

dlnd_face_generation

July 6, 2018

1 Face Generation

In this project, you'll use generative adversarial networks to generate new images of faces. ###
Get the Data You'll be using two datasets in this project: - MNIST - CelebA

Since the celebA dataset is complex and you're doing GANs in a project for the first time, we want you to test your neural network on MNIST before CelebA. Running the GANs on MNIST will allow you to see how well your model trains sooner.

If you're using [FloydHub](#), set `data_dir` to `"/input"` and use the [FloydHub data ID](#) `"R5KrjnANiKVhLWApXhNBe"`.

```
In [1]: data_dir = '/data'
        !pip install matplotlib==2.0.2
        # FloydHub - Use with data ID "R5KrjnANiKVhLWApXhNBe"
        #data_dir = '/input'

        """
        DON'T MODIFY ANYTHING IN THIS CELL
        """

        import helper

        helper.download_extract('mnist', data_dir)
        helper.download_extract('celeba', data_dir)
```

Collecting matplotlib==2.0.2

Downloading <https://files.pythonhosted.org/packages/60/d4/6b6d8a7a6bc69a1602ab372f6fc6e88ef88a>
100% || 14.6MB 46kB/s eta 0:00:01

Requirement already satisfied: python-dateutil in /opt/conda/lib/python3.6/site-packages (from m

Requirement already satisfied: pyparsing!=2.0.0,!=2.0.4,!=2.1.2,!=2.1.6,>=1.5.6 in /opt/conda/li

Requirement already satisfied: pytz in /opt/conda/lib/python3.6/site-packages (from matplotlib==

Requirement already satisfied: numpy>=1.7.1 in /opt/conda/lib/python3.6/site-packages (from matp

Requirement already satisfied: cyclor>=0.10 in /opt/conda/lib/python3.6/site-packages/cyclor-0.1

Requirement already satisfied: six>=1.10 in /opt/conda/lib/python3.6/site-packages (from matplot

Installing collected packages: matplotlib

Found existing installation: matplotlib 2.1.0

Uninstalling matplotlib-2.1.0:

Successfully uninstalled matplotlib-2.1.0

Successfully installed matplotlib-2.0.2

You are using pip version 9.0.1, however version 10.0.1 is available.You should consider upgrading to the latest pip version. To update to the latest pip version, run: `python -m pip install --upgrade pip`

Found mnist Data

Found celeba Data

1.1 Explore the Data

1.1.1 MNIST

As you're aware, the [MNIST](#) dataset contains images of handwritten digits. You can view the first number of examples by changing `show_n_images`.

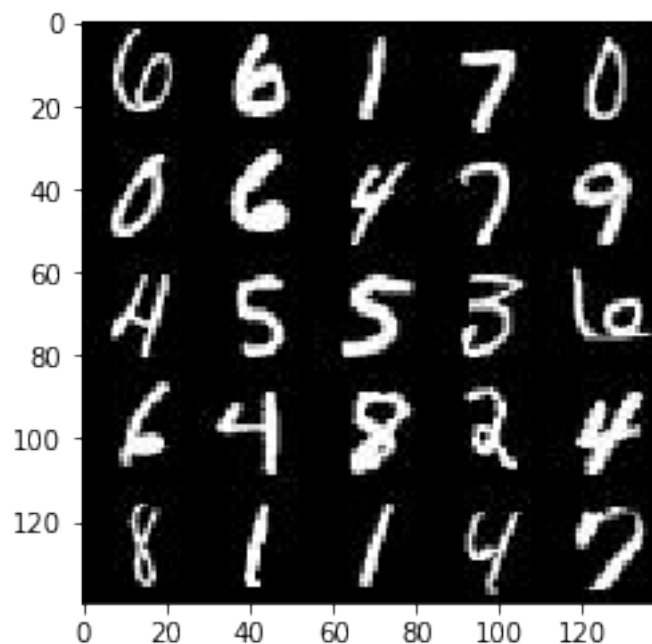
```
In [2]: show_n_images = 25
```

```
"""
DON'T MODIFY ANYTHING IN THIS CELL
"""

%matplotlib inline
import os
from glob import glob
from matplotlib import pyplot

mnist_images = helper.get_batch(glob(os.path.join(data_dir, 'mnist/*.jpg'))[:show_n_images])
pyplot.imshow(helper.images_square_grid(mnist_images, 'L'), cmap='gray')
```

```
Out[2]: <matplotlib.image.AxesImage at 0x7f00c29cae80>
```



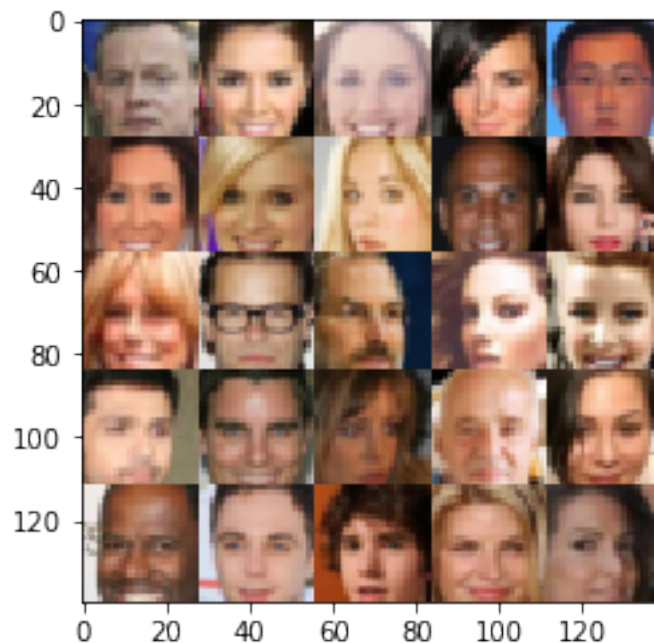
1.1.2 CelebA

The [CelebFaces Attributes Dataset \(CelebA\)](#) dataset contains over 200,000 celebrity images with annotations. Since you're going to be generating faces, you won't need the annotations. You can view the first number of examples by changing `show_n_images`.

```
In [3]: show_n_images = 25
```

```
"""  
DON'T MODIFY ANYTHING IN THIS CELL  
"""  
mnist_images = helper.get_batch(glob(os.path.join(data_dir, 'img_align_celeba/*.jpg'))[:  
pyplot.imshow(helper.images_square_grid(mnist_images, 'RGB'))
```

```
Out[3]: <matplotlib.image.AxesImage at 0x7f00c28b4b38>
```



1.2 Preprocess the Data

Since the project's main focus is on building the GANs, we'll preprocess the data for you. The values of the MNIST and CelebA dataset will be in the range of -0.5 to 0.5 of 28x28 dimensional images. The CelebA images will be cropped to remove parts of the image that don't include a face, then resized down to 28x28.

The MNIST images are black and white images with a single [color channel](https://en.wikipedia.org/wiki/Channel_(digital_image%29) while the CelebA images have [3 color channels (RGB color channel)](https://en.wikipedia.org/wiki/Channel_(digital_image%29#RGB_Images). ## Build

the Neural Network You'll build the components necessary to build a GANs by implementing the following functions below: - model_inputs - discriminator - generator - model_loss - model_opt - train

1.2.1 Check the Version of TensorFlow and Access to GPU

This will check to make sure you have the correct version of TensorFlow and access to a GPU

```
In [4]: """
        DON'T MODIFY ANYTHING IN THIS CELL
        """

        from distutils.version import LooseVersion
        import warnings
        import tensorflow as tf

        # Check TensorFlow Version
        assert LooseVersion(tf.__version__) >= LooseVersion('1.0'), 'Please use TensorFlow version 1.0 or higher'
        print('TensorFlow Version: {}'.format(tf.__version__))

        # Check for a GPU
        if not tf.test.gpu_device_name():
            warnings.warn('No GPU found. Please use a GPU to train your neural network.')
        else:
            print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
```

```
TensorFlow Version: 1.3.0
Default GPU Device: /gpu:0
```

1.2.2 Input

Implement the model_inputs function to create TF Placeholders for the Neural Network. It should create the following placeholders: - Real input images placeholder with rank 4 using image_width, image_height, and image_channels. - Z input placeholder with rank 2 using z_dim. - Learning rate placeholder with rank 0.

Return the placeholders in the following the tuple (tensor of real input images, tensor of z data)

```
In [5]: import problem_unittests as tests

        def model_inputs(image_width, image_height, image_channels, z_dim):
            """
            Create the model inputs
            :param image_width: The input image width
            :param image_height: The input image height
            :param image_channels: The number of image channels
            :param z_dim: The dimension of Z
            :return: Tuple of (tensor of real input images, tensor of z data, learning rate)
            """
```

```

# TODO: Implement Function
real_inputs = tf.placeholder(tf.float32, (None, image_width, image_height, image_channels))
z_inputs = tf.placeholder(tf.float32, (None, z_dim), name='z_inputs')
learning_rate = tf.placeholder(tf.float32, name='learning_rate')
return real_inputs, z_inputs, learning_rate

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

tests.test_model_inputs(model_inputs)

ERROR:tensorflow:=====
Object was never used (type <class 'tensorflow.python.framework.ops.Operation'>):
<tf.Operation 'assert_rank_2/Assert/Assert' type=Assert>
If you want to mark it as used call its "mark_used()" method.
It was originally created here:
['File "/opt/conda/lib/python3.6/runpy.py", line 193, in _run_module_as_main\n      "__main__", mo
=====
Tests Passed

```

1.2.3 Discriminator

Implement discriminator to create a discriminator neural network that discriminates on images. This function should be able to reuse the variables in the neural network. Use `tf.variable_scope` with a scope name of “discriminator” to allow the variables to be reused. The function should return a tuple of (tensor output of the discriminator, tensor logits of the discriminator).

```

In [6]: def discriminator(images, reuse=False):
        """
        Create the discriminator network
        :param images: Tensor of input image(s)
        :param reuse: Boolean if the weights should be reused
        :return: Tuple of (tensor output of the discriminator, tensor logits of the discriminator)
        """
        # TODO: Implement Function
        alpha = 0.2
        with tf.variable_scope('discriminator', reuse=reuse):
            # input layer is 28x28x3 (faces) or 28x28x1 (mnist)
            x1 = tf.layers.conv2d(images, 64, 5, strides=2, padding='same')
            x1 = tf.maximum(alpha * x1, x1)
            # 14x14x64

            x2 = tf.layers.conv2d(x1, 128, 5, strides=2, padding='same')
            x2 = tf.layers.batch_normalization(x2, training=True)
            x2 = tf.maximum(alpha * x2, x2)
            # 7x7x128

```

```

x3 = tf.layers.conv2d(x2, 256, 5, strides=2, padding='same')
x3 = tf.layers.batch_normalization(x3, training=True)
x3 = tf.maximum(alpha * x3, x3)
# 4x4x256

# last layer is fully connected
x4 = tf.reshape(x3, (-1, 4*4*256))
logits = tf.layers.dense(x4, 1)
out = tf.sigmoid(logits)

return out, logits

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""
tests.test_discriminator(discriminator, tf)

```

Tests Passed

1.2.4 Generator

Implement generator to generate an image using z . This function should be able to reuse the variables in the neural network. Use `tf.variable_scope` with a scope name of “generator” to allow the variables to be reused. The function should return the generated $28 \times 28 \times \text{out_channel_dim}$ images.

```

In [23]: def generator(z, out_channel_dim, is_train=True):
        """
        Create the generator network
        :param z: Input z
        :param out_channel_dim: The number of channels in the output image
        :param is_train: Boolean if generator is being used for training
        :return: The tensor output of the generator
        """
        # TODO: Implement Function
        alpha = 0.2
        with tf.variable_scope('generator', reuse=(not is_train)):
            # start with a fully connected layer
            x1 = tf.layers.dense(z, 4*4*1024)

            # reshape it for a convolutional stack
            x1 = tf.reshape(x1, (-1, 4, 4, 1024))
            x1 = tf.layers.batch_normalization(x1, training=is_train)
            x1 = tf.maximum(alpha * x1, x1)
            # 4x4x1024 now

```

```

# first convolutional layer
# formula for converting 4x4 input to 7x7 output:
#     https://discussions.udacity.com/t/project5-discriminator-and-generator-l
conv1 = tf.layers.conv2d_transpose(x1, 512, 4, strides=1, padding='valid')
conv1 = tf.layers.batch_normalization(conv1, training=is_train)
conv1 = tf.maximum(alpha*conv1, conv1)
# now 7x7x512

# second convolutional layer
x2 = tf.layers.conv2d_transpose(conv1, 256, 5, strides=2, padding='same')
x2 = tf.layers.batch_normalization(x2, training=is_train)
x2 = tf.maximum(alpha * x2, x2)
# 14x14x256 now

# final convolutional layer.
# Don't use batch normalization.
# Use a tanh activation function
logits = tf.layers.conv2d_transpose(x2, out_channel_dim, 5, strides=2, padding='valid')
out = tf.tanh(logits)
# 28x28xOut_channel_dim now

return out

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

tests.test_generator(generator, tf)

