

Convolutional Neural Networks

Project: Write an Algorithm for a Dog Identification App

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

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

Why We're Here

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

 Sample Dog Output

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

nonetheless create a fun user experience!

The Road Ahead

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

- [Step 0](#): Import Datasets
- [Step 1](#): Detect Humans
- [Step 2](#): Detect Dogs
- [Step 3](#): Create a CNN to Classify Dog Breeds (from Scratch)
- [Step 4](#): 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

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 [2]: from sklearn.datasets import load_files
        from keras.utils import np_utils
        import numpy as np
        from glob import glob
        import random
        import cv2
        import matplotlib.pyplot as plt
        from keras.preprocessing import image
        from tqdm import tqdm
        from keras.applications.resnet50 import preprocess_input, decode_predictions
        from PIL import ImageFile
        from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D
        from keras.layers import Dropout, Flatten, Dense
        from keras.models import Sequential
        from keras.callbacks import ModelCheckpoint
        from extract_bottleneck_features import *
        import cv2
        import matplotlib.pyplot as plt
```

```
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('/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[20:-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))
print(train_targets)
```

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.

```
[[ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 ...,
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]]
```

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 [8]: import random
        random.seed(8675309)

        # Load filenames in shuffled human dataset
        human_files = np.array(glob("/data/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) (<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 [9]: import cv2
import matplotlib.pyplot as plt
%matplotlib inline

# extract pre-trained face detector
face_cascade = cv2.CascadeClassifier('haarcascades/haarcascade_frontalface_al
t.xml')

# Load color (BGR) image
img = cv2.imread(human_files[3])
# convert BGR image to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

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

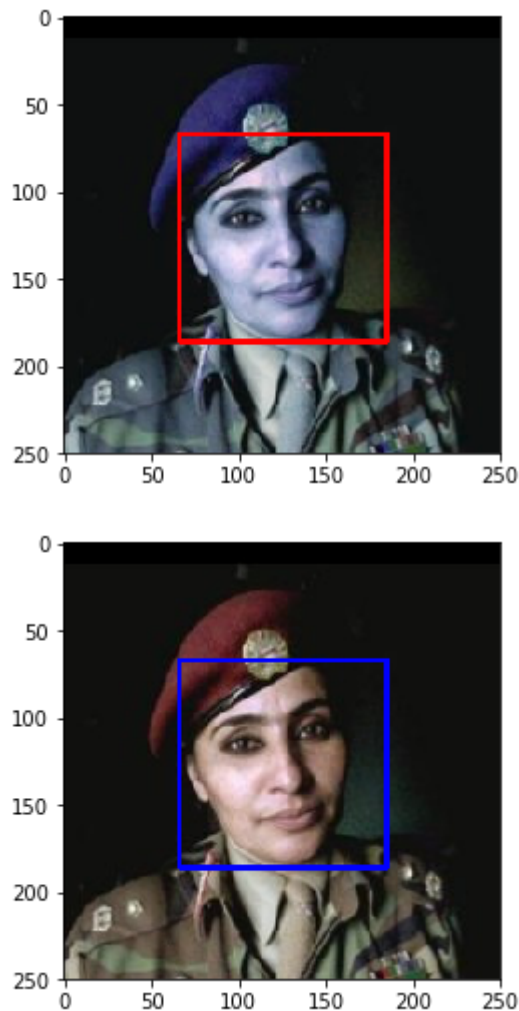
# print number of faces detected in the image
print('Number of faces detected:', len(faces))

# 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(img)
plt.show()
plt.imshow(cv_rgb)
plt.show()
```

Number of faces detected: 1



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

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

Write a Human Face Detector

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

```
In [10]: # 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 [ ]: human_files_short = human_files[:100]
dog_files_short = train_files[:100]
# Do NOT modify the code above this line.

h_face = 0
d_face = 0
for i in range(100):
    isFace = face_detector(human_files_short[i])
    isDog = face_detector(dog_files_short[i])
    if isFace:
        h_face = h_face + 1
    if isDog:
        d_face = d_face + 1
print("percentage of the first 100 images in human_files have a detected human face is {}".format(h_face))

print("percentage of the first 100 images in dog_files have a detected human face is {}".format(d_face))
## TODO: Test the performance of the face_detector algorithm
## on the images in human_files_short and dog_files_short.
```


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

__Answer:__

I think the image needs to have certain standard of quality. If the face **is** covered mostly **or if** the face **is** completey back to camera **or** partilly **and** it si **not** cleare

we cant expect alghorithm to detect face properly. I dont expect alghorithm de tect face **with** poor light **and** quality, but **if** the face **is** upside down **or is** to side **or any** other orientationn I would expect the alghorithm detects the face .Here **as** we anyalized 10% of the dogs are detected **as** human face **for** solving this might need to consider more fetures **in** addition to (eyes, mouth, nose, etc

somthing like head shape **or** cheek

File "<ipython-input-7-1d6d8344a97f>", line 5

I think the image needs to have certain standard of quality. If the face is covered mostly or if the face is completey back to camera or partilly and it si not cleare

SyntaxError: invalid syntax

Step 2: Detect Dogs

In this section, we use a pre-trained [ResNet-50](https://ethereon.github.io/netscope/#/gist/db945b393d40bfa26006) ([http://ethereon.github.io/netscope/#/gist/db945b393d40bfa26006](https://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/) (<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 [18]: 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 [=====] - 2s 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

(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 224×224 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 [16]: 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).

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 [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 [12]: ### 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 [ ]: ### TODO: Test the performance of the dog_detector function  
### on the images in human_files_short and dog_files_short.  
h_face = 0  
d_face = 0  
for i in range(100):  
    isFace = dog_detector(human_files_short[i])  
    isDog = dog_detector(dog_files_short[i])  
    if isFace:  
        h_face = h_face + 1  
    if isDog:  
        d_face = d_face + 1  
print("percentage of the first 100 images in human_files have a detected human face is {}".format(h_face))  
  
print("percentage of the first 100 images in dog_files have a detected human face is {}".format(d_face))  
## TODO: Test the performance of the face_detector algorithm  
## on the images in human_files_short and dog_files_short.
```

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.

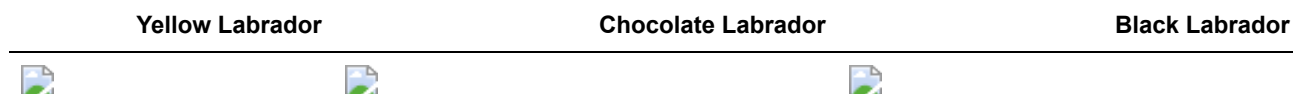
We mention that the task of assigning breed to dogs from images is considered exceptionally challenging. To see why, consider that *even a human* would have great difficulty in distinguishing between a Brittany and a Welsh Springer Spaniel.



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.



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 [8]: 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 [01:29<00:00, 75.06it/s]
100%|██████████| 835/835 [00:09<00:00, 83.62it/s]
100%|██████████| 836/836 [00:09<00:00, 86.04it/s]
```

(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:

 Sample CNN

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 [10]: 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(GlobalAveragePooling2D())
model.add(Dense(133, activation='relu'))

# summarize the model
model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 224, 224, 16)	208
max_pooling2d_5 (MaxPooling2D)	(None, 112, 112, 16)	0
conv2d_5 (Conv2D)	(None, 112, 112, 32)	2080
max_pooling2d_6 (MaxPooling2D)	(None, 56, 56, 32)	0
conv2d_6 (Conv2D)	(None, 56, 56, 64)	8256
max_pooling2d_7 (MaxPooling2D)	(None, 28, 28, 64)	0
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 64)	0
dense_2 (Dense)	(None, 133)	8645
Total params: 19,189		
Trainable params: 19,189		
Non-trainable params: 0		

```
In [14]: model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
```

Compile the Model

(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 [15]: from keras.callbacks import ModelCheckpoint

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

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(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 1/20

6660/6680 [=====>.] - ETA: 0s - loss: 11.3008 - acc: 0.0081
Epoch 00001: val_loss improved from inf to 12.30782, saving model to saved_models/weights.best.from_scratch.hdf5

6680/6680 [=====] - 25s 4ms/step - loss: 11.3064 - acc: 0.0081 - val_loss: 12.3078 - val_acc: 0.0108

Epoch 2/20

6660/6680 [=====>.] - ETA: 0s - loss: 12.9217 - acc: 0.0072
Epoch 00002: val_loss improved from 12.30782 to 12.29474, saving model to saved_models/weights.best.from_scratch.hdf5

6680/6680 [=====] - 22s 3ms/step - loss: 12.9239 - acc: 0.0072 - val_loss: 12.2947 - val_acc: 0.0096

Epoch 3/20

6660/6680 [=====>.] - ETA: 0s - loss: 12.3246 - acc: 0.0105
Epoch 00003: val_loss improved from 12.29474 to 11.73374, saving model to saved_models/weights.best.from_scratch.hdf5

6680/6680 [=====] - 22s 3ms/step - loss: 12.3198 - acc: 0.0105 - val_loss: 11.7337 - val_acc: 0.0096

Epoch 4/20

6660/6680 [=====>.] - ETA: 0s - loss: 11.6408 - acc: 0.0096
Epoch 00004: val_loss did not improve

6680/6680 [=====] - 21s 3ms/step - loss: 11.6415 - acc: 0.0096 - val_loss: 11.9196 - val_acc: 0.0108

Epoch 5/20

6660/6680 [=====>.] - ETA: 0s - loss: 13.0199 - acc: 0.0090
Epoch 00005: val_loss did not improve

6680/6680 [=====] - 22s 3ms/step - loss: 13.0292 - acc: 0.0090 - val_loss: 14.5551 - val_acc: 0.0096

Epoch 6/20

6660/6680 [=====>.] - ETA: 0s - loss: 13.7346 - acc: 0.0114
Epoch 00006: val_loss did not improve

6680/6680 [=====] - 22s 3ms/step - loss: 13.7320 - acc: 0.0114 - val_loss: 13.4172 - val_acc: 0.0084

Epoch 7/20

6660/6680 [=====>.] - ETA: 0s - loss: 14.1382 - acc: 0.0090
Epoch 00007: val_loss did not improve

6680/6680 [=====] - 22s 3ms/step - loss: 14.1420 - acc: 0.0090 - val_loss: 14.9622 - val_acc: 0.0096

Epoch 8/20

6660/6680 [=====>.] - ETA: 0s - loss: 15.6113 - acc: 0.0099
Epoch 00008: val_loss did not improve

6680/6680 [=====] - 22s 3ms/step - loss: 15.6105 - acc: 0.0100 - val_loss: 15.8229 - val_acc: 0.0096

Epoch 9/20

6660/6680 [=====>.] - ETA: 0s - loss: 15.7919 - acc: 0.0078
Epoch 00009: val_loss did not improve

6680/6680 [=====] - 22s 3ms/step - loss: 15.7929 - acc: 0.0078 - val_loss: 15.7493 - val_acc: 0.0096

Epoch 10/20

6660/6680 [=====>.] - ETA: 0s - loss: 15.9046 - acc: 0.0071
Epoch 00010: val_loss did not improve

6680/6680 [=====] - 22s 3ms/step - loss: 15.9052 - acc: 0.0070 - val_loss: 16.0216 - val_acc: 0.0060

Epoch 11/20

6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc: 0.0060
Epoch 00011: val_loss did not improve

```

6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 12/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00012: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 13/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0237 - acc:
0.0059Epoch 00013: val_loss did not improve
6680/6680 [=====] - 23s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 14/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00014: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 15/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00015: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 16/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00016: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 17/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00017: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 18/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00018: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 19/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00019: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060
Epoch 20/20
6660/6680 [=====>.] - ETA: 0s - loss: 16.0213 - acc:
0.0060Epoch 00020: val_loss did not improve
6680/6680 [=====] - 22s 3ms/step - loss: 16.0216 - a
cc: 0.0060 - val_loss: 16.0216 - val_acc: 0.0060

```

Out[15]: <keras.callbacks.History at 0x7f03358df2b0>

Load the Model with the Best Validation Loss

```
In [16]: 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 [17]: # 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_targets, axis=1))/len(dog_breed_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
```

Test accuracy: 0.9569%

```
In [ ]: ###Lenet
```

```

In [ ]: 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('/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[20:-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))
        #print( train_targets)
        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.
        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)
        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 [01:27<00:00, 76.69it/s]
100%|██████████| 835/835 [00:09<00:00, 85.24it/s]
100%|██████████| 836/836 [00:09<00:00, 85.82it/s]
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D, MaxPool2D, AveragePooling2D
from keras.layers import Dropout, Flatten, Dense, Input, concatenate
from keras.models import Sequential, Model
from keras.layers.core import Activation
from keras.layers.core import Flatten
from pyimagesearch.cnn.networks.lenet import LeNet
from sklearn.model_selection import train_test_split
from keras.datasets import mnist
from keras.optimizers import SGD
from keras.utils import np_utils
from keras import backend as K
import numpy as np
import argparse
import cv2
model = Sequential()
Using TensorFlow backend.

-----
ModuleNotFoundError                                Traceback (most recent call last)
<ipython-input-1-b69f81eb32f8> in <module>()
      4 from keras.layers.core import Activation
      5 from keras.layers.core import Flatten
----> 6 from pyimagesearch.cnn.networks.lenet import LeNet
      7 from sklearn.model_selection import train_test_split
      8 from keras.datasets import mnist

ModuleNotFoundError: No module named 'pyimagesearch'

# define the first set of CONV => ACTIVATION => POOL Layers
model.add(Conv2D(20, 5, padding="same", input_shape=(224,224,3)))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
# define the second set of CONV => ACTIVATION => POOL Layers
model.add(Conv2D(50, 5, padding="same"))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
# define the first FC => ACTIVATION Layers
model.add(Flatten())
model.add(Dense(500))
model.add(Activation("relu"))

# define the second FC Layer
model.add(Dense(100))

# Lastly, define the soft-max classifier
model.add(Activation("softmax"))

model.compile(loss="categorical_crossentropy", optimizer=opt, metrics=["accuracy"])
model.fit(train_tensors, train_targets, validation_data=(valid_tensors, valid_t

```

```
targets ), batch_size=128, epochs=20,verbose=1)
```

```
-----
NameError                                Traceback (most recent call last)
<ipython-input-20-dd58505724a0> in <module>()
----> 1 model.compile(loss="categorical_crossentropy", optimizer=opt,metrics=[
"accuracy"])
      2 model.fit(train_tensors, train_targets,validation_data =(valid_tensors
,valid_targets ), batch_size=128, epochs=20,verbose=1)
```

NameError: name 'opt' is not defined

```
# show the accuracy on the testing set
print("[INFO] evaluating...")
(loss, accuracy) = model.evaluate(testData, testLabels,
batch_size=128, verbose=1)
print("[INFO] accuracy: {:.2f}%".format(accuracy * 100))
model.summary()
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 224, 224, 3)	0	
conv_1_7x7/2 (Conv2D)	(None, 112, 112, 64)	9472	input_1[0][0]
max_pool_1_3x3/2 (MaxPooling2D)	(None, 56, 56, 64)	0	conv_1_7x7/2[0][0]
conv_2a_3x3/1 (Conv2D)	(None, 56, 56, 64)	4160	max_pool_1_3x3/2[0][0]
conv_2b_3x3/1 (Conv2D)	(None, 56, 56, 192)	110784	conv_2a_3x3/1[0][0]
max_pool_2_3x3/2 (MaxPooling2D)	(None, 28, 28, 192)	0	conv_2b_3x3/1[0][0]
conv2d_2 (Conv2D)	(None, 28, 28, 96)	18528	max_pool_2_3x3/2[0][0]
conv2d_4 (Conv2D)	(None, 28, 28, 16)	3088	max_pool_2_3x3/2[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 28, 28, 192)	0	max_pool_2_3x3/2[0][0]

conv2d_1 (Conv2D) 3/2[0][0]	(None, 28, 28, 64)	12352	max_pool_2_3x
conv2d_3 (Conv2D)]	(None, 28, 28, 128)	110720	conv2d_2[0][0]
conv2d_5 (Conv2D)]	(None, 28, 28, 32)	12832	conv2d_4[0][0]
conv2d_6 (Conv2D) _1[0][0]	(None, 28, 28, 32)	6176	max_pooling2d
inception_3a (Concatenate)]]]]	(None, 28, 28, 256)	0	conv2d_1[0][0] conv2d_3[0][0] conv2d_5[0][0] conv2d_6[0][0]
conv2d_8 (Conv2D) 0][0]	(None, 28, 28, 128)	32896	inception_3a[
conv2d_10 (Conv2D) 0][0]	(None, 28, 28, 32)	8224	inception_3a[
max_pooling2d_2 (MaxPooling2D) 0][0]	(None, 28, 28, 256)	0	inception_3a[
conv2d_7 (Conv2D) 0][0]	(None, 28, 28, 128)	32896	inception_3a[
conv2d_9 (Conv2D)]	(None, 28, 28, 192)	221376	conv2d_8[0][0]
conv2d_11 (Conv2D) 0]	(None, 28, 28, 96)	76896	conv2d_10[0][
conv2d_12 (Conv2D) _2[0][0]	(None, 28, 28, 64)	16448	max_pooling2d
inception_3b (Concatenate)]	(None, 28, 28, 480)	0	conv2d_7[0][0]

]			conv2d_9[0][0]
0]			conv2d_11[0][
0]			conv2d_12[0][
<hr/>			
max_pool_3_3x3/2 (MaxPooling2D)	(None, 14, 14, 480)	0	inception_3b[0][0]
<hr/>			
conv2d_14 (Conv2D)	(None, 14, 14, 96)	46176	max_pool_3_3x3/2[0][0]
<hr/>			
conv2d_16 (Conv2D)	(None, 14, 14, 16)	7696	max_pool_3_3x3/2[0][0]
<hr/>			
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 480)	0	max_pool_3_3x3/2[0][0]
<hr/>			
conv2d_13 (Conv2D)	(None, 14, 14, 192)	92352	max_pool_3_3x3/2[0][0]
<hr/>			
conv2d_15 (Conv2D)	(None, 14, 14, 208)	179920	conv2d_14[0][0]
<hr/>			
conv2d_17 (Conv2D)	(None, 14, 14, 48)	19248	conv2d_16[0][0]
<hr/>			
conv2d_18 (Conv2D)	(None, 14, 14, 64)	30784	max_pooling2d_3[0][0]
<hr/>			
inception_4a (Concatenate)	(None, 14, 14, 512)	0	conv2d_13[0][0]
0]			conv2d_15[0][0]
0]			conv2d_17[0][0]
0]			conv2d_18[0][0]
<hr/>			
conv2d_21 (Conv2D)	(None, 14, 14, 112)	57456	inception_4a[0][0]
<hr/>			
conv2d_23 (Conv2D)	(None, 14, 14, 24)	12312	inception_4a[0][0]
<hr/>			

max_pooling2d_4 (MaxPooling2D)	(None, 14, 14, 512)	0	inception_4a[0][0]
conv2d_20 (Conv2D)	(None, 14, 14, 160)	82080	inception_4a[0][0]
conv2d_22 (Conv2D)	(None, 14, 14, 224)	226016	conv2d_21[0][0]
conv2d_24 (Conv2D)	(None, 14, 14, 64)	38464	conv2d_23[0][0]
conv2d_25 (Conv2D)	(None, 14, 14, 64)	32832	max_pooling2d_4[0][0]
inception_4b (Concatenate)	(None, 14, 14, 512)	0	conv2d_20[0][0] conv2d_22[0][0] conv2d_24[0][0] conv2d_25[0][0]
conv2d_27 (Conv2D)	(None, 14, 14, 128)	65664	inception_4b[0][0]
conv2d_29 (Conv2D)	(None, 14, 14, 24)	12312	inception_4b[0][0]
max_pooling2d_5 (MaxPooling2D)	(None, 14, 14, 512)	0	inception_4b[0][0]
conv2d_26 (Conv2D)	(None, 14, 14, 128)	65664	inception_4b[0][0]
conv2d_28 (Conv2D)	(None, 14, 14, 256)	295168	conv2d_27[0][0]
conv2d_30 (Conv2D)	(None, 14, 14, 64)	38464	conv2d_29[0][0]
conv2d_31 (Conv2D)	(None, 14, 14, 64)	32832	max_pooling2d_5[0][0]

inception_4c (Concatenate) 0]	(None, 14, 14, 512) 0	conv2d_26[0][0] 0] 0] 0]
conv2d_33 (Conv2D) 0][0]	(None, 14, 14, 144) 73872	inception_4c[
conv2d_35 (Conv2D) 0][0]	(None, 14, 14, 32) 16416	inception_4c[
max_pooling2d_6 (MaxPooling2D) 0][0]	(None, 14, 14, 512) 0	inception_4c[
conv2d_32 (Conv2D) 0][0]	(None, 14, 14, 112) 57456	inception_4c[
conv2d_34 (Conv2D) 0]	(None, 14, 14, 288) 373536	conv2d_33[0][
conv2d_36 (Conv2D) 0]	(None, 14, 14, 64) 51264	conv2d_35[0][
conv2d_37 (Conv2D) _6[0][0]	(None, 14, 14, 64) 32832	max_pooling2d
inception_4d (Concatenate) 0] 0] 0] 0]	(None, 14, 14, 528) 0	conv2d_32[0][conv2d_34[0][conv2d_36[0][conv2d_37[0][
conv2d_40 (Conv2D) 0][0]	(None, 14, 14, 160) 84640	inception_4d[
conv2d_42 (Conv2D) 0][0]	(None, 14, 14, 32) 16928	inception_4d[

max_pooling2d_7 (MaxPooling2D)	(None, 14, 14, 528)	0	inception_4d[0][0]
conv2d_39 (Conv2D)	(None, 14, 14, 256)	135424	inception_4d[0][0]
conv2d_41 (Conv2D)	(None, 14, 14, 320)	461120	conv2d_40[0][0]
conv2d_43 (Conv2D)	(None, 14, 14, 128)	102528	conv2d_42[0][0]
conv2d_44 (Conv2D)	(None, 14, 14, 128)	67712	max_pooling2d_7[0][0]
inception_4e (Concatenate)	(None, 14, 14, 832)	0	conv2d_39[0][0] conv2d_41[0][0] conv2d_43[0][0] conv2d_44[0][0]
max_pool_4_3x3/2 (MaxPooling2D)	(None, 7, 7, 832)	0	inception_4e[0][0]
conv2d_46 (Conv2D)	(None, 7, 7, 160)	133280	max_pool_4_3x3/2[0][0]
conv2d_48 (Conv2D)	(None, 7, 7, 32)	26656	max_pool_4_3x3/2[0][0]
max_pooling2d_8 (MaxPooling2D)	(None, 7, 7, 832)	0	max_pool_4_3x3/2[0][0]
conv2d_45 (Conv2D)	(None, 7, 7, 256)	213248	max_pool_4_3x3/2[0][0]
conv2d_47 (Conv2D)	(None, 7, 7, 320)	461120	conv2d_46[0][0]
conv2d_49 (Conv2D)	(None, 7, 7, 128)	102528	conv2d_48[0][0]

conv2d_50 (Conv2D) _8[0][0]	(None, 7, 7, 128)	106624	max_pooling2d
inception_5a (Concatenate) 0]	(None, 7, 7, 832)	0	conv2d_45[0][
0]			conv2d_47[0][
0]			conv2d_49[0][
0]			conv2d_50[0][
conv2d_52 (Conv2D) 0][0]	(None, 7, 7, 192)	159936	inception_5a[
conv2d_54 (Conv2D) 0][0]	(None, 7, 7, 48)	39984	inception_5a[
max_pooling2d_9 (MaxPooling2D) 0][0]	(None, 7, 7, 832)	0	inception_5a[
average_pooling2d_1 (AveragePool) 0][0]	(None, 4, 4, 512)	0	inception_4a[
average_pooling2d_2 (AveragePool) 0][0]	(None, 4, 4, 528)	0	inception_4d[
conv2d_51 (Conv2D) 0][0]	(None, 7, 7, 384)	319872	inception_5a[
conv2d_53 (Conv2D) 0]	(None, 7, 7, 384)	663936	conv2d_52[0][
conv2d_55 (Conv2D) 0]	(None, 7, 7, 128)	153728	conv2d_54[0][
conv2d_56 (Conv2D) _9[0][0]	(None, 7, 7, 128)	106624	max_pooling2d
conv2d_19 (Conv2D) ng2d_1[0][0]	(None, 4, 4, 128)	65664	average_pooli
conv2d_38 (Conv2D)	(None, 4, 4, 128)	67712	average_pooli

ng2d_2[0][0]

inception_5b (Concatenate)	(None, 7, 7, 1024)	0	conv2d_51[0][0]
			conv2d_53[0][0]
			conv2d_55[0][0]
			conv2d_56[0][0]

flatten_1 (Flatten)	(None, 2048)	0	conv2d_19[0][0]
---------------------	--------------	---	-----------------

flatten_2 (Flatten)	(None, 2048)	0	conv2d_38[0][0]
---------------------	--------------	---	-----------------

avg_pool_5_3x3/1 (GlobalAverage)	(None, 1024)	0	inception_5b[0][0]
----------------------------------	--------------	---	--------------------

dense_1 (Dense)	(None, 1024)	2098176	flatten_1[0][0]
-----------------	--------------	---------	-----------------

dense_2 (Dense)	(None, 1024)	2098176	flatten_2[0][0]
-----------------	--------------	---------	-----------------

dropout_3 (Dropout)	(None, 1024)	0	avg_pool_5_3x3/1[0][0]
---------------------	--------------	---	------------------------

dropout_1 (Dropout)	(None, 1024)	0	dense_1[0][0]
---------------------	--------------	---	---------------

dropout_2 (Dropout)	(None, 1024)	0	dense_2[0][0]
---------------------	--------------	---	---------------

output (Dense)	(None, 133)	136325	dropout_3[0][0]
----------------	-------------	--------	-----------------

auxilliary_output_1 (Dense)	(None, 133)	136325	dropout_1[0][0]
-----------------------------	-------------	--------	-----------------

auxilliary_output_2 (Dense)	(None, 133)	136325	dropout_2[0][0]
-----------------------------	-------------	--------	-----------------

=====
 Total params: 10,712,255
 Trainable params: 10,712,255

Non-trainable params: 0

```

import cv2
import numpy as np
from keras.datasets import cifar10
from keras import backend as K
from keras.utils import np_utils

import math
from keras.optimizers import SGD
from keras.callbacks import LearningRateScheduler

epochs = 25
initial_lr = 0.01

def decay(epoch, steps=100):
    initial_lr = 0.01
    drop = 0.96
    epochs_drop = 8
    lr = initial_lr * math.pow(drop, math.floor((1+epoch)/epochs_drop))
    return lr

sgd = SGD(lr=initial_lr, momentum=0.9, nesterov=False)

lr_sc = LearningRateScheduler(decay)

#model.compile(loss=['categorical_crossentropy', 'categorical_crossentropy',
#                    'categorical_crossentropy'], loss_weights=[1, 0.3, 0.3], optimizer=sgd, metrics=
#                    ['accuracy'])
#model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=
#                    ['accuracy'])
model.compile(loss=['categorical_crossentropy', 'categorical_crossentropy', 'c
ategorical_crossentropy'], loss_weights=[1, 0.3, 0.3], optimizer=sgd, metrics=
                    ['accuracy'])

history = model.fit(train_tensors, [train_targets, train_targets, train_target
s], validation_data=(valid_tensors, [valid_targets, valid_targets, valid_targe
ts]), epochs=epochs, batch_size=256, callbacks=[lr_sc])
Train on 6680 samples, validate on 835 samples
Epoch 1/25
6680/6680 [=====] - 73s 11ms/step - loss: 7.9343 - ou
tput_loss: 4.9714 - auxilliary_output_1_loss: 4.9415 - auxilliary_output_2_lo
s: 4.9346 - output_acc: 0.0091 - auxilliary_output_1_acc: 0.0076 - auxilliary_
output_2_acc: 0.0067 - val_loss: 7.8149 - val_output_loss: 4.8810 - val_auxill
iary_output_1_loss: 4.8901 - val_auxilliary_output_2_loss: 4.8897 - val_output
_acc: 0.0096 - val_auxilliary_output_1_acc: 0.0048 - val_auxilliary_output_2_a
cc: 0.0096
Epoch 2/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.8485 - out
put_loss: 4.9136 - auxilliary_output_1_loss: 4.8926 - auxilliary_output_2_loss
: 4.8907 - output_acc: 0.0075 - auxilliary_output_1_acc: 0.0073 - auxilliary_o
utput_2_acc: 0.0081 - val_loss: 7.8110 - val_output_loss: 4.8783 - val_auxilli
ary_output_1_loss: 4.8888 - val_auxilliary_output_2_loss: 4.8869 - val_output
_acc: 0.0132 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_ac
c: 0.0108
Epoch 3/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.8267 - out

```

put_loss: 4.8932 - auxilliary_output_1_loss: 4.8895 - auxilliary_output_2_loss : 4.8888 - output_acc: 0.0087 - auxilliary_output_1_acc: 0.0069 - auxilliary_output_2_acc: 0.0079 - val_loss: 7.8064 - val_output_loss: 4.8742 - val_auxilliary_output_1_loss: 4.8883 - val_auxilliary_output_2_loss: 4.8857 - val_output_acc: 0.0096 - val_auxilliary_output_1_acc: 0.0072 - val_auxilliary_output_2_acc: 0.0108

Epoch 4/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8208 - output_loss: 4.8870 - auxilliary_output_1_loss: 4.8902 - auxilliary_output_2_loss : 4.8892 - output_acc: 0.0090 - auxilliary_output_1_acc: 0.0096 - auxilliary_output_2_acc: 0.0100 - val_loss: 7.8030 - val_output_loss: 4.8710 - val_auxilliary_output_1_loss: 4.8875 - val_auxilliary_output_2_loss: 4.8858 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108

Epoch 5/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8173 - output_loss: 4.8845 - auxilliary_output_1_loss: 4.8881 - auxilliary_output_2_loss : 4.8879 - output_acc: 0.0106 - auxilliary_output_1_acc: 0.0079 - auxilliary_output_2_acc: 0.0079 - val_loss: 7.8029 - val_output_loss: 4.8709 - val_auxilliary_output_1_loss: 4.8870 - val_auxilliary_output_2_loss: 4.8862 - val_output_acc: 0.0084 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2_acc: 0.0108

Epoch 6/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8115 - output_loss: 4.8790 - auxilliary_output_1_loss: 4.8882 - auxilliary_output_2_loss : 4.8868 - output_acc: 0.0078 - auxilliary_output_1_acc: 0.0091 - auxilliary_output_2_acc: 0.0085 - val_loss: 7.8022 - val_output_loss: 4.8707 - val_auxilliary_output_1_loss: 4.8867 - val_auxilliary_output_2_loss: 4.8849 - val_output_acc: 0.0096 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108

Epoch 7/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8102 - output_loss: 4.8784 - auxilliary_output_1_loss: 4.8867 - auxilliary_output_2_loss : 4.8859 - output_acc: 0.0094 - auxilliary_output_1_acc: 0.0094 - auxilliary_output_2_acc: 0.0096 - val_loss: 7.8016 - val_output_loss: 4.8709 - val_auxilliary_output_1_loss: 4.8856 - val_auxilliary_output_2_loss: 4.8835 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108

Epoch 8/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8068 - output_loss: 4.8757 - auxilliary_output_1_loss: 4.8844 - auxilliary_output_2_loss : 4.8857 - output_acc: 0.0081 - auxilliary_output_1_acc: 0.0105 - auxilliary_output_2_acc: 0.0093 - val_loss: 7.8010 - val_output_loss: 4.8710 - val_auxilliary_output_1_loss: 4.8837 - val_auxilliary_output_2_loss: 4.8830 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108

Epoch 9/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8086 - output_loss: 4.8780 - auxilliary_output_1_loss: 4.8851 - auxilliary_output_2_loss : 4.8836 - output_acc: 0.0078 - auxilliary_output_1_acc: 0.0076 - auxilliary_output_2_acc: 0.0103 - val_loss: 7.7991 - val_output_loss: 4.8698 - val_auxilliary_output_1_loss: 4.8831 - val_auxilliary_output_2_loss: 4.8813 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108

Epoch 10/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8039 - output_loss: 4.8739 - auxilliary_output_1_loss: 4.8824 - auxilliary_output_2_loss

: 4.8843 - output_acc: 0.0082 - auxilliary_output_1_acc: 0.0091 - auxilliary_output_2_acc: 0.0096 - val_loss: 7.7987 - val_output_loss: 4.8696 - val_auxilliary_output_1_loss: 4.8816 - val_auxilliary_output_2_loss: 4.8820 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0072 - val_auxilliary_output_2_acc: 0.0108

Epoch 11/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8014 - output_loss: 4.8730 - auxilliary_output_1_loss: 4.8806 - auxilliary_output_2_loss: 4.8806 - output_acc: 0.0079 - auxilliary_output_1_acc: 0.0085 - auxilliary_output_2_acc: 0.0108 - val_loss: 7.7970 - val_output_loss: 4.8698 - val_auxilliary_output_1_loss: 4.8796 - val_auxilliary_output_2_loss: 4.8779 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108

Epoch 12/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8013 - output_loss: 4.8727 - auxilliary_output_1_loss: 4.8809 - auxilliary_output_2_loss: 4.8809 - output_acc: 0.0097 - auxilliary_output_1_acc: 0.0099 - auxilliary_output_2_acc: 0.0085 - val_loss: 7.7975 - val_output_loss: 4.8701 - val_auxilliary_output_1_loss: 4.8791 - val_auxilliary_output_2_loss: 4.8788 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0072 - val_auxilliary_output_2_acc: 0.0108

Epoch 13/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.8008 - output_loss: 4.8727 - auxilliary_output_1_loss: 4.8805 - auxilliary_output_2_loss: 4.8798 - output_acc: 0.0091 - auxilliary_output_1_acc: 0.0082 - auxilliary_output_2_acc: 0.0111 - val_loss: 7.7968 - val_output_loss: 4.8701 - val_auxilliary_output_1_loss: 4.8781 - val_auxilliary_output_2_loss: 4.8775 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2_acc: 0.0108

Epoch 14/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.7999 - output_loss: 4.8727 - auxilliary_output_1_loss: 4.8783 - auxilliary_output_2_loss: 4.8788 - output_acc: 0.0105 - auxilliary_output_1_acc: 0.0123 - auxilliary_output_2_acc: 0.0103 - val_loss: 7.7963 - val_output_loss: 4.8705 - val_auxilliary_output_1_loss: 4.8761 - val_auxilliary_output_2_loss: 4.8765 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0048 - val_auxilliary_output_2_acc: 0.0108

Epoch 15/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.7983 - output_loss: 4.8716 - auxilliary_output_1_loss: 4.8781 - auxilliary_output_2_loss: 4.8775 - output_acc: 0.0118 - auxilliary_output_1_acc: 0.0099 - auxilliary_output_2_acc: 0.0111 - val_loss: 7.7954 - val_output_loss: 4.8698 - val_auxilliary_output_1_loss: 4.8768 - val_auxilliary_output_2_loss: 4.8753 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0084 - val_auxilliary_output_2_acc: 0.0108

Epoch 16/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.7970 - output_loss: 4.8703 - auxilliary_output_1_loss: 4.8768 - auxilliary_output_2_loss: 4.8787 - output_acc: 0.0091 - auxilliary_output_1_acc: 0.0103 - auxilliary_output_2_acc: 0.0073 - val_loss: 7.7944 - val_output_loss: 4.8695 - val_auxilliary_output_1_loss: 4.8745 - val_auxilliary_output_2_loss: 4.8754 - val_output_acc: 0.0096 - val_auxilliary_output_1_acc: 0.0084 - val_auxilliary_output_2_acc: 0.0108

Epoch 17/25

6680/6680 [=====] - 63s 9ms/step - loss: 7.7952 - output_loss: 4.8694 - auxilliary_output_1_loss: 4.8753 - auxilliary_output_2_loss: 4.8776 - output_acc: 0.0123 - auxilliary_output_1_acc: 0.0100 - auxilliary_o

```
utput_2_acc: 0.0088 - val_loss: 7.7937 - val_output_loss: 4.8692 - val_auxilliary_output_1_loss: 4.8734 - val_auxilliary_output_2_loss: 4.8749 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0084 - val_auxilliary_output_2_acc: 0.0108
Epoch 18/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7949 - output_loss: 4.8695 - auxiliary_output_1_loss: 4.8746 - auxiliary_output_2_loss: 4.8768 - output_acc: 0.0082 - auxiliary_output_1_acc: 0.0112 - auxiliary_output_2_acc: 0.0088 - val_loss: 7.7937 - val_output_loss: 4.8695 - val_auxilliary_output_1_loss: 4.8731 - val_auxilliary_output_2_loss: 4.8741 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2_acc: 0.0108
Epoch 19/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7948 - output_loss: 4.8699 - auxiliary_output_1_loss: 4.8740 - auxiliary_output_2_loss: 4.8757 - output_acc: 0.0097 - auxiliary_output_1_acc: 0.0090 - auxiliary_output_2_acc: 0.0100 - val_loss: 7.7927 - val_output_loss: 4.8691 - val_auxilliary_output_1_loss: 4.8720 - val_auxilliary_output_2_loss: 4.8732 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2_acc: 0.0108
Epoch 20/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7917 - output_loss: 4.8677 - auxiliary_output_1_loss: 4.8717 - auxiliary_output_2_loss: 4.8749 - output_acc: 0.0099 - auxiliary_output_1_acc: 0.0109 - auxiliary_output_2_acc: 0.0111 - val_loss: 7.7922 - val_output_loss: 4.8689 - val_auxilliary_output_1_loss: 4.8710 - val_auxilliary_output_2_loss: 4.8734 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0096 - val_auxilliary_output_2_acc: 0.0108
Epoch 21/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7952 - output_loss: 4.8719 - auxiliary_output_1_loss: 4.8692 - auxiliary_output_2_loss: 4.8753 - output_acc: 0.0114 - auxiliary_output_1_acc: 0.0112 - auxiliary_output_2_acc: 0.0105 - val_loss: 7.7916 - val_output_loss: 4.8688 - val_auxilliary_output_1_loss: 4.8698 - val_auxilliary_output_2_loss: 4.8728 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2_acc: 0.0108
Epoch 22/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7911 - output_loss: 4.8679 - auxiliary_output_1_loss: 4.8709 - auxiliary_output_2_loss: 4.8732 - output_acc: 0.0096 - auxiliary_output_1_acc: 0.0126 - auxiliary_output_2_acc: 0.0090 - val_loss: 7.7910 - val_output_loss: 4.8687 - val_auxilliary_output_1_loss: 4.8690 - val_auxilliary_output_2_loss: 4.8718 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0060 - val_auxilliary_output_2_acc: 0.0108
Epoch 23/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7915 - output_loss: 4.8689 - auxiliary_output_1_loss: 4.8685 - auxiliary_output_2_loss: 4.8734 - output_acc: 0.0106 - auxiliary_output_1_acc: 0.0114 - auxiliary_output_2_acc: 0.0102 - val_loss: 7.7915 - val_output_loss: 4.8690 - val_auxilliary_output_1_loss: 4.8683 - val_auxilliary_output_2_loss: 4.8731 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0120 - val_auxilliary_output_2_acc: 0.0108
Epoch 24/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7925 - output_loss: 4.8701 - auxiliary_output_1_loss: 4.8686 - auxiliary_output_2_loss: 4.8729 - output_acc: 0.0099 - auxiliary_output_1_acc: 0.0126 - auxiliary_output_2_acc: 0.0124 - val_loss: 7.7903 - val_output_loss: 4.8690 - val_auxilliary_output_1_loss: 4.8686 - val_auxilliary_output_2_loss: 4.8729 - val_output_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2_acc: 0.0108
```

```

ary_output_1_loss: 4.8671 - val_auxilliary_output_2_loss: 4.8706 - val_output_
acc: 0.0096 - val_auxilliary_output_1_acc: 0.0144 - val_auxilliary_output_2_ac
c: 0.0108
Epoch 25/25
6680/6680 [=====] - 63s 9ms/step - loss: 7.7903 - out
put_loss: 4.8673 - auxilliary_output_1_loss: 4.8695 - auxilliary_output_2_loss
: 4.8736 - output_acc: 0.0123 - auxilliary_output_1_acc: 0.0094 - auxilliary_o
utput_2_acc: 0.0126 - val_loss: 7.7901 - val_output_loss: 4.8686 - val_auxilli
ary_output_1_loss: 4.8661 - val_auxilliary_output_2_loss: 4.8720 - val_output_
acc: 0.0120 - val_auxilliary_output_1_acc: 0.0084 - val_auxilliary_output_2_ac
c: 0.0108
#model.load_weights('saved_models/weights.best.from_scratch.hdf5')
# 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_tar
gets, axis=1))/len(dog_breed_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
Test accuracy: 0.0000%

```

In []: `###LeNet 5`

```

In [ ]: 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('/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[20:-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))
        #print( train_targets)
        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.
        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)
        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 [01:25<00:00, 78.06it/s]
100%|██████████| 835/835 [00:09<00:00, 97.09it/s]
100%|██████████| 836/836 [00:09<00:00, 86.46it/s]
from keras.models import Sequential
from keras import models, layers
import keras
#Instantiate an empty model
model = Sequential()

# C1 Convolutional Layer
model.add(layers.Conv2D(6, kernel_size=(5, 5), strides=(1, 1), activation="tanh", input_shape=(224,224,3), padding="same"))

# S2 Pooling Layer
model.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(1, 1), padding="valid"))

# C3 Convolutional Layer
model.add(layers.Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation="tanh", padding="valid"))

# S4 Pooling Layer
model.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding="valid"))

# C5 Fully Connected Convolutional Layer
model.add(layers.Conv2D(120, kernel_size=(5, 5), strides=(1, 1), activation="tanh", padding="valid"))
#Flatten the CNN output so that we can connect it with fully connected layers
model.add(layers.Flatten())

# FC6 Fully Connected Layer
model.add(layers.Dense(84, activation="tanh"))

#Output Layer with softmax activation
model.add(layers.Dense(133, activation="softmax"))

# Compile the model

model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 224, 224, 6)	456
average_pooling2d_3 (Average)	(None, 223, 223, 6)	0
conv2d_5 (Conv2D)	(None, 219, 219, 16)	2416
average_pooling2d_4 (Average)	(None, 109, 109, 16)	0
conv2d_6 (Conv2D)	(None, 105, 105, 120)	48120

flatten_2 (Flatten)	(None, 1323000)	0
dense_3 (Dense)	(None, 84)	111132084
dense_4 (Dense)	(None, 133)	11305
=====		
Total params: 111,194,381		
Trainable params: 111,194,381		
Non-trainable params: 0		

```

from keras.callbacks import ModelCheckpoint
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=[
    'accuracy'])
#model.compile(loss=keras.losses.categorical_crossentropy, optimizer="SGD", me
    trics=["accuracy"])
#hist = model.fit(x=train_tensors,y=train_targets, epochs=10, batch_size=128,
    validation_data=(x_test, y_test), verbose=1)
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.from_scratc
    h.hdf5',
                                verbose=1, save_best_only=True)

hist =model.fit(train_tensors, train_targets,
                validation_data=(valid_tensors,valid_targets),
                epochs=20, batch_size=256, callbacks=[checkpointer], verbose=1)
Train on 6680 samples, validate on 835 samples
Epoch 1/20
6656/6680 [=====>.] - ETA: 0s - loss: 5.0172 - acc: 0.0
065Epoch 00001: val_loss improved from inf to 4.90717, saving model to saved_m
    odels/weights.best.from_scratch.hdf5
6680/6680 [=====] - 71s 11ms/step - loss: 5.0165 - ac
    c: 0.0064 - val_loss: 4.9072 - val_acc: 0.0096
Epoch 2/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8890 - acc: 0.0
114Epoch 00002: val_loss improved from 4.90717 to 4.88528, saving model to sav
    ed_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 59s 9ms/step - loss: 4.8888 - acc
    : 0.0114 - val_loss: 4.8853 - val_acc: 0.0108
Epoch 3/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8852 - acc: 0.0
092Epoch 00003: val_loss improved from 4.88528 to 4.88348, saving model to sav
    ed_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 59s 9ms/step - loss: 4.8851 - acc
    : 0.0091 - val_loss: 4.8835 - val_acc: 0.0096
Epoch 4/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8851 - acc: 0.0
090Epoch 00004: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8849 - acc
    : 0.0090 - val_loss: 4.8841 - val_acc: 0.0096
Epoch 5/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8845 - acc: 0.0
093Epoch 00005: val_loss improved from 4.88348 to 4.88197, saving model to sav
    ed_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 59s 9ms/step - loss: 4.8849 - acc
    : 0.0093 - val_loss: 4.8820 - val_acc: 0.0096
Epoch 6/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8826 - acc: 0.0
098Epoch 00006: val_loss did not improve

```

```
6680/6680 [=====] - 58s 9ms/step - loss: 4.8826 - acc
: 0.0097 - val_loss: 4.8851 - val_acc: 0.0096
Epoch 7/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8836 - acc: 0.0
096Epoch 00007: val_loss improved from 4.88197 to 4.87965, saving model to sav
ed_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 59s 9ms/step - loss: 4.8839 - acc
: 0.0096 - val_loss: 4.8797 - val_acc: 0.0096
Epoch 8/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8844 - acc: 0.0
107Epoch 00008: val_loss did not improve
6680/6680 [=====] - 59s 9ms/step - loss: 4.8844 - acc
: 0.0108 - val_loss: 4.8822 - val_acc: 0.0108
Epoch 9/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8843 - acc: 0.0
096Epoch 00009: val_loss did not improve
6680/6680 [=====] - 57s 9ms/step - loss: 4.8840 - acc
: 0.0096 - val_loss: 4.8855 - val_acc: 0.0108
Epoch 10/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8850 - acc: 0.0
087Epoch 00010: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8848 - acc
: 0.0087 - val_loss: 4.8826 - val_acc: 0.0108
Epoch 11/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8838 - acc: 0.0
081Epoch 00011: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8839 - acc
: 0.0081 - val_loss: 4.8838 - val_acc: 0.0108
Epoch 12/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8849 - acc: 0.0
086Epoch 00012: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8852 - acc
: 0.0085 - val_loss: 4.8799 - val_acc: 0.0096
Epoch 13/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8821 - acc: 0.0
095Epoch 00013: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8820 - acc
: 0.0094 - val_loss: 4.8859 - val_acc: 0.0108
Epoch 14/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8840 - acc: 0.0
092Epoch 00014: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8840 - acc
: 0.0093 - val_loss: 4.8843 - val_acc: 0.0096
Epoch 15/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8856 - acc: 0.0
090Epoch 00015: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8854 - acc
: 0.0090 - val_loss: 4.8829 - val_acc: 0.0096
Epoch 16/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8845 - acc: 0.0
090Epoch 00016: val_loss did not improve
6680/6680 [=====] - 57s 9ms/step - loss: 4.8846 - acc
: 0.0090 - val_loss: 4.8816 - val_acc: 0.0096
Epoch 17/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8831 - acc: 0.0
072Epoch 00017: val_loss did not improve
6680/6680 [=====] - 57s 9ms/step - loss: 4.8831 - acc
```

```

: 0.0072 - val_loss: 4.8856 - val_acc: 0.0108
Epoch 18/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8839 - acc: 0.0081
Epoch 00018: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8838 - acc: 0.0081 - val_loss: 4.8808 - val_acc: 0.0096
Epoch 19/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8840 - acc: 0.0095
Epoch 00019: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8839 - acc: 0.0096 - val_loss: 4.8855 - val_acc: 0.0108
Epoch 20/20
6656/6680 [=====>.] - ETA: 0s - loss: 4.8857 - acc: 0.0105
Epoch 00020: val_loss did not improve
6680/6680 [=====] - 58s 9ms/step - loss: 4.8858 - acc: 0.0105 - val_loss: 4.8814 - val_acc: 0.0096
# 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_targets, axis=1))/len(dog_breed_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
# 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_targets, axis=1))/len(dog_breed_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
Test accuracy: 1.0766%

```

In []: *##GoogleNet 5*


```

In [ ]: 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('/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[20:-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))
        #print( train_targets)
        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.
        [[ 0.  0.  0. ...,  0.  0.  0.]
         [ 0.  0.  0. ...,  0.  0.  0.]
         [ 0.  0.  0. ...,  0.  0.  0.]
         ...,
         [ 0.  0.  0. ...,  0.  0.  0.]
         [ 0.  0.  0. ...,  0.  0.  0.]
         [ 0.  0.  0. ...,  0.  0.  0.]]

        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)
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 [01:27<00:00, 49.00it/s]
100%|██████████| 835/835 [00:09<00:00, 85.71it/s]
100%|██████████| 836/836 [00:09<00:00, 85.73it/s]
from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D, MaxPool2
D, AveragePooling2D
from keras.layers import Dropout, Flatten, Dense, Input, concatenate
from keras.models import Sequential, Model
model = Sequential()
def inception_module(x,
                    filters_1x1,
                    filters_3x3_reduce,
                    filters_3x3,
                    filters_5x5_reduce,
                    filters_5x5,
                    filters_pool_proj,
                    name=None):
    conv_1x1 = Conv2D(filters_1x1, (1, 1), padding='same', activation='relu',
kernel_initializer=kernel_init, bias_initializer=bias_init)(x)
    conv_3x3 = Conv2D(filters_3x3_reduce, (1, 1), padding='same', activation=
'relu', kernel_initializer=kernel_init, bias_initializer=bias_init)(x)
    conv_3x3 = Conv2D(filters_3x3, (3, 3), padding='same', activation='relu',
kernel_initializer=kernel_init, bias_initializer=bias_init)(conv_3x3)
    conv_5x5 = Conv2D(filters_5x5_reduce, (1, 1), padding='same', activation=
'relu', kernel_initializer=kernel_init, bias_initializer=bias_init)(x)
    conv_5x5 = Conv2D(filters_5x5, (5, 5), padding='same', activation='relu',
kernel_initializer=kernel_init, bias_initializer=bias_init)(conv_5x5)
    pool_proj = MaxPool2D((3, 3), strides=(1, 1), padding='same')(x)
    pool_proj = Conv2D(filters_pool_proj, (1, 1), padding='same', activation=
'relu', kernel_initializer=kernel_init, bias_initializer=bias_init)(pool_proj)
    output = concatenate([conv_1x1, conv_3x3, conv_5x5, pool_proj], axis=3, na
me=name)
    return output
from keras import initializers
kernel_init = initializers.glorot_uniform()
bias_init = initializers.Constant(value=0.2)
input_layer = Input(shape=(224, 224, 3))
x = Conv2D(64, (7, 7), padding='same', strides=(2, 2), activation='relu', name
='conv_1_7x7/2', kernel_initializer=kernel_init, bias_initializer=bias_init)(i

```

```

nput_layer)
x = MaxPool2D((3, 3), padding='same', strides=(2, 2), name='max_pool_1_3x3/2')(x)
x = Conv2D(64, (1, 1), padding='same', strides=(1, 1), activation='relu', name='conv_2a_3x3/1')(x)
x = Conv2D(192, (3, 3), padding='same', strides=(1, 1), activation='relu', name='conv_2b_3x3/1')(x)
x = MaxPool2D((3, 3), padding='same', strides=(2, 2), name='max_pool_2_3x3/2')(x)
x = inception_module(x,
                     filters_1x1=64,
                     filters_3x3_reduce=96,
                     filters_3x3=128,
                     filters_5x5_reduce=16,
                     filters_5x5=32,
                     filters_pool_proj=32,
                     name='inception_3a')
x = inception_module(x,
                     filters_1x1=128,
                     filters_3x3_reduce=128,
                     filters_3x3=192,
                     filters_5x5_reduce=32,
                     filters_5x5=96,
                     filters_pool_proj=64,
                     name='inception_3b')
x = MaxPool2D((3, 3), padding='same', strides=(2, 2), name='max_pool_3_3x3/2')(x)
x = inception_module(x,
                     filters_1x1=192,
                     filters_3x3_reduce=96,
                     filters_3x3=208,
                     filters_5x5_reduce=16,
                     filters_5x5=48,
                     filters_pool_proj=64,
                     name='inception_4a')
x1 = AveragePooling2D((5, 5), strides=3)(x)
x1 = Conv2D(128, (1, 1), padding='same', activation='relu')(x1)
x1 = Flatten()(x1)
x1 = Dense(1024, activation='relu')(x1)
x1 = Dropout(0.7)(x1)
x1 = Dense(133, activation='softmax', name='auxilliary_output_1')(x1)
x = inception_module(x,
                     filters_1x1=160,
                     filters_3x3_reduce=112,
                     filters_3x3=224,
                     filters_5x5_reduce=24,
                     filters_5x5=64,
                     filters_pool_proj=64,
                     name='inception_4b')

```

```
x = inception_module(x,
                    filters_1x1=128,
                    filters_3x3_reduce=128,
                    filters_3x3=256,
                    filters_5x5_reduce=24,
                    filters_5x5=64,
                    filters_pool_proj=64,
                    name='inception_4c')

x = inception_module(x,
                    filters_1x1=112,
                    filters_3x3_reduce=144,
                    filters_3x3=288,
                    filters_5x5_reduce=32,
                    filters_5x5=64,
                    filters_pool_proj=64,
                    name='inception_4d')

x2 = AveragePooling2D((5, 5), strides=3)(x)
x2 = Conv2D(128, (1, 1), padding='same', activation='relu')(x2)
x2 = Flatten()(x2)
x2 = Dense(1024, activation='relu')(x2)
x2 = Dropout(0.7)(x2)
x2 = Dense(133, activation='softmax', name='auxilliary_output_2')(x2)

x = inception_module(x,
                    filters_1x1=256,
                    filters_3x3_reduce=160,
                    filters_3x3=320,
                    filters_5x5_reduce=32,
                    filters_5x5=128,
                    filters_pool_proj=128,
                    name='inception_4e')

x = MaxPool2D((3, 3), padding='same', strides=(2, 2), name='max_pool_4_3x3/2')(x)

x = inception_module(x,
                    filters_1x1=256,
                    filters_3x3_reduce=160,
                    filters_3x3=320,
                    filters_5x5_reduce=32,
                    filters_5x5=128,
                    filters_pool_proj=128,
                    name='inception_5a')

x = inception_module(x,
                    filters_1x1=384,
                    filters_3x3_reduce=192,
                    filters_3x3=384,
                    filters_5x5_reduce=48,
                    filters_5x5=128,
                    filters_pool_proj=128,
                    name='inception_5b')

x = GlobalAveragePooling2D(name='avg_pool_5_3x3/1')(x)
```

```

x = Dropout(0.4)(x)
x = Dense(133, activation='softmax', name='output')(x)
model = Model(input_layer, [x, x1, x2], name='inception_v1')
model.summary()

```

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	(None, 224, 224, 3)	0	
conv_1_7x7/2 (Conv2D)	(None, 112, 112, 64)	9472	input_1[0][0]
max_pool_1_3x3/2 (MaxPooling2D)	(None, 56, 56, 64)	0	conv_1_7x7/2[0][0]
conv_2a_3x3/1 (Conv2D)	(None, 56, 56, 64)	4160	max_pool_1_3x3/2[0][0]
conv_2b_3x3/1 (Conv2D)	(None, 56, 56, 192)	110784	conv_2a_3x3/1[0][0]
max_pool_2_3x3/2 (MaxPooling2D)	(None, 28, 28, 192)	0	conv_2b_3x3/1[0][0]
conv2d_2 (Conv2D)	(None, 28, 28, 96)	18528	max_pool_2_3x3/2[0][0]
conv2d_4 (Conv2D)	(None, 28, 28, 16)	3088	max_pool_2_3x3/2[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 28, 28, 192)	0	max_pool_2_3x3/2[0][0]
conv2d_1 (Conv2D)	(None, 28, 28, 64)	12352	max_pool_2_3x3/2[0][0]
conv2d_3 (Conv2D)	(None, 28, 28, 128)	110720	conv2d_2[0][0]
conv2d_5 (Conv2D)	(None, 28, 28, 32)	12832	conv2d_4[0][0]

conv2d_6 (Conv2D) _1[0][0]	(None, 28, 28, 32)	6176	max_pooling2d
inception_3a (Concatenate)]]]]]	(None, 28, 28, 256)	0	conv2d_1[0][0] conv2d_3[0][0] conv2d_5[0][0] conv2d_6[0][0]
conv2d_8 (Conv2D) 0][0]	(None, 28, 28, 128)	32896	inception_3a[
conv2d_10 (Conv2D) 0][0]	(None, 28, 28, 32)	8224	inception_3a[
max_pooling2d_2 (MaxPooling2D) 0][0]	(None, 28, 28, 256)	0	inception_3a[
conv2d_7 (Conv2D) 0][0]	(None, 28, 28, 128)	32896	inception_3a[
conv2d_9 (Conv2D)]	(None, 28, 28, 192)	221376	conv2d_8[0][0]
conv2d_11 (Conv2D) 0]	(None, 28, 28, 96)	76896	conv2d_10[0][
conv2d_12 (Conv2D) _2[0][0]	(None, 28, 28, 64)	16448	max_pooling2d
inception_3b (Concatenate)]] 0] 0]	(None, 28, 28, 480)	0	conv2d_7[0][0] conv2d_9[0][0] conv2d_11[0][conv2d_12[0][
max_pool_3_3x3/2 (MaxPooling2D) 0][0]	(None, 14, 14, 480)	0	inception_3b[
conv2d_14 (Conv2D)	(None, 14, 14, 96)	46176	max_pool_3_3x

3/2[0][0]			
conv2d_16 (Conv2D) 3/2[0][0]	(None, 14, 14, 16)	7696	max_pool_3_3x
max_pooling2d_3 (MaxPooling2D) 3/2[0][0]	(None, 14, 14, 480)	0	max_pool_3_3x
conv2d_13 (Conv2D) 3/2[0][0]	(None, 14, 14, 192)	92352	max_pool_3_3x
conv2d_15 (Conv2D) 0]	(None, 14, 14, 208)	179920	conv2d_14[0][
conv2d_17 (Conv2D) 0]	(None, 14, 14, 48)	19248	conv2d_16[0][
conv2d_18 (Conv2D) _3[0][0]	(None, 14, 14, 64)	30784	max_pooling2d
inception_4a (Concatenate) 0]	(None, 14, 14, 512)	0	conv2d_13[0][
0]			conv2d_15[0][
0]			conv2d_17[0][
0]			conv2d_18[0][
conv2d_21 (Conv2D) 0][0]	(None, 14, 14, 112)	57456	inception_4a[
conv2d_23 (Conv2D) 0][0]	(None, 14, 14, 24)	12312	inception_4a[
max_pooling2d_4 (MaxPooling2D) 0][0]	(None, 14, 14, 512)	0	inception_4a[
conv2d_20 (Conv2D) 0][0]	(None, 14, 14, 160)	82080	inception_4a[
conv2d_22 (Conv2D) 0]	(None, 14, 14, 224)	226016	conv2d_21[0][

conv2d_24 (Conv2D) 0]	(None, 14, 14, 64)	38464	conv2d_23[0][
conv2d_25 (Conv2D) _4[0][0]	(None, 14, 14, 64)	32832	max_pooling2d
inception_4b (Concatenate) 0]	(None, 14, 14, 512)	0	conv2d_20[0][
0]			conv2d_22[0][
0]			conv2d_24[0][
0]			conv2d_25[0][
conv2d_27 (Conv2D) 0][0]	(None, 14, 14, 128)	65664	inception_4b[
conv2d_29 (Conv2D) 0][0]	(None, 14, 14, 24)	12312	inception_4b[
max_pooling2d_5 (MaxPooling2D) 0][0]	(None, 14, 14, 512)	0	inception_4b[
conv2d_26 (Conv2D) 0][0]	(None, 14, 14, 128)	65664	inception_4b[
conv2d_28 (Conv2D) 0]	(None, 14, 14, 256)	295168	conv2d_27[0][
conv2d_30 (Conv2D) 0]	(None, 14, 14, 64)	38464	conv2d_29[0][
conv2d_31 (Conv2D) _5[0][0]	(None, 14, 14, 64)	32832	max_pooling2d
inception_4c (Concatenate) 0]	(None, 14, 14, 512)	0	conv2d_26[0][
0]			conv2d_28[0][
0]			conv2d_30[0][
0]			conv2d_31[0][
conv2d_33 (Conv2D)	(None, 14, 14, 144)	73872	inception_4c[

0][0]			
conv2d_35 (Conv2D) 0][0]	(None, 14, 14, 32)	16416	inception_4c[0][0]
max_pooling2d_6 (MaxPooling2D) 0][0]	(None, 14, 14, 512)	0	inception_4c[0][0]
conv2d_32 (Conv2D) 0][0]	(None, 14, 14, 112)	57456	inception_4c[0][0]
conv2d_34 (Conv2D) 0]	(None, 14, 14, 288)	373536	conv2d_33[0][0]
conv2d_36 (Conv2D) 0]	(None, 14, 14, 64)	51264	conv2d_35[0][0]
conv2d_37 (Conv2D) _6[0][0]	(None, 14, 14, 64)	32832	max_pooling2d_6[0][0]
inception_4d (Concatenate) 0]	(None, 14, 14, 528)	0	conv2d_32[0][0]
0]			conv2d_34[0][0]
0]			conv2d_36[0][0]
0]			conv2d_37[0][0]
conv2d_40 (Conv2D) 0][0]	(None, 14, 14, 160)	84640	inception_4d[0][0]
conv2d_42 (Conv2D) 0][0]	(None, 14, 14, 32)	16928	inception_4d[0][0]
max_pooling2d_7 (MaxPooling2D) 0][0]	(None, 14, 14, 528)	0	inception_4d[0][0]
conv2d_39 (Conv2D) 0][0]	(None, 14, 14, 256)	135424	inception_4d[0][0]
conv2d_41 (Conv2D) 0]	(None, 14, 14, 320)	461120	conv2d_40[0][0]

conv2d_43 (Conv2D) 0]	(None, 14, 14, 128)	102528	conv2d_42[0][
conv2d_44 (Conv2D) _7[0][0]	(None, 14, 14, 128)	67712	max_pooling2d
inception_4e (Concatenate) 0]	(None, 14, 14, 832)	0	conv2d_39[0][
0]			conv2d_41[0][
0]			conv2d_43[0][
0]			conv2d_44[0][
max_pool_4_3x3/2 (MaxPooling2D) 0][0]	(None, 7, 7, 832)	0	inception_4e[
conv2d_46 (Conv2D) 3/2[0][0]	(None, 7, 7, 160)	133280	max_pool_4_3x
conv2d_48 (Conv2D) 3/2[0][0]	(None, 7, 7, 32)	26656	max_pool_4_3x
max_pooling2d_8 (MaxPooling2D) 3/2[0][0]	(None, 7, 7, 832)	0	max_pool_4_3x
conv2d_45 (Conv2D) 3/2[0][0]	(None, 7, 7, 256)	213248	max_pool_4_3x
conv2d_47 (Conv2D) 0]	(None, 7, 7, 320)	461120	conv2d_46[0][
conv2d_49 (Conv2D) 0]	(None, 7, 7, 128)	102528	conv2d_48[0][
conv2d_50 (Conv2D) _8[0][0]	(None, 7, 7, 128)	106624	max_pooling2d
inception_5a (Concatenate) 0]	(None, 7, 7, 832)	0	conv2d_45[0][
0]			conv2d_47[0][
0]			conv2d_49[0][
0]			conv2d_50[0][

0]			
conv2d_52 (Conv2D)	(None, 7, 7, 192)	159936	inception_5a[0][0]
conv2d_54 (Conv2D)	(None, 7, 7, 48)	39984	inception_5a[0][0]
max_pooling2d_9 (MaxPooling2D)	(None, 7, 7, 832)	0	inception_5a[0][0]
average_pooling2d_1 (AveragePool)	(None, 4, 4, 512)	0	inception_4a[0][0]
average_pooling2d_2 (AveragePool)	(None, 4, 4, 528)	0	inception_4d[0][0]
conv2d_51 (Conv2D)	(None, 7, 7, 384)	319872	inception_5a[0][0]
conv2d_53 (Conv2D)	(None, 7, 7, 384)	663936	conv2d_52[0][0]
conv2d_55 (Conv2D)	(None, 7, 7, 128)	153728	conv2d_54[0][0]
conv2d_56 (Conv2D)	(None, 7, 7, 128)	106624	max_pooling2d_9[0][0]
conv2d_19 (Conv2D)	(None, 4, 4, 128)	65664	average_pooling2d_1[0][0]
conv2d_38 (Conv2D)	(None, 4, 4, 128)	67712	average_pooling2d_2[0][0]
inception_5b (Concatenate)	(None, 7, 7, 1024)	0	conv2d_51[0][0]
			conv2d_53[0][0]
			conv2d_55[0][0]
			conv2d_56[0][0]

flatten_1 (Flatten) 0]	(None, 2048)	0	conv2d_19[0][
flatten_2 (Flatten) 0]	(None, 2048)	0	conv2d_38[0][
avg_pool_5_3x3/1 (GlobalAverage 0][0]	(None, 1024)	0	inception_5b[
dense_1 (Dense) 0]	(None, 1024)	2098176	flatten_1[0][
dense_2 (Dense) 0]	(None, 1024)	2098176	flatten_2[0][
dropout_3 (Dropout) 3/1[0][0]	(None, 1024)	0	avg_pool_5_3x
dropout_1 (Dropout)	(None, 1024)	0	dense_1[0][0]
dropout_2 (Dropout)	(None, 1024)	0	dense_2[0][0]
output (Dense) 0]	(None, 133)	136325	dropout_3[0][
auxilliary_output_1 (Dense) 0]	(None, 133)	136325	dropout_1[0][
auxilliary_output_2 (Dense) 0]	(None, 133)	136325	dropout_2[0][
=====			
Total params: 10,712,255			
Trainable params: 10,712,255			
Non-trainable params: 0			
=====			
<pre> from keras.optimizers import SGD from keras.callbacks import LearningRateScheduler epochs = 25 initial_lr = 0.01 def decay(epoch, steps=100): initial_lr = 0.01 drop = 0.96 epochs_drop = 8 lr = initial_lr * math.pow(drop, math.floor((1+epoch)/epochs_drop)) </pre>			

```

    return lr_rate

sgd = SGD(lr=initial_lr_rate, momentum=0.9, nesterov=False)

lr_scheduler = LearningRateScheduler(decay)

#model.compile(loss=['categorical_crossentropy', 'categorical_crossentropy',
#                    'categorical_crossentropy'], loss_weights=[1, 0.3, 0.3], optimizer=sgd, metrics=
#                    ['accuracy'])
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=[
    'accuracy'])
from keras.callbacks import ModelCheckpoint

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

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(train_tensors, train_targets,
#          validation_data=(valid_tensors, valid_targets),
#          epochs=epochs, batch_size=20, callbacks=[checkpointer], verbose=1)
model.fit(train_tensors, [train_targets, train_targets, train_targets],
          validation_data=(valid_tensors, [valid_targets, valid_targets, valid_targets]),
          epochs=epochs, batch_size=20, callbacks=[checkpointer], verbose=1)
Train on 6680 samples, validate on 835 samples
Epoch 1/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6447 - output_loss: 4.8881 - auxiliary_output_1_loss: 4.8776 - auxiliary_output_2_loss: 4.8790 - output_acc: 0.0083 - auxiliary_output_1_acc: 0.0095 - auxiliary_output_2_acc: 0.0104Epoch 00001: val_loss improved from inf to 14.61411, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6454 - output_loss: 4.8883 - auxiliary_output_1_loss: 4.8779 - auxiliary_output_2_loss: 4.8792 - output_acc: 0.0082 - auxiliary_output_1_acc: 0.0094 - auxiliary_output_2_acc: 0.0105 - val_loss: 14.6141 - val_output_loss: 4.8759 - val_auxiliary_output_1_loss: 4.8690 - val_auxiliary_output_2_loss: 4.8692 - val_output_acc: 0.0096 - val_auxiliary_output_1_acc: 0.0108 - val_auxiliary_output_2_acc: 0.0108
Epoch 2/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6310 - output_loss: 4.8799 - auxiliary_output_1_loss: 4.8736 - auxiliary_output_2_loss: 4.8775 - output_acc: 0.0099 - auxiliary_output_1_acc: 0.0098 - auxiliary_output_2_acc: 0.0113Epoch 00002: val_loss improved from 14.61411 to 14.61234, saving model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6310 - output_loss: 4.8799 - auxiliary_output_1_loss: 4.8736 - auxiliary_output_2_loss: 4.8775 - output_acc: 0.0099 - auxiliary_output_1_acc: 0.0097 - auxiliary_output_2_acc: 0.0112 - val_loss: 14.6123 - val_output_loss: 4.8743 - val_auxiliary_output_1_loss: 4.8690 - val_auxiliary_output_2_loss: 4.8690 - val_output_acc: 0.0084 - val_auxiliary_output_1_acc: 0.0108 - val_auxiliary_output_2_acc: 0.0108

```

```
_acc: 0.0108
Epoch 3/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6178 - output_
loss: 4.8784 - auxilliary_output_1_loss: 4.8691 - auxilliary_output_2_loss: 4.
8703 - output_acc: 0.0087 - auxilliary_output_1_acc: 0.0110 - auxilliary_outpu
t_2_acc: 0.0105Epoch 00003: val_loss improved from 14.61234 to 14.61001, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6173 - o
utput_loss: 4.8782 - auxilliary_output_1_loss: 4.8689 - auxilliary_output_2_lo
ss: 4.8702 - output_acc: 0.0087 - auxilliary_output_1_acc: 0.0109 - auxilliary
_output_2_acc: 0.0105 - val_loss: 14.6100 - val_output_loss: 4.8721 - val_auxi
lliary_output_1_loss: 4.8690 - val_auxilliary_output_2_loss: 4.8689 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 4/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6130 - output_
loss: 4.8743 - auxilliary_output_1_loss: 4.8684 - auxilliary_output_2_loss: 4.
8703 - output_acc: 0.0086 - auxilliary_output_1_acc: 0.0098 - auxilliary_outpu
t_2_acc: 0.0099Epoch 00004: val_loss improved from 14.61001 to 14.60823, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6130 - o
utput_loss: 4.8743 - auxilliary_output_1_loss: 4.8684 - auxilliary_output_2_lo
ss: 4.8703 - output_acc: 0.0085 - auxilliary_output_1_acc: 0.0097 - auxilliary
_output_2_acc: 0.0099 - val_loss: 14.6082 - val_output_loss: 4.8708 - val_auxi
lliary_output_1_loss: 4.8688 - val_auxilliary_output_2_loss: 4.8687 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 5/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6167 - output_
loss: 4.8723 - auxilliary_output_1_loss: 4.8742 - auxilliary_output_2_loss: 4.
8702 - output_acc: 0.0104 - auxilliary_output_1_acc: 0.0107 - auxilliary_outpu
t_2_acc: 0.0110Epoch 00005: val_loss improved from 14.60823 to 14.60783, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6164 - o
utput_loss: 4.8722 - auxilliary_output_1_loss: 4.8741 - auxilliary_output_2_lo
ss: 4.8701 - output_acc: 0.0103 - auxilliary_output_1_acc: 0.0106 - auxilliary
_output_2_acc: 0.0109 - val_loss: 14.6078 - val_output_loss: 4.8699 - val_auxi
lliary_output_1_loss: 4.8690 - val_auxilliary_output_2_loss: 4.8690 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 6/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6086 - output_
loss: 4.8702 - auxilliary_output_1_loss: 4.8699 - auxilliary_output_2_loss: 4.
8685 - output_acc: 0.0101 - auxilliary_output_1_acc: 0.0098 - auxilliary_outpu
t_2_acc: 0.0113Epoch 00006: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.6086 - o
utput_loss: 4.8702 - auxilliary_output_1_loss: 4.8699 - auxilliary_output_2_lo
ss: 4.8685 - output_acc: 0.0100 - auxilliary_output_1_acc: 0.0097 - auxilliary
_output_2_acc: 0.0112 - val_loss: 14.6108 - val_output_loss: 4.8732 - val_auxi
lliary_output_1_loss: 4.8689 - val_auxilliary_output_2_loss: 4.8687 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 7/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6125 - output_
loss: 4.8689 - auxilliary_output_1_loss: 4.8685 - auxilliary_output_2_loss: 4.
8751 - output_acc: 0.0108 - auxilliary_output_1_acc: 0.0110 - auxilliary_outpu
t_2_acc: 0.0098Epoch 00007: val_loss improved from 14.60783 to 14.60660, savin
```

```

g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6128 - o
utput_loss: 4.8690 - auxilliary_output_1_loss: 4.8686 - auxilliary_output_2_lo
ss: 4.8752 - output_acc: 0.0108 - auxilliary_output_1_acc: 0.0109 - auxilliary
_output_2_acc: 0.0097 - val_loss: 14.6066 - val_output_loss: 4.8691 - val_auxi
lliary_output_1_loss: 4.8687 - val_auxilliary_output_2_loss: 4.8688 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 8/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6127 - output_
loss: 4.8696 - auxilliary_output_1_loss: 4.8722 - auxilliary_output_2_loss: 4.
8709 - output_acc: 0.0110 - auxilliary_output_1_acc: 0.0107 - auxilliary_outpu
t_2_acc: 0.0114Epoch 00008: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.6124 - o
utput_loss: 4.8695 - auxilliary_output_1_loss: 4.8720 - auxilliary_output_2_lo
ss: 4.8708 - output_acc: 0.0109 - auxilliary_output_1_acc: 0.0106 - auxilliary
_output_2_acc: 0.0114 - val_loss: 14.6078 - val_output_loss: 4.8696 - val_auxi
lliary_output_1_loss: 4.8692 - val_auxilliary_output_2_loss: 4.8689 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 9/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6043 - output_
loss: 4.8685 - auxilliary_output_1_loss: 4.8690 - auxilliary_output_2_loss: 4.
8669 - output_acc: 0.0105 - auxilliary_output_1_acc: 0.0119 - auxilliary_outpu
t_2_acc: 0.0104Epoch 00009: val_loss improved from 14.60660 to 14.60644, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6046 - o
utput_loss: 4.8686 - auxilliary_output_1_loss: 4.8690 - auxilliary_output_2_lo
ss: 4.8669 - output_acc: 0.0106 - auxilliary_output_1_acc: 0.0120 - auxilliary
_output_2_acc: 0.0105 - val_loss: 14.6064 - val_output_loss: 4.8691 - val_auxi
lliary_output_1_loss: 4.8687 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 10/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6032 - output_
loss: 4.8674 - auxilliary_output_1_loss: 4.8687 - auxilliary_output_2_loss: 4.
8670 - output_acc: 0.0096 - auxilliary_output_1_acc: 0.0116 - auxilliary_outpu
t_2_acc: 0.0104Epoch 00010: val_loss improved from 14.60644 to 14.60636, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6030 - o
utput_loss: 4.8673 - auxilliary_output_1_loss: 4.8687 - auxilliary_output_2_lo
ss: 4.8670 - output_acc: 0.0096 - auxilliary_output_1_acc: 0.0115 - auxilliary
_output_2_acc: 0.0103 - val_loss: 14.6064 - val_output_loss: 4.8689 - val_auxi
lliary_output_1_loss: 4.8687 - val_auxilliary_output_2_loss: 4.8688 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 11/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5995 - output_
loss: 4.8671 - auxilliary_output_1_loss: 4.8652 - auxilliary_output_2_loss: 4.
8672 - output_acc: 0.0111 - auxilliary_output_1_acc: 0.0113 - auxilliary_outpu
t_2_acc: 0.0119Epoch 00011: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.5989 - o
utput_loss: 4.8669 - auxilliary_output_1_loss: 4.8651 - auxilliary_output_2_lo
ss: 4.8670 - output_acc: 0.0111 - auxilliary_output_1_acc: 0.0112 - auxilliary
_output_2_acc: 0.0118 - val_loss: 14.6065 - val_output_loss: 4.8686 - val_auxi
lliary_output_1_loss: 4.8689 - val_auxilliary_output_2_loss: 4.8690 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2

```

```
_acc: 0.0108
Epoch 12/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5997 - output_
loss: 4.8660 - auxilliary_output_1_loss: 4.8670 - auxilliary_output_2_loss: 4.
8667 - output_acc: 0.0093 - auxilliary_output_1_acc: 0.0123 - auxilliary_outpu
t_2_acc: 0.0116Epoch 00012: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.5997 - o
utput_loss: 4.8660 - auxilliary_output_1_loss: 4.8669 - auxilliary_output_2_lo
ss: 4.8668 - output_acc: 0.0094 - auxilliary_output_1_acc: 0.0124 - auxilliary
_output_2_acc: 0.0117 - val_loss: 14.6068 - val_output_loss: 4.8693 - val_auxi
lliary_output_1_loss: 4.8687 - val_auxilliary_output_2_loss: 4.8688 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 13/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5984 - output_
loss: 4.8659 - auxilliary_output_1_loss: 4.8658 - auxilliary_output_2_loss: 4.
8666 - output_acc: 0.0101 - auxilliary_output_1_acc: 0.0119 - auxilliary_outpu
t_2_acc: 0.0111Epoch 00013: val_loss improved from 14.60636 to 14.60619, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.5980 - o
utput_loss: 4.8659 - auxilliary_output_1_loss: 4.8657 - auxilliary_output_2_lo
ss: 4.8665 - output_acc: 0.0100 - auxilliary_output_1_acc: 0.0118 - auxilliary
_output_2_acc: 0.0111 - val_loss: 14.6062 - val_output_loss: 4.8689 - val_auxi
lliary_output_1_loss: 4.8686 - val_auxilliary_output_2_loss: 4.8687 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 14/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6077 - output_
loss: 4.8672 - auxilliary_output_1_loss: 4.8671 - auxilliary_output_2_loss: 4.
8734 - output_acc: 0.0104 - auxilliary_output_1_acc: 0.0122 - auxilliary_outpu
t_2_acc: 0.0117Epoch 00014: val_loss improved from 14.60619 to 14.60593, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.6080 - o
utput_loss: 4.8673 - auxilliary_output_1_loss: 4.8672 - auxilliary_output_2_lo
ss: 4.8735 - output_acc: 0.0103 - auxilliary_output_1_acc: 0.0121 - auxilliary
_output_2_acc: 0.0117 - val_loss: 14.6059 - val_output_loss: 4.8688 - val_auxi
lliary_output_1_loss: 4.8686 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 15/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5965 - output_
loss: 4.8651 - auxilliary_output_1_loss: 4.8650 - auxilliary_output_2_loss: 4.
8665 - output_acc: 0.0114 - auxilliary_output_1_acc: 0.0114 - auxilliary_outpu
t_2_acc: 0.0113Epoch 00015: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.5971 - o
utput_loss: 4.8653 - auxilliary_output_1_loss: 4.8651 - auxilliary_output_2_lo
ss: 4.8667 - output_acc: 0.0114 - auxilliary_output_1_acc: 0.0114 - auxilliary
_output_2_acc: 0.0112 - val_loss: 14.6087 - val_output_loss: 4.8711 - val_auxi
lliary_output_1_loss: 4.8690 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 16/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6061 - output_
loss: 4.8666 - auxilliary_output_1_loss: 4.8669 - auxilliary_output_2_loss: 4.
8727 - output_acc: 0.0120 - auxilliary_output_1_acc: 0.0129 - auxilliary_outpu
t_2_acc: 0.0117Epoch 00016: val_loss improved from 14.60593 to 14.60559, savin
g model to saved_models/weights.best.from_scratch.hdf5
```



```

6680/6680 [=====] - 91s 14ms/step - loss: 14.6063 - o
utput_loss: 4.8667 - auxilliary_output_1_loss: 4.8669 - auxilliary_output_2_lo
ss: 4.8727 - output_acc: 0.0120 - auxilliary_output_1_acc: 0.0129 - auxilliary
_output_2_acc: 0.0117 - val_loss: 14.6056 - val_output_loss: 4.8685 - val_auxi
llary_output_1_loss: 4.8686 - val_auxilliary_output_2_loss: 4.8685 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 17/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5957 - output_
loss: 4.8652 - auxilliary_output_1_loss: 4.8650 - auxilliary_output_2_loss: 4.
8656 - output_acc: 0.0117 - auxilliary_output_1_acc: 0.0113 - auxilliary_outpu
t_2_acc: 0.0114Epoch 00017: val_loss improved from 14.60559 to 14.60557, savin
g model to saved_models/weights.best.from_scratch.hdf5
6680/6680 [=====] - 91s 14ms/step - loss: 14.5963 - o
utput_loss: 4.8654 - auxilliary_output_1_loss: 4.8652 - auxilliary_output_2_lo
ss: 4.8658 - output_acc: 0.0117 - auxilliary_output_1_acc: 0.0112 - auxilliary
_output_2_acc: 0.0114 - val_loss: 14.6056 - val_output_loss: 4.8685 - val_auxi
llary_output_1_loss: 4.8685 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 18/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5964 - output_
loss: 4.8652 - auxilliary_output_1_loss: 4.8649 - auxilliary_output_2_loss: 4.
8663 - output_acc: 0.0111 - auxilliary_output_1_acc: 0.0114 - auxilliary_outpu
t_2_acc: 0.0114Epoch 00018: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.5962 - o
utput_loss: 4.8652 - auxilliary_output_1_loss: 4.8648 - auxilliary_output_2_lo
ss: 4.8662 - output_acc: 0.0112 - auxilliary_output_1_acc: 0.0115 - auxilliary
_output_2_acc: 0.0115 - val_loss: 14.6212 - val_output_loss: 4.8840 - val_auxi
llary_output_1_loss: 4.8686 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0096 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 19/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.5986 - output_
loss: 4.8657 - auxilliary_output_1_loss: 4.8653 - auxilliary_output_2_loss: 4.
8676 - output_acc: 0.0108 - auxilliary_output_1_acc: 0.0111 - auxilliary_outpu
t_2_acc: 0.0113Epoch 00019: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.5979 - o
utput_loss: 4.8654 - auxilliary_output_1_loss: 4.8651 - auxilliary_output_2_lo
ss: 4.8673 - output_acc: 0.0111 - auxilliary_output_1_acc: 0.0114 - auxilliary
_output_2_acc: 0.0115 - val_loss: 14.6060 - val_output_loss: 4.8688 - val_auxi
llary_output_1_loss: 4.8686 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
Epoch 20/20
6660/6680 [=====>.] - ETA: 0s - loss: 14.6003 - output_
loss: 4.8651 - auxilliary_output_1_loss: 4.8703 - auxilliary_output_2_loss: 4.
8649 - output_acc: 0.0111 - auxilliary_output_1_acc: 0.0114 - auxilliary_outpu
t_2_acc: 0.0117Epoch 00020: val_loss did not improve
6680/6680 [=====] - 91s 14ms/step - loss: 14.6003 - o
utput_loss: 4.8652 - auxilliary_output_1_loss: 4.8703 - auxilliary_output_2_lo
ss: 4.8649 - output_acc: 0.0111 - auxilliary_output_1_acc: 0.0114 - auxilliary
_output_2_acc: 0.0117 - val_loss: 14.6061 - val_output_loss: 4.8687 - val_auxi
llary_output_1_loss: 4.8689 - val_auxilliary_output_2_loss: 4.8686 - val_outp
ut_acc: 0.0108 - val_auxilliary_output_1_acc: 0.0108 - val_auxilliary_output_2
_acc: 0.0108
<keras.callbacks.History at 0x7f8b926e2e48>

```

```

model.load_weights('saved_models/weights.best.from_scratch.hdf5')
# 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_targets, axis=1))/len(dog_breed_predictions)
print('Test accuracy: %.4f%%' % test_accuracy)
Test accuracy: 0.0000%

```

In []: I have tried GoogleNet 5 , LeNet and LeNet5 and LeNet 5 has highest accuracy but compare to suggested model it has much much parameter than suggested one So for performance i chose the suggested one for simplest and according to my cpu it is faster

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 [18]: 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 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 [19]: 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_3 ((None, 512)	0
=====		
dense_3 (Dense)	(None, 133)	68229
=====		
Total params: 68,229		
Trainable params: 68,229		
Non-trainable params: 0		
=====		

Compile the Model

```
In [20]: VGG16_model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
```

Train the Model

```
In [21]: 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=[checker], verbose=1)
```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

6620/6680 [=====>.] - ETA: 0s - loss: 12.9514 - acc: 0.1044
Epoch 00001: val_loss improved from inf to 11.54031, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 338us/step - loss: 12.9433 - acc: 0.1048 - val_loss: 11.5403 - val_acc: 0.1952

Epoch 2/20

6660/6680 [=====>.] - ETA: 0s - loss: 11.2073 - acc: 0.2336
Epoch 00002: val_loss improved from 11.54031 to 11.01780, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 266us/step - loss: 11.2054 - acc: 0.2337 - val_loss: 11.0178 - val_acc: 0.2431

Epoch 3/20

6460/6680 [=====>.] - ETA: 0s - loss: 10.7185 - acc: 0.2834
Epoch 00003: val_loss improved from 11.01780 to 10.82729, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 266us/step - loss: 10.7285 - acc: 0.2832 - val_loss: 10.8273 - val_acc: 0.2563

Epoch 4/20

6560/6680 [=====>.] - ETA: 0s - loss: 10.4754 - acc: 0.3145
Epoch 00004: val_loss improved from 10.82729 to 10.67333, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 264us/step - loss: 10.4868 - acc: 0.3141 - val_loss: 10.6733 - val_acc: 0.2802

Epoch 5/20

6460/6680 [=====>.] - ETA: 0s - loss: 10.4038 - acc: 0.3297
Epoch 00005: val_loss did not improve

6680/6680 [=====] - 2s 269us/step - loss: 10.4020 - acc: 0.3292 - val_loss: 10.6848 - val_acc: 0.2922

Epoch 6/20

6520/6680 [=====>.] - ETA: 0s - loss: 10.2926 - acc: 0.3396
Epoch 00006: val_loss improved from 10.67333 to 10.50736, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 266us/step - loss: 10.2933 - acc: 0.3388 - val_loss: 10.5074 - val_acc: 0.2922

Epoch 7/20

6480/6680 [=====>.] - ETA: 0s - loss: 10.0086 - acc: 0.3535
Epoch 00007: val_loss improved from 10.50736 to 10.20887, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 267us/step - loss: 10.0283 - acc: 0.3521 - val_loss: 10.2089 - val_acc: 0.3234

Epoch 8/20

6480/6680 [=====>.] - ETA: 0s - loss: 9.9248 - acc: 0.3633
Epoch 00008: val_loss improved from 10.20887 to 10.15315, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 267us/step - loss: 9.8819 - acc: 0.3650 - val_loss: 10.1532 - val_acc: 0.3246

Epoch 9/20

6560/6680 [=====>.] - ETA: 0s - loss: 9.7705 - acc: 0.3758
Epoch 00009: val_loss improved from 10.15315 to 10.14385, saving model to saved_models/weights.best.VGG16.hdf5

6680/6680 [=====] - 2s 262us/step - loss: 9.7608 - acc: 0.3762 - val_loss: 10.1439 - val_acc: 0.3222

Epoch 10/20

6560/6680 [=====>.] - ETA: 0s - loss: 9.7160 - acc: 0.3841
Epoch 00010: val_loss did not improve

```
6680/6680 [=====] - 2s 261us/step - loss: 9.7154 - a
cc: 0.3844 - val_loss: 10.1591 - val_acc: 0.3198
Epoch 11/20
6460/6680 [=====>.] - ETA: 0s - loss: 9.6825 - acc: 0.
3896Epoch 00011: val_loss improved from 10.14385 to 10.13183, saving model to
saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 267us/step - loss: 9.6996 - a
cc: 0.3877 - val_loss: 10.1318 - val_acc: 0.3293
Epoch 12/20
6460/6680 [=====>.] - ETA: 0s - loss: 9.6429 - acc: 0.
3944Epoch 00012: val_loss improved from 10.13183 to 10.10367, saving model to
saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 267us/step - loss: 9.6784 - a
cc: 0.3922 - val_loss: 10.1037 - val_acc: 0.3317
Epoch 13/20
6660/6680 [=====>.] - ETA: 0s - loss: 9.6637 - acc: 0.
3941Epoch 00013: val_loss did not improve
6680/6680 [=====] - 2s 262us/step - loss: 9.6638 - a
cc: 0.3942 - val_loss: 10.1175 - val_acc: 0.3329
Epoch 14/20
6520/6680 [=====>.] - ETA: 0s - loss: 9.5708 - acc: 0.
3957Epoch 00014: val_loss improved from 10.10367 to 10.06252, saving model to
saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 265us/step - loss: 9.5516 - a
cc: 0.3972 - val_loss: 10.0625 - val_acc: 0.3305
Epoch 15/20
6580/6680 [=====>.] - ETA: 0s - loss: 9.4896 - acc: 0.
4035Epoch 00015: val_loss improved from 10.06252 to 9.93964, saving model to
saved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 262us/step - loss: 9.4878 - a
cc: 0.4036 - val_loss: 9.9396 - val_acc: 0.3377
Epoch 16/20
6560/6680 [=====>.] - ETA: 0s - loss: 9.4139 - acc: 0.
4084Epoch 00016: val_loss improved from 9.93964 to 9.89933, saving model to s
aved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 265us/step - loss: 9.3935 - a
cc: 0.4093 - val_loss: 9.8993 - val_acc: 0.3413
Epoch 17/20
6480/6680 [=====>.] - ETA: 0s - loss: 9.3309 - acc: 0.
4119Epoch 00017: val_loss improved from 9.89933 to 9.79955, saving model to s
aved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 263us/step - loss: 9.3152 - a
cc: 0.4129 - val_loss: 9.7996 - val_acc: 0.3389
Epoch 18/20
6540/6680 [=====>.] - ETA: 0s - loss: 9.2134 - acc: 0.
4188Epoch 00018: val_loss improved from 9.79955 to 9.72994, saving model to s
aved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 264us/step - loss: 9.2110 - a
cc: 0.4190 - val_loss: 9.7299 - val_acc: 0.3437
Epoch 19/20
6480/6680 [=====>.] - ETA: 0s - loss: 9.1427 - acc: 0.
4228Epoch 00019: val_loss did not improve
6680/6680 [=====] - 2s 264us/step - loss: 9.1347 - a
cc: 0.4228 - val_loss: 9.7915 - val_acc: 0.3389
Epoch 20/20
6560/6680 [=====>.] - ETA: 0s - loss: 9.0479 - acc: 0.
4265Epoch 00020: val_loss improved from 9.72994 to 9.64054, saving model to s
```

```

aved_models/weights.best.VGG16.hdf5
6680/6680 [=====] - 2s 262us/step - loss: 9.0449 - a
cc: 0.4268 - val_loss: 9.6405 - val_acc: 0.3461

```

Out[21]: <keras.callbacks.History at 0x7f03345687f0>

Load the Model with the Best Validation Loss

```
In [22]: 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 [23]: # 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: 34.5694%

Predict Dog Breed with the Model

```
In [24]: 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. These are already in the workspace, at `/data/bottleneck_features`. If you wish to download them on a different machine, they can be found at:

- [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`.

The above architectures are downloaded and stored for you in the `/data/bottleneck_features/` folder.

This means the following will be in the `/data/bottleneck_features/` folder:

`DogVGG19Data.npz` `DogResnet50Data.npz` `DogInceptionV3Data.npz` `DogXceptionData.npz`

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



```
In [25]: ### TODO: Obtain bottleneck features from another pre-trained CNN.
network = 'Xception'
if network == 'ResNet-50':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogResnet
50Data.npz')
elif network == 'Inception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogIncept
ionV3Data.npz')
elif network == 'Xception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogXcepti
onData.npz')
elif network == 'VGG-19':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogVGG19D
ata.npz')

train_network = bottleneck_features_network['train']
valid_network = bottleneck_features_network['valid']
test_network = bottleneck_features_network['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 [27]: ### TODO: Define your architecture.
Xception_model = Sequential()
Xception_model.add(GlobalAveragePooling2D(input_shape=train_network.shape[1
:]))
Xception_model.add(Dense(133, activation='softmax'))
```

(IMPLEMENTATION) Compile the Model

```
In [28]: ### TODO: Compile the model.
Xception_model.compile(loss='categorical_crossentropy', optimizer='rmsprop')
```

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

Xception_model.fit(train_network, train_targets,
                   validation_data=(valid_network, valid_targets),
                   epochs=20, batch_size=20, callbacks=[checkpointer], verbose=1)
```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

6660/6680 [=====>.] - ETA: 0s - loss: 1.0589Epoch 0000
1: val_loss improved from inf to 0.52986, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 4s 529us/step - loss: 1.0572 - val_loss: 0.5299

Epoch 2/20

6620/6680 [=====>.] - ETA: 0s - loss: 0.3999Epoch 0000
2: val_loss improved from 0.52986 to 0.47970, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 3s 522us/step - loss: 0.3989 - val_loss: 0.4797

Epoch 3/20

6560/6680 [=====>.] - ETA: 0s - loss: 0.3206Epoch 0000
3: val_loss improved from 0.47970 to 0.47003, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 4s 551us/step - loss: 0.3205 - val_loss: 0.4700

Epoch 4/20

6540/6680 [=====>.] - ETA: 0s - loss: 0.2768Epoch 0000
4: val_loss did not improve

6680/6680 [=====] - 3s 459us/step - loss: 0.2766 - val_loss: 0.5070

Epoch 5/20

6560/6680 [=====>.] - ETA: 0s - loss: 0.2419Epoch 0000
5: val_loss did not improve

6680/6680 [=====] - 3s 495us/step - loss: 0.2448 - val_loss: 0.4961

Epoch 6/20

6620/6680 [=====>.] - ETA: 0s - loss: 0.2193Epoch 0000
6: val_loss did not improve

6680/6680 [=====] - 3s 480us/step - loss: 0.2186 - val_loss: 0.5260

Epoch 7/20

6640/6680 [=====>.] - ETA: 0s - loss: 0.1948Epoch 0000
7: val_loss did not improve

6680/6680 [=====] - 3s 505us/step - loss: 0.1962 - val_loss: 0.5316

Epoch 8/20

6620/6680 [=====>.] - ETA: 0s - loss: 0.1812Epoch 0000
8: val_loss did not improve

6680/6680 [=====] - 3s 516us/step - loss: 0.1806 - val_loss: 0.5732

Epoch 9/20

6540/6680 [=====>.] - ETA: 0s - loss: 0.1597Epoch 0000
9: val_loss did not improve

6680/6680 [=====] - 3s 482us/step - loss: 0.1598 - val_loss: 0.5945

Epoch 10/20

6600/6680 [=====>.] - ETA: 0s - loss: 0.1497Epoch 0001
0: val_loss did not improve

6680/6680 [=====] - 3s 454us/step - loss: 0.1496 - val_loss: 0.6041

Epoch 11/20

6600/6680 [=====>.] - ETA: 0s - loss: 0.1371Epoch 0001
1: val_loss did not improve

```

6680/6680 [=====] - 3s 457us/step - loss: 0.1376 - v
al_loss: 0.5959
Epoch 12/20
6660/6680 [=====>.] - ETA: 0s - loss: 0.1248Epoch 0001
2: val_loss did not improve
6680/6680 [=====] - 3s 503us/step - loss: 0.1246 - v
al_loss: 0.6231
Epoch 13/20
6660/6680 [=====>.] - ETA: 0s - loss: 0.1176Epoch 0001
3: val_loss did not improve
6680/6680 [=====] - 3s 417us/step - loss: 0.1177 - v
al_loss: 0.6275
Epoch 14/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.1098Epoch 0001
4: val_loss did not improve
6680/6680 [=====] - 3s 428us/step - loss: 0.1100 - v
al_loss: 0.5983
Epoch 15/20
6620/6680 [=====>.] - ETA: 0s - loss: 0.0982Epoch 0001
5: val_loss did not improve
6680/6680 [=====] - 3s 480us/step - loss: 0.0982 - v
al_loss: 0.6509
Epoch 16/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0944Epoch 0001
6: val_loss did not improve
6680/6680 [=====] - 3s 468us/step - loss: 0.0940 - v
al_loss: 0.6499
Epoch 17/20
6540/6680 [=====>.] - ETA: 0s - loss: 0.0840Epoch 0001
7: val_loss did not improve
6680/6680 [=====] - 3s 442us/step - loss: 0.0848 - v
al_loss: 0.6474
Epoch 18/20
6580/6680 [=====>.] - ETA: 0s - loss: 0.0836Epoch 0001
8: val_loss did not improve
6680/6680 [=====] - 3s 431us/step - loss: 0.0827 - v
al_loss: 0.6645
Epoch 19/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0766Epoch 0001
9: val_loss did not improve
6680/6680 [=====] - 3s 455us/step - loss: 0.0762 - v
al_loss: 0.6906
Epoch 20/20
6580/6680 [=====>.] - ETA: 0s - loss: 0.0728Epoch 0002
0: val_loss did not improve
6680/6680 [=====] - 3s 423us/step - loss: 0.0734 - v
al_loss: 0.6937

```

Out[31]: <keras.callbacks.History at 0x7f033425a5c0>

(IMPLEMENTATION) Load the Model with the Best Validation Loss

```

In [32]: ### TODO: Load the model weights with the best validation loss.
Xception_model.load_weights('saved_models/weights.best.Xception.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 [34]: ### TODO: Calculate classification accuracy on the test dataset.

Xception_predictions = [np.argmax(Xception_model.predict(np.expand_dims(feature, axis=0))) for feature in test_network]

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

Test accuracy: 84.4498%

```
In [ ]: ### ResNet-50
```

```

In [35]: ### TODO: Obtain bottleneck features from another pre-trained CNN.
network = 'ResNet-50'
if network == 'ResNet-50':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogResnet
50Data.npz')
elif network == 'Inception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogIncept
ionV3Data.npz')
elif network == 'Xception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogXcepti
onData.npz')
elif network == 'VGG-19':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogVGG19D
ata.npz')

train_network = bottleneck_features_network['train']
valid_network = bottleneck_features_network['valid']
test_network = bottleneck_features_network['test']

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

### TODO: Compile the model.
Xception_model.compile(loss='categorical_crossentropy', optimizer='rmsprop')

### TODO: Train the model.
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.Xception.hd
f5',
                                verbose=1, save_best_only=True)

Xception_model.fit(train_network, train_targets,
                    validation_data=(valid_network, valid_targets),
                    epochs=20, batch_size=20, callbacks=[checkpointer], verbose=1)

### TODO: Load the model weights with the best validation loss.
Xception_model.load_weights('saved_models/weights.best.Xception.hdf5')

### TODO: Calculate classification accuracy on the test dataset.

Xception_predictions = [np.argmax(Xception_model.predict(np.expand_dims(featur
e, axis=0))) for feature in test_network]

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

```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

6520/6680 [=====>.] - ETA: 0s - loss: 1.6661Epoch 0000
1: val_loss improved from inf to 0.78518, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 279us/step - loss: 1.6478 - val_loss: 0.7852

Epoch 2/20

6600/6680 [=====>.] - ETA: 0s - loss: 0.4326Epoch 0000
2: val_loss improved from 0.78518 to 0.74410, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 231us/step - loss: 0.4327 - val_loss: 0.7441

Epoch 3/20

6520/6680 [=====>.] - ETA: 0s - loss: 0.2659Epoch 0000
3: val_loss improved from 0.74410 to 0.66815, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 225us/step - loss: 0.2644 - val_loss: 0.6682

Epoch 4/20

6520/6680 [=====>.] - ETA: 0s - loss: 0.1812Epoch 0000
4: val_loss improved from 0.66815 to 0.65669, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 1s 224us/step - loss: 0.1800 - val_loss: 0.6567

Epoch 5/20

6600/6680 [=====>.] - ETA: 0s - loss: 0.1176Epoch 0000
5: val_loss did not improve

6680/6680 [=====] - 1s 222us/step - loss: 0.1180 - val_loss: 0.6636

Epoch 6/20

6640/6680 [=====>.] - ETA: 0s - loss: 0.0867Epoch 0000
6: val_loss did not improve

6680/6680 [=====] - 1s 221us/step - loss: 0.0866 - val_loss: 0.6889

Epoch 7/20

6660/6680 [=====>.] - ETA: 0s - loss: 0.0605Epoch 0000
7: val_loss did not improve

6680/6680 [=====] - 1s 220us/step - loss: 0.0606 - val_loss: 0.7447

Epoch 8/20

6580/6680 [=====>.] - ETA: 0s - loss: 0.0481Epoch 0000
8: val_loss did not improve

6680/6680 [=====] - 1s 221us/step - loss: 0.0477 - val_loss: 0.7012

Epoch 9/20

6500/6680 [=====>.] - ETA: 0s - loss: 0.0325Epoch 0000
9: val_loss did not improve

6680/6680 [=====] - 1s 223us/step - loss: 0.0323 - val_loss: 0.7491

Epoch 10/20

6660/6680 [=====>.] - ETA: 0s - loss: 0.0275Epoch 0001
0: val_loss did not improve

6680/6680 [=====] - 1s 220us/step - loss: 0.0274 - val_loss: 0.7608

Epoch 11/20

6660/6680 [=====>.] - ETA: 0s - loss: 0.0205Epoch 0001


```

1: val_loss did not improve
6680/6680 [=====] - 1s 221us/step - loss: 0.0205 - v
al_loss: 0.7138
Epoch 12/20
6600/6680 [=====>.] - ETA: 0s - loss: 0.0156Epoch 0001
2: val_loss did not improve
6680/6680 [=====] - 1s 221us/step - loss: 0.0155 - v
al_loss: 0.7803
Epoch 13/20
6600/6680 [=====>.] - ETA: 0s - loss: 0.0131Epoch 0001
3: val_loss did not improve
6680/6680 [=====] - 1s 222us/step - loss: 0.0131 - v
al_loss: 0.8263
Epoch 14/20
6580/6680 [=====>.] - ETA: 0s - loss: 0.0118Epoch 0001
4: val_loss did not improve
6680/6680 [=====] - 1s 223us/step - loss: 0.0116 - v
al_loss: 0.8319
Epoch 15/20
6600/6680 [=====>.] - ETA: 0s - loss: 0.0098Epoch 0001
5: val_loss did not improve
6680/6680 [=====] - 1s 221us/step - loss: 0.0102 - v
al_loss: 0.8675
Epoch 16/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0085Epoch 0001
6: val_loss did not improve
6680/6680 [=====] - 2s 226us/step - loss: 0.0084 - v
al_loss: 0.8593
Epoch 17/20
6560/6680 [=====>.] - ETA: 0s - loss: 0.0065Epoch 0001
7: val_loss did not improve
6680/6680 [=====] - 1s 223us/step - loss: 0.0064 - v
al_loss: 0.8560
Epoch 18/20
6440/6680 [=====>..] - ETA: 0s - loss: 0.0057Epoch 0001
8: val_loss did not improve
6680/6680 [=====] - 1s 218us/step - loss: 0.0067 - v
al_loss: 0.9047
Epoch 19/20
6520/6680 [=====>.] - ETA: 0s - loss: 0.0069Epoch 0001
9: val_loss did not improve
6680/6680 [=====] - 1s 224us/step - loss: 0.0068 - v
al_loss: 0.9122
Epoch 20/20
6460/6680 [=====>.] - ETA: 0s - loss: 0.0062Epoch 0002
0: val_loss did not improve
6680/6680 [=====] - 1s 224us/step - loss: 0.0060 - v
al_loss: 0.9160
Test accuracy: 81.2201%

```

In []: #VGG-19

```

In [36]: ### TODO: Obtain bottleneck features from another pre-trained CNN.
network = 'VGG-19'
if network == 'ResNet-50':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogResnet
50Data.npz')
elif network == 'Inception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogIncept
ionV3Data.npz')
elif network == 'Xception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogXcepti
onData.npz')
elif network == 'VGG-19':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogVGG19D
ata.npz')

train_network = bottleneck_features_network['train']
valid_network = bottleneck_features_network['valid']
test_network = bottleneck_features_network['test']

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

### TODO: Compile the model.
Xception_model.compile(loss='categorical_crossentropy', optimizer='rmsprop')

### TODO: Train the model.
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.Xception.hd
f5',
                                verbose=1, save_best_only=True)

Xception_model.fit(train_network, train_targets,
                    validation_data=(valid_network, valid_targets),
                    epochs=20, batch_size=20, callbacks=[checkpointer], verbose=1)

### TODO: Load the model weights with the best validation loss.
Xception_model.load_weights('saved_models/weights.best.Xception.hdf5')

### TODO: Calculate classification accuracy on the test dataset.

Xception_predictions = [np.argmax(Xception_model.predict(np.expand_dims(featur
e, axis=0))) for feature in test_network]

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

```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

6540/6680 [=====>.] - ETA: 0s - loss: 12.2815Epoch 000
01: val_loss improved from inf to 10.73971, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 321us/step - loss: 12.2570 -
val_loss: 10.7397

Epoch 2/20

6580/6680 [=====>.] - ETA: 0s - loss: 10.1915Epoch 000
02: val_loss improved from 10.73971 to 10.20255, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 258us/step - loss: 10.1919 -
val_loss: 10.2026

Epoch 3/20

6480/6680 [=====>.] - ETA: 0s - loss: 9.7654Epoch 000
03: val_loss improved from 10.20255 to 9.98180, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 254us/step - loss: 9.7887 - v
al_loss: 9.9818

Epoch 4/20

6620/6680 [=====>.] - ETA: 0s - loss: 9.5521Epoch 000
04: val_loss improved from 9.98180 to 9.78641, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 257us/step - loss: 9.5453 - v
al_loss: 9.7864

Epoch 5/20

6620/6680 [=====>.] - ETA: 0s - loss: 9.2765Epoch 000
05: val_loss improved from 9.78641 to 9.63579, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 259us/step - loss: 9.2875 - v
al_loss: 9.6358

Epoch 6/20

6600/6680 [=====>.] - ETA: 0s - loss: 9.0250Epoch 000
06: val_loss improved from 9.63579 to 9.29517, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 258us/step - loss: 9.0101 - v
al_loss: 9.2952

Epoch 7/20

6520/6680 [=====>.] - ETA: 0s - loss: 8.7664Epoch 000
07: val_loss improved from 9.29517 to 9.25001, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 253us/step - loss: 8.7722 - v
al_loss: 9.2500

Epoch 8/20

6600/6680 [=====>.] - ETA: 0s - loss: 8.6278Epoch 000
08: val_loss improved from 9.25001 to 9.11837, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 256us/step - loss: 8.6314 - v
al_loss: 9.1184

Epoch 9/20

6440/6680 [=====>..] - ETA: 0s - loss: 8.5083Epoch 000
09: val_loss improved from 9.11837 to 9.03088, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 2s 256us/step - loss: 8.5287 - v
al_loss: 9.0309

Epoch 10/20

6620/6680 [=====>.] - ETA: 0s - loss: 8.3500Epoch 0001

```
0: val_loss improved from 9.03088 to 8.86494, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 260us/step - loss: 8.3479 - val_loss: 8.8649
Epoch 11/20
6480/6680 [=====>.] - ETA: 0s - loss: 8.1487Epoch 0001
1: val_loss improved from 8.86494 to 8.77736, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 255us/step - loss: 8.1509 - val_loss: 8.7774
Epoch 12/20
6580/6680 [=====>.] - ETA: 0s - loss: 8.0856Epoch 0002
2: val_loss improved from 8.77736 to 8.71500, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 262us/step - loss: 8.0876 - val_loss: 8.7150
Epoch 13/20
6660/6680 [=====>.] - ETA: 0s - loss: 7.9739Epoch 0003
3: val_loss improved from 8.71500 to 8.48897, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 256us/step - loss: 7.9719 - val_loss: 8.4890
Epoch 14/20
6580/6680 [=====>.] - ETA: 0s - loss: 7.6841Epoch 0004
4: val_loss improved from 8.48897 to 8.33156, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 253us/step - loss: 7.6711 - val_loss: 8.3316
Epoch 15/20
6620/6680 [=====>.] - ETA: 0s - loss: 7.5583Epoch 0005
5: val_loss improved from 8.33156 to 8.27690, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 259us/step - loss: 7.5566 - val_loss: 8.2769
Epoch 16/20
6660/6680 [=====>.] - ETA: 0s - loss: 7.5042Epoch 0006
6: val_loss improved from 8.27690 to 8.20567, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 255us/step - loss: 7.5035 - val_loss: 8.2057
Epoch 17/20
6660/6680 [=====>.] - ETA: 0s - loss: 7.4657Epoch 0007
7: val_loss improved from 8.20567 to 8.12725, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 257us/step - loss: 7.4650 - val_loss: 8.1272
Epoch 18/20
6460/6680 [=====>.] - ETA: 0s - loss: 7.3376Epoch 0008
8: val_loss improved from 8.12725 to 8.01355, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 256us/step - loss: 7.3710 - val_loss: 8.0135
Epoch 19/20
6600/6680 [=====>.] - ETA: 0s - loss: 7.2494Epoch 0009
9: val_loss improved from 8.01355 to 7.96707, saving model to saved_models/weights.best.Xception.hdf5
6680/6680 [=====] - 2s 260us/step - loss: 7.2626 - val_loss: 7.96707
```

```
al_loss: 7.9671
Epoch 20/20
6620/6680 [=====>.] - ETA: 0s - loss: 7.1952Epoch 0002
0: val_loss improved from 7.96707 to 7.87576, saving model to saved_models/we
ights.best.Xception.hdf5
6680/6680 [=====] - 2s 257us/step - loss: 7.1982 - v
al_loss: 7.8758
Test accuracy: 45.2153%
```

```

In [37]: ### TODO: Obtain bottleneck features from another pre-trained CNN.
network = 'Inception'
if network == 'ResNet-50':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogResnet
50Data.npz')
elif network == 'Inception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogIncept
ionV3Data.npz')
elif network == 'Xception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogXcepti
onData.npz')
elif network == 'VGG-19':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogVGG19D
ata.npz')

train_network = bottleneck_features_network['train']
valid_network = bottleneck_features_network['valid']
test_network = bottleneck_features_network['test']

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

### TODO: Compile the model.
Xception_model.compile(loss='categorical_crossentropy', optimizer='rmsprop')

### TODO: Train the model.
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.Xception.hd
f5',
                               verbose=1, save_best_only=True)

Xception_model.fit(train_network, train_targets,
                   validation_data=(valid_network, valid_targets),
                   epochs=20, batch_size=20, callbacks=[checkpointer], verbose=1)

### TODO: Load the model weights with the best validation loss.
Xception_model.load_weights('saved_models/weights.best.Xception.hdf5')

### TODO: Calculate classification accuracy on the test dataset.

Xception_predictions = [np.argmax(Xception_model.predict(np.expand_dims(featur
e, axis=0))) for feature in test_network]

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

```

Train on 6680 samples, validate on 835 samples

Epoch 1/20

6660/6680 [=====>.] - ETA: 0s - loss: 1.1626Epoch 0000
1: val_loss improved from inf to 0.60340, saving model to saved_models/weights.best.Xception.hdf5

6680/6680 [=====] - 3s 465us/step - loss: 1.1608 - val_loss: 0.6034

Epoch 2/20

6620/6680 [=====>.] - ETA: 0s - loss: 0.4734Epoch 0000
2: val_loss did not improve

6680/6680 [=====] - 2s 367us/step - loss: 0.4732 - val_loss: 0.6488

Epoch 3/20

6500/6680 [=====>.] - ETA: 0s - loss: 0.3637Epoch 0000
3: val_loss did not improve

6680/6680 [=====] - 2s 318us/step - loss: 0.3652 - val_loss: 0.7619

Epoch 4/20

6540/6680 [=====>.] - ETA: 0s - loss: 0.2872Epoch 0000
4: val_loss did not improve

6680/6680 [=====] - 2s 315us/step - loss: 0.2876 - val_loss: 0.7154

Epoch 5/20

6660/6680 [=====>.] - ETA: 0s - loss: 0.2352Epoch 0000
5: val_loss did not improve

6680/6680 [=====] - 2s 319us/step - loss: 0.2349 - val_loss: 0.6942

Epoch 6/20

6600/6680 [=====>.] - ETA: 0s - loss: 0.2028Epoch 0000
6: val_loss did not improve

6680/6680 [=====] - 2s 322us/step - loss: 0.2029 - val_loss: 0.7500

Epoch 7/20

6660/6680 [=====>.] - ETA: 0s - loss: 0.1754Epoch 0000
7: val_loss did not improve

6680/6680 [=====] - 2s 320us/step - loss: 0.1755 - val_loss: 0.7009

Epoch 8/20

6560/6680 [=====>.] - ETA: 0s - loss: 0.1393Epoch 0000
8: val_loss did not improve

6680/6680 [=====] - 2s 370us/step - loss: 0.1409 - val_loss: 0.7681

Epoch 9/20

6600/6680 [=====>.] - ETA: 0s - loss: 0.1246Epoch 0000
9: val_loss did not improve

6680/6680 [=====] - 2s 369us/step - loss: 0.1238 - val_loss: 0.7771

Epoch 10/20

6540/6680 [=====>.] - ETA: 0s - loss: 0.1115Epoch 0001
0: val_loss did not improve

6680/6680 [=====] - 2s 371us/step - loss: 0.1104 - val_loss: 0.7821

Epoch 11/20

6520/6680 [=====>.] - ETA: 0s - loss: 0.0902Epoch 0001
1: val_loss did not improve

6680/6680 [=====] - 2s 367us/step - loss: 0.0917 - val_loss: 0.8221

```

Epoch 12/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0841Epoch 0001
2: val_loss did not improve
6680/6680 [=====] - 2s 350us/step - loss: 0.0842 - v
al_loss: 0.8468
Epoch 13/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0689Epoch 0001
3: val_loss did not improve
6680/6680 [=====] - 2s 335us/step - loss: 0.0687 - v
al_loss: 0.8661
Epoch 14/20
6600/6680 [=====>.] - ETA: 0s - loss: 0.0674Epoch 0001
4: val_loss did not improve
6680/6680 [=====] - 2s 332us/step - loss: 0.0668 - v
al_loss: 0.8636
Epoch 15/20
6540/6680 [=====>.] - ETA: 0s - loss: 0.0546Epoch 0001
5: val_loss did not improve
6680/6680 [=====] - 2s 336us/step - loss: 0.0555 - v
al_loss: 0.9089
Epoch 16/20
6560/6680 [=====>.] - ETA: 0s - loss: 0.0511Epoch 0001
6: val_loss did not improve
6680/6680 [=====] - 2s 336us/step - loss: 0.0508 - v
al_loss: 0.8676
Epoch 17/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0392Epoch 0001
7: val_loss did not improve
6680/6680 [=====] - 2s 341us/step - loss: 0.0393 - v
al_loss: 0.9199
Epoch 18/20
6660/6680 [=====>.] - ETA: 0s - loss: 0.0404Epoch 0001
8: val_loss did not improve
6680/6680 [=====] - 2s 370us/step - loss: 0.0402 - v
al_loss: 0.9048
Epoch 19/20
6640/6680 [=====>.] - ETA: 0s - loss: 0.0382Epoch 0001
9: val_loss did not improve
6680/6680 [=====] - 2s 340us/step - loss: 0.0380 - v
al_loss: 0.9022
Epoch 20/20
6520/6680 [=====>.] - ETA: 0s - loss: 0.0349Epoch 0002
0: val_loss did not improve
6680/6680 [=====] - 2s 328us/step - loss: 0.0348 - v
al_loss: 0.9164
Test accuracy: 80.0239%

```

```

In [39]: ##best One xception
Xception : Test accuracy: 84.4498%
ResNet-50 : Test accuracy: 81.2201%
VGG-19 : Test accuracy: 45.2153%
Inception :Test accuracy: 80.0239%
the Xception is selecetd beacouse has hieghst accuracy

```


In []:

```

In [21]: ### TODO: Obtain bottleneck features from another pre-trained CNN.
network = 'Xception'
if network == 'ResNet-50':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogResnet
50Data.npz')
elif network == 'Inception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogIncept
ionV3Data.npz')
elif network == 'Xception':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogXcepti
onData.npz')
elif network == 'VGG-19':
    bottleneck_features_network = np.load('/data/bottleneck_features/DogVGG19D
ata.npz')

train_network = bottleneck_features_network['train']
valid_network = bottleneck_features_network['valid']
test_network = bottleneck_features_network['test']

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

### TODO: Compile the model.
Xception_model.compile(loss='categorical_crossentropy', optimizer='rmsprop')
### TODO: Train the model.
checkpointer = ModelCheckpoint(filepath='saved_models/weights.best.Xception.hd
f5',
                               verbose=1, save_best_only=True)

Xception_model.fit(train_network, train_targets,
                   validation_data=(valid_network, valid_targets),
                   epochs=20, batch_size=20, callbacks=[checkpointer], verbose=1)

### TODO: Load the model weights with the best validation loss.
Xception_model.load_weights('saved_models/weights.best.Xception.hdf5')

### TODO: Calculate classification accuracy on the test dataset.

Xception_predictions = [np.argmax(Xception_model.predict(np.expand_dims(featur
e, axis=0))) for feature in test_network]

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

```

(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 []:

```
In [20]: ### 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 Xception_predict_breed(img_path):  
    # extract bottleneck features  
    bottleneck_feature = extract_Xception(path_to_tensor(img_path))  
    # obtain predicted vector  
    predicted_vector = Xception_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.

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

 Sample Human Output

(IMPLEMENTATION) Write your Algorithm

```
In [5]: ### TODO: Write your algorithm.  
### Feel free to use as many code cells as needed.  
def detect_breed(image_path):  
    if face_detector(image_path):  
        print("Hello, human!")  
    elif dog_detector(image_path):  
        print("Hello, dog!")  
    else:  
        print("Error: Neither a human face or a dog was detected.\n")  
        return  
  
    # Use same Image Pipeline as used earlier  
    img = cv2.imread(image_path)  
    # Convert from BGR to RGB  
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  
    # Plot the  
    plt.imshow(cv_rgb)  
    plt.show()  
  
    print("You look like a ...")  
    print(Xception_predict_breed(image_path))  
    print()
```

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:

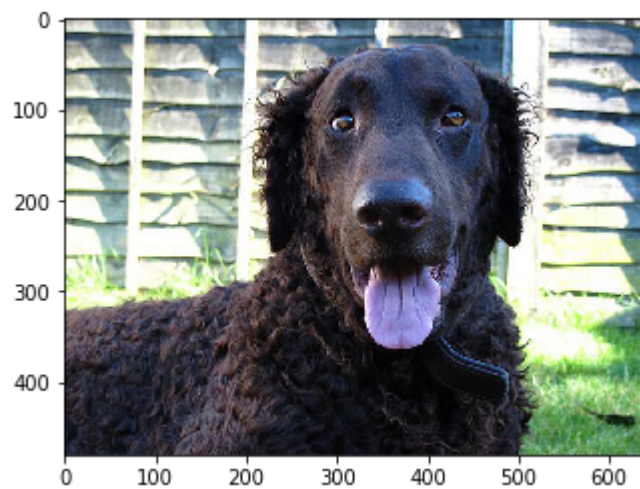
```
In [26]: ## TODO: Execute your algorithm from Step 6 on  
## at least 6 images on your computer.  
## Feel free to use as many code cells as needed.  
import cv2  
import matplotlib.pyplot as plt  
detect_breed("images/American_water_spaniel_00648.jpg")  
#detect_breed("images/Brittany_02625.jpg.jpg")  
detect_breed("images/Curly-coated_retriever_03896.jpg")  
detect_breed("images/Labrador_retriever_06449.jpg")  
detect_breed("images/Labrador_retriever_06455.jpg")  
detect_breed("images/Labrador_retriever_06457.jpg")  
#detect_breed("images/sample_human_output.png")  
detect_breed("images/Welsh_springer_spaniel_08203.jpg")
```

Hello, dog!



You look like a ...
in/045.Cardigan_welsh_corgi

Hello, dog!



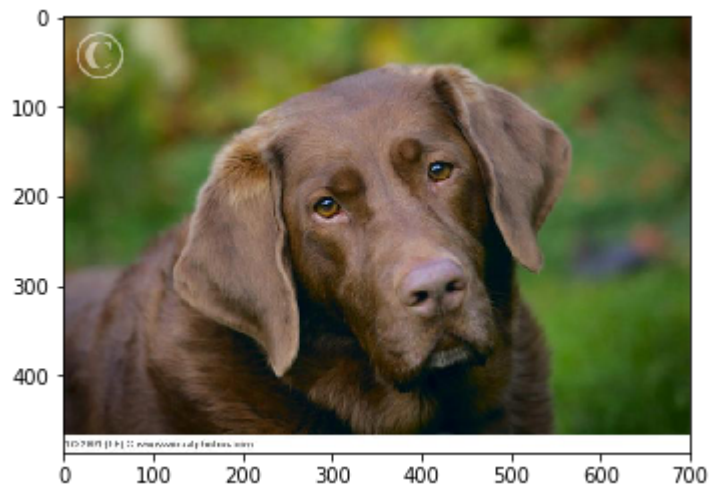
You look like a ...
in/083.Ibizan_hound

Hello, dog!



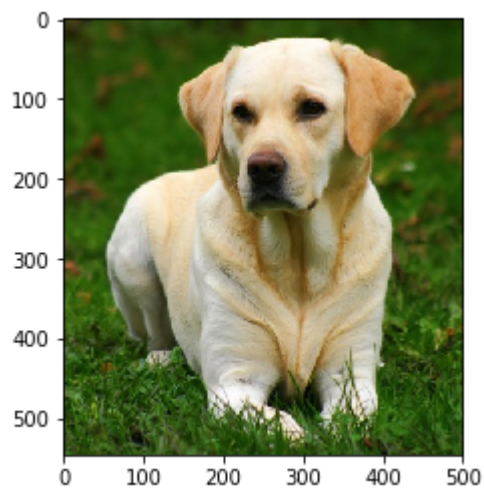
You look like a ...
in/060.Dogue_de_bordeaux

Hello, dog!



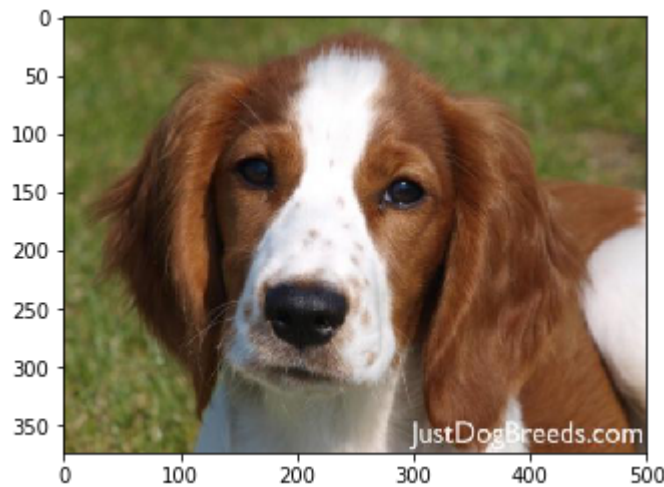
You look like a ...
in/060.Dogue_de_bordeaux

Hello, dog!



```
You look like a ...  
in/060.Dogue_de_bordeaux
```

Hello, dog!



```
You look like a ...  
in/068.Flat-coated_retriever
```

it seems my alghorithm is not succesful on defining the breed of dogs I need help and advise to improve my alghorithm ¶

Please download your notebook to submit

In order to submit, please do the following:

1. Download an HTML version of the notebook to your computer using 'File: Download as...'
2. Click on the orange Jupyter circle on the top left of the workspace.
3. Navigate into the dog-project folder to ensure that you are using the provided dog_images, lfw, and bottleneck_features folders; this means that those folders will *not* appear in the dog-project folder. If they do appear because you downloaded them, delete them.
4. While in the dog-project folder, upload the HTML version of this notebook you just downloaded. The upload button is on the top right.
5. Navigate back to the home folder by clicking on the two dots next to the folder icon, and then open up a terminal under the 'new' tab on the top right
6. Zip the dog-project folder with the following command in the terminal: `zip -r dog-project.zip dog-project`
7. Download the zip file by clicking on the square next to it and selecting 'download'. This will be the zip file you turn in on the next node after this workspace!