 - val\_loss: 8.7244 - val\_acc: 0.3796  
Epoch 8/20  
6580/6680 [=====>.] - ETA: 0s - loss: 8.0125  
- acc: 0.4824 Epoch 00007: val\_loss improved from 8.72444 to 8.64307,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 8.0159 - acc  
: 0.4823 - val\_loss: 8.6431 - val\_acc: 0.4000  
Epoch 9/20  
6600/6680 [=====>.] - ETA: 0s - loss: 7.9491  
- acc: 0.4938 Epoch 00008: val\_loss improved from 8.64307 to 8.60258,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.9725 - acc  
: 0.4924 - val\_loss: 8.6026 - val\_acc: 0.4144  
Epoch 10/20  
6560/6680 [=====>.] - ETA: 0s - loss: 7.9361  
- acc: 0.4936 Epoch 00009: val\_loss improved from 8.60258 to 8.55289  
, saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.9452 - acc  
: 0.4928 - val\_loss: 8.5529 - val\_acc: 0.4072  
Epoch 11/20  
6640/6680 [=====>.] - ETA: 0s - loss: 7.8123  
- acc: 0.5003 Epoch 00010: val\_loss improved from 8.55289 to 8.42376,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.8067 - acc  
: 0.5006 - val\_loss: 8.4238 - val\_acc: 0.4204  
Epoch 12/20  
6640/6680 [=====>.] - ETA: 0s - loss: 7.7642  
- acc: 0.5053 Epoch 00011: val\_loss improved from 8.42376 to 8.38813,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.7588 - acc  
: 0.5057 - val\_loss: 8.3881 - val\_acc: 0.4156  
Epoch 13/20  
6600/6680 [=====>.] - ETA: 0s - loss: 7.5807  
- acc: 0.5156 Epoch 00012: val\_loss improved from 8.38813 to 8.17177,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.5862 - acc  
: 0.5153 - val\_loss: 8.1718 - val\_acc: 0.4275  
Epoch 14/20  
6620/6680 [=====>.] - ETA: 0s - loss: 7.3889  
- acc: 0.5237 Epoch 00013: val\_loss improved from 8.17177 to 8.09891  
, saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.3884 - acc  
: 0.5237 - val\_loss: 8.0989 - val\_acc: 0.4240  
Epoch 15/20  
6600/6680 [=====>.] - ETA: 0s - loss: 7.2143  
- acc: 0.5383 Epoch 00014: val\_loss improved from 8.09891 to 7.96166,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.2212 - acc  
: 0.5380 - val\_loss: 7.9617 - val\_acc: 0.4335  
Epoch 16/20  
6560/6680 [=====>.] - ETA: 0s - loss: 7.0736  
- acc: 0.5500 Epoch 00015: val\_loss improved from 7.96166 to 7.84283,  
saving model to saved\_models/weights.best.VGG16.hdf5  
6680/6680 [=====] - 2s - loss: 7.0922 - acc  
: 0.5487 - val\_loss: 7.8428 - val\_acc: 0.4467

```
Epoch 17/20
6660/6680 [=====>.] - ETA: 0s - loss: 7.0204
- acc: 0.5521Epoch 00016: val_loss improved from 7.84283 to 7.78671,
saving model to saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s - loss: 7.0139 - acc
: 0.5525 - val_loss: 7.7867 - val_acc: 0.4479
Epoch 18/20
6620/6680 [=====>.] - ETA: 0s - loss: 6.9247
- acc: 0.5595Epoch 00017: val_loss improved from 7.78671 to 7.70664,
saving model to saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s - loss: 6.9091 - acc
: 0.5603 - val_loss: 7.7066 - val_acc: 0.4575
Epoch 19/20
6580/6680 [=====>.] - ETA: 0s - loss: 6.8714
- acc: 0.5657Epoch 00018: val_loss improved from 7.70664 to 7.69289,
saving model to saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s - loss: 6.8688 - acc
: 0.5656 - val_loss: 7.6929 - val_acc: 0.4647
Epoch 20/20
6620/6680 [=====>.] - ETA: 0s - loss: 6.8043
- acc: 0.5693Epoch 00019: val_loss improved from 7.69289 to 7.61691,
saving model to saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s - loss: 6.8162 - acc
: 0.5684 - val_loss: 7.6169 - val_acc: 0.4707
```

Out[39]:

<keras.callbacks.History at 0x127aebd68>

## Load the Model with the Best Validation Loss

In [40]:

```
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 [41]:

```
# 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))

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

Test accuracy: 44.9761%

## Predict Dog Breed with the Model

In [42]:

```
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 [44]:

```
### TODO: Obtain bottleneck features from another pre-trained CNN.
bottleneck_features = np.load('bottleneck_features/DogResnet50Data.npz')
train_Resnet50 = bottleneck_features['train']
valid_Resnet50 = bottleneck_features['valid']
test_Resnet50 = 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:** My final architecture name is Resnet50\_model. It has 2 layers.

```
flatten_3 (Flatten) (None, 2048)
dense_13 (Dense) (None, 133)
```

ResNet50 bottle neck features has (1, 1, 2048) demension output. This output has 2048 values and each values represent some features. I flattend this (1, 1, 2048) tensor to 2048 values, then connected to Dense layer that has 133 output. 133 is the number of dog breed and this layer output is activated by Softmax to get the percentage of dog breed prediction.

In [56]:

```
### TODO: Define your architecture.
Resnet50_model = Sequential()
#Resnet50_model.add(GlobalAveragePooling2D(input_shape=train_Resnet50.shape[1:]))
#Resnet50_model.add(Dense(133, activation='softmax'))
Resnet50_model.add(Flatten(input_shape=train_Resnet50.shape[1:]))
Resnet50_model.add(Dense(133, activation='softmax'))

Resnet50_model.summary()
```

Layer (type)	Output Shape	Param #
=====		
flatten_3 (Flatten)	(None, 2048)	0
=====		
dense_13 (Dense)	(None, 133)	272517
=====		
Total params: 272,517.0		
Trainable params: 272,517.0		
Non-trainable params: 0.0		
=====		

## (IMPLEMENTATION) Compile the Model

In [58]:

```
### TODO: Compile the model.  
Resnet50_model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metr
```

## (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>), but this is not a requirement.

In [60]:

```
### TODO: Train the model.  
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.Resnet50.hdf5',  
                               verbose=1, save_best_only=True)  
  
Resnet50_model.fit(train_Resnet50, train_targets,  
                  validation_data=(valid_Resnet50, valid_targets),  
                  epochs=20, batch_size=20, callbacks=[checkpointer], verbose=1)
```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

```
6580/6680 [=====>.] - ETA: 0s - loss: 1.6486  
- acc: 0.5950      Epoch 00000: val_loss improved from inf to 0.8071  
2, saving model to saved_models/weights.best.Resnet50.hdf5  
6680/6680 [=====] - 6s - loss: 1.6350 - acc  
: 0.5973 - val_loss: 0.8071 - val_acc: 0.7653
```

Epoch 2/20

```
6660/6680 [=====>.] - ETA: 0s - loss: 0.4309  
- acc: 0.8614Epoch 00001: val_loss improved from 0.80712 to 0.68131,  
saving model to saved_models/weights.best.Resnet50.hdf5  
6680/6680 [=====] - 4s - loss: 0.4306 - acc  
: 0.8617 - val_loss: 0.6813 - val_acc: 0.7844
```

Epoch 3/20

```
6620/6680 [=====>.] - ETA: 0s - loss: 0.2618  
- acc: 0.9154Epoch 00002: val_loss improved from 0.68131 to 0.65487,  
saving model to saved_models/weights.best.Resnet50.hdf5  
6680/6680 [=====] - 3s - loss: 0.2620 - acc  
: 0.9153 - val_loss: 0.6549 - val_acc: 0.8180
```

Epoch 4/20

```
6580/6680 [=====>.] - ETA: 0s - loss: 0.1727  
- acc: 0.9444Epoch 00003: val_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.1738 - acc  
: 0.9440 - val_loss: 0.6640 - val_acc: 0.8000
```

Epoch 5/20

```
6640/6680 [=====>.] - ETA: 0s - loss: 0.1219  
- acc: 0.9639Epoch 00004: val_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.1215 - acc  
: 0.9639 - val_loss: 0.6595 - val_acc: 0.8192
```

