

Below are important research of neural networks which will be implemented in the code:

Steps to create a neural network:

1. Learn a model that generates sensory data rather than classifying it. Eliminates the need for large amounts of labeled data.
 2. Learn one layer of representation at a time using restricted boltzmann machines. This decomposes the overall learning task into multiple simpler tasks and eliminates the inference problems that arise in generative models.
 3. Use a separate fine-tuning stage to improve the generative or discriminative abilities of the composite model.
- A combination of these ideas leads to a novel and effective way of learning multiple layers of representation.

- Geoffrey E. Hinton

Optimization:

Steps to improve on a neural network from Geoffrey E. Hinton:

Allow higher-level feature detectors to communicate their needs to lower-level ones whilst also being easy to implement in layered networks of stochastic binary neurons that have activation states of 1 or 0 turned on with a probability that is a smooth non-linear function of the total input they receive.

Without the layer-by-layer learning, fine-tuning alone is hopelessly slow. Instead of fine-tuning the model to be a better at generating data, back-propagation can be used to fine-tune it to be better at discrimination. This works well.

To infer a probability distribution over the various possible settings of the hidden variables.

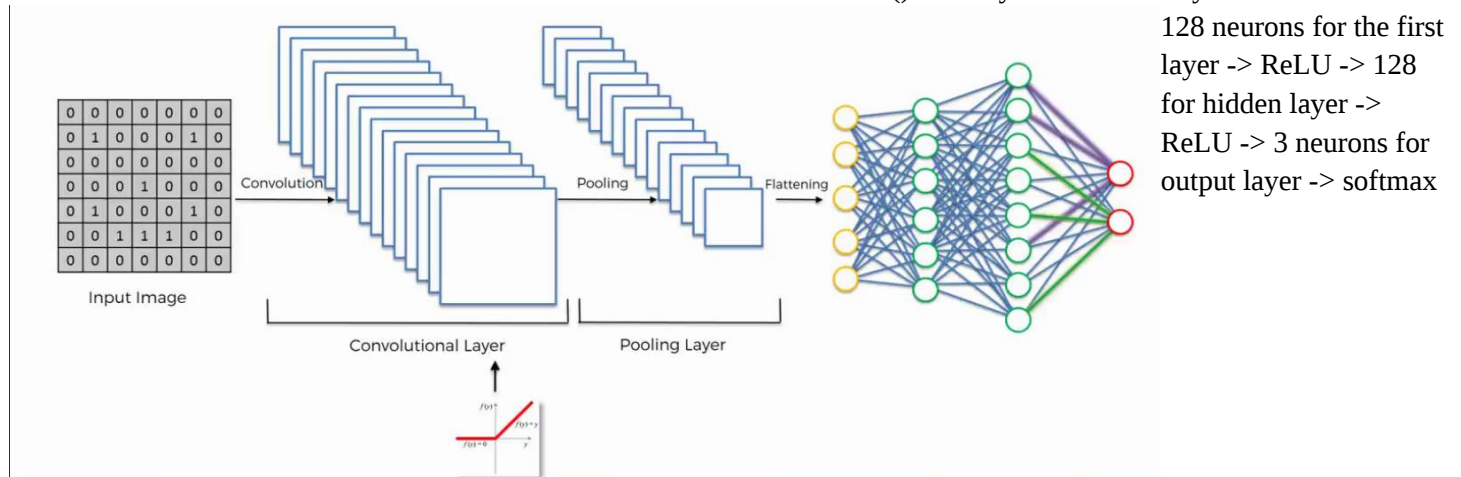
Gaussian distribution, Restricted Boltzmann Machines.

Learning feature detectors

The optimizer function in Kera's `classifier.compile(optimizer, loss, metrics)` is the algorithm you are going to use to find the optimal set of weights of the network. The "adam" optimizer using stochastic gradient descent algorithm that's efficient. What about the rmsprop? It computes the single gradient in batches and is slower. A sigmoid loss function is similar to logistic regression. After weight updates, the model uses metrics accuracy to improve the model's performance.

CNN Architecture:

2DConv -> ReLU -> MaxPool -> 2DConv -> ReLU -> MaxPool -> Flatten() -> Fully connected 2-layer neural network



Deep Learning A-Z

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Learning/Training

The training process will use the cross-entropy error with activation functions of sigmoid or softmax. The softmax produces probability of the output. The starting loss, given at training, need to be consistent with the number of classes in the network. The training process will use stochastic gradient where the gradient is computed per input instead of in a batch. I will also try rmsprop, which is a batch training. I also forgot to use the prediction function if the output is 0/1 but that can be adjusted for a multi-class output. Here's an example from the "Deep-Learning in Python" on-line lecture that uses a simple ANN:

```
#Part 3: Making predictions and evaluating the model
```

```
#Predicting the test results
```

```
y_prediction = classifier.predict(x_test_scaled)
```

```
y_prediction = (y_prediction > 0.5)
```

#neural network's final output will be true if the activation function is greater than 0.5, which means greater than 50% chance of leaving the bank

```
#Predicting a single new observation
```

```
new_prediction = classifier.predict(sc.transform(np.array( [[0.0,0,600,1,40,3,60000,2,1,1,50000]] )))
```

```
new_prediction = (new_prediction > 0.5)
```

```
#Making the Confusion Matrix
```

```
from sklearn.metrics import confusion_matrix
```

```
cm = confusion_matrix(y_test, y_pred) #so far we just split your dataset into a training set and a test set
```

The variance problem of using validation sets is because validation sets can represent very different accuracy on another test, which is very inconsistent. Judging model on just one accuracy and one test set is not super relevant for knowing how well the model does in terms of loss, accuracy and generalization. The K-Fold Cross Validation will fix this variance problem because it splits the training set into 10 folds where $k = 10$ in 10 different iterations. Nine folds will represent the training set and 1 fold is to test the neural network. It is much more relevant because it takes the average.

First few weeks of September:

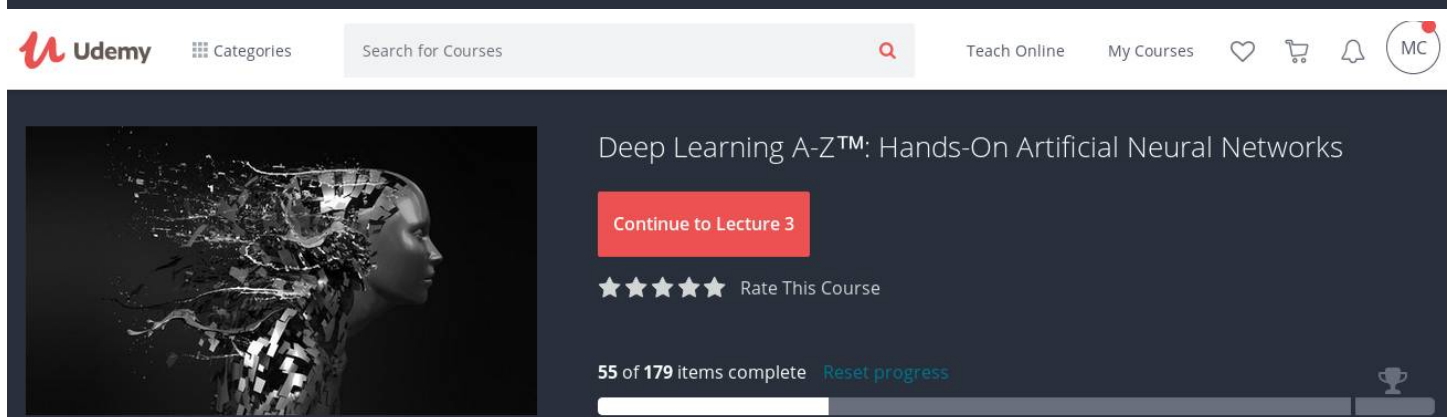
Research on Neural Network's and programming in Python

Paid \$100 to go to an in-person group for deep learning, which uses the cloud to train on images of cats and dogs. The lecturer told me I should use Tensorflow or one of the popular libraries. Since I'm interested in extracting features of shapes for the neural network to learn, he told me that a convolutional network will do the job. This is because a convolutional neural network is designed to learn the pixels of images in a three dimensional output space. It does this by pooling and flattening the layers of a constant pixel size, or use padding if the size doesn't fit the dimensions of the image.

