In [1]: # imports
 import tensorflow as tf
 import numpy as np
 import matplotlib.pyplot as plt
 %matplotlib inline
draw plots in notebook not new window

/Users/mengningshang/Desktop/Dev_Env/carAI/CarND-Alexnet-Feature-Extrac tion/wcd-ml-b2/lib/python3.6/site-packages/h5py/__init__.py:36: FutureW arning: Conversion of the second argument of issubdtype from `float` to `np.floating` is deprecated. In future, it will be treated as `np.float 64 == np.dtype(float).type`.

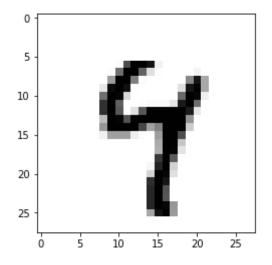
from ._conv import register_converters as _register_converters

Extracting ./MNIST_DATA/train-images-idx3-ubyte.gz Extracting ./MNIST_DATA/train-labels-idx1-ubyte.gz Extracting ./MNIST_DATA/t10k-images-idx3-ubyte.gz Extracting ./MNIST_DATA/t10k-labels-idx1-ubyte.gz

In [3]: print('shape of image is: ', mn.train.images[0].shape) # image
 is a long flat vector
plt.imshow(mn.train.images[23].reshape(28,28), cmap="Greys") # ref
 ormat long flat img vector in to 28x28 square img
 plt.imshow(mn.train.images[2].reshape(28,28), cmap="Greys") # reform
 at long flat img vector in to 28x28 square img

shape of image is: (784,)

Out[3]: <matplotlib.image.AxesImage at 0x11fad9a58>



```
In [4]: # define generator/faker net with own var scope
        def gen(z, reuse=None, extra layer=0):
            input: takes random seed z
            outputs: a 784 pixel img vector
            with tf.variable_scope('gen', reuse=reuse):
                leaky relu const = 0.01 # using RELU (sparse activation) causes
         instability, use leaky relu
                hid1 = tf.layers.dense(inputs=z, units=128)
                hid1 = tf.maximum(leaky relu const*hid1, hid1)
                hid2 = tf.layers.dense(inputs=hid1, units=128)
                hid2 = tf.maximum(leaky_relu_const*hid2, hid2)
                if extra layer:
                    hid3 = tf.layers.dense(inputs=hid2, units=256)
                    hid3 = tf.maximum(leaky_relu_const*hid3, hid3)
                    outl = tf.layers.dense(hid3, units=784, activation=tf.nn.tan
        h)
                else:
                    outl = tf.layers.dense(hid2, units=784, activation=tf.nn.tan
        h)
                return outl
In [5]: # define descriminator/judge net with own var scope
        def judge(x, reuse=None, extra layer=0):
            input: a 784 pixel img vector (either generated by the faker or a re
        al example from MNIST)
            output: tuple (Boolean (0 or 1) where 1 = image is real (MNIST) and
         not generated, prediction proability)
            with tf.variable scope('jud', reuse=reuse):
                hid1 = tf.layers.dense(inputs=x, units=128)
                leaky relu const = 0.01
                hid1 = tf.maximum(leaky_relu_const*hid1, hid1)
                hid2 = tf.layers.dense(inputs=hid1, units=128)
                hid2 = tf.maximum(leaky relu const*hid2, hid2)
                if extra layer:
                    hid3 = tf.layers.dense(inputs=hid2, units=256)
                    hid3 = tf.maximum(leaky relu const*hid3, hid3)
                    logits = tf.layers.dense(hid3, units=1)
                    logits = tf.layers.dense(hid2, units=1)
                outl = tf.sigmoid(logits)
                return outl, logits
In [6]: # define placeholders
        extra layer=False # use 1 for fashion, 0 for MNIST
```

real img = tf.placeholder(tf.float32, shape=[None, 784])

G = gen(z, extra_layer=extra_layer) # initate a faker

faker

z= tf.placeholder(tf.float32, shape=[None, 100]) # random seed for the

```
In [7]: JoutReal, JlogitsReal = judge(real_img, extra_layer=extra_layer)
          is a tensorFlow node, this version takes in real MNIST images
         JoutFake, JlogitsFake = judge(G, reuse=True, extra_layer=extra_layer) #
          this is a tensorFlow node, this version takes in faked images
 In [8]: # losses: how "off" was the model?
         def lossfunc (logitsin, yin):
             for each 0/1 prediction, calculate the error, and return the average
          for the batch
             111
             return tf.reduce mean(tf.nn.sigmoid cross entropy with logits(logits
         =logitsin, labels=yin))
 In [9]: # define labels (either 0 or 1 because we know if the image is a fake or
          real MNIST data)
         JlossReal = lossfunc(JlogitsReal, tf.ones_like(JlogitsReal)*0.90)
         tf.ones like(JlogitsReal) *0.9 is applying a smoothing factor to real ima
         ges (lablel = 1)
         so the model genearlize better
         111
         JlossFake = lossfunc(JlogitsFake, tf.zeros_like(JlogitsFake))
         Jloss = JlossReal + JlossFake # overall error for the judge-net
          , , ,
         overall error for the faker net, it doesn't care about loss on real MNIS
         is labeled 1 (a lil counter-intuitive maybe):
         - but since if the judge thinks the image is real, it'll output value
         - then the generator won, we want to label genenerator images with 1
         (other wise we would be punishing the generator for it's sucess)
         Gloss=lossfunc(JlogitsFake, tf.ones like(JlogitsFake))
In [10]: # define visualizer function
         skip = 5
         def visualize_sample(imgarray, pos, greyscale=0):
             img = imgarray.reshape(28,28)
             fig = plt.figure()
             fig.suptitle("after {} epochs".format(pos), fontsize=14, fontweight=
          'bold')
             if greyscale == 1:
                 plt.imshow(img, cmap='Greys')
             else:
                 plt.imshow(img)
```

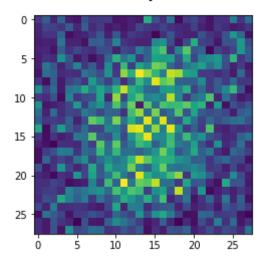
```
In [11]: # define pipeline parameters
         batchsz=100 # number of images processed before we make a update
         rounds = 256 # number of times we train over the whole data-set
         samples = [] # a array to store the random samples at each epoch
         lr = 0.001 # learning rate
         # define what to optimize
         allvars = tf.trainable_variables()
         jvars = [var for var in allvars if 'jud' in var.name]
         gvars = [var for var in allvars if 'gen' in var.name]
         jtrain = tf.train.AdamOptimizer(lr).minimize(Jloss, var_list=jvars) # tr
         ain judge only
         gtrain = tf.train.AdamOptimizer(lr).minimize(Gloss, var_list=gvars) # tr
         ain generator only
         init = tf.global variables initializer()
In [36]: with tf.Session() as sess:
             sess.run(init)
             for e in range(rounds):
                 nbatch = mn.train.num examples // batchsz
                 # train the network for 1 batch (there are # of Images/Bach size
          batches in each epoch)
                 for i in range(nbatch):
                     batch = mn.train.next batch(batchsz) # get the next batch of
          training data
                     batchimgs = batch[0].reshape((batchsz, 784))
                     batchimgs = batchimgs * 2 - 1 # adjust values for tanh activ
         ation, batch imgs are pre-normalized
                     batch z = np.random.uniform(-1,1,size=(batchsz,100)) # gener
         ate random seed batch for faker
                     sess.run(jtrain, feed dict={real img: batchimgs, z: batch z
         }) # train one batch on judge
                     sess.run(gtrain, feed dict={z:batch z}) # train one batch on
          faker
                 print("on epoch {}".format(e))
                 samplez = np.random.uniform(-1,1,size=(1,100)) # make random se
         ed vector for sampling
                 fakeimg = sess.run(gen(z, reuse=True, extra layer=extra layer),
         feed dict={z: samplez}) # make fake images
                 samples.extend(fakeimg)
```

```
In [35]: for pos, imgs in enumerate(loaded_samples):
    if pos%skip ==0 or pos==250-1:
        visualize_sample(imgs, pos)
```

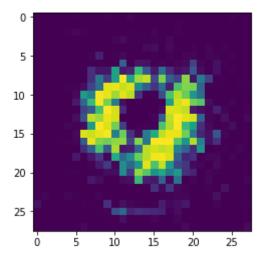
/Users/mengningshang/Desktop/Dev_Env/carAI/CarND-Alexnet-Feature-Extrac tion/wcd-ml-b2/lib/python3.6/site-packages/matplotlib/pyplot.py:524: Ru ntimeWarning: More than 20 figures have been opened. Figures created th rough the pyplot interface (`matplotlib.pyplot.figure`) are retained un til explicitly closed and may consume too much memory. (To control this warning, see the rcParam `figure.max_open_warning`).

max open warning, RuntimeWarning)

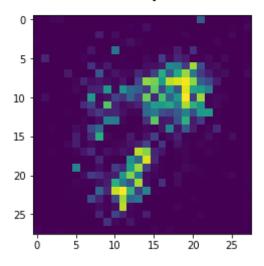
after 0 epochs



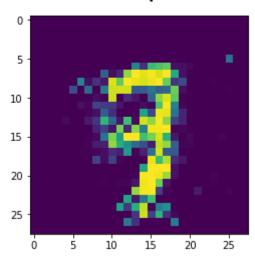
after 5 epochs



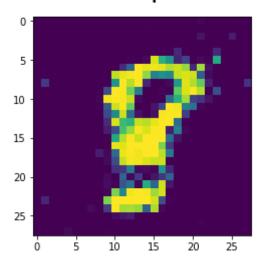
after 10 epochs



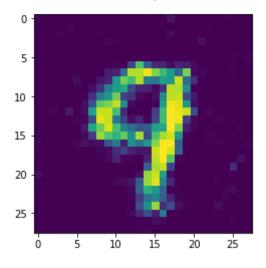
after 15 epochs



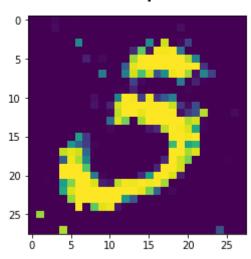
after 20 epochs



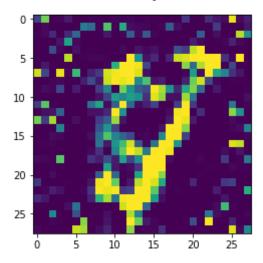
after 25 epochs



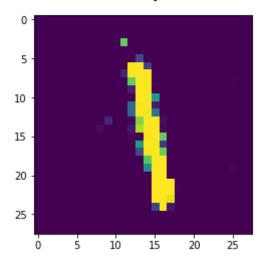
after 30 epochs



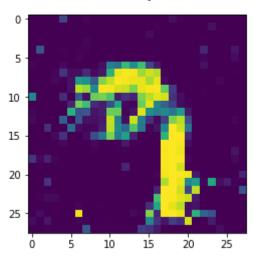
after 35 epochs



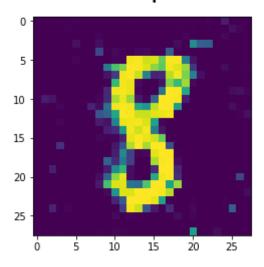
after 40 epochs



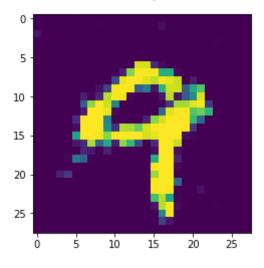
after 45 epochs



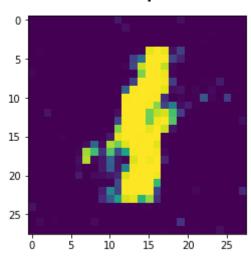
after 50 epochs



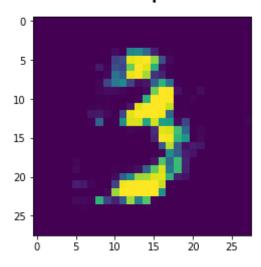
after 55 epochs



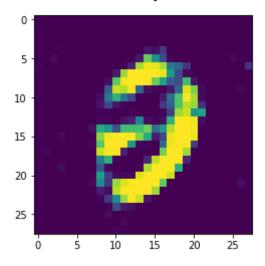
after 60 epochs



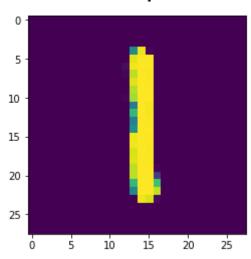
after 65 epochs



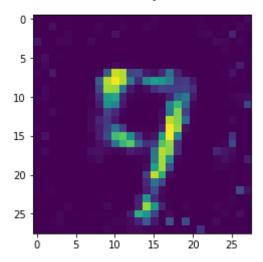
after 70 epochs



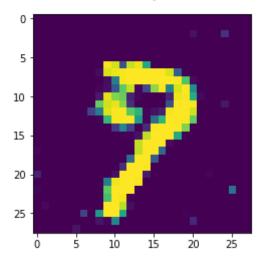
after 75 epochs



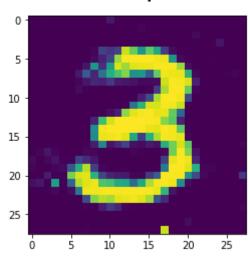
after 80 epochs



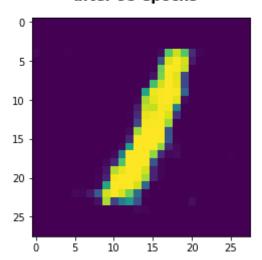
after 85 epochs



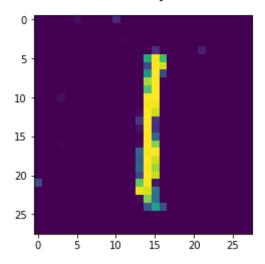
after 90 epochs



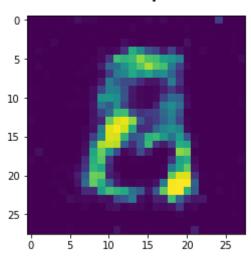
after 95 epochs



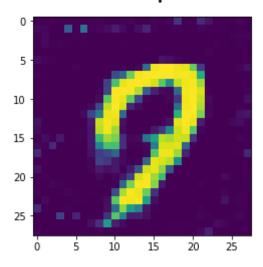
after 100 epochs



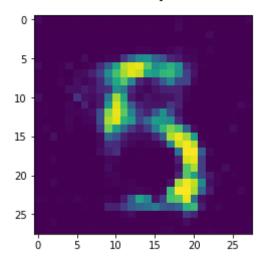
after 105 epochs



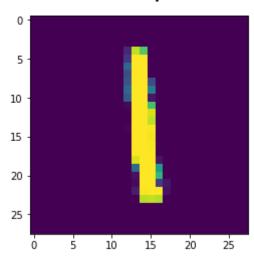
after 110 epochs



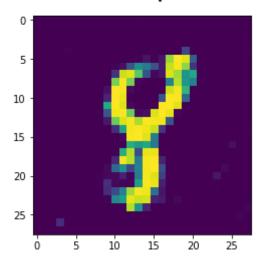
after 115 epochs



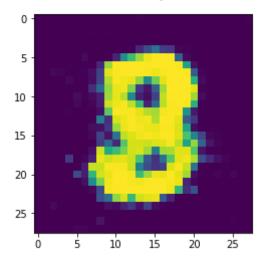
after 120 epochs



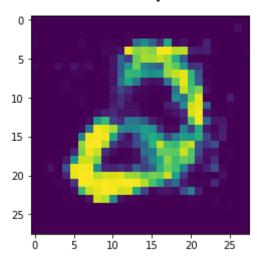
after 125 epochs



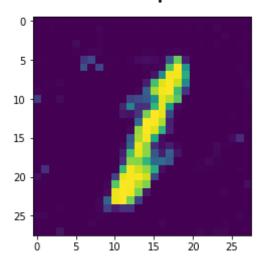
after 130 epochs



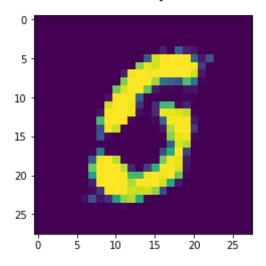
after 135 epochs



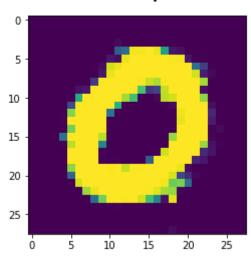
after 140 epochs



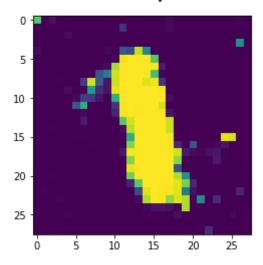
after 145 epochs



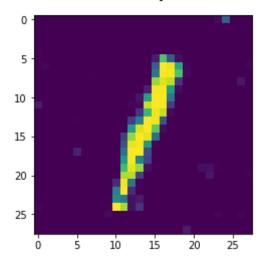
after 150 epochs



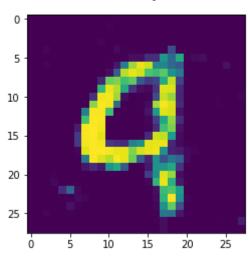
after 155 epochs



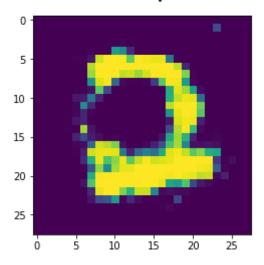
after 160 epochs



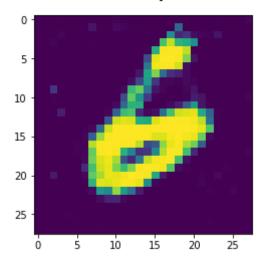
after 165 epochs



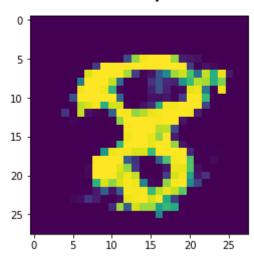
after 170 epochs



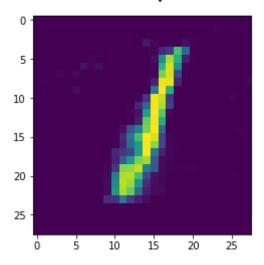
after 175 epochs



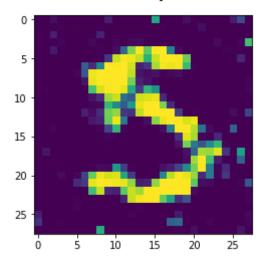
after 180 epochs



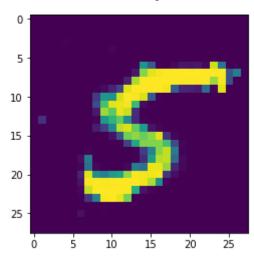
after 185 epochs



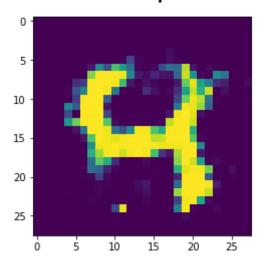
after 190 epochs



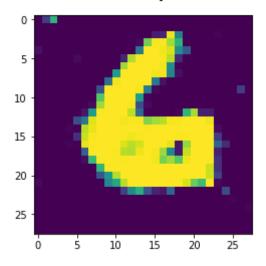
after 195 epochs



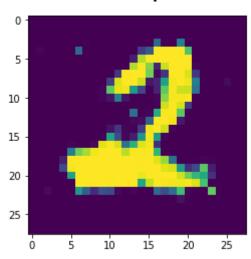
after 200 epochs



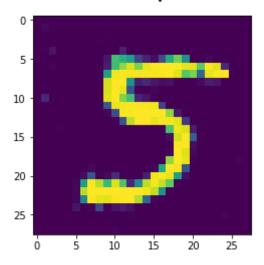
after 205 epochs



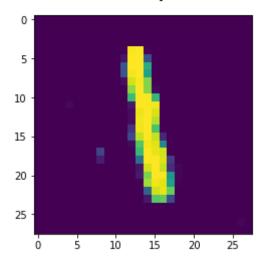
after 210 epochs



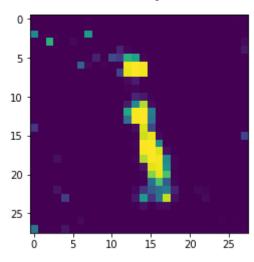
after 215 epochs



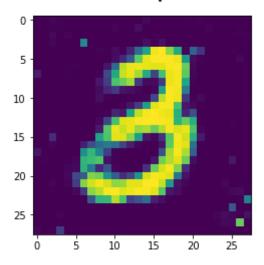
after 220 epochs



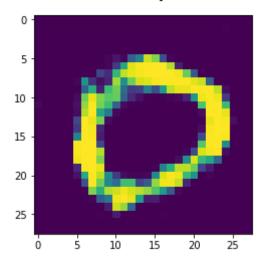
after 225 epochs



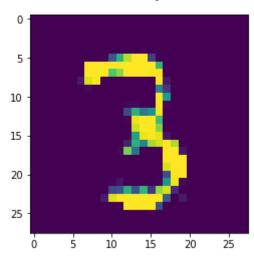
after 230 epochs



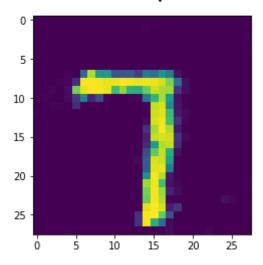
after 235 epochs



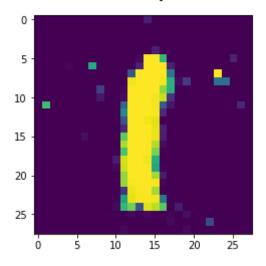
after 240 epochs



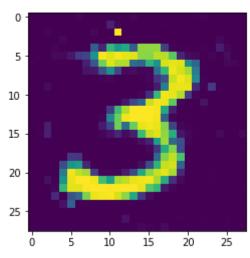
after 245 epochs



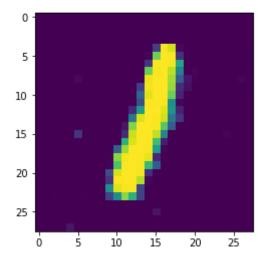
after 249 epochs



after 250 epochs



after 255 epochs



In [15]: len(samples)

Out[15]: 256