Epoch 6/20

```
6620/6680 [=====>.] - ETA: 0s - loss: 0.0877
```



- acc: 0.9727Epoch 00005: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0878 - acc  
: 0.9726 - val\_loss: 0.6823 - val\_acc: 0.8072  
Epoch 7/20  
6600/6680 [=====>.] - ETA: 0s - loss: 0.0647  
- acc: 0.9814Epoch 00006: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0650 - acc  
: 0.9814 - val\_loss: 0.6765 - val\_acc: 0.8240  
Epoch 8/20  
6660/6680 [=====>.] - ETA: 0s - loss: 0.0446  
- acc: 0.9869Epoch 00007: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0446 - acc  
: 0.9870 - val\_loss: 0.7073 - val\_acc: 0.8263  
Epoch 9/20  
6660/6680 [=====>.] - ETA: 0s - loss: 0.0360  
- acc: 0.9899Epoch 00008: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0360 - acc  
: 0.9900 - val\_loss: 0.7102 - val\_acc: 0.8132  
Epoch 10/20  
6660/6680 [=====>.] - ETA: 0s - loss: 0.0294  
- acc: 0.9920Epoch 00009: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0294 - acc  
: 0.9921 - val\_loss: 0.7269 - val\_acc: 0.8275  
Epoch 11/20  
6600/6680 [=====>.] - ETA: 0s - loss: 0.0214  
- acc: 0.9942 Epoch 00010: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0216 - acc  
: 0.9942 - val\_loss: 0.7073 - val\_acc: 0.8263  
Epoch 12/20  
6620/6680 [=====>.] - ETA: 0s - loss: 0.0158  
- acc: 0.9964 Epoch 00011: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0158 - acc  
: 0.9963 - val\_loss: 0.7593 - val\_acc: 0.8395  
Epoch 13/20  
6620/6680 [=====>.] - ETA: 0s - loss: 0.0142  
- acc: 0.9968 Epoch 00012: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0142 - acc  
: 0.9969 - val\_loss: 0.7860 - val\_acc: 0.8287  
Epoch 14/20  
6660/6680 [=====>.] - ETA: 0s - loss: 0.0113  
- acc: 0.9971Epoch 00013: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0113 - acc  
: 0.9972 - val\_loss: 0.7970 - val\_acc: 0.8216  
Epoch 15/20  
6600/6680 [=====>.] - ETA: 0s - loss: 0.0109  
- acc: 0.9971 Epoch 00014: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0108 - acc  
: 0.9972 - val\_loss: 0.7814 - val\_acc: 0.8192  
Epoch 16/20  
6660/6680 [=====>.] - ETA: 0s - loss: 0.0097  
- acc: 0.9971Epoch 00015: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0097 - acc  
: 0.9972 - val\_loss: 0.8694 - val\_acc: 0.8275  
Epoch 17/20  
6580/6680 [=====>.] - ETA: 0s - loss: 0.0070  
- acc: 0.9983 Epoch 00016: val\_loss did not improve  
6680/6680 [=====] - 4s - loss: 0.0069 - acc

```

: 0.9984 - val_loss: 0.8491 - val_acc: 0.8263
Epoch 18/20
6660/6680 [=====>.] - ETA: 0s - loss: 0.0063
- acc: 0.9983      Epoch 00017: val_loss did not improve
6680/6680 [=====] - 4s - loss: 0.0063 - acc
: 0.9984 - val_loss: 0.8871 - val_acc: 0.8192
Epoch 19/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0054
- acc: 0.9988      Epoch 00018: val_loss did not improve
6680/6680 [=====] - 4s - loss: 0.0053 - acc
: 0.9988 - val_loss: 0.8914 - val_acc: 0.8263
Epoch 20/20
6600/6680 [=====>.] - ETA: 0s - loss: 0.0048
- acc: 0.9983      Epoch 00019: val_loss did not improve
6680/6680 [=====] - 4s - loss: 0.0047 - acc
: 0.9984 - val_loss: 0.9165 - val_acc: 0.8275

Out[60]:

<keras.callbacks.History at 0x128206e48>