Last 3 weeks of September:



The screenshot shows the Udey interface for the course "Complete Python Bootcamp: Go from zero to hero in P...". The course title is partially visible. Below the title is a red button labeled "Continue to Lecture 70". Underneath the button is a star rating system with five stars and the text "Rate This Course". At the bottom of the course card, it says "67 of 120 items complete" with a "Reset progress" link and a progress bar. The Udey logo and navigation menu are visible at the top.



The screenshot shows the Udey interface for the course "Deep Learning A-Z™: Hands-On Artificial Neural Networks". The course title is fully visible. Below the title is a red button labeled "Continue to Lecture 3". Underneath the button is a star rating system with five stars and the text "Rate This Course". At the bottom of the course card, it says "55 of 179 items complete" with a "Reset progress" link and a progress bar. The Udey logo and navigation menu are visible at the top.

I spent this time taking udey's online courses in learning the basics of python, first two week's of Andrew Ng's machine learning course. I have tried training a basic convolutional neural network of cats and dogs using the tutorial online but since my laptop doesn't have a Nvidia GPU I can't use GPU computation locally. It will take a couple of days just to get the output of the convolutional network.

First 3 weeks of October:

khanacademy.org/math/multivariable-calculus 80% Search

Multivariable calculus

Continue Applications of multivariable derivatives
Up next: Lagrange multipliers and constrained optimization

Continue



Thinking about multivariable functions

8 of 22 complete

The only thing separating multivariable calculus from ordinary calculus is this newfangled word "multivariable". It means we will deal with functions whose inputs or outputs live in two or more dimensions. Here we lay the foundations for thinking about and visualizing multivariable functions.

Introduction to multivariable calculus

Visualizing scalar-valued functions

Visualizing vector-valued functions

Transformations

Visualizing multivariable functions (art...



Derivatives of multivariable functions

63 of 72 complete

What does it mean to take the derivative of a function whose input lives in multiple dimensions? What about when its output is a vector? Here we go over many different ways to extend the idea of a derivative to higher dimensions, including partial derivatives, directional derivatives, the gradient, vector derivatives, divergence, curl, etc.

Partial derivatives

Gradient and directional derivatives

Partial derivative and gradient (articles)

Differentiating parametric curves

Multivariable chain rule

Curvature

Partial derivatives of vector-valued fun...

Differentiating vector-valued function...

Divergence

Curl

Divergence and curl (articles)

Laplacian

Jacobian



Applications of multivariable derivatives

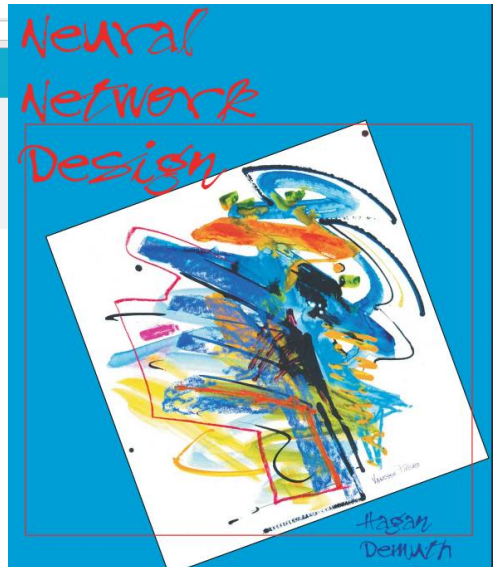
28 of 37 complete

Tangent planes and local linearization

Quadratic approximations

Optimizing multivariable functions (art...

Lagrange multipliers and constrained ...



I decided to use the machine learning library Keras instead because it uses Tensorflow (in python 3) and Theano (in python 2) as backend. I spent 3 weeks reading Hagan's Neural Network Design book (2 weeks), reviewing on linear algebra (1 week) and learning and taking notes on multi-variable calculus on Kahn academy (1 week).

Week of October 23:

The baby AI image dataset is very old and has bugs in it. I wasn't able to extract the dataset by running their python program. So, I spent all this time creating my own dataset and preparing it for loading using pickle's serialization format into Google Cloud's Machine Learning Engine. I created my own python class called Draw.py, which uses multiprocessing of Pool workers in a class to draw images themselves as well as the intersection of images. Multiprocessing allows me to make as many images as possible by using parallel computing of 4 cores in a CPU.

draw.py X

```
45 canvas.save_img(filename)
46
47 def draw_square(object, filename):
48     canvas = object(500,500)
49     bg_obj = canvas.background_color()
50     canvas.line_square(bg_obj)
51     context_obj = canvas.new_context()
52     canvas.fill_square(context_obj)
53     canvas.save_img(filename)
54
55 def draw_triangle(object, filename):
56     canvas = object(500,500)
57     bg_obj = canvas.background_color()
58     canvas.line_triangle(bg_obj)
59     context_obj = canvas.new_context()
60     canvas.fill_triangle(context_obj)
61     canvas.save_img(filename)
62
63 class Draw(object):
64
65     def __init__(self, canvas_width, canvas_height):
66         import numpy as np
67         self.canvas_width = canvas_width
68         self.canvas_height = canvas_height
69         self.data = np.zeros((self.canvas_width, self.canvas_height, 4),
70                             dtype = np.uint64)
71         self.surface = cairo.ImageSurface.create_for_data(self.data,
72                                                         cairo.FORMAT_ARGB32,
73                                                         self.canvas_width,
74                                                         self.canvas_height)
75
76     def run(self):
77         p = Pool(processes=4)
78
79         for x in range(2000):
80             p.apply_async(draw_triangle, (Draw, str(x)))
81         p.close()
82         p.join()
83
84     def new_context(self):
85         return cairo.Context(self.surface)
```

```
1 """
2 Created on Fri Oct 27 18:41:03 2017
3 Draws images of shapes of circles, rectangles, squares, triangles
4 @author: maggie
5 """
6 from __future__ import print_function
7 import cairo
8 import random
9 from multiprocessing import Pool
10
11 def draw_objects(object, filename):
12     canvas = object(500,500)
13     obj1 = canvas.background_color()
14     canvas.fill_circle(obj1)
15     obj2 = canvas.new_context()
16     canvas.line_circle(obj2)
17     obj3 = canvas.new_context()
18     canvas.line_triangle(obj3)
19     obj4 = canvas.new_context()
20     canvas.fill_triangle(obj4)
21     obj5 = canvas.new_context()
22     canvas.line_rectangle(obj5)
23     obj6 = canvas.new_context()
24     canvas.fill_rectangle(obj6)
25     obj7 = canvas.new_context()
26     canvas.line_square(obj7)
27     obj8 = canvas.new_context()
28     canvas.fill_square(obj8)
29     canvas.save_img(filename)
30
31 def draw_rectangle(object, filename):
32     canvas = object(500,500)
33     bg_obj = canvas.background_color()
34     canvas.line_rectangle(bg_obj)
35     context_obj = canvas.new_context()
36     canvas.fill_rectangle(context_obj)
37     canvas.save_img(filename)
38
39 def draw_circle(object, filename):
40     canvas = object(500,500)
41     bg_obj = canvas.background_color()
42     canvas.fill_circle(bg_obj)
43     context_obj = canvas.new_context()
44     canvas.line_circle(context_obj)
```

```

87 #the next image drawn on background color must have :
88 #the parameter in background_color
89 def background_color(self):
90     r = random.uniform(0,1)
91     g = random.uniform(0,1)
92     b = random.uniform(0,1)
93     name = self.new_context()
94     name.set_source_rgb(r,g,b)
95     name.paint()
96     return name
97
98 def fill_circle(self, object):
99     import math
100     r = random.uniform(0,1)
101     g = random.uniform(0,1)
102     b = random.uniform(0,1)
103     xc = random.randint(10,500)
104     yc = random.randint(10,500)
105     radius = random.randint(50,250)
106     object.arc(xc, yc, radius, 0, 2*math.pi)
107     object.set_source_rgb(r, g, b)
108     object.fill()
109
110 def line_circle(self, object):
111     import math
112     r = random.uniform(0,1)
113     g = random.uniform(0,1)
114     b = random.uniform(0,1)
115     xc = random.randint(10,500)
116     yc = random.randint(10,500)
117     radius = random.randint(50,250)
118     w = random.uniform(0,10)
119     object.arc(xc, yc, radius, 0, 2*math.pi)
120     object.set_line_width(w)
121     object.set_source_rgb(r, g, b)
122     object.stroke()
123
124 def fill_rectangle(self, object):
125     r = random.uniform(0,1)
126     g = random.uniform(0,1)
127     b = random.uniform(0,1)
128     x = random.randint(10,500)
129     y = random.randint(10,500)
130     width = random.randint(50,250)
131     height = random.randint(50,250)
132     object.rectangle(x, y, width, height)
133     object.set_source_rgb(r, g, b)
134     object.fill()
135
136 def line_rectangle(self, object):
137     r = random.uniform(0,1)
138     g = random.uniform(0,1)
139     b = random.uniform(0,1)
140     x = random.randint(10,500)
141     y = random.randint(10,500)
142     w = random.uniform(0,10)
143     width = random.randint(50,250)
144     height = random.randint(50,250)
145     object.rectangle(x, y, width, height)
146     object.set_line_width(w)
147     object.set_source_rgb(r, g, b)
148     object.stroke()
149
150 def fill_square(self, object):
151     r = random.uniform(0,1)
152     g = random.uniform(0,1)
153     b = random.uniform(0,1)
154     x = random.randint(10,500)
155     y = random.randint(10,500)
156     width = random.randint(50,250)
157     object.rectangle(x, y, width, width)
158     object.set_source_rgb(r, g, b)
159     object.fill()
160
161 def line_square(self, object):
162     r = random.uniform(0,1)
163     g = random.uniform(0,1)
164     b = random.uniform(0,1)
165     x = random.randint(10,500)
166     y = random.randint(10,500)
167     w = random.uniform(0,10)
168     width = random.randint(50,250)
169     object.rectangle(x, y, width, width)
170     object.set_line_width(w)
171
172     object.set_source_rgb(r, g, b)
173     object.stroke()
174
175 def fill_triangle(self, object):
176     r = random.uniform(0,1)
177     g = random.uniform(0,1)
178     b = random.uniform(0,1)
179     x = random.randint(10,500)
180     y = random.randint(10,500)
181     x1 = random.randint(10,500)
182     y1 = random.randint(10,500)
183     y2 = random.randint(10,500)
184     object.move_to(x,y)
185     object.line_to(x, y1)
186     object.line_to(x1, y2)
187     object.line_to(x, y)
188     object.set_source_rgb(r, g, b)
189     object.fill()
190
191 def line_triangle(self, object):
192     r = random.uniform(0,1)
193     g = random.uniform(0,1)
194     b = random.uniform(0,1)
195     x = random.randint(10,500)
196     y = random.randint(10,500)
197     x1 = random.randint(10,500)
198     y1 = random.randint(10,500)
199     y2 = random.randint(10,500)
200     w = random.uniform(0,3)
201     object.move_to(x,y)
202     object.line_to(x, y1)
203     object.line_to(x1, y2)
204     object.line_to(x, y)
205     object.set_line_width(w)
206     object.set_source_rgb(r, g, b)
207     object.stroke()
208
209 def save_img(self, filename):
210     print(filename)
211     dir = "test_set/triangle/"
212     intersection = "triangle."
213     self.surface.write_to_png(dir + intersection + filename + ".png")
214
215 if __name__ == '__main__':
216     d = Draw(500, 500)
217     d.run()

```

This file reduces the image's quality to reduce the file size:

```

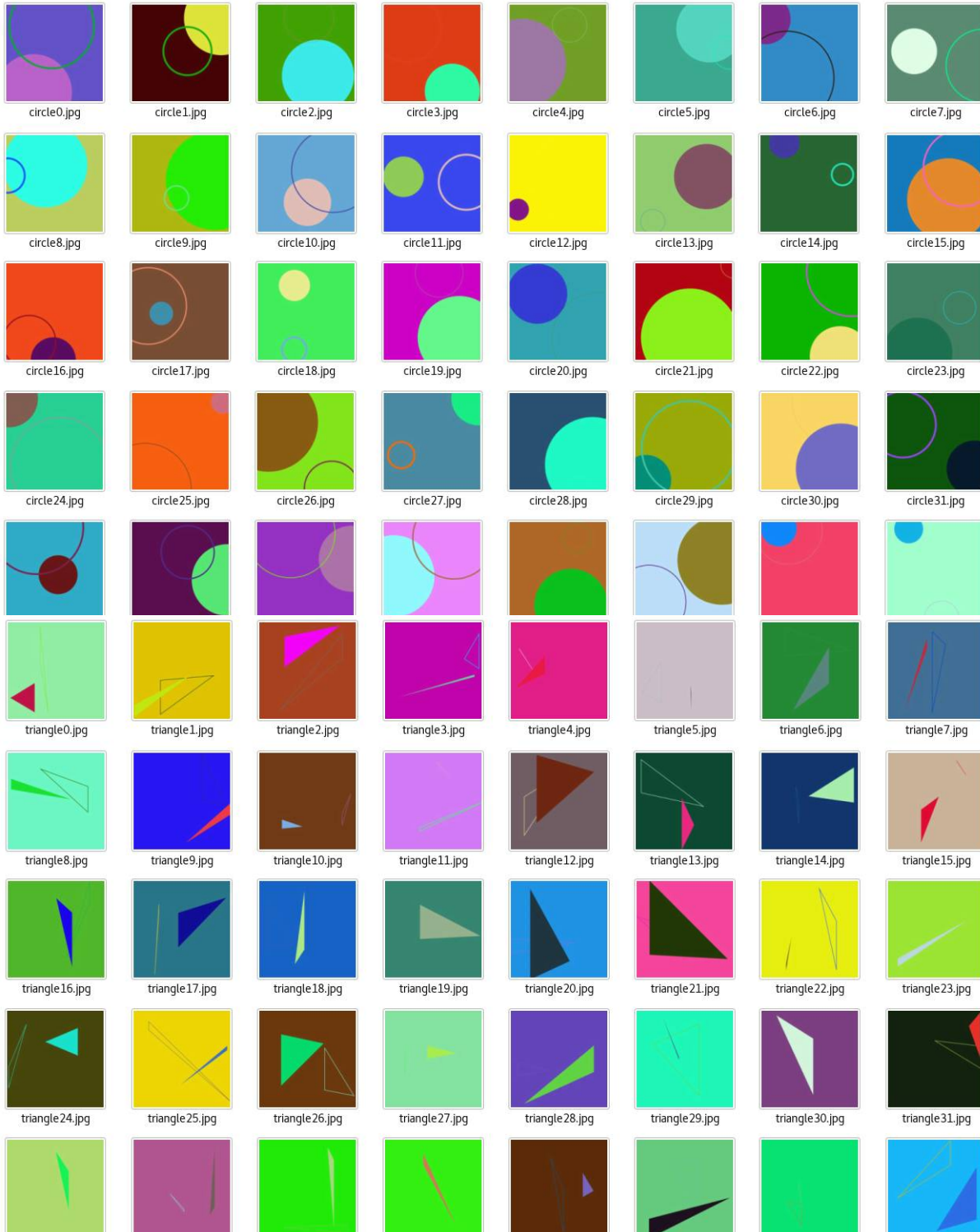
1 """
2 Created on Thu Oct 26 20:50:49 2017
3
4 @author: maggie
5 """
6 from __future__ import print function
7 from __future__ import division
8 from PIL import Image
9 import glob
10 import pickle
11 import scipy.misc
12 import numpy as np
13 from multiprocessing import Lock
14 from multiprocessing import Pool
15
16 def init(lock):
17     global childs_lock
18     childs_lock = lock
19
20 """each pool worker gets original img data to reduce file size"""
21 def reduce_images(image_path):
22     childs_lock.acquire()
23     img = Image.open(image_path)
24     childs_lock.release()
25     basewidth = 300
26     percent = (basewidth / float(img.size[0]))
27     hsize = int((float(img.size[1]) * float(percent)))
28     img = img.resize((basewidth, hsize), Image.ANTIALIAS) #ANTIALIAS reserves quality
29     x_train = np.array(img)
30     #x_train = np.array(img, dtype = np.uint8) #a numpy array with data type CV_8UC1
31     #x_train = x_train[:, :, 0] #slice out the color dimension
32     print(x_train.shape)
33     img.close()
34     return x_train
35
36 #global storage variable for both main and pool of workers
37 result_list = []
38
39 """result(data) is called whenever process_images(path) returns a result
40 result_list is modified by main process not by pool of workers"""
41 def result(data):
42     result_list.append(data)

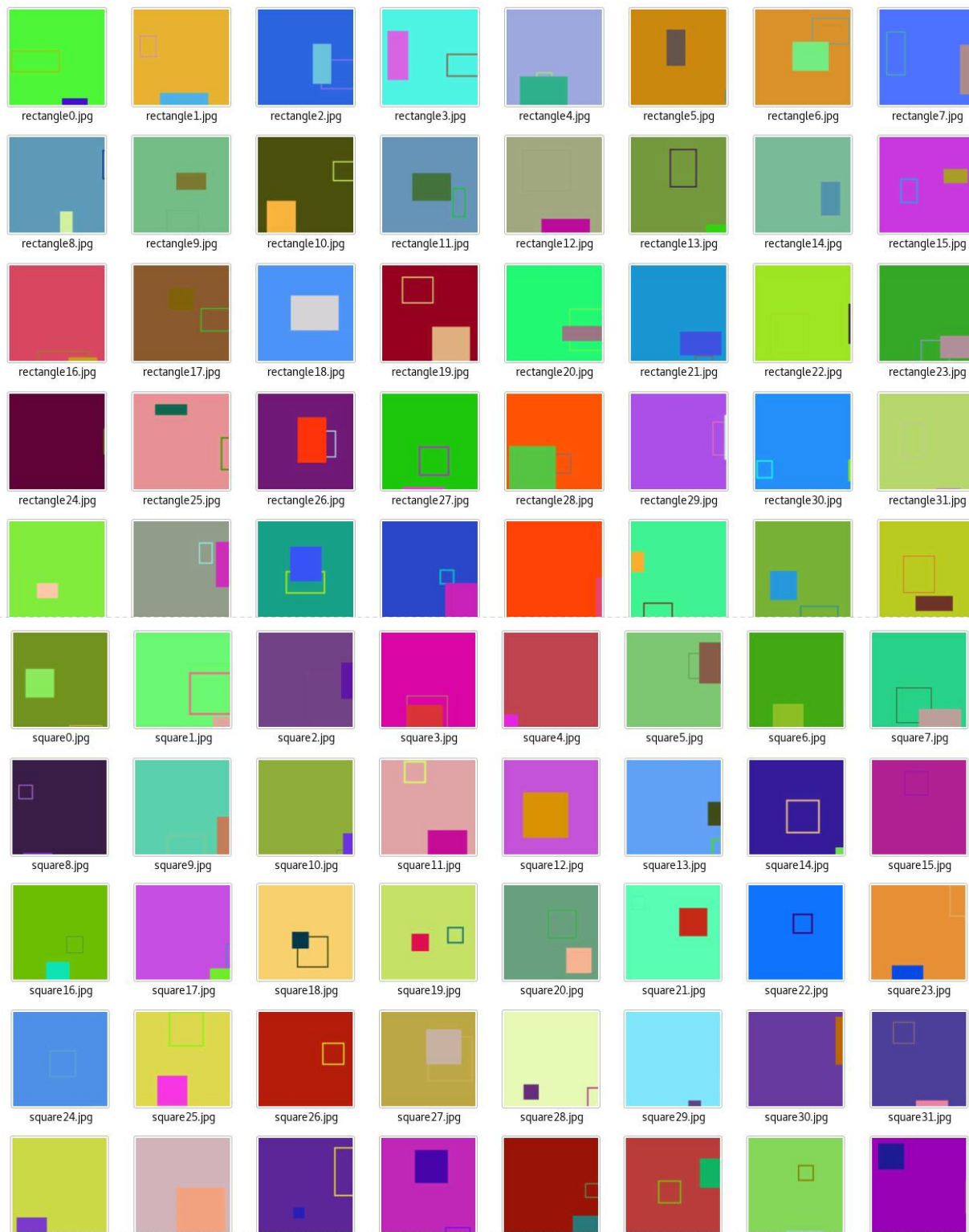
```

```

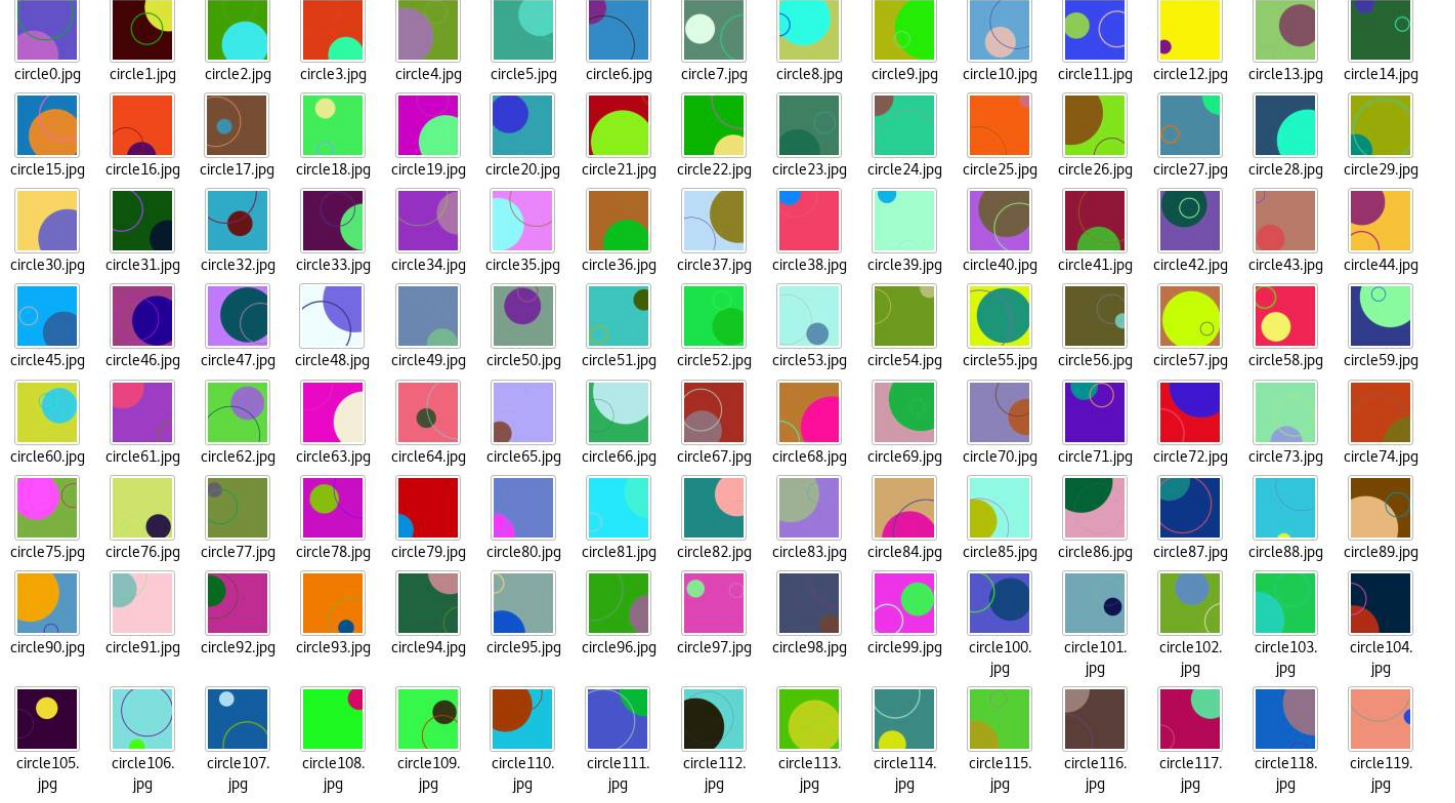
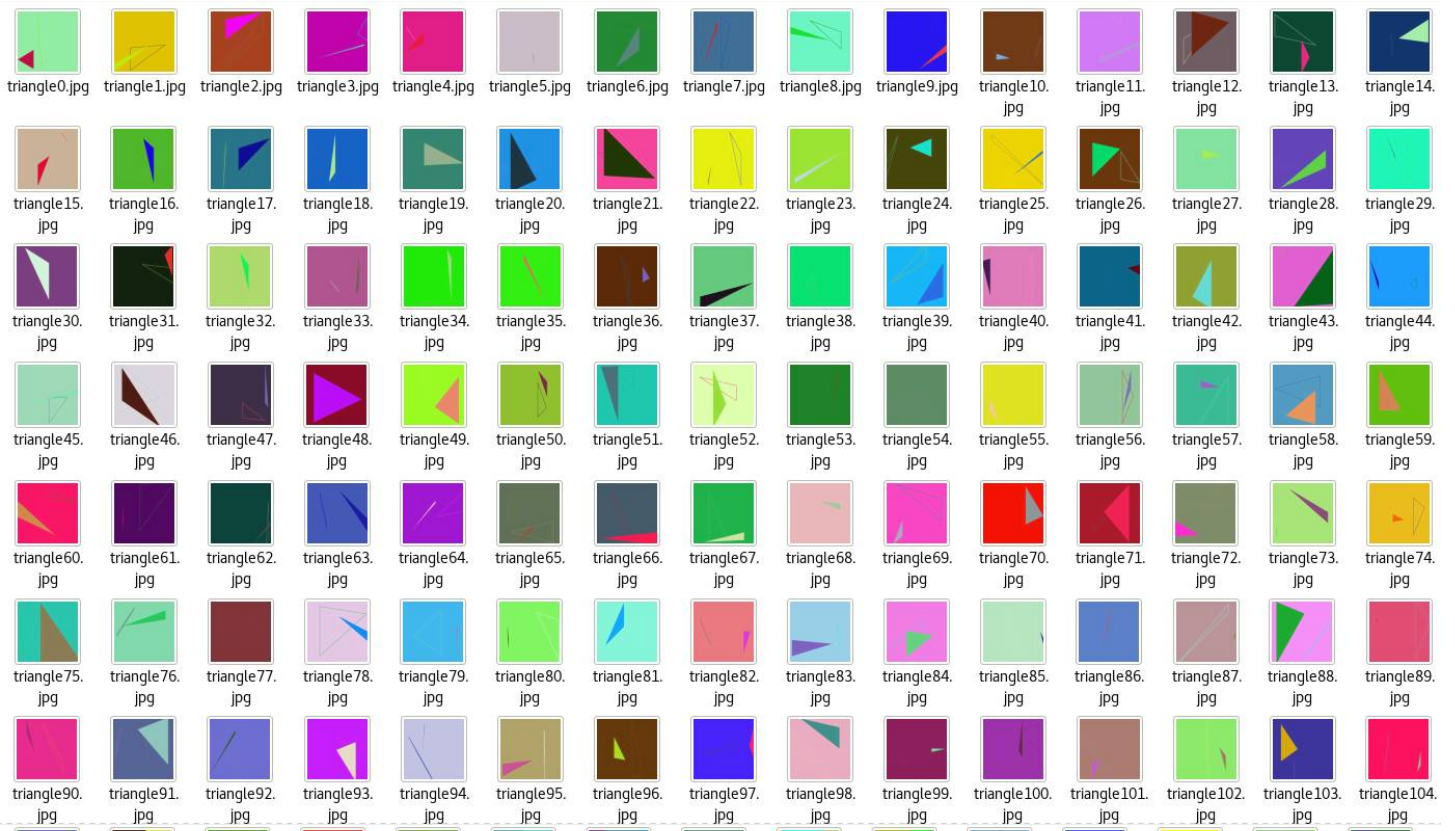
44 #create empty pickle file first then append to file
45 output = open (pickle_file, 'wb')
46 output.close()
47
48 def result(data):
49     output = open (pickle_file, 'ab')
50     print ("in pickle file: ", pickle_file)
51     pickle.dump(data, output, pickle.HIGHEST_PROTOCOL)
52     output.close()
53
54 if __name__ == '__main__':
55
56     shape_path = "test_set/circle1/"
57     lock = Lock()
58     p = Pool(processes=4, initargs = (lock, ), initializer = init)
59     #for shapes in shape_path:
60     for image_path in glob.glob(shape_path + "*jpg"):
61         p.apply_async(process_images, (image_path, shape_path), callback = result)
62     p.close() # no more tasks
63     p.join() #wrap up current tasks
64

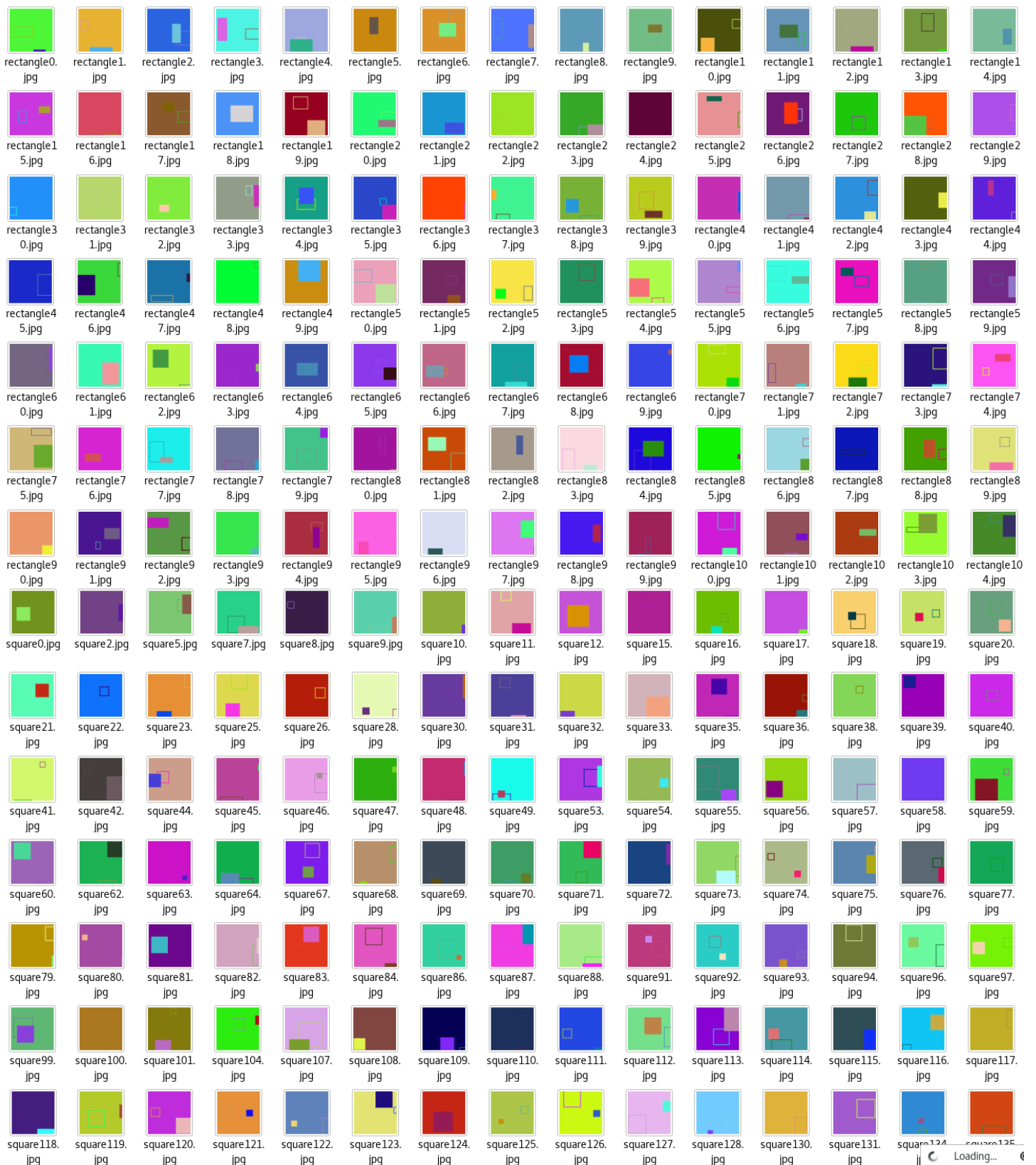
```





Below are more examples of the training dataset in JPEG extension:





I had problems loading the images to a pickle file because I originally stored the images as a dictionary which represents in a string format. Numpy wants a float object, so I decided to use Python's list data structure to store all the numpy arrays.


```
maggie@debian:~/Downloads/Convolutional_Neural_Networks$ python trainer/cnncopy.py --job-dir ./ --train-file compressedImages.pkl
Using TensorFlow backend.
Using logs path located at ../logs/2017-10-19T19:34:32.050048
Traceback (most recent call last):
  File "trainer/cnncopy.py", line 145, in <module>
    train_model(**arguments)
  File "trainer/cnncopy.py", line 105, in train_model
    save_format = 'jpeg'):
  File "/home/maggie/anaconda3/lib/python3.6/site-packages/keras/preprocessing/image.py", line 461, in flow
    save_format=save_format)
  File "/home/maggie/anaconda3/lib/python3.6/site-packages/keras/preprocessing/image.py", line 774, in __init__
    self.x = np.asarray(x, dtype=K.floatx())
  File "/home/maggie/anaconda3/lib/python3.6/site-packages/numpy/core/numeric.py", line 531, in asarray
    return array(a, dtype, copy=False, order=order)
ValueError: could not convert string to float: '{"dataset/training set/cats/cat.175.jpg': <PIL.Image.Image image mode=RGB size=300x226 at 0x7F760CECD860>, 'dataset/training set/cats/cat.2192.jpg': <PIL.Image.Image image mode=RGB size=500x474 at 0x7F760CECDFD0>, 'dataset/training set/cats/cat.2420.jpg': <PIL.Image.Image image mode=RGB size=499x480 at 0x7F760CECDF28>, 'dataset/training set/cats/cat.2652.jpg': <PIL.Image.Image image mode=RGB size=378x498 at 0x7F760CECEB8>, 'dataset/training set/cats/cat.3026.jpg': <PIL.Image.Image image mode=RGB size=499x375 at 0x7F760CECE48>, 'dataset/training set/cats/cat.1317.jpg': <PIL.Image.Image image mode=RGB size=360x449 at 0x7F760CECDD08>, 'dataset/training set/cats/cat.224.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CECD068>, 'dataset/training set/cats/cat.3110.jpg': <PIL.Image.Image image mode=RGB size=499x375 at 0x7F760CECDF8>, 'dataset/training set/cats/cat.975.jpg': <PIL.Image.Image image mode=RGB size=384x383 at 0x7F760CECDB8>, 'dataset/training set/cats/cat.2902.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CECDC18>, 'dataset/training set/cats/cat.997.jpg': <PIL.Image.Image image mode=RGB size=500x320 at 0x7F760CECDF60>, 'dataset/training set/cats/cat.497.jpg': <PIL.Image.Image image mode=RGB size=469x303 at 0x7F760CEDEF0>, 'dataset/training set/cats/cat.2623.jpg': <PIL.Image.Image image mode=RGB size=499x274 at 0x7F760DA2EDA0>, 'dataset/training set/cats/cat.1246.jpg': <PIL.Image.Image image mode=RGB size=359x270 at 0x7F760DA2ECC0>, 'dataset/training set/cats/cat.3521.jpg': <PIL.Image.Image image mode=RGB size=276x225 at 0x7F760CB7CBA8>, 'dataset/training set/cats/cat.955.jpg': <PIL.Image.Image image mode=RGB size=400x235 at 0x7F760CB7CB38>, 'dataset/training set/cats/cat.1301.jpg': <PIL.Image.Image image mode=RGB size=499x375 at 0x7F760CB7CAC8>, 'dataset/training set/cats/cat.171.jpg': <PIL.Image.Image image mode=RGB size=312x280 at 0x7F760CB7CA58>, 'dataset/training set/cats/cat.2079.jpg': <PIL.Image.Image image mode=RGB size=405x403 at 0x7F760CB7C9E8>, 'dataset/training set/cats/cat.1736.jpg': <PIL.Image.Image image mode=RGB size=229x448 at 0x7F760CB7C978>, 'dataset/training set/cats/cat.2542.jpg': <PIL.Image.Image image mode=RGB size=211x250 at 0x7F760CB7C908>, 'dataset/training set/cats/cat.3488.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CB7C898>, 'dataset/training set/cats/cat.1319.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CB7C828>, 'dataset/training set/cats/cat.1683.jpg': <PIL.Image.Image image mode=RGB size=369x402 at 0x7F760CB7C7B8>, 'dataset/training set/cats/cat.2299.jpg': <PIL.Image.Image image mode=RGB size=500x335 at 0x7F760CB7C748>, 'dataset/training set/cats/cat.3699.jpg': <PIL.Image.Image image mode=RGB size=140x92 at 0x7F760CB7C6D8>, 'dataset/training set/cats/cat.1356.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CB7C668>, 'dataset/training set/cats/cat.1908.jpg': <PIL.Image.Image image mode=RGB size=240x179 at 0x7F760CB7C5F8>, 'dataset/training set/cats/cat.881.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CB7C588>, 'dataset/training set/cats/cat.537.jpg': <PIL.Image.Image image mode=RGB size=450x367 at 0x7F760CB7C518>, 'dataset/training set/cats/cat.1397.jpg': <PIL.Image.Image image mode=RGB size=499x375 at 0x7F760CB7C4A8>, 'dataset/training set/cats/cat.881.jpg': <PIL.Image.Image image mode=RGB size=500x395 at 0x7F760CB7C438>, 'dataset/training set/cats/cat.2151.jpg': <PIL.Image.Image image mode=RGB size=349x265 at 0x7F760CB7C3C8>, 'dataset/training set/cats/cat.464.jpg': <PIL.Image.Image image mode=RGB size=319x240 at 0x7F760CB7C358>, 'dataset/training set/cats/cat.2610.jpg': <PIL.Image.Image image mode=RGB size=374x500 at 0x7F760CB7C2E8>, 'dataset/training set/cats/cat.1191.jpg': <PIL.Image.Image image mode=RGB size=399x499 at 0x7F760CB7C278>, 'dataset/training set/cats/cat.1880.jpg': <PIL.Image.Image image mode=RGB size=126x141 at 0x7F760CB7C208>, 'dataset/training set/cats/cat.703.jpg': <PIL.Image.Image image mode=RGB size=407x500 at 0x7F760CB7C198>, 'dataset/training set/cats/cat.517.jpg': <PIL.Image.Image image mode=RGB size=321x500 at 0x7F760CB7C128>, 'dataset/training set/cats/cat.3942.jpg': <PIL.Image.Image image mode=RGB size=349x262 at 0x7F760CB7CD08>, 'dataset/training set/cats/cat.563.jpg': <PIL.Image.Image image mode=RGB size=499x476 at 0x7F760CB7CEB0>, 'dataset/training set/cats/cat.552.jpg': <PIL.Image.Image image mode=RGB size=375x499 at 0x7F760CB7CF28>, 'dataset/training set/cats/cat.1239.jpg': <PIL.Image.Image image mode=RGB size=500x465 at 0x7F760CB7CF98>, 'dataset/training set/cats/cat.3774.jpg': <PIL.Image.Image image mode=RGB size=500x374 at 0x7F760CB7C18>, 'dataset/training set/cats/cat.2020.jpg': <PIL.Image.Image image mode=RGB size=255x192 at 0x7F760CB7CEB0>, 'dataset/training set/cats/cat.3613.jpg': <PIL.Image.Image image mode=RGB size=320x323 at 0x7F760CF4128>, 'dataset/training set/cats/cat.958.jpg': <PIL.Image.Image image mode=RGB size=425x201 at 0x7F760CF4198>, 'dataset/training set/cats/cat.2712.jpg':
```

10.31.17:

The training set consists of a total of 6,200 images. Before being serialized into a pickle file, the training set is organized in a tuple structure (numpy array, y_label). The numpy array is the data array processed by the PIL module in (300, 300, 3) format. The numpy array represents the matrix in float32 of the image. The y_label represents the target values of the shapes, which is the expected output of the convolutional neural network. Keras requires categorical crossentropy loss to be computed with categorical encodings. The categorical one hot encoding transfers integers (0...number of classes) into binary format. My y_label is a series of categorical hot encodings of 0, 1, 2 in binary format of three classes (circles, rectangles and squares, triangle).

I had to change the numpy array data structure from a default float to float32 bit since the loading of the pickle files in the default float structure consumes too much memory in megabytes per file. The difference almost reduced the entire file size from 3.0 GB (without compression) to 1.7 G.B. The pickle files are too huge, so I have to reduce the quality and size of each image to reduce the pickle files. Pickle loads and image creation of the shapes are created using multiprocessing of independent Pool workers. I have been trying to figure out how to create a pickle file, organize numpy arrays and store them in a huge list, dump that huge list using joblib. Use memmap to store large numpy arrays because it's inefficient for the list to increase in data memory allocation in list comprehension of pickle loading. The file below create (numpy arrays, y_label) tuples and stores them in a pickle file.

The short-term goal is to train the shapes individually first and then figure out how to get the model to generalize on the “intersection” of shapes either by using recurrent convolutional neural networks or multi-label output using supervised learning. How will the network learn? I need to adjust the architecture of the CNN. The multi-label output is simpler and much easier. This requires sigmoid activation and loss = binary_crossentropy at the output layer for multi-label output to work.

```

draw.py x googlecloud_config_cnn.txt x load_merge_files.py x 45 if __name__ == '__main__':
46
47     circle_path = "test_set/rectangle/"
48     lock = Lock()
49     p = Pool(processes=4, initargs = (lock, ), initializer = init)
50
51     for image_path in glob.glob(circle_path + "*.png"):
52         p.apply_async(reduce_images, (image_path,), callback = result)
53
54
55     p.close() # no more tasks
56     p.join() #wrap up current tasks
57
58     output = open ('test_rectangle.pkl', 'wb')
59     for x in result_list:
60         pickle.dump(x, output, -1)
61     output.close()
62
63     name = []
64     num_files = 2000
65     for i in range(num_files):
66         name.append("test_set/rectangle1/rectangle" + str(i) + ".jpg")
67
68     #save resized data to a folder
69     with open('test_rectangle.pkl', 'rb') as pkl_file:
70         data1 = [pickle.load(pkl_file) for i in range(num_files)]
71     for i in range(num_files):
72         scipy.misc.imsave(name[i], data1[i])

```

This file merges all the pickled files that each represents the individual shape data and their y_labels from training, validation and testing set.

```

draw.py x googlecloud_config_cnn.txt x load_merge_files.py x merge_files.py x
1 from future import print_function
2 import pickle
3 import joblib
4 #import numpy as np
5 #from tempfile import mkdtemp
6 #import os.path as path
7
8 def load_train_or_test(files):
9     with open(files, 'rb') as f:
10         try:
11             print ("Opening files")
12             print (files)
13             while True:
14                 yield pickle.load(f) #python version 2.7
15         except EOFError:
16             pass
17
18 if __name__ == '__main__':
19
20     #include (shape array,y labels) as a tuple returned by the pickle
21     circle_dataset = [item for item in load_train_or_test ("circle.pkl")]
22     triangle_dataset = [item for item in load_train_or_test ("triangle.pkl")]
23     rectangle_dataset = [item for item in load_train_or_test ("rectangle.pkl")]
24     square_dataset = [item for item in load_train_or_test ("square.pkl")]
25
26     #merge the individual shape data into one train data
27     train_data = circle_dataset + triangle_dataset + rectangle_dataset + square_dataset
28
29     validation_circle_dataset = [item for item in load_train_or_test ("validate_circle.pkl")]
30     validation_triangle_dataset = [item for item in load_train_or_test ("validate_triangle.pkl")]
31     validation_rectangle_dataset = [item for item in load_train_or_test ("validate_rectangle.pkl")]
32     validation_square_dataset = [item for item in load_train_or_test ("validate_square.pkl")]
33
34     validation_data = validation_circle_dataset + validation_triangle_dataset + validation_rectangle_dataset + validation_square_dataset
35
36     pickle_file = 'shape_data.pkl'
37     try:
38         f = open(pickle_file, 'wb')
39         save = {'train_shape_dataset': train_shape_dataset,
40               'train_data': train_data,
41               'validation_data': validation_data,
42               }
43         #pickle.dump(save, f, pickle.HIGHEST_PROTOCOL)
44         joblib.dump(save, f, compress = True)
45         f.close()
46     except Exception as e:
47         print('Unable to save data to', pickle_file, ':', e)
48         raise
49
50
51
52

```

This file uses memory mapping to store large numpy arrays, and randomize the data arrays. It then stores all the data in a compressed pickle file for Google Cloud to load. Google Cloud uses python 2, so the CNN loader file will also use python 2.

```

draw.py x googlecloud_config_cnn.txt x load_merge_files.py x
1 from __future__ import print_function
2 import joblib
3 import pickle
4 import numpy as np
5 from tempfile import mkdtemp
6 import os.path as path
7
8 '''returns individual list data info and y label data in numpy arrays'''
9 def get_data(shape_temp_file, label_temp_file, dataset):
10     #use memory mapping to store large datasets
11     temp_filename = path.join(mkdtemp(), shape_temp_file)
12     train_shape_dataset = np.memmap(temp_filename, dtype = np.float16, mode = 'w+', shape = (300, 300, 3))
13     temp_filename1 = path.join(mkdtemp(), label_temp_file)
14     train_y_dataset = np.memmap(temp_filename1, dtype = np.float16, mode = 'w+', shape = (3))
15
16     train_shape_dataset = [x[0] for x in dataset]
17     #convert list back to np array for keras to process
18     train_shape_dataset = np.array(train_shape_dataset)
19     print ("in get_data function for dataset")
20     print (train_shape_dataset.shape)
21     train_y_dataset = [x[1] for x in dataset]
22     train_y_dataset = np.array(train_y_dataset)
23     print (train_y_dataset.shape)
24
25     return train_shape_dataset, train_y_dataset
26
27 if __name__ == '__main__':
28
29     pickle_file = 'shape_data.pkl'
30     np.random.seed(135)
31     with open(pickle_file, 'rb') as f:
32         #save = pickle.load(f)
33         save = joblib.load(f)
34         train_data = save['train_data']
35         validation_data = save['validation_data']
36         del save # hint to help gc free up memory
37
38     #shuffle the tuple (shape_info, y_label) dataset
39     np.random.seed(135)
40     np.random.shuffle(train_data)
41
42     #split list in half
43     train_data_half = train_data[ :: 3]
44     #train_data_other_half = train_data[1 :: 2]
45     validation_data_half = validation_data[ :: 3]
46
47     train_shape_dataset, train_y_dataset = get_data('shapes.dat', 'shapes_y.dat', train_data_half)
48     #train_shape_halfdataset, train_y_halfdataset = get_data('shapes.dat', 'shapes_y.dat', train_data_other_half)
49     validate_shape_dataset, validate_y_dataset = get_data('validate_shapes.dat', 'validate_shapes_y.dat', validation_da
50
51     print ("in main: 1/half train", train_shape_dataset.shape)
52     print ("in main: 1/half y_label", train_y_dataset.shape)
53     #print ("in main: 2/half train", train_shape_halfdataset.shape)
54     #print ("in main: 2/half y_label", train_y_halfdataset.shape)
55     print ("in main: validate", validate_shape_dataset.shape)
56     print ("in main: validate y_label", validate_y_dataset.shape)
57
58     pickle_file = 'random_shapes.pkl'
59     try:
60         f = open(pickle_file, 'wb')
61         save = {'train_shape_dataset': train_shape_dataset,
62               'train_y_dataset': train_y_dataset,
63               #'train_shape_halfdataset': train_shape_halfdataset,
64               #'train_y_halfdataset': train_y_halfdataset,
65               'validate_shape_dataset': validate_shape_dataset,
66               'validate_y_dataset': validate_y_dataset,
67               }
68         #pickle.dump(save, f, pickle.HIGHEST_PROTOCOL)
69         joblib.dump(save, f, compress = True)
70         f.close()
71     except Exception as e:
72         print('Unable to save data to', pickle_file, ':', e)
73         raise

```

11.3-11.5.17:

Google cloud works locally but had errors of loading pickle file remotely on google cloud because the Cloud Compute Engine doesn't recognize python's file descriptor. I need to use tensorflow's open method, need to set gs:// for every input file data for Google Cloud to recognized it. Here are the steps to run the CNN loader file in Google Cloud:

```
draw.py x googlecloud_config_cnn.txt x
3 gsutil cp -r trainer/cloudml-gpu.yaml gs://cnninput_dataset/trainer/cloudml-gpu.yaml
4 gsutil cp -r trainer/__init__.py gs://cnninput_dataset/trainer/__init__.py
5
6 data folder
7 gsutil cp -r data/random_shapes.pkl gs://cnninput_dataset/data/random_shapes.pkl
8
9 bucket folder
10 gsutil cp -r setup.py gs://cnninput_dataset/setup.py
11
12
13 export BUCKET_NAME=cnninput_dataset
14 export JOB_NAME="cnncopy_train_$(date +%Y%m%d_%H%M%S)"
15 export JOB_DIR=gs://$BUCKET_NAME/$JOB_NAME
16 export REGION=us-east1
17
18 train on machine locally
19 gcloud ml-engine local train \
20 --job-dir $JOB_DIR \
21 --module-name trainer.cnncopy \
22 --package-path ./trainer \
23 -- \
24 --train-file ./data/random_shapes.pkl
25
26 submit a job to cloud ML engine
27 gcloud ml-engine jobs submit training $JOB_NAME \
28 --job-dir $JOB_DIR \
29 --runtime-version 1.0 \
30 --module-name trainer.cnncopy \
31 --package-path ./trainer \
32 --region $REGION \
33 --config trainer/cloudml-gpu.yaml \
34 -- \
35 --train-file gs://$BUCKET_NAME/data/random_shapes.pkl
36
37 submit a job to cloud ML engine
38 gcloud ml-engine jobs submit training $JOB_NAME \
39 --job-dir $JOB_DIR \
40 --runtime-version 1.0 \
41 --module-name trainer.cnncopy \
42 --package-path ./trainer \
43 --region $REGION \
44 -- \
45 --train-file gs://$BUCKET_NAME/data/random_shapes.pkl
46
```

11.6.17:

There is an memory error when running on Google Cloud's regular CPU after one set of 10 epochs for the first half of the dataset. There is not enough memory allocated and training took 1 hour, which is too slow. I decided to use yaml configuration to run on a single NVIDIA K80 GPU processor on Google Cloud Compute Engine.

11.7.17:

I executed this with no errors in Google Cloud with GPU computing on a validation set 1000 images and training set of 6000 images with roughly 60 percent accuracy, 3 percent error rate in 3 series of 10 epochs per training set each. The learning model is able to be saved. Google Cloud automatically plots the gradient on Tensorboard. The reason the error rate is so high and accuracy is low is because there are alot of background samples that the CNN intakes as pool sizes. Background colored samples are data that contains no linear information - unimportant numpy array figures. so when the network does the maxpool of background samples near the 'important line samples', if the background samples are in greater distribution than the amount of important line samples, maxpool will label that area as background sample which makes the neurons increase the weights for backgrounds instead of the contour images itself.

11.8.17:

I increased the y-label output from 3 classes to 4 classes. Keras does the automatic shuffle at every epoch in fit_generator. I changed the architecture of the CNN, add drop out layers that might drop out neurons that have no data of contour characteristics being drawn or do some cropping of batches that do not consist of contour information beforehand. I increased the pool size of the CNN and changed it from adam optimizer to rms optimizer. The CNN will do fit the generator model from data augmentation in 20 epochs with validation and training inputs inputted. I also implemented the validation set correctly during the fitting of the network with real data augmentation. The CNN does poorly during training, with an accuracy of 59 percent and 6 percent loss. This is because I used 3,000 images to train the dataset, which is 1/3 of the total training set, which might not contain evenly distributed images of each type of shape. I reduced the total

training set by a third because I want to focus on getting the architecture of the CNN right and there is memory error at the Tesla K80 GPU from the loading of the images since the validation data increased by twice as much as the previous one.

11.9.17:

Trying to figure out how to redesign the architecture of my CNN by looking back on the research I did in Neural Network Design. I also need to create my own data generator (augmentation) function that crops large scaled images to reduce unnecessary background sampling of images in Pooling. I don't want to separate the contours and filling of the images from the background because the background plays an important part in the composition of the entire image object. Such images that need to be cropped, where the dotted lines represent the cropping location, in a generator function are:

