Food Classification with Deep Learning in Keras / Tensorflow

Computer, what am I eating anyway?

```
from IPython.display import HTML, Image

url = 'http://stratospark.com/demos/food-101/'
el = '<' + 'iframe src="{}"'.format(url) + ' width="100%" height=600></iframe
HTML(el)
```

If you are reading this on GitHub, the demo looks like this. Please follow the link below to view the live demo on my blog.

```
Image('demo.jpg')
```

jpeg

Demo available @ http://blog.stratospark.com/deep-learning-applied-food-classification-deep-learning-keras.html

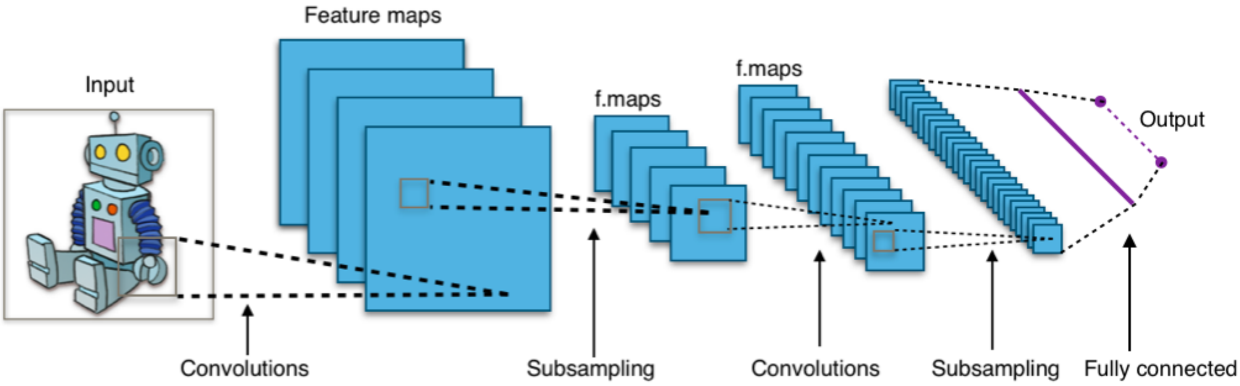
Code available @ https://github.com/stratospark/food-101-keras

UPDATES

- **2017-03-22** Learn how to use this model in a mobile app: http://blog.stratospark.com/creating-a-deep-learning-ios-app-with-keras-and-tensorflow.html

Introduction

Convolutional Neural Networks (CNN), a technique within the broader Deep Learning field, have been a revolutionary force in Computer Vision applications, especially in the past half-decade or so. One main use-case is that of image classification, e.g. determining whether a picture is that of a dog or cat.



You don't have to limit yourself to a binary classifier of course; CNNs can easily scale to thousands of different classes, as seen in the well-known ImageNet dataset of 1000 classes, used to benchmark computer vision algorithm performance.

In the past couple of years, these cutting edge techniques have started to become available to the broader software development community. Industrial strength packages such as Tensorflow have given us the same building blocks that Google uses to write deep learning applications for embedded/mobile devices to scalable clusters in the cloud – *Without having to handcode the GPU matrix operations, partial derivative gradients, and stochastic optimizers that make efficient applications possible.*

On top of all of this, are user-friendly APIs such as Keras that abstract away some of the lower level details and allow us to focus on rapidly prototyping a deep learning computation graph. Much like we would mix and match Legos to get a desired result.

Project Description

As an introductory project for myself, I chose to use a pre-trained image classifier that comes with Keras, and retrain it on a dataset that I find interesting. I'm very much into good food and home cooking, so something along those lines was appetizing.

In the paper, Food-101 – Mining Discriminative Components with Random Forests, they introduce the Food-101 dataset. There are 101 different classes of food, with 1000 labeled images per class available for supervised training.

Approach

I was inspired by this Keras blog post: Building powerful image classification models using very little data, and a related script I found on github: keras-finetuning.

I built a system recently for the purpose of experimenting with Deep Learning. The key components are an Nvidia Titan X Pascal w/12 GB of memory, 96 GB of system RAM, as well as a 12-core Intel Core i7. It is running 64-bit Ubuntu 16.04 and using the Anaconda Python distribution. Unfortunately, you won't be able to follow along with this notebook on your own system unless you have enough RAM. In the future, I would like to learn how to handle larger than RAM datasets in a performant way. **Please get in touch if you have any ideas!**

I've spent about 1 month on and off building this project, trying to train dozens of models and exploring various areas such as multiprocessing for faster image augmentation. This is a cleaned up version of the notebook that contains my best performing model as of Jan 22, 2017.

Results

After fine-tuning a pre-trained Google InceptionV3 model, I was able to achieve about **82.03% Top-1 Accuracy** on the test set using a single crop per item. Using 10 crops per example and taking the most frequent predicted class(es), I was able to achieve **86.97% Top-1 Accuracy** and **97.42% Top-5 Accuracy**

Others have been able to achieve more accurate results:

- **InceptionV3: 88.28% Top-1 Accuracy** with unknown-crops. Hassannejad, Hamid, et al. "Food Image Recognition Using Very Deep Convolutional Networks." Proceedings of the 2nd International Workshop on Multimedia Assisted Dietary Management. ACM, 2016.

- **ResNet200: 90.14% Top-1 Accuracy** on the Food-101 dataset augmented with 19 Korean dishes. NVIDIA DEEP LEARNING CONTEST 2016, Keun-dong Lee, DaUn Jeong, Seungjae Lee, Hyung Kwan Son (ETRI VisualBrowsing Team), Oct.7, 2016.
- **WISeR: 90.27% Top-1 Accuracy** with 10-crops. Martinel, Niki, Gian Luca Foresti, and Christian Micheloni. "Wide-Slice Residual Networks for Food Recognition." arXiv preprint arXiv:1612.06543 (2016).

Thoughts

- Loading a large amount of data into memory, how to avoid?
- Saving the data into h5py file for out of band processing?
- Using Dask for distributed processing?
- Improving multiprocessing image augmentation?

- Exporting to Tensorflow mobile app?

Implemented! Check out: http://blog.stratospark.com/creating-a-deep-learning-ios-app-with-keras-and-tensorflow.html

Experiment

Loading and Preprocessing Dataset

Let's import all of the packages needed for the rest of the notebook:

```
import matplotlib.pyplot as plt
import matplotlib.image as img
import numpy as np
from scipy.misc import imresize

%matplotlib inline

import os
from os import listdir
from os.path import isfile, join
import shutil
import stat
import collections
from collections import defaultdict

from ipywidgets import interact, interactive, fixed
import ipywidgets as widgets

import h5py
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical
from keras.applications.inception_v3 import preprocess_input
from keras.models import load_model
```

```
Using TensorFlow backend.
```

Download the dataset and extract it within the notebook folder. It may be easier to do this in a separate terminal window.

```
# !wget http://data.vision.ee.ethz.ch/cvl/food-101.tar.gz
```

```
# !tar xzvf food-101.tar.gz
```

Let's see what sort of foods are represented here:

```
!ls food-101/images
```

```
apple_pie       eggs_benedict        onion_rings
baby_back_ribs      escargots            oysters
baklava         falafel          pad_thai
beef_carpaccio      filet_mignon         paella
beef_tartare        fish_and_chips       pancakes
beet_salad      foie_gras            panna_cotta
beignets        french_fries         peking_duck
bibimbap        french_onion_soup        pho
bread_pudding       french_toast         pizza
breakfast_burrito   fried_calamari       pork_chop
bruschetta      fried_rice           poutine
caesar_salad        frozen_yogurt        prime_rib
cannoli         garlic_bread         pulled_pork_sandwich
caprese_salad       gnocchi          ramen
carrot_cake     greek_salad          ravioli
ceviche         grilled_cheese_sandwich  red_velvet_cake
cheesecake      grilled_salmon       risotto
cheese_plate        guacamole            samosa
chicken_curry       gyoza            sashimi
chicken_quesadilla  hamburger            scallops
chicken_wings       hot_and_sour_soup        seaweed_salad
chocolate_cake      hot_dog          shrimp_and_grits
chocolate_mousse    huevos_rancheros         spaghetti_bolognese
churros         hummus           spaghetti_carbonara
clam_chowder        ice_cream            spring_rolls
club_sandwich       lasagna          steak
crab_cakes      lobster_bisque       strawberry_shortcake
creme_brulee        lobster_roll_sandwich    sushi
croque_madame       macaroni_and_cheese      tacos
cup_cakes       macarons             takoyaki
deviled_eggs        miso_soup            tiramisu
donuts          mussels          tuna_tartare
dumplings       nachos           waffles
edamame         omelette
```

```
!ls food-101/images/apple_pie/ | head -10
```

```
1005649.jpg
1011328.jpg
101251.jpg
1014775.jpg
1026328.jpg
1028787.jpg
1034399.jpg
103801.jpg
1038694.jpg
1043283.jpg
ls: write error: Broken pipe
```

Let's look at some random images from each food class. You can right click and open the image in a new window or save it in order to see it at a higher resolution.

```
root_dir = 'food-101/images/'
rows = 17
cols = 6
fig, ax = plt.subplots(rows, cols, frameon=False, figsize=(15, 25))
fig.suptitle('Random Image from Each Food Class', fontsize=20)
sorted_food_dirs = sorted(os.listdir(root_dir))
for i in range(rows):
    for j in range(cols):
        try:
            food_dir = sorted_food_dirs[i*cols + j]
        except:
            break
        all_files = os.listdir(os.path.join(root_dir, food_dir))
        rand_img = np.random.choice(all_files)
        img = plt.imread(os.path.join(root_dir, food_dir, rand_img))
        ax[i][j].imshow(img)
        ec = (0, .6, .1)
        fc = (0, .7, .2)
        ax[i][j].text(0, -20, food_dir, size=10, rotation=0,
                ha="left", va="top",
                bbox=dict(boxstyle="round", ec=ec, fc=fc))
plt.setp(ax, xticks=[], yticks=[])
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```

png

A `multiprocessing.Pool` will be used to accelerate image augmentation during training.

```
# Setup multiprocessing pool
# Do this early, as once images are loaded into memory there will be Errno 12
# http://stackoverflow.com/questions/14749897/python-multiprocessing-memory-u
import multiprocessing as mp

num_processes = 6
pool = mp.Pool(processes=num_processes)
```

We need maps from class to index and vice versa, for proper label encoding and pretty printing.

```
class_to_ix = {}
ix_to_class = {}
with open('food-101/meta/classes.txt', 'r') as txt:
    classes = [l.strip() for l in txt.readlines()]
    class_to_ix = dict(zip(classes, range(len(classes))))
    ix_to_class = dict(zip(range(len(classes)), classes))
    class_to_ix = {v: k for k, v in ix_to_class.items()}
sorted_class_to_ix = collections.OrderedDict(sorted(class_to_ix.items()))
```

The Food-101 dataset has a provided train/test split. We want to use this in order to compare our classifcation performance with other implementations.

```
# Only split files if haven't already
if not os.path.isdir('./food-101/test') and not os.path.isdir('./food-101/tra

    def copytree(src, dst, symlinks = False, ignore = None):
        if not os.path.exists(dst):
            os.makedirs(dst)
            shutil.copystat(src, dst)
        lst = os.listdir(src)
        if ignore:
            excl = ignore(src, lst)
            lst = [x for x in lst if x not in excl]
        for item in lst:
            s = os.path.join(src, item)
            d = os.path.join(dst, item)
            if symlinks and os.path.islink(s):
                if os.path.lexists(d):
                    os.remove(d)
                os.symlink(os.readlink(s), d)
                try:
                    st = os.lstat(s)
                    mode = stat.S_IMODE(st.st_mode)
                    os.lchmod(d, mode)
                except:
                    pass # lchmod not available
            elif os.path.isdir(s):
                copytree(s, d, symlinks, ignore)
            else:
                shutil.copy2(s, d)

    def generate_dir_file_map(path):
        dir_files = defaultdict(list)
        with open(path, 'r') as txt:
            files = [l.strip() for l in txt.readlines()]
            for f in files:
                dir_name, id = f.split('/')
                dir_files[dir_name].append(id + '.jpg')
        return dir_files

    train_dir_files = generate_dir_file_map('food-101/meta/train.txt')
    test_dir_files = generate_dir_file_map('food-101/meta/test.txt')


    def ignore_train(d, filenames):
        print(d)
        subdir = d.split('/')[-1]
        to_ignore = train_dir_files[subdir]
        return to_ignore

    def ignore_test(d, filenames):
        print(d)
        subdir = d.split('/')[-1]
        to_ignore = test_dir_files[subdir]
        return to_ignore
```

```

    copytree('food-101/images', 'food-101/test', ignore=ignore_train)
    copytree('food-101/images', 'food-101/train', ignore=ignore_test)

else:
    print('Train/Test files already copied into separate folders.')
```

```
Train/Test files already copied into separate folders.
```

We are now ready to load the training and testing images into memory. After everything is loaded, about 80 GB of memory will be allocated.

Any images that have a width or length smaller than `min_size` will be resized. This is so that we can take proper-sized crops during image augmentation.

```
%%time

# Load dataset images and resize to meet minimum width and height pixel size
def load_images(root, min_side=299):
    all_imgs = []
    all_classes = []
    resize_count = 0
    invalid_count = 0
    for i, subdir in enumerate(listdir(root)):
        imgs = listdir(join(root, subdir))
        class_ix = class_to_ix[subdir]
        print(i, class_ix, subdir)
        for img_name in imgs:
            img_arr = img.imread(join(root, subdir, img_name))
            img_arr_rs = img_arr
            try:
                w, h, _ = img_arr.shape
                if w < min_side:
                    wpercent = (min_side/float(w))
                    hsize = int((float(h)*float(wpercent)))
                    #print('new dims:', min_side, hsize)
                    img_arr_rs = imresize(img_arr, (min_side, hsize))
                    resize_count += 1
                elif h < min_side:
                    hpercent = (min_side/float(h))
                    wsize = int((float(w)*float(hpercent)))
                    #print('new dims:', wsize, min_side)
                    img_arr_rs = imresize(img_arr, (wsize, min_side))
                    resize_count += 1
                all_imgs.append(img_arr_rs)
                all_classes.append(class_ix)
            except:
                print('Skipping bad image: ', subdir, img_name)
                invalid_count += 1
    print(len(all_imgs), 'images loaded')
    print(resize_count, 'images resized')
    print(invalid_count, 'images skipped')
    return np.array(all_imgs), np.array(all_classes)

X_test, y_test = load_images('food-101/test', min_side=299)
```

```
0 41 french_onion_soup
1 99 tuna_tartare
2 2 baklava
3 12 cannoli
4 8 bread_pudding
5 58 ice_cream
6 63 macarons
7 38 fish_and_chips
8 3 beef_carpaccio
9 59 lasagna
10 84 risotto
11 53 hamburger
12 7 bibimbap
13 15 ceviche
14 92 spring_rolls
15 78 poutine
16 76 pizza
17 19 chicken_quesadilla
18 71 paella
19 11 caesar_salad
20 30 deviled_eggs
21 40 french_fries
22 25 club_sandwich
23 77 pork_chop
24 31 donuts
25 93 steak
26 43 fried_calamari
27 52 gyoza
28 20 chicken_wings
29 47 gnocchi
30 46 garlic_bread
31 81 ramen
32 86 sashimi
33 100 waffles
34 60 lobster_bisque
35 23 churros
36 1 baby_back_ribs
37 0 apple_pie
38 27 creme_brulee
39 79 prime_rib
40 54 hot_and_sour_soup
41 55 hot_dog
42 82 ravioli
43 66 nachos
44 85 samosa
45 95 sushi
46 70 pad_thai
47 87 scallops
48 42 french_toast
49 13 caprese_salad
50 21 chocolate_cake
```

```
51 83 red_velvet_cake
52 88 seaweed_salad
53 96 tacos
54 16 cheesecake
55 90 spaghetti_bolognese
56 94 strawberry_shortcake
57 64 miso_soup
58 98 tiramisu
59 74 peking_duck
60 17 cheese_plate
61 69 oysters
62 14 carrot_cake
63 6 beignets
64 61 lobster_roll_sandwich
65 45 frozen_yogurt
66 24 clam_chowder
67 9 breakfast_burrito
68 72 pancakes
69 32 dumplings
70 57 hummus
71 10 bruschetta
72 44 fried_rice
73 97 takoyaki
74 50 grilled_salmon
75 4 beef_tartare
76 89 shrimp_and_grits
77 28 croque_madame
78 49 grilled_cheese_sandwich
79 80 pulled_pork_sandwich
80 56 huevos_rancheros
81 35 escargots
82 91 spaghetti_carbonara
83 34 eggs_benedict
84 33 edamame
85 22 chocolate_mousse
86 18 chicken_curry
87 65 mussels
88 36 falafel
89 37 filet_mignon
90 26 crab_cakes
91 48 greek_salad
92 5 beet_salad
93 51 guacamole
94 29 cup_cakes
95 68 onion_rings
96 39 foie_gras
97 67 omelette
98 73 panna_cotta
99 75 pho
100 62 macaroni_and_cheese
25250 images loaded
```

```
693 images resized
0 images skipped
CPU times: user 1min 18s, sys: 4.82 s, total: 1min 23s
Wall time: 1min 23s
```

```
%%time
X_train, y_train = load_images('food-101/train', min_side=299)
```

```
0 41 french_onion_soup
1 99 tuna_tartare
2 2 baklava
3 12 cannoli
4 8 bread_pudding
Skipping bad image:  bread_pudding 1375816.jpg
5 58 ice_cream
6 63 macarons
7 38 fish_and_chips
8 3 beef_carpaccio
9 59 lasagna
Skipping bad image:  lasagna 3787908.jpg
10 84 risotto
11 53 hamburger
12 7 bibimbap
13 15 ceviche
14 92 spring_rolls
15 78 poutine
16 76 pizza
17 19 chicken_quesadilla
18 71 paella
19 11 caesar_salad
20 30 deviled_eggs
21 40 french_fries
22 25 club_sandwich
23 77 pork_chop
24 31 donuts
25 93 steak
Skipping bad image:  steak 1340977.jpg
26 43 fried_calamari
27 52 gyoza
28 20 chicken_wings
29 47 gnocchi
30 46 garlic_bread
31 81 ramen
32 86 sashimi
33 100 waffles
34 60 lobster_bisque
35 23 churros
36 1 baby_back_ribs
37 0 apple_pie
38 27 creme_brulee
39 79 prime_rib
40 54 hot_and_sour_soup
41 55 hot_dog
42 82 ravioli
43 66 nachos
44 85 samosa
45 95 sushi
46 70 pad_thai
47 87 scallops
```

```
48 42 french_toast
49 13 caprese_salad
50 21 chocolate_cake
51 83 red_velvet_cake
52 88 seaweed_salad
53 96 tacos
54 16 cheesecake
55 90 spaghetti_bolognese
56 94 strawberry_shortcake
57 64 miso_soup
58 98 tiramisu
59 74 peking_duck
60 17 cheese_plate
61 69 oysters
62 14 carrot_cake
63 6 beignets
64 61 lobster_roll_sandwich
65 45 frozen_yogurt
66 24 clam_chowder
67 9 breakfast_burrito
68 72 pancakes
69 32 dumplings
70 57 hummus
71 10 bruschetta
72 44 fried_rice
73 97 takoyaki
74 50 grilled_salmon
75 4 beef_tartare
76 89 shrimp_and_grits
77 28 croque_madame
78 49 grilled_cheese_sandwich
79 80 pulled_pork_sandwich
80 56 huevos_rancheros
81 35 escargots
82 91 spaghetti_carbonara
83 34 eggs_benedict
84 33 edamame
85 22 chocolate_mousse
86 18 chicken_curry
87 65 mussels
88 36 falafel
89 37 filet_mignon
90 26 crab_cakes
91 48 greek_salad
92 5 beet_salad
93 51 guacamole
94 29 cup_cakes
95 68 onion_rings
96 39 foie_gras
97 67 omelette
98 73 panna_cotta
```

```
99 75 pho
100 62 macaroni_and_cheese
75747 images loaded
2091 images resized
3 images skipped
CPU times: user 3min 51s, sys: 13.9 s, total: 4min 5s
Wall time: 4min 5s
```

```
print('X_train shape', X_train.shape)
print('y_train shape', y_train.shape)
print('X_test shape', X_test.shape)
print('y_test shape', y_test.shape)
```

```
X_train shape (75747,)
y_train shape (75747,)
X_test shape (25250,)
y_test shape (25250,)
```

Visualization Tools

```
@interact(n=(0, len(X_train)))
def show_pic(n):
    plt.imshow(X_train[n])
    print('class:', y_train[n], ix_to_class[y_train[n]])
```

```
class: 21 chocolate_cake
```

png

```
@interact(n=(0, len(X_test)))
def show_pic(n):
    plt.imshow(X_test[n])
    print('class:', y_test[n], ix_to_class[y_test[n]])
```

```
class: 21 chocolate_cake
```

png

```
@interact(n_class=sorted_class_to_ix)
def show_random_images_of_class(n_class=0):
    print(n_class)
    nrows = 4
    ncols = 8
    fig, axes = plt.subplots(nrows=nrows, ncols=ncols)
    fig.set_size_inches(12, 8)
    #fig.tight_layout()
    imgs = np.random.choice((y_train == n_class).nonzero()[0], nrows * ncols)
    for i, ax in enumerate(axes.flat):
        im = ax.imshow(X_train[imgs[i]])
        ax.set_axis_off()
        ax.title.set_visible(False)
        ax.xaxis.set_ticks([])
        ax.yaxis.set_ticks([])
        for spine in ax.spines.values():
            spine.set_visible(False)
    plt.subplots_adjust(left=0, wspace=0, hspace=0)
    plt.show()
```

```
0
```

png

```
@interact(n_class=sorted_class_to_ix)
def show_random_images_of_class(n_class=0):
    print(n_class)
    nrows = 4
    ncols = 8
    fig, axes = plt.subplots(nrows=nrows, ncols=ncols)
    fig.set_size_inches(12, 8)
    #fig.tight_layout()
    imgs = np.random.choice((y_test == n_class).nonzero()[0], nrows * ncols)
    for i, ax in enumerate(axes.flat):
        im = ax.imshow(X_test[imgs[i]])
        ax.set_axis_off()
        ax.title.set_visible(False)
        ax.xaxis.set_ticks([])
        ax.yaxis.set_ticks([])
        for spine in ax.spines.values():
            spine.set_visible(False)
    plt.subplots_adjust(left=0, wspace=0, hspace=0)
    plt.show()
```

```
0
```

png

Image Augmentation

We need to one-hot encode each label value to create a vector of binary features rather than one feature that can take on `n_classes` values.

```
from keras.utils.np_utils import to_categorical

n_classes = 101
y_train_cat = to_categorical(y_train, nb_classes=n_classes)
y_test_cat = to_categorical(y_test, nb_classes=n_classes)
```

```
from keras.applications.inception_v3 import InceptionV3
from keras.applications.inception_v3 import preprocess_input, decode_predicti
from keras.preprocessing import image
from keras.layers import Input

import tools.image_gen_extended as T

# Useful for checking the output of the generators after code change
#from importlib import reload
#reload(T)
```

I needed to have a more powerful Image Augmentation pipeline than the one that ships with Keras. Luckily, I was able to find this modified version to use as my base.

The author had added an extensible pipeline, which made it possible to specify additional modifications such as custom cropping functions and being able to use the Inception image preprocessor. Being able to apply preprocessing dynamically was necessary, as I did not have enough memory to keep all of the training set as `float32s` . I was able to load the entire training set as `uint8s` .

Furthermore, I was not fully utilizing either my GPU or my multicore CPU. By default, Python is only able to use a single core, thereby limiting the amount of processed/augmented images I could send to the GPU for training. Based on some performance monitoring, I was only using a small percentage of the GPU on average. By incorporating a python `multiprocessing Pool` , I was able to get about 50% CPU utilization and 90% GPU utilization.

The end result is that each epoch of training went from 45 minutes to 22 minutes! You can run the GPU graphs yourselves while training in this notebook. The inspiration for trying to improve data augmentation and GPU performance came from Jimmie Goode: Buffered Python generators for data augmentation

At the moment, the code is fairly buggy and requires restarting the Python kernel whenever training is manually interrupted. The code is quite hacked together and certain features, like those that involve fitting, are disabled. I hope to improve this ImageDataGenerator and release it to the community in the future.

```
display(Image('./gpu.png'))
```

png

```
%%time

# this is the augmentation configuration we will use for training
train_datagen = T.ImageDataGenerator(
    featurewise_center=False,  # set input mean to 0 over the dataset
    samplewise_center=False,  # set each sample mean to 0
    featurewise_std_normalization=False,  # divide inputs by std of the datas
    samplewise_std_normalization=False,  # divide each input by its std
    zca_whitening=False,  # apply ZCA whitening
    rotation_range=0,  # randomly rotate images in the range (degrees, 0 to 1
    width_shift_range=0.2,  # randomly shift images horizontally (fraction of
    height_shift_range=0.2,  # randomly shift images vertically (fraction of
    horizontal_flip=True,  # randomly flip images
    vertical_flip=False, # randomly flip images
    zoom_range=[.8, 1],
    channel_shift_range=30,
    fill_mode='reflect')
train_datagen.config['random_crop_size'] = (299, 299)
train_datagen.set_pipeline([T.random_transform, T.random_crop, T.preprocess_i
train_generator = train_datagen.flow(X_train, y_train_cat, batch_size=64, see
```

```
test_datagen = T.ImageDataGenerator()
test_datagen.config['random_crop_size'] = (299, 299)
test_datagen.set_pipeline([T.random_transform, T.random_crop, T.preprocess_ir
test_generator = test_datagen.flow(X_test, y_test_cat, batch_size=64, seed=11
```

We can see what sorts of images are coming out of these ImageDataGenerators:

```
def reverse_preprocess_input(x0):
    x = x0 / 2.0
    x += 0.5
    x *= 255.
    return x
```

```
%%time
@interact()
def show_images(unprocess=True):
    for x in test_generator:
        fig, axes = plt.subplots(nrows=8, ncols=4)
        fig.set_size_inches(8, 8)
        page = 0
        page_size = 32
        start_i = page * page_size
        for i, ax in enumerate(axes.flat):
            img = x[0][i+start_i]
            if unprocess:
                im = ax.imshow( reverse_preprocess_input(img).astype('uint8')
            else:
                im = ax.imshow(img)
            ax.set_axis_off()
            ax.title.set_visible(False)
            ax.xaxis.set_ticks([])
            ax.yaxis.set_ticks([])
            for spine in ax.spines.values():
                spine.set_visible(False)

        plt.subplots_adjust(left=0, wspace=0, hspace=0)
        plt.show()
        break
```

png

```
CPU times: user 1.54 s, sys: 524 ms, total: 2.06 s
Wall time: 2.24 s
```

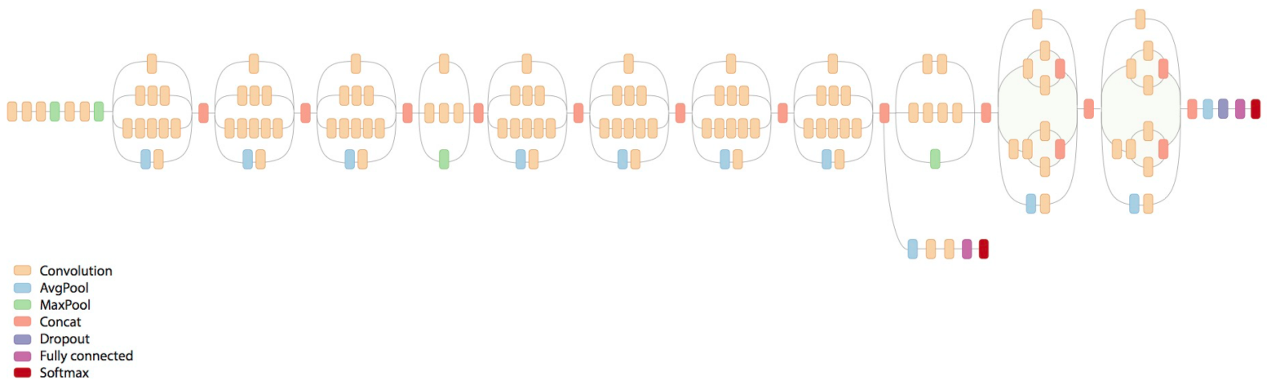
```
%%time
show_images(unprocess=False)
```

png

```
CPU times: user 1.58 s, sys: 300 ms, total: 1.88 s
Wall time: 2.11 s
```

Training

We will be retraining a Google InceptionV3 model, pretrained on ImageNet. The neural network architecture is shown below.


Convolution
AvgPool
MaxPool
Concat
Dropout
Fully connected
Softmax

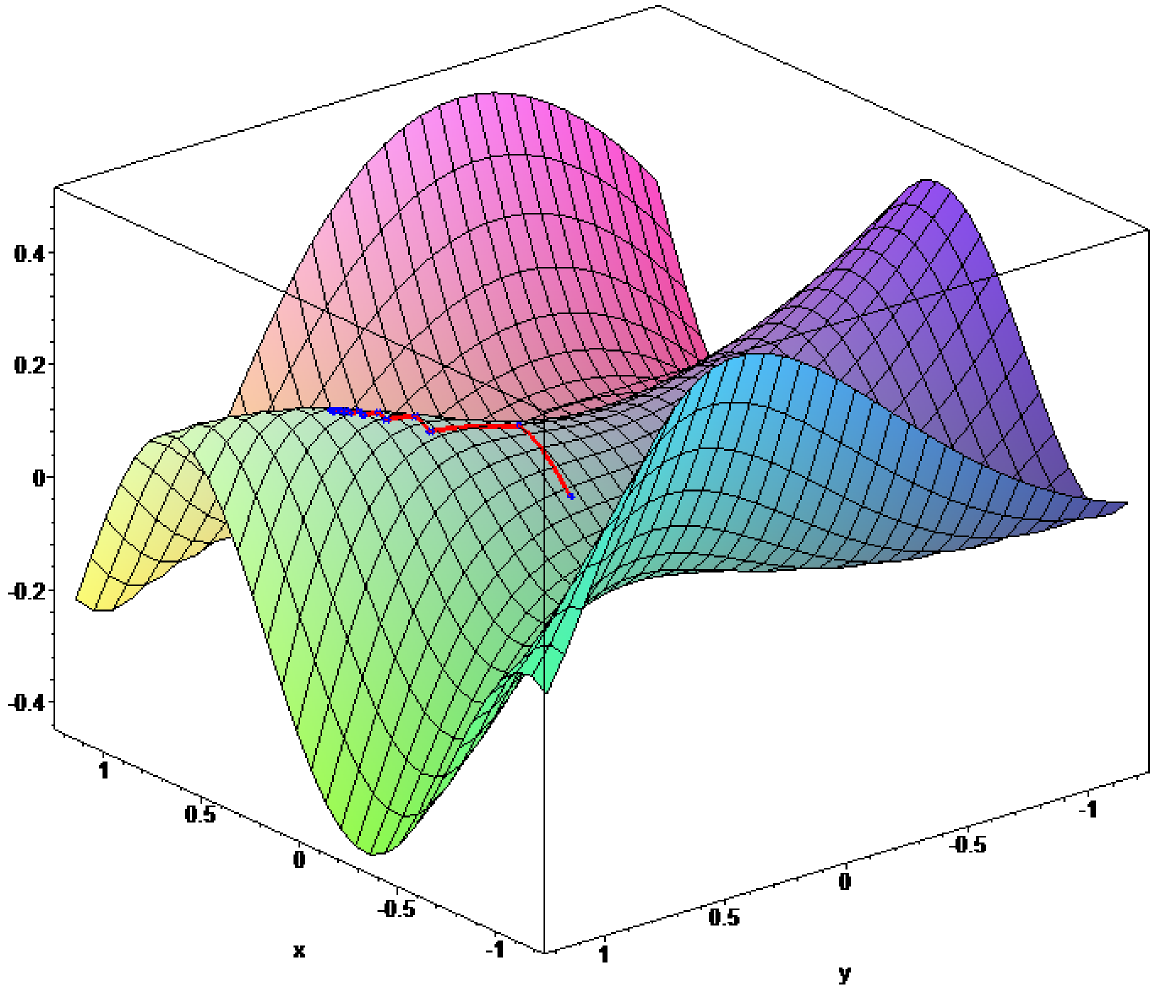
```
%%time
from keras.models import Sequential, Model
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Convolution2D, MaxPooling2D, ZeroPadding2D, GlobalAv
from keras.layers.normalization import BatchNormalization
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, CSVLogger, LearningRateScheduler
from keras.optimizers import SGD
from keras.regularizers import l2
import keras.backend as K
import math

K.clear_session()

base_model = InceptionV3(weights='imagenet', include_top=False, input_tensor=
x = base_model.output
x = AveragePooling2D(pool_size=(8, 8))(x)
x = Dropout(.4)(x)
x = Flatten()(x)
predictions = Dense(n_classes, init='glorot_uniform', W_regularizer=l2(.0005)

model = Model(input=base_model.input, output=predictions)

opt = SGD(lr=.01, momentum=.9)
model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accur

checkpointer = ModelCheckpoint(filepath='model4.{epoch:02d}-{val_loss:.2f}.hc
csv_logger = CSVLogger('model4.log')

def schedule(epoch):
    if epoch < 15:
        return .01
    elif epoch < 28:
        return .002
    else:
        return .0004
lr_scheduler = LearningRateScheduler(schedule)

model.fit_generator(train_generator,
                    validation_data=test_generator,
                    nb_val_samples=X_test.shape[0],
                    samples_per_epoch=X_train.shape[0],
                    nb_epoch=32,
                    verbose=2,
                    callbacks=[lr_scheduler, csv_logger, checkpointer])
```

```
Epoch 1/32
Epoch 00000: val_loss improved from inf to 3.37355, saving model to model4.00-3.37
1342s - loss: 4.2541 - acc: 0.0810 - val_loss: 3.3736 - val_acc: 0.2010
Epoch 2/32
Epoch 00001: val_loss improved from 3.37355 to 2.36625, saving model to model4.01-2
1329s - loss: 2.9745 - acc: 0.3075 - val_loss: 2.3662 - val_acc: 0.4071
Epoch 3/32
Epoch 00002: val_loss improved from 2.36625 to 1.79355, saving model to model4.02-1
1329s - loss: 2.3080 - acc: 0.4539 - val_loss: 1.7935 - val_acc: 0.5338
Epoch 4/32
Epoch 00003: val_loss improved from 1.79355 to 1.48898, saving model to model4.03-1
1356s - loss: 2.0102 - acc: 0.5216 - val_loss: 1.4890 - val_acc: 0.6068
Epoch 5/32
Epoch 00004: val_loss improved from 1.48898 to 1.34121, saving model to model4.04-1
1330s - loss: 1.8436 - acc: 0.5577 - val_loss: 1.3412 - val_acc: 0.6431
Epoch 6/32
Epoch 00005: val_loss improved from 1.34121 to 1.22485, saving model to model4.05-1
1329s - loss: 1.7057 - acc: 0.5909 - val_loss: 1.2248 - val_acc: 0.6740
Epoch 7/32
Epoch 00006: val_loss did not improve
1328s - loss: 1.5996 - acc: 0.6126 - val_loss: 1.2310 - val_acc: 0.6716
Epoch 8/32
Epoch 00007: val_loss improved from 1.22485 to 1.11248, saving model to model4.07-1
1331s - loss: 1.5148 - acc: 0.6314 - val_loss: 1.1125 - val_acc: 0.7022
Epoch 9/32
Epoch 00008: val_loss improved from 1.11248 to 1.07145, saving model to model4.08-1
1331s - loss: 1.4395 - acc: 0.6506 - val_loss: 1.0714 - val_acc: 0.7095
Epoch 10/32
Epoch 00009: val_loss improved from 1.07145 to 1.05129, saving model to model4.09-1
1333s - loss: 1.3900 - acc: 0.6637 - val_loss: 1.0513 - val_acc: 0.7181
Epoch 11/32
Epoch 00010: val_loss improved from 1.05129 to 1.03356, saving model to model4.10-1
1331s - loss: 1.3316 - acc: 0.6780 - val_loss: 1.0336 - val_acc: 0.7250
Epoch 12/32
Epoch 00011: val_loss improved from 1.03356 to 1.00622, saving model to model4.11-1
1331s - loss: 1.2850 - acc: 0.6893 - val_loss: 1.0062 - val_acc: 0.7275
Epoch 13/32
Epoch 00012: val_loss improved from 1.00622 to 0.94016, saving model to model4.12-0
1330s - loss: 1.2325 - acc: 0.7003 - val_loss: 0.9402 - val_acc: 0.7461
Epoch 14/32
Epoch 00013: val_loss did not improve
1330s - loss: 1.1970 - acc: 0.7086 - val_loss: 0.9461 - val_acc: 0.7453
Epoch 15/32
Epoch 00014: val_loss did not improve
1329s - loss: 1.1683 - acc: 0.7154 - val_loss: 0.9691 - val_acc: 0.7396
Epoch 16/32
Epoch 00015: val_loss improved from 0.94016 to 0.71776, saving model to model4.15-0
1329s - loss: 0.9398 - acc: 0.7724 - val_loss: 0.7178 - val_acc: 0.8055
Epoch 17/32
Epoch 00016: val_loss improved from 0.71776 to 0.70245, saving model to model4.16-0
1329s - loss: 0.8591 - acc: 0.7916 - val_loss: 0.7025 - val_acc: 0.8069
```

```
Epoch 18/32
Epoch 00017: val_loss did not improve
1327s - loss: 0.8238 - acc: 0.8023 - val_loss: 0.7093 - val_acc: 0.8053
Epoch 19/32
Epoch 00018: val_loss did not improve
1327s - loss: 0.7947 - acc: 0.8093 - val_loss: 0.7048 - val_acc: 0.8059
Epoch 20/32
Epoch 00019: val_loss did not improve
1327s - loss: 0.7713 - acc: 0.8143 - val_loss: 0.7097 - val_acc: 0.8061
Epoch 21/32
Epoch 00020: val_loss improved from 0.70245 to 0.69545, saving model to model4.20-0
1329s - loss: 0.7458 - acc: 0.8195 - val_loss: 0.6955 - val_acc: 0.8104
Epoch 22/32
Epoch 00021: val_loss did not improve
1328s - loss: 0.7282 - acc: 0.8232 - val_loss: 0.6977 - val_acc: 0.8119
Epoch 23/32
Epoch 00022: val_loss improved from 0.69545 to 0.69190, saving model to model4.22-0
1328s - loss: 0.7114 - acc: 0.8284 - val_loss: 0.6919 - val_acc: 0.8150
Epoch 24/32
Epoch 00023: val_loss did not improve
1325s - loss: 0.6983 - acc: 0.8311 - val_loss: 0.7002 - val_acc: 0.8116
Epoch 25/32
Epoch 00024: val_loss did not improve
1330s - loss: 0.6719 - acc: 0.8381 - val_loss: 0.7031 - val_acc: 0.8112
Epoch 26/32
Epoch 00025: val_loss did not improve
1382s - loss: 0.6607 - acc: 0.8407 - val_loss: 0.7115 - val_acc: 0.8083
Epoch 27/32
Epoch 00026: val_loss did not improve
1330s - loss: 0.6479 - acc: 0.8439 - val_loss: 0.7037 - val_acc: 0.8126
Epoch 28/32
Epoch 00027: val_loss did not improve
1328s - loss: 0.6292 - acc: 0.8478 - val_loss: 0.7122 - val_acc: 0.8086
Epoch 29/32
Epoch 00028: val_loss improved from 0.69190 to 0.68908, saving model to model4.28-0
1330s - loss: 0.5983 - acc: 0.8580 - val_loss: 0.6891 - val_acc: 0.8165
Epoch 30/32
Epoch 00029: val_loss improved from 0.68908 to 0.68740, saving model to model4.29-0
1330s - loss: 0.5817 - acc: 0.8612 - val_loss: 0.6874 - val_acc: 0.8149
Epoch 31/32
Epoch 00030: val_loss did not improve
1328s - loss: 0.5729 - acc: 0.8642 - val_loss: 0.6912 - val_acc: 0.8143
Epoch 32/32
Epoch 00031: val_loss did not improve
1329s - loss: 0.5638 - acc: 0.8663 - val_loss: 0.6895 - val_acc: 0.8159
CPU times: user 8h 49min 20s, sys: 1h 55min 54s, total: 10h 45min 14s
Wall time: 11h 51min 18s
```

At this point, we are seeing up to 81.65 single crop Top-1 accuracy on the test set. We can continue to train the model at an even slower learning rate to see if it improves more.

My initial experiments used more modern optimizers such as Adam and AdaDelta, along with higher learning rates. I was stuck for a while below 80% accuracy before I decided to follow the literature more closely and use Stochastic Gradient Descent (SGD) with a quickly decreasing learning schedule. When we are searching through the multidimensional surface, sometimes going slower goes a long way.



Due to some instability with my multiprocessing code, sometimes I need to restart the notebook, load the latest model, then continue training.

```
%%time
from keras.models import Sequential, Model, load_model
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Convolution2D, MaxPooling2D, ZeroPadding2D, GlobalAv
from keras.layers.normalization import BatchNormalization
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ModelCheckpoint, CSVLogger, LearningRateScheduler
from keras.optimizers import SGD
from keras.regularizers import l2
import keras.backend as K
import math

model = load_model(filepath='./model4.29-0.69.hdf5')

opt = SGD(lr=.01, momentum=.9)
model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accur

checkpointer = ModelCheckpoint(filepath='model4b.{epoch:02d}-{val_loss:.2f}.h
csv_logger = CSVLogger('model4b.log')

def schedule(epoch):
    if epoch < 10:
        return .00008
    elif epoch < 20:
        return .000016
    else:
        return .0000032

lr_scheduler = LearningRateScheduler(schedule)

model.fit_generator(train_generator,
                    validation_data=test_generator,
                    nb_val_samples=X_test.shape[0],
                    samples_per_epoch=X_train.shape[0],
                    nb_epoch=32,
                    verbose=2,
                    callbacks=[lr_scheduler, csv_logger, checkpointer])
```

Model Evaluation

At this point, we should have multiple trained models saved to disk. We can go through them and use the `load_model` function to load the model with the lowest loss / highest accuracy.

```
%%time
#model = load_model(filepath='./model4.29-0.69.hdf5') # 86.8039 10-crop Top-1
model = load_model(filepath='./model4b.10-0.68.hdf5') # 86.9703
```

```
CPU times: user 36.4 s, sys: 1.11 s, total: 37.5 s
Wall time: 36.5 s
```

We also want to evaluate the test set using multiple crops. This can yield an accuracy boost of 5% compared to single crop evaluation. It is common to use the following crops: Upper Left, Upper Right, Lower Left, Lower Right, Center. We also take the same crops on the image flipped left to right, creating a total of 10 crops.

In addition, we want to return the top-N predictions for each crop in order to calculate Top-5 accuracy, for instance.

```
def center_crop(x, center_crop_size, **kwargs):
    centerw, centerh = x.shape[0]//2, x.shape[1]//2
    halfw, halfh = center_crop_size[0]//2, center_crop_size[1]//2
    return x[centerw-halfw:centerw+halfw+1,centerh-halfh:centerh+halfh+1, :]
```

```
def predict_10_crop(img, ix, top_n=5, plot=False, preprocess=True, debug=Fals
    flipped_X = np.fliplr(img)
    crops = [
        img[:299,:299, :], # Upper Left
        img[:299, img.shape[1]-299:, :], # Upper Right
        img[img.shape[0]-299:, :299, :], # Lower Left
        img[img.shape[0]-299:, img.shape[1]-299:, :], # Lower Right
        center_crop(img, (299, 299)),

        flipped_X[:299,:299, :],
        flipped_X[:299, flipped_X.shape[1]-299:, :],
        flipped_X[flipped_X.shape[0]-299:, :299, :],
        flipped_X[flipped_X.shape[0]-299:, flipped_X.shape[1]-299:, :],
        center_crop(flipped_X, (299, 299))
    ]
    if preprocess:
        crops = [preprocess_input(x.astype('float32')) for x in crops]

    if plot:
        fig, ax = plt.subplots(2, 5, figsize=(10, 4))
        ax[0][0].imshow(crops[0])
        ax[0][1].imshow(crops[1])
        ax[0][2].imshow(crops[2])
        ax[0][3].imshow(crops[3])
        ax[0][4].imshow(crops[4])
        ax[1][0].imshow(crops[5])
        ax[1][1].imshow(crops[6])
        ax[1][2].imshow(crops[7])
        ax[1][3].imshow(crops[8])
        ax[1][4].imshow(crops[9])

    y_pred = model.predict(np.array(crops))
    preds = np.argmax(y_pred, axis=1)
    top_n_preds= np.argpartition(y_pred, -top_n)[:,-top_n:]
    if debug:
        print('Top-1 Predicted:', preds)
        print('Top-5 Predicted:', top_n_preds)
        print('True Label:', y_test[ix])
    return preds, top_n_preds


ix = 13001
predict_10_crop(X_test[ix], ix, top_n=5, plot=True, preprocess=False, debug=T
```

```
Top-1 Predicted: [74 74 74 74 74 74 74 74 74 74]
Top-5 Predicted: [[33 97 37 39 74]
 [28 52 37 39 74]
 [73 39 52 37 74]
 [35 33 37 39 74]
 [35 33 37 39 74]
 [35 33 37 39 74]
 [35 33 37 39 74]
 [97 37 73 39 74]
 [73 52 37 39 74]
 [34 35 33 39 74]]
True Label: 88





(array([74, 74, 74, 74, 74, 74, 74, 74, 74, 74]), array([[33, 97, 37, 39, 74],
        [28, 52, 37, 39, 74],
        [73, 39, 52, 37, 74],
        [35, 33, 37, 39, 74],
        [35, 33, 37, 39, 74],
        [35, 33, 37, 39, 74],
        [35, 33, 37, 39, 74],
        [97, 37, 73, 39, 74],
        [73, 52, 37, 39, 74],
        [34, 35, 33, 39, 74]]))
```

png

We also need to preprocess the images for the Inception model:

```
ix = 13001
predict_10_crop(X_test[ix], ix, top_n=5, plot=True, preprocess=True, debug=Tr
```

```
Top-1 Predicted: [51 51 88 88 88 51 51 88 88 88]
Top-5 Predicted: [[18 79 51 13 48]
 [48 79 11 55 51]
 [79 93 81 37 88]
 [51 86 93 81 88]
 [11 79 51 81 88]
 [19 79 51 56 13]
 [11 88 48 51 13]
 [37 93 86 88 81]
 [37 79 93 88 81]
 [84 81 11 79 88]]
True Label: 88





(array([51, 51, 88, 88, 88, 51, 51, 88, 88, 88]), array([[18, 79, 51, 13, 48],
        [48, 79, 11, 55, 51],
        [79, 93, 81, 37, 88],
        [51, 86, 93, 81, 88],
        [11, 79, 51, 81, 88],
        [19, 79, 51, 56, 13],
        [11, 88, 48, 51, 13],
        [37, 93, 86, 88, 81],
        [37, 79, 93, 88, 81],
        [84, 81, 11, 79, 88]]))
```

png

Now we create crops for each item in the test set and get the predictions. This is a slow process at the moment as I am not taking advantage of multiprocessing or other types of parallelism.

```
%%time
preds_10_crop = {}
for ix in range(len(X_test)):
    if ix % 1000 == 0:
        print(ix)
    preds_10_crop[ix] = predict_10_crop(X_test[ix], ix)
```

```
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
11000
12000
13000
14000
15000
16000
17000
18000
19000
20000
21000
22000
23000
24000
25000
CPU times: user 50min 3s, sys: 5min 13s, total: 55min 16s
Wall time: 31min 28s
```

We now have a set of 10 predictions for each image. Using a histogram, I'm able to see how the # of unique predictions for each image are distributed.

```
preds_uniq = {k: np.unique(v[0]) for k, v in preds_10_crop.items()}
preds_hist = np.array([len(x) for x in preds_uniq.values()])

plt.hist(preds_hist, bins=11)
plt.title('Number of unique predictions per image')
```

```
<matplotlib.text.Text at 0x7fe30c3daa20>
```

png

Let's create a dictionary to map test item index to its top-1 / top-5 predictions.

```
preds_top_1 = {k: collections.Counter(v[0]).most_common(1) for k, v in preds_

top_5_per_ix = {k: collections.Counter(preds_10_crop[k][1].reshape(-1)).most_
                for k, v in preds_10_crop.items()}
preds_top_5 = {k: [y[0] for y in v] for k, v in top_5_per_ix.items()}
```

```
%%time
right_counter = 0
for i in range(len(y_test)):
    guess, actual = preds_top_1[i][0][0], y_test[i]
    if guess == actual:
        right_counter += 1

print('Top-1 Accuracy, 10-Crop: {0:.2f}%'.format(right_counter / len(y_test)
```

```
Top-1 Accuracy, 10-Crop: 86.97%
CPU times: user 28 ms, sys: 0 ns, total: 28 ms
Wall time: 27.3 ms
```

```
%%time
top_5_counter = 0
for i in range(len(y_test)):
    guesses, actual = preds_top_5[i], y_test[i]
    if actual in guesses:
        top_5_counter += 1

print('Top-5 Accuracy, 10-Crop: {0:.2f}%'.format(top_5_counter / len(y_test)
```

```
Top-5 Accuracy, 10-Crop: 97.42%
CPU times: user 28 ms, sys: 0 ns, total: 28 ms
Wall time: 27 ms
```

Results Visualization

```
y_pred = [x[0][0] for x in preds_top_1.values()]
```

```
@interact(page=[0, int(len(X_test)/20)])
def show_images_prediction(page=0):
    page_size = 20
    nrows = 4
    ncols = 5
    fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(12, 12))
    fig.set_size_inches(12, 8)
    #fig.tight_layout()
    #imgs = np.random.choice((y_all == n_class).nonzero()[0], nrows * ncols)
    start_i = page * page_size
    for i, ax in enumerate(axes.flat):
        im = ax.imshow(X_test[i+start_i])
        ax.set_axis_off()
        ax.title.set_visible(False)
        ax.xaxis.set_ticks([])
        ax.yaxis.set_ticks([])
        for spine in ax.spines.values():
            spine.set_visible(False)
        predicted = ix_to_class[y_pred[i+start_i]]
        match = predicted ==  ix_to_class[y_test[start_i + i]]
        ec = (1, .5, .5)
        fc = (1, .8, .8)
        if match:
            ec = (0, .6, .1)
            fc = (0, .7, .2)
        # predicted label
        ax.text(0, 400, 'P: ' + predicted, size=10, rotation=0,
            ha="left", va="top",
             bbox=dict(boxstyle="round",
                   ec=ec,
                   fc=fc,
                   )
             )
        if not match:
            # true label
            ax.text(0, 480, 'A: ' + ix_to_class[y_test[start_i + i]], size=1
                ha="left", va="top",
                 bbox=dict(boxstyle="round",
                       ec=ec,
                       fc=fc,
                       )
                 )
    plt.subplots_adjust(left=0, wspace=1, hspace=0)
    plt.show()
```

png

A confusion matrix will plot each class label and how many times it was correctly labeled vs. the other times it was incorrectly labeled as a different class.

```
%%time
from sklearn.metrics import confusion_matrix
import itertools

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')


# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

class_names = [ix_to_class[i] for i in range(101)]

plt.figure()
fig = plt.gcf()
fig.set_size_inches(32, 32)
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization',
                      cmap=plt.cm.cool)
plt.show()
```

```
Confusion matrix, without normalization
[[179   0   4 ...,   2   0   5]
 [  0 218   0 ...,   0   0   0]
 [  4   0 228 ...,   1   0   0]
 ...,
 [  0   0   0 ..., 212   0   1]
 [  0   0   0 ...,   0 208   0]
 [  0   0   0 ...,   0   0 224]]
```

png

```
CPU times: user 16.4 s, sys: 1.22 s, total: 17.6 s
Wall time: 16.4 s
```

We want to see if the accuracy was consistent across all classes, or if some classes were much easier / harder to label than others. According to our plot, a few classes were outliers in terms of being much more difficult to label correctly.

```
corrects = collections.defaultdict(int)
incorrects = collections.defaultdict(int)
for (pred, actual) in zip(y_pred, y_test):
    if pred == actual:
        corrects[actual] += 1
    else:
        incorrects[actual] += 1

class_accuracies = {}
for ix in range(101):
    class_accuracies[ix] = corrects[ix]/250

plt.hist(list(class_accuracies.values()), bins=20)
plt.title('Accuracy by Class histogram')
```

```
<matplotlib.text.Text at 0x7fe2d5d4f860>
```

png

```
sorted_class_accuracies = sorted(class_accuracies.items(), key=lambda x: -x[1
[(ix_to_class[c[0]], c[1]) for c in sorted_class_accuracies]
```

```
[('edamame', 0.996),
 ('hot_and_sour_soup', 0.964),
 ('oysters', 0.964),
 ('seaweed_salad', 0.96),
 ('macarons', 0.956),
 ('pad_thai', 0.956),
 ('spaghetti_bolognese', 0.956),
 ('french_fries', 0.952),
 ('frozen_yogurt', 0.952),
 ('takoyaki', 0.952),
 ('spaghetti_carbonara', 0.948),
 ('clam_chowder', 0.944),
 ('deviled_eggs', 0.944),
 ('churros', 0.94),
 ('miso_soup', 0.94),
 ('creme_brulee', 0.936),
 ('pho', 0.936),
 ('cannoli', 0.932),
 ('guacamole', 0.932),
 ('mussels', 0.932),
 ('sashimi', 0.932),
 ('caesar_salad', 0.928),
 ('lobster_roll_sandwich', 0.928),
 ('bibimbap', 0.924),
 ('cup_cakes', 0.924),
 ('dumplings', 0.924),
 ('ramen', 0.924),
 ('beef_carpaccio', 0.92),
 ('eggs_benedict', 0.92),
 ('pancakes', 0.92),
 ('red_velvet_cake', 0.92),
 ('beignets', 0.916),
 ('club_sandwich', 0.916),
 ('escargots', 0.916),
 ('french_onion_soup', 0.916),
 ('onion_rings', 0.916),
 ('baklava', 0.912),
 ('croque_madame', 0.912),
 ('fish_and_chips', 0.908),
 ('poutine', 0.908),
 ('cheese_plate', 0.904),
 ('chicken_wings', 0.904),
 ('fried_rice', 0.904),
 ('sushi', 0.904),
 ('fried_calamari', 0.9),
 ('pulled_pork_sandwich', 0.896),
 ('waffles', 0.896),
 ('crab_cakes', 0.892),
 ('gyoza', 0.892),
 ('paella', 0.892),
 ('caprese_salad', 0.888),
```

```
 ('lobster_bisque', 0.888),
 ('peking_duck', 0.888),
 ('pizza', 0.888),
 ('greek_salad', 0.88),
 ('hot_dog', 0.88),
 ('samosa', 0.88),
 ('donuts', 0.876),
 ('spring_rolls', 0.876),
 ('baby_back_ribs', 0.872),
 ('strawberry_shortcake', 0.872),
 ('shrimp_and_grits', 0.868),
 ('tacos', 0.86),
 ('beef_tartare', 0.856),
 ('prime_rib', 0.856),
 ('chicken_quesadilla', 0.852),
 ('hummus', 0.852),
 ('grilled_salmon', 0.848),
 ('tiramisu', 0.848),
 ('macaroni_and_cheese', 0.844),
 ('carrot_cake', 0.836),
 ('nachos', 0.836),
 ('falafel', 0.832),
 ('tuna_tartare', 0.832),
 ('panna_cotta', 0.828),
 ('bruschetta', 0.824),
 ('grilled_cheese_sandwich', 0.824),
 ('risotto', 0.812),
 ('french_toast', 0.808),
 ('gnocchi', 0.808),
 ('garlic_bread', 0.804),
 ('breakfast_burrito', 0.8),
 ('beet_salad', 0.796),
 ('hamburger', 0.796),
 ('cheesecake', 0.792),
 ('lasagna', 0.792),
 ('ceviche', 0.784),
 ('chicken_curry', 0.784),
 ('omelette', 0.784),
 ('scallops', 0.784),
 ('chocolate_cake', 0.78),
 ('huevos_rancheros', 0.78),
 ('ravioli', 0.776),
 ('ice_cream', 0.764),
 ('bread_pudding', 0.748),
 ('foie_gras', 0.72),
 ('apple_pie', 0.716),
 ('filet_mignon', 0.716),
 ('chocolate_mousse', 0.7),
 ('pork_chop', 0.676),
 ('steak', 0.576)]
```

Interactive Classification

Predicting from a local file

```
pic_path = '/home/stratospark/Downloads/soup.jpg'
pic = img.imread(pic_path)
preds = predict_10_crop(np.array(pic), 0)[0]
best_pred = collections.Counter(preds).most_common(1)[0][0]
print(ix_to_class[best_pred])
plt.imshow(pic)
```

```
french_onion_soup





<matplotlib.image.AxesImage at 0x7fe2d59eb5c0>
```

png

Predicting from an image on the Internet

```
import urllib.request

@interact
def predict_remote_image(url='http://themodelhouse.tv/wp-content/uploads/2016
    with urllib.request.urlopen(url) as f:
        pic = plt.imread(f, format='jpg')
        preds = predict_10_crop(np.array(pic), 0)[0]
        best_pred = collections.Counter(preds).most_common(1)[0][0]
        print(ix_to_class[best_pred])
        plt.imshow(pic)
```

```
hummus
```

png

Keras.js Export

```
with open('model.json', 'w') as f:
    f.write(model.to_json())
```

```
import json

json.dumps(ix_to_class)
```

'{"0": "apple_pie", "1": "baby_back_ribs", "2": "baklava", "3": "beef_carpaccio", '