```

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

In [61]:

```

### TODO: Load the model weights with the best validation loss.
Resnet50_model.load_weights('saved_models/weights.best.Resnet50.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 [62]:

```

### TODO: Calculate classification accuracy on the test dataset.
Resnet50_predictions = [np.argmax(Resnet50_model.predict(np.expand_dims(feature,
# report test accuracy
test_accuracy = 100*np.sum(np.array(Resnet50_predictions)==np.argmax(test_targets
print('Test accuracy: %.4f%%' % test_accuracy)

```

Test accuracy: 81.1005%

## (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 [63]:

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

def Resnet50_predict_breed(img_path):
    # extract bottleneck features
    bottleneck_feature = extract_Resnet50(path_to_tensor(img_path))
    # obtain predicted vector
    predicted_vector = Resnet50_model.predict(bottleneck_feature)
    # return dog breed that is predicted by the model
    return dog_names[np.argmax(predicted_vector)]
```

In [86]:

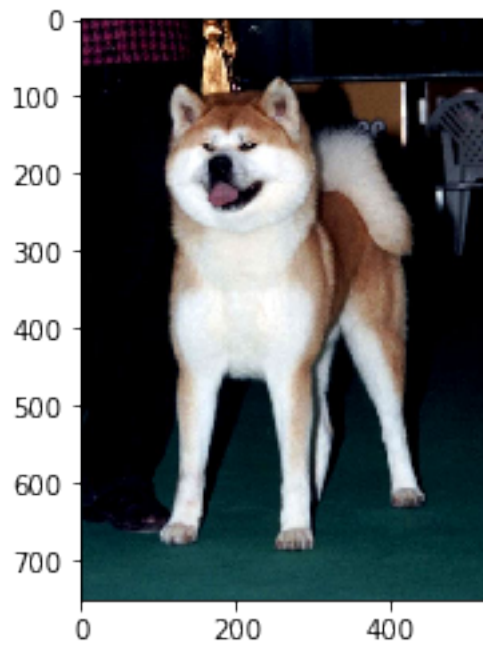
```
def show_picture2(path):
    # load color (BGR) image
    img = cv2.imread(path)

    # 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()
    return
```

In [87]:

```
path = 'dogImages/test/004.Akita/Akita_00296.jpg'  
show_picture2(path)  
Resnet50_predict_breed(path)
```



Out[87]:

'Akita'

In [88]:

```
path = 'dogImages/test/048.Chihuahua/Chihuahua_03448.jpg'  
show_picture2(path)  
Resnet50_predict_breed(path)
```



Out[88]:

'Chihuahua'

---

## 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.

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

```
hello, human!  
  
0  
200  
400  
600  
800  
1000  
1200  
1400  
0 500 1000  
  
You look like a ...  
Chinese_shar-pei
```



## (IMPLEMENTATION) Write your Algorithm

In [108]:

```
### TODO: Write your algorithm.  
### Feel free to use as many code cells as needed.  
  
def dog_human_detector(path):  
    show_picture2(path)  
    if dog_detector(path) == True:  
        return print('Dog breed is', Resnet50_predict_breed(path))  
    elif face_detector(path) == True:  
        return print('You looks like', Resnet50_predict_breed(path))  
    else:  
        return print('error')
```

## 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 [109]:

```
## 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.
path = 'dogImages/test/048.Chihuahua/Chihuahua_03448.jpg'
dog_human_detector(path)
path = 'lfw/Yoko_Ono/Yoko_Ono_0003.jpg'
dog_human_detector(path)
path = 'dogImages/test/004.Akita/Akita_00296.jpg'
dog_human_detector(path)
path = 'lfw/Yukio_Hatoyama/Yukio_Hatoyama_0001.jpg'
dog_human_detector(path)
path = 'dogImages/test/043.Canaan_dog/Canaan_dog_03072.jpg'
dog_human_detector(path)
path = 'lfw/Uma_Thurman/Uma_Thurman_0002.jpg'
dog_human_detector(path)
path = 'dogImages/test/101.Maltese/Maltese_06728.jpg'
dog_human_detector(path)
```



Dog breed is Chihuahua



In [ ]: