def visualize\_img(img\_path, ax):
 img = cv2.imread(img\_path)

ax.imshow(cv2.cvtColor(img, cv2.COLOR\_BGR2RGB))

# **Convolutional Neural Networks**

In this notebook, we use transfer learning to train a CNN to classify dog breeds.

### 1. Load Dog Dataset

```
Before running the code cell below, download the dataset of dog images here and place it in the respository.
```

```
In [1]:
from sklearn.datasets import load_files
from keras.utils import np_utils
import numpy as np
from glob import glob
# define function to load train, test, and validation datasets
def load_dataset(path):
    data = load_files(path)
    dog_files = np.array(data['filenames'])
    dog_targets = np_utils.to_categorical(np.array(data['target']), 133)
    return dog_files, dog_targets
# load train, test, and validation datasets
train_files, train_targets = load_dataset('dogImages/train')
valid_files, valid_targets = load_dataset('dogImages/valid')
test_files, test_targets = load_dataset('dogImages/test')
# load ordered list of dog names
dog_names = [item[25:-1] for item in glob('dogImages/train/*/')]
# print statistics about the dataset
print('There are %d total dog categories.' % len(dog_names))
print('There are %s total dog images.\n' % str(len(train_files) +
len(valid_files) + len(test_files)))
print('There are %d training dog images.' % len(train_files))
print('There are %d validation dog images.' % len(valid_files))
print('There are %d test dog images.'% len(test_files))
Using TensorFlow backend.
There are 133 total dog categories.
There are 8351 total dog images.
There are 6680 training dog images.
There are 835 validation dog images.
There are 836 test dog images.
2. Visualize the First 12 Training Images
                                                                          In [2]:
import cv2
import matplotlib.pyplot as plt
%matplotlib inline
```

```
fig = plt.figure(figsize=(20, 10))
for i in range(12):
    ax = fig.add_subplot(3, 4, i + 1, xticks=[], yticks=[])
    visualize_img(train_files[i], ax)
```

























#### 3. Obtain the VGG-16 Bottleneck Features

Before running the code cell below, download the file linked  $\underline{\text{here}}$  and place it in the bottleneck features/ folder.

```
bottleneck_features = np.load('bottleneck_features/DogVGG16Data.npz')
train_vgg16 = bottleneck_features['train']
valid_vgg16 = bottleneck_features['valid']
test_vgg16 = bottleneck_features['test']
```

### 4. Define a Model Architecture (Model 1)

from keras.layers import Dense, Flatten
from keras.models import Sequential

model = Sequential()
model.add(Flatten(input\_shape=(7, 7, 512)))
model.add(Dense(133, activation='softmax'))

model.summary()

Total params: 3,336,837.0

Trainable params: 3,336,837.0

Non-trainable params: 0.0

In [3]:

In [4]:

# 5. Define another Model Architecture (Model 2)

```
In [5]:
from keras.layers import GlobalAveragePooling2D
model = Sequential()
model.add(GlobalAveragePooling2D(input_shape=(7, 7, 512)))
model.add(Dense(133, activation='softmax'))
model.summary()
Layer (type)
                        Output Shape
                                              Param #
______
global average pooling2d 1 ( (None, 512)
dense 2 (Dense)
                       (None, 133)
                                              68229
______
Total params: 68,229.0
Trainable params: 68,229.0
Non-trainable params: 0.0
6. Compile the Model (Model 2)
                                                              In [6]:
model.compile(loss='categorical_crossentropy', optimizer='rmsprop',
               metrics=['accuracy'])
7. Train the Model (Model 2)
                                                              In [7]:
from keras.callbacks import ModelCheckpoint
# train the model
checkpointer = ModelCheckpoint(filepath='dogvgg16.weights.best.hdf5',
verbose=1,
                          save_best_only=True)
model.fit(train_vgg16, train_targets, epochs=20, validation_data=(valid_vgg16,
valid_targets),
        callbacks=[checkpointer], verbose=1, shuffle=True)
Train on 6680 samples, validate on 835 samples
Epoch 1/20
```

poch 00019: val loss improved from 7.19605 to 7.12832, saving model to

<keras.callbacks.History at 0x126f5b898>

val loss: 7.1283 - val acc: 0.4659

dogvgg16.weights.best.hdf5

Out[7]:

# 8. Load the Model with the Best Validation Accuracy (Model 2)

Test accuracy: 46.6507%