```

Tests Passed

1.2.5 Loss

Implement `model_loss` to build the GANs for training and calculate the loss. The function should return a tuple of (discriminator loss, generator loss). Use the following functions you implemented: - `discriminator(images, reuse=False)` - `generator(z, out_channel_dim, is_train=True)`

```

In [8]: def model_loss(input_real, input_z, out_channel_dim):
        """
        Get the loss for the discriminator and generator
        :param input_real: Images from the real dataset
        :param input_z: Z input
        :param out_channel_dim: The number of channels in the output image
        :return: A tuple of (discriminator loss, generator loss)
        """

```

```

# TODO: Implement Function
g_model = generator(input_z, out_channel_dim, is_train=True)
d_model_real, d_logits_real = discriminator(input_real, reuse=False)
d_model_fake, d_logits_fake = discriminator(g_model, reuse=True)

d_loss_real = tf.reduce_mean(
    tf.nn.sigmoid_cross_entropy_with_logits(logits=d_logits_real, labels=tf.ones_like(d_logits_real))
)
d_loss_fake = tf.reduce_mean(
    tf.nn.sigmoid_cross_entropy_with_logits(logits=d_logits_fake, labels=tf.zeros_like(d_logits_fake))
)
g_loss = tf.reduce_mean(
    tf.nn.sigmoid_cross_entropy_with_logits(logits=d_logits_fake, labels=tf.ones_like(d_logits_fake))
)

d_loss = d_loss_real + d_loss_fake

return d_loss, g_loss

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""

tests.test_model_loss(model_loss)

```

Tests Passed

1.2.6 Optimization

Implement `model_opt` to create the optimization operations for the GANs. Use `tf.trainable_variables` to get all the trainable variables. Filter the variables with names that are in the discriminator and generator scope names. The function should return a tuple of (discriminator training operation, generator training operation).

```

In [9]: def model_opt(d_loss, g_loss, learning_rate, beta1):
        """
        Get optimization operations
        :param d_loss: Discriminator loss Tensor
        :param g_loss: Generator loss Tensor
        :param learning_rate: Learning Rate Placeholder
        :param beta1: The exponential decay rate for the 1st moment in the optimizer
        :return: A tuple of (discriminator training operation, generator training operation)
        """

        # TODO: Implement Function
        # get the discriminator and generator variables
        train_vars = tf.trainable_variables()
        d_vars = [v for v in train_vars if v.name.startswith('discriminator')]
        g_vars = [v for v in train_vars if v.name.startswith('generator')]

        with tf.control_dependencies(tf.get_collection(tf.GraphKeys.UPDATE_OPS)):

```



```

        d_train_opt = tf.train.AdamOptimizer(learning_rate=learning_rate, beta1=beta1).m
        g_train_opt = tf.train.AdamOptimizer(learning_rate=learning_rate, beta1=beta1).m

    return d_train_opt, g_train_opt

"""
DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
"""
tests.test_model_opt(model_opt, tf)

```

Tests Passed

1.3 Neural Network Training

1.3.1 Show Output

Use this function to show the current output of the generator during training. It will help you determine how well the GANs is training.

```

In [10]: """
        DON'T MODIFY ANYTHING IN THIS CELL
        """
        import numpy as np

        def show_generator_output(sess, n_images, input_z, out_channel_dim, image_mode):
            """
            Show example output for the generator
            :param sess: TensorFlow session
            :param n_images: Number of Images to display
            :param input_z: Input Z Tensor
            :param out_channel_dim: The number of channels in the output image
            :param image_mode: The mode to use for images ("RGB" or "L")
            """
            cmap = None if image_mode == 'RGB' else 'gray'
            z_dim = input_z.get_shape().as_list()[-1]
            example_z = np.random.uniform(-1, 1, size=[n_images, z_dim])

            samples = sess.run(
                generator(input_z, out_channel_dim, False),
                feed_dict={input_z: example_z})

            images_grid = helper.images_square_grid(samples, image_mode)
            pyplot.imshow(images_grid, cmap=cmap)
            pyplot.show()

In [11]: %matplotlib inline
        from matplotlib import pyplot as plt

```

```
def plot_losses(d_loss, g_loss):
    """
    Plot the discriminator and generator losses on the same graph
    :param d_loss: list of loss values for the discriminator
    :param g_loss: list of loss values for the generator
    """
    fig, ax = plt.subplots()
    plt.plot(d_loss, label='Discriminator', alpha=0.5)
    plt.plot(g_loss, label='Generator', alpha=0.5)
    plt.title("Training Losses")
    plt.legend()
```

1.3.2 Train

Implement train to build and train the GANs. Use the following functions you implemented:

- model_inputs(image_width, image_height, image_channels, z_dim)
- model_loss(input_real, input_z, out_channel_dim)
- model_opt(d_loss, g_loss, learning_rate, beta1)

Use the show_generator_output to show generator output while you train. Running show_generator_output for every batch will drastically increase training time and increase the size of the notebook. It's recommended to print the generator output every 100 batches.

```
In [24]: def train(epoch_count, batch_size, z_dim, learning_rate, beta1, get_batches, data_shape)
    """
    Train the GAN
    :param epoch_count: Number of epochs
    :param batch_size: Batch Size
    :param z_dim: Z dimension
    :param learning_rate: Learning Rate
    :param beta1: The exponential decay rate for the 1st moment in the optimizer
    :param get_batches: Function to get batches
    :param data_shape: Shape of the data
    :param data_image_mode: The image mode to use for images ("RGB" or "L")
    """
    # TODO: Build Model
    import time
    real_inputs, z_inputs, lr = model_inputs(data_shape[1], data_shape[2], data_shape[3])
    d_loss, g_loss = model_loss(real_inputs, z_inputs, data_shape[-1])
    d_train_opt, g_train_opt = model_opt(d_loss, g_loss, learning_rate, beta1)

    batch_no = 0
    show_every = 100
    stats_every = 5
    n_images_to_show = 25
    n_images = data_shape[0]
    total_batches = (n_images // batch_size) * epoch_count
    start_time = time.time()
```

```

d_losses = []
g_losses = []

with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    for epoch_i in range(epoch_count):
        for batch_images in get_batches(batch_size):
            # TODO: Train Model
            # batch_start = time.time()
            batch_no += 1

            # scale batch images to [-1.0, 1.0]
            batch_images = batch_images * 2
            batch_z = np.random.uniform(-1, 1, size=(batch_size, z_dim))

            _ = sess.run(d_train_opt, feed_dict={real_inputs: batch_images, z_inputs: batch_z})
            _ = sess.run(g_train_opt, feed_dict={real_inputs: batch_images, z_inputs: batch_z})

            # compute some execution time stats for each batch
            if batch_no % stats_every == 0:
                current_time = time.time()
                total_time = current_time - start_time
                # time_this_batch = current_time - batch_start
                time_per_batch = total_time / batch_no
                remaining_time = int(time_per_batch * (total_batches - batch_no))

                train_loss_d = d_loss.eval({z_inputs: batch_z, real_inputs: batch_images})
                train_loss_g = g_loss.eval({z_inputs: batch_z, lr: learning_rate})
                d_losses.append(train_loss_d)
                g_losses.append(train_loss_g)
                print("Epoch {}/ {}: batch {}/ {}: \ttime/batch: {:.2f}s\tremaining time: {:.2f}s".format(
                    epoch_i, epoch_count, batch_no, total_batches, time_per_batch, remaining_time))

            # show generator output every show_every steps
            if batch_no % show_every == 0:
                show_generator_output(sess, n_images_to_show, z_inputs, data_shape[1:])

        # show the final output
        show_generator_output(sess, n_images_to_show, z_inputs, data_shape[-1], data_inputs)
    return d_losses, g_losses

```

1.3.3 MNIST

Test your GANs architecture on MNIST. After 2 epochs, the GANs should be able to generate images that look like handwritten digits. Make sure the loss of the generator is lower than the loss of the discriminator or close to 0.

1.3.4 MNIST Run 1

Generator shape: - layer 1: 4x4x1024 with LRELU activation - layer 2: 7x7x512 with LRELU - layer 3: 14x14x256 with LRELU - layer 4: 28x28xOutput_Channel with TANH

```
In [13]: batch_size = 128
         z_dim = 100
         learning_rate = 0.0002
         beta1 = 0.5

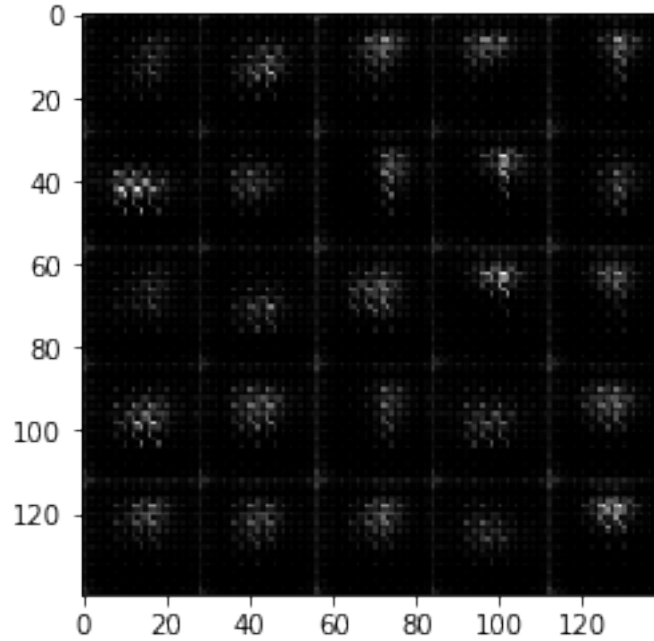
         d_losses = []
         g_losses = []

         """
         DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
         """

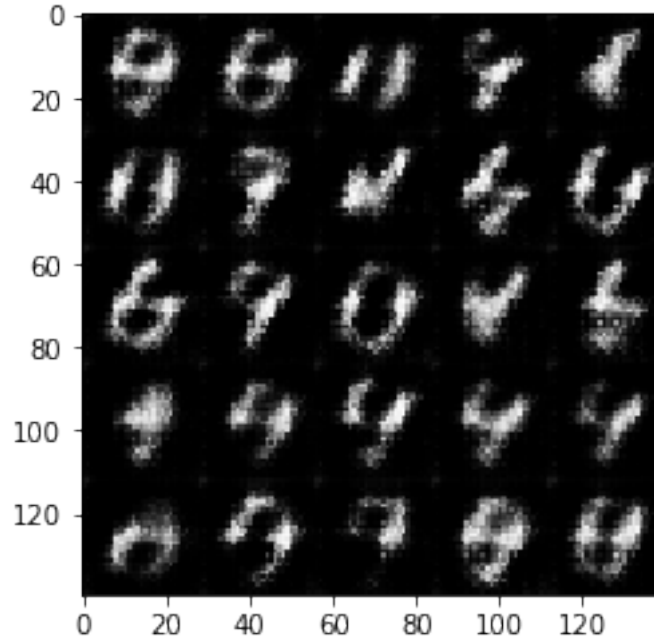
         epochs = 2

         mnist_dataset = helper.Dataset('mnist', glob(os.path.join(data_dir, 'mnist/*.jpg')))
         with tf.Graph().as_default():
             # jcc: added lists for plotting discriminator and generator losses
             d_losses, g_losses = train(epochs, batch_size, z_dim, learning_rate, beta1, mnist_d,
                                         mnist_dataset.shape, mnist_dataset.image_mode)

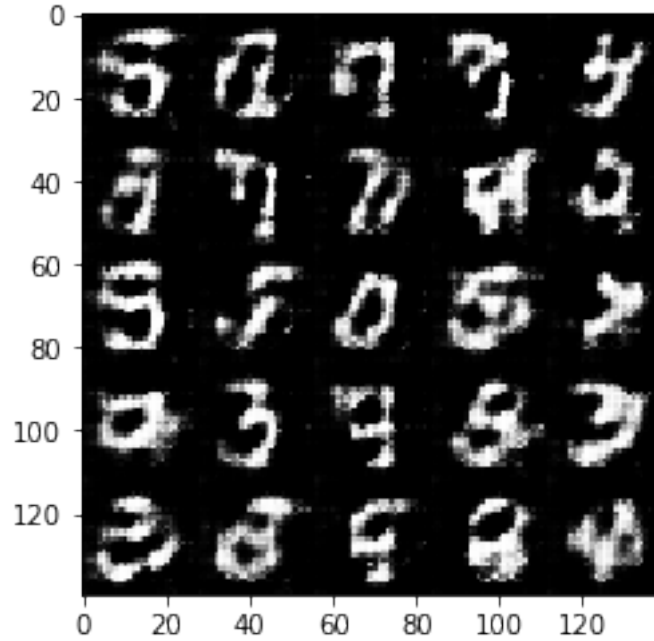
Epoch 1/2: batch 5/936:      time/batch: 1.68s      remaining time: 1565s      d_loss: 1
Epoch 1/2: batch 10/936:    time/batch: 1.12s      remaining time: 1036s      d_loss:
Epoch 1/2: batch 15/936:    time/batch: 0.93s      remaining time: 855s       d_loss: 0
Epoch 1/2: batch 20/936:    time/batch: 0.83s      remaining time: 764s       d_loss: 0
Epoch 1/2: batch 25/936:    time/batch: 0.78s      remaining time: 708s       d_loss: 0
Epoch 1/2: batch 30/936:    time/batch: 0.74s      remaining time: 669s       d_loss: 0
Epoch 1/2: batch 35/936:    time/batch: 0.71s      remaining time: 642s       d_loss: 0
Epoch 1/2: batch 40/936:    time/batch: 0.69s      remaining time: 619s       d_loss: 0
Epoch 1/2: batch 45/936:    time/batch: 0.68s      remaining time: 602s       d_loss: 0
Epoch 1/2: batch 50/936:    time/batch: 0.66s      remaining time: 588s       d_loss: 0
Epoch 1/2: batch 55/936:    time/batch: 0.65s      remaining time: 575s       d_loss: 0
Epoch 1/2: batch 60/936:    time/batch: 0.64s      remaining time: 564s       d_loss: 0
Epoch 1/2: batch 65/936:    time/batch: 0.64s      remaining time: 554s       d_loss: 4
Epoch 1/2: batch 70/936:    time/batch: 0.63s      remaining time: 546s       d_loss: 0
Epoch 1/2: batch 75/936:    time/batch: 0.63s      remaining time: 538s       d_loss: 0
Epoch 1/2: batch 80/936:    time/batch: 0.62s      remaining time: 531s       d_loss: 0
Epoch 1/2: batch 85/936:    time/batch: 0.62s      remaining time: 525s       d_loss: 0
Epoch 1/2: batch 90/936:    time/batch: 0.61s      remaining time: 518s       d_loss: 0
Epoch 1/2: batch 95/936:    time/batch: 0.61s      remaining time: 512s       d_loss: 0
Epoch 1/2: batch 100/936:   time/batch: 0.61s      remaining time: 507s       d_loss:
```



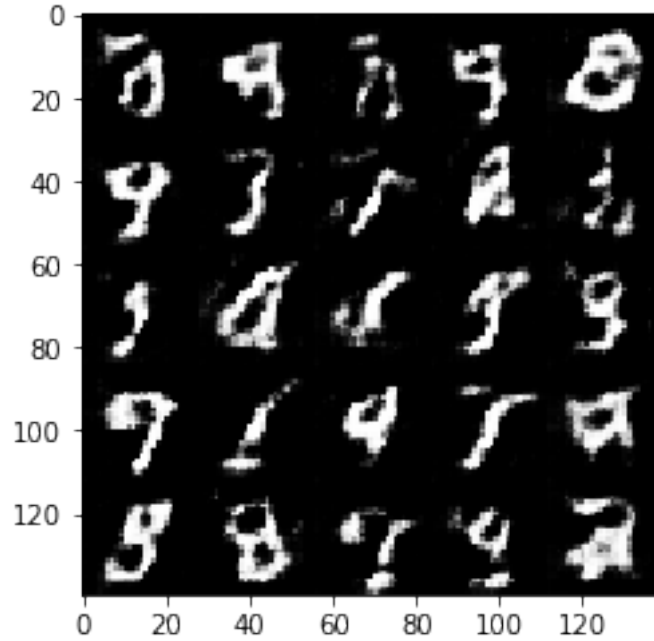
Epoch 1/2: batch 105/936:	time/batch: 0.61s	remaining time: 506s	d_loss:
Epoch 1/2: batch 110/936:	time/batch: 0.61s	remaining time: 500s	d_loss:
Epoch 1/2: batch 115/936:	time/batch: 0.60s	remaining time: 495s	d_loss:
Epoch 1/2: batch 120/936:	time/batch: 0.60s	remaining time: 491s	d_loss:
Epoch 1/2: batch 125/936:	time/batch: 0.60s	remaining time: 486s	d_loss:
Epoch 1/2: batch 130/936:	time/batch: 0.60s	remaining time: 482s	d_loss:
Epoch 1/2: batch 135/936:	time/batch: 0.60s	remaining time: 477s	d_loss:
Epoch 1/2: batch 140/936:	time/batch: 0.60s	remaining time: 473s	d_loss:
Epoch 1/2: batch 145/936:	time/batch: 0.59s	remaining time: 469s	d_loss:
Epoch 1/2: batch 150/936:	time/batch: 0.59s	remaining time: 465s	d_loss:
Epoch 1/2: batch 155/936:	time/batch: 0.59s	remaining time: 461s	d_loss:
Epoch 1/2: batch 160/936:	time/batch: 0.59s	remaining time: 457s	d_loss:
Epoch 1/2: batch 165/936:	time/batch: 0.59s	remaining time: 453s	d_loss:
Epoch 1/2: batch 170/936:	time/batch: 0.59s	remaining time: 449s	d_loss:
Epoch 1/2: batch 175/936:	time/batch: 0.59s	remaining time: 446s	d_loss:
Epoch 1/2: batch 180/936:	time/batch: 0.59s	remaining time: 442s	d_loss:
Epoch 1/2: batch 185/936:	time/batch: 0.58s	remaining time: 438s	d_loss:
Epoch 1/2: batch 190/936:	time/batch: 0.58s	remaining time: 435s	d_loss:
Epoch 1/2: batch 195/936:	time/batch: 0.58s	remaining time: 431s	d_loss:
Epoch 1/2: batch 200/936:	time/batch: 0.58s	remaining time: 428s	d_loss:



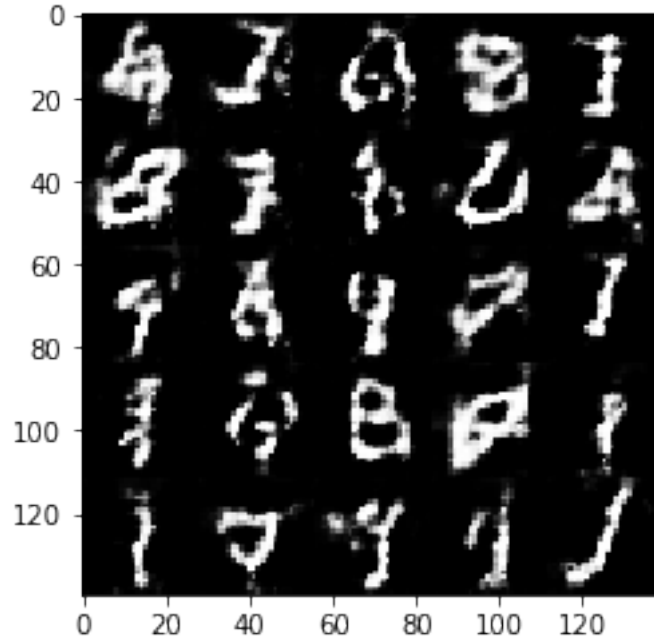
Epoch 1/2: batch 205/936:	time/batch: 0.58s	remaining time: 425s	d_loss:
Epoch 1/2: batch 210/936:	time/batch: 0.58s	remaining time: 422s	d_loss:
Epoch 1/2: batch 215/936:	time/batch: 0.58s	remaining time: 419s	d_loss:
Epoch 1/2: batch 220/936:	time/batch: 0.58s	remaining time: 415s	d_loss:
Epoch 1/2: batch 225/936:	time/batch: 0.58s	remaining time: 412s	d_loss:
Epoch 1/2: batch 230/936:	time/batch: 0.58s	remaining time: 408s	d_loss:
Epoch 1/2: batch 235/936:	time/batch: 0.58s	remaining time: 405s	d_loss:
Epoch 1/2: batch 240/936:	time/batch: 0.58s	remaining time: 402s	d_loss:
Epoch 1/2: batch 245/936:	time/batch: 0.58s	remaining time: 399s	d_loss:
Epoch 1/2: batch 250/936:	time/batch: 0.58s	remaining time: 395s	d_loss:
Epoch 1/2: batch 255/936:	time/batch: 0.58s	remaining time: 392s	d_loss:
Epoch 1/2: batch 260/936:	time/batch: 0.58s	remaining time: 389s	d_loss:
Epoch 1/2: batch 265/936:	time/batch: 0.58s	remaining time: 386s	d_loss:
Epoch 1/2: batch 270/936:	time/batch: 0.58s	remaining time: 383s	d_loss:
Epoch 1/2: batch 275/936:	time/batch: 0.57s	remaining time: 379s	d_loss:
Epoch 1/2: batch 280/936:	time/batch: 0.57s	remaining time: 376s	d_loss:
Epoch 1/2: batch 285/936:	time/batch: 0.57s	remaining time: 373s	d_loss:
Epoch 1/2: batch 290/936:	time/batch: 0.57s	remaining time: 370s	d_loss:
Epoch 1/2: batch 295/936:	time/batch: 0.57s	remaining time: 367s	d_loss:
Epoch 1/2: batch 300/936:	time/batch: 0.57s	remaining time: 364s	d_loss:



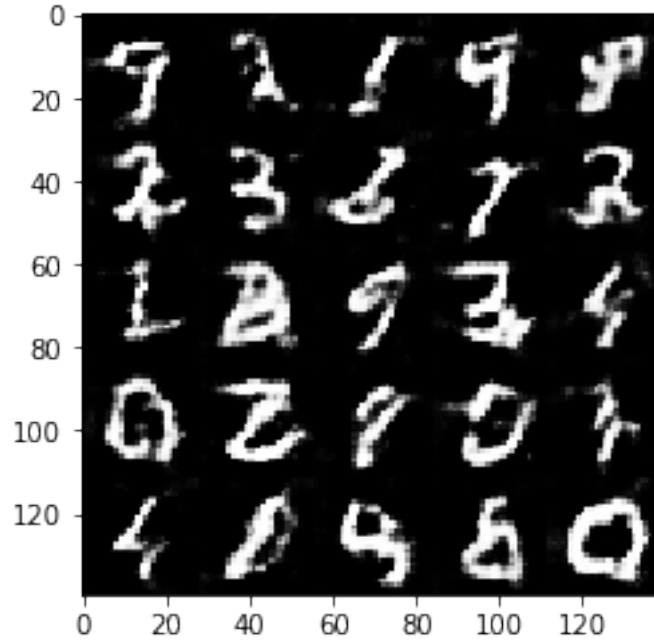
Epoch 1/2: batch 305/936:	time/batch: 0.57s	remaining time: 361s	d_loss:
Epoch 1/2: batch 310/936:	time/batch: 0.57s	remaining time: 358s	d_loss:
Epoch 1/2: batch 315/936:	time/batch: 0.57s	remaining time: 355s	d_loss:
Epoch 1/2: batch 320/936:	time/batch: 0.57s	remaining time: 352s	d_loss:
Epoch 1/2: batch 325/936:	time/batch: 0.57s	remaining time: 349s	d_loss:
Epoch 1/2: batch 330/936:	time/batch: 0.57s	remaining time: 346s	d_loss:
Epoch 1/2: batch 335/936:	time/batch: 0.57s	remaining time: 343s	d_loss:
Epoch 1/2: batch 340/936:	time/batch: 0.57s	remaining time: 340s	d_loss:
Epoch 1/2: batch 345/936:	time/batch: 0.57s	remaining time: 337s	d_loss:
Epoch 1/2: batch 350/936:	time/batch: 0.57s	remaining time: 334s	d_loss:
Epoch 1/2: batch 355/936:	time/batch: 0.57s	remaining time: 331s	d_loss:
Epoch 1/2: batch 360/936:	time/batch: 0.57s	remaining time: 328s	d_loss:
Epoch 1/2: batch 365/936:	time/batch: 0.57s	remaining time: 325s	d_loss:
Epoch 1/2: batch 370/936:	time/batch: 0.57s	remaining time: 322s	d_loss:
Epoch 1/2: batch 375/936:	time/batch: 0.57s	remaining time: 319s	d_loss:
Epoch 1/2: batch 380/936:	time/batch: 0.57s	remaining time: 316s	d_loss:
Epoch 1/2: batch 385/936:	time/batch: 0.57s	remaining time: 313s	d_loss:
Epoch 1/2: batch 390/936:	time/batch: 0.57s	remaining time: 310s	d_loss:
Epoch 1/2: batch 395/936:	time/batch: 0.57s	remaining time: 307s	d_loss:
Epoch 1/2: batch 400/936:	time/batch: 0.57s	remaining time: 304s	d_loss:



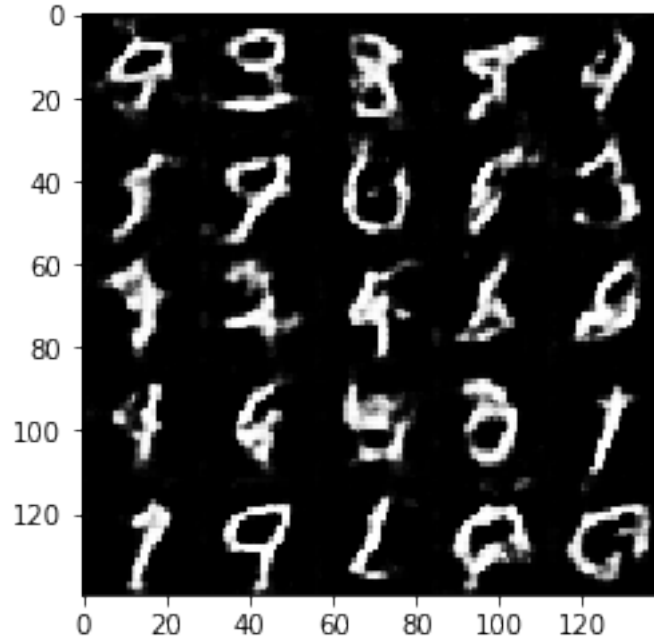
Epoch 1/2: batch 405/936:	time/batch: 0.57s	remaining time: 301s	d_loss:
Epoch 1/2: batch 410/936:	time/batch: 0.57s	remaining time: 298s	d_loss:
Epoch 1/2: batch 415/936:	time/batch: 0.57s	remaining time: 296s	d_loss:
Epoch 1/2: batch 420/936:	time/batch: 0.57s	remaining time: 293s	d_loss:
Epoch 1/2: batch 425/936:	time/batch: 0.57s	remaining time: 290s	d_loss:
Epoch 1/2: batch 430/936:	time/batch: 0.57s	remaining time: 287s	d_loss:
Epoch 1/2: batch 435/936:	time/batch: 0.57s	remaining time: 284s	d_loss:
Epoch 1/2: batch 440/936:	time/batch: 0.57s	remaining time: 281s	d_loss:
Epoch 1/2: batch 445/936:	time/batch: 0.57s	remaining time: 278s	d_loss:
Epoch 1/2: batch 450/936:	time/batch: 0.57s	remaining time: 275s	d_loss:
Epoch 1/2: batch 455/936:	time/batch: 0.57s	remaining time: 272s	d_loss:
Epoch 1/2: batch 460/936:	time/batch: 0.57s	remaining time: 269s	d_loss:
Epoch 1/2: batch 465/936:	time/batch: 0.57s	remaining time: 266s	d_loss:
Epoch 2/2: batch 470/936:	time/batch: 0.57s	remaining time: 263s	d_loss:
Epoch 2/2: batch 475/936:	time/batch: 0.56s	remaining time: 260s	d_loss:
Epoch 2/2: batch 480/936:	time/batch: 0.56s	remaining time: 257s	d_loss:
Epoch 2/2: batch 485/936:	time/batch: 0.56s	remaining time: 253s	d_loss:
Epoch 2/2: batch 490/936:	time/batch: 0.56s	remaining time: 250s	d_loss:
Epoch 2/2: batch 495/936:	time/batch: 0.56s	remaining time: 247s	d_loss:
Epoch 2/2: batch 500/936:	time/batch: 0.56s	remaining time: 243s	d_loss:



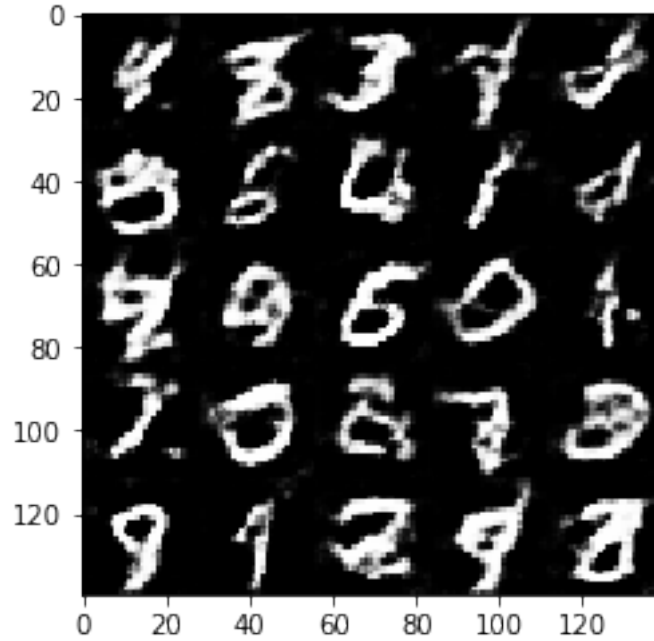
Epoch 2/2: batch 505/936:	time/batch: 0.56s	remaining time: 241s	d_loss:
Epoch 2/2: batch 510/936:	time/batch: 0.56s	remaining time: 237s	d_loss:
Epoch 2/2: batch 515/936:	time/batch: 0.56s	remaining time: 234s	d_loss:
Epoch 2/2: batch 520/936:	time/batch: 0.56s	remaining time: 231s	d_loss:
Epoch 2/2: batch 525/936:	time/batch: 0.56s	remaining time: 228s	d_loss:
Epoch 2/2: batch 530/936:	time/batch: 0.55s	remaining time: 225s	d_loss:
Epoch 2/2: batch 535/936:	time/batch: 0.55s	remaining time: 222s	d_loss:
Epoch 2/2: batch 540/936:	time/batch: 0.55s	remaining time: 218s	d_loss:
Epoch 2/2: batch 545/936:	time/batch: 0.55s	remaining time: 215s	d_loss:
Epoch 2/2: batch 550/936:	time/batch: 0.55s	remaining time: 212s	d_loss:
Epoch 2/2: batch 555/936:	time/batch: 0.55s	remaining time: 209s	d_loss:
Epoch 2/2: batch 560/936:	time/batch: 0.55s	remaining time: 206s	d_loss:
Epoch 2/2: batch 565/936:	time/batch: 0.55s	remaining time: 203s	d_loss:
Epoch 2/2: batch 570/936:	time/batch: 0.55s	remaining time: 200s	d_loss:
Epoch 2/2: batch 575/936:	time/batch: 0.55s	remaining time: 197s	d_loss:
Epoch 2/2: batch 580/936:	time/batch: 0.55s	remaining time: 194s	d_loss:
Epoch 2/2: batch 585/936:	time/batch: 0.55s	remaining time: 191s	d_loss:
Epoch 2/2: batch 590/936:	time/batch: 0.54s	remaining time: 188s	d_loss:
Epoch 2/2: batch 595/936:	time/batch: 0.54s	remaining time: 185s	d_loss:
Epoch 2/2: batch 600/936:	time/batch: 0.54s	remaining time: 182s	d_loss:



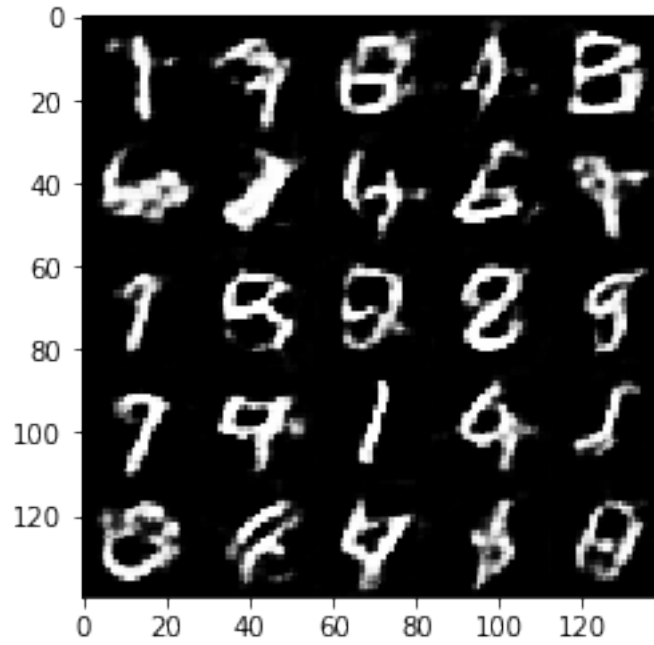
Epoch 2/2: batch 605/936:	time/batch: 0.54s	remaining time: 179s	d_loss:
Epoch 2/2: batch 610/936:	time/batch: 0.54s	remaining time: 176s	d_loss:
Epoch 2/2: batch 615/936:	time/batch: 0.54s	remaining time: 173s	d_loss:
Epoch 2/2: batch 620/936:	time/batch: 0.54s	remaining time: 171s	d_loss:
Epoch 2/2: batch 625/936:	time/batch: 0.54s	remaining time: 168s	d_loss:
Epoch 2/2: batch 630/936:	time/batch: 0.54s	remaining time: 165s	d_loss:
Epoch 2/2: batch 635/936:	time/batch: 0.54s	remaining time: 162s	d_loss:
Epoch 2/2: batch 640/936:	time/batch: 0.54s	remaining time: 159s	d_loss:
Epoch 2/2: batch 645/936:	time/batch: 0.54s	remaining time: 156s	d_loss:
Epoch 2/2: batch 650/936:	time/batch: 0.54s	remaining time: 153s	d_loss:
Epoch 2/2: batch 655/936:	time/batch: 0.54s	remaining time: 150s	d_loss:
Epoch 2/2: batch 660/936:	time/batch: 0.54s	remaining time: 148s	d_loss:
Epoch 2/2: batch 665/936:	time/batch: 0.54s	remaining time: 145s	d_loss:
Epoch 2/2: batch 670/936:	time/batch: 0.54s	remaining time: 142s	d_loss:
Epoch 2/2: batch 675/936:	time/batch: 0.53s	remaining time: 139s	d_loss:
Epoch 2/2: batch 680/936:	time/batch: 0.53s	remaining time: 136s	d_loss:
Epoch 2/2: batch 685/936:	time/batch: 0.53s	remaining time: 133s	d_loss:
Epoch 2/2: batch 690/936:	time/batch: 0.53s	remaining time: 131s	d_loss:
Epoch 2/2: batch 695/936:	time/batch: 0.53s	remaining time: 128s	d_loss:
Epoch 2/2: batch 700/936:	time/batch: 0.53s	remaining time: 125s	d_loss:



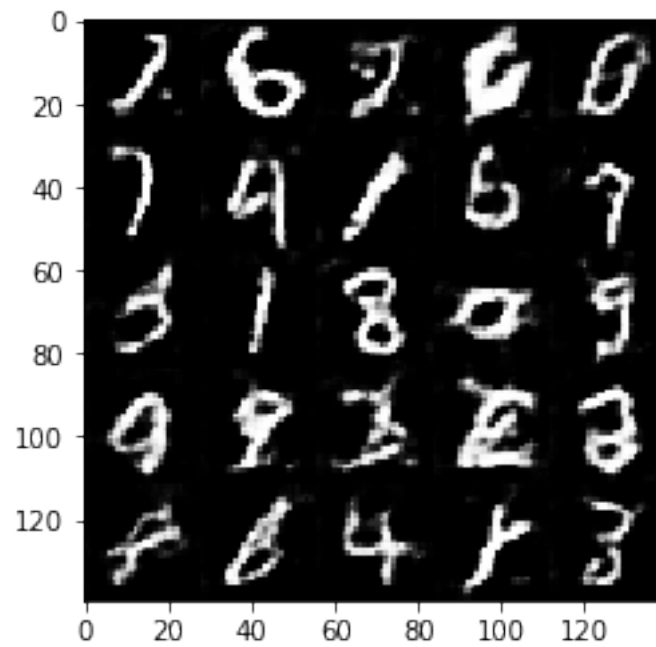
Epoch 2/2: batch 705/936:	time/batch: 0.53s	remaining time: 122s	d_loss:
Epoch 2/2: batch 710/936:	time/batch: 0.53s	remaining time: 120s	d_loss:
Epoch 2/2: batch 715/936:	time/batch: 0.53s	remaining time: 117s	d_loss:
Epoch 2/2: batch 720/936:	time/batch: 0.53s	remaining time: 114s	d_loss:
Epoch 2/2: batch 725/936:	time/batch: 0.53s	remaining time: 111s	d_loss:
Epoch 2/2: batch 730/936:	time/batch: 0.53s	remaining time: 109s	d_loss:
Epoch 2/2: batch 735/936:	time/batch: 0.53s	remaining time: 106s	d_loss:
Epoch 2/2: batch 740/936:	time/batch: 0.53s	remaining time: 103s	d_loss:
Epoch 2/2: batch 745/936:	time/batch: 0.53s	remaining time: 100s	d_loss:
Epoch 2/2: batch 750/936:	time/batch: 0.53s	remaining time: 98s	d_loss: 1
Epoch 2/2: batch 755/936:	time/batch: 0.53s	remaining time: 95s	d_loss: 1
Epoch 2/2: batch 760/936:	time/batch: 0.53s	remaining time: 92s	d_loss: 1
Epoch 2/2: batch 765/936:	time/batch: 0.53s	remaining time: 90s	d_loss: 1
Epoch 2/2: batch 770/936:	time/batch: 0.53s	remaining time: 87s	d_loss: 0
Epoch 2/2: batch 775/936:	time/batch: 0.53s	remaining time: 84s	d_loss: 0
Epoch 2/2: batch 780/936:	time/batch: 0.53s	remaining time: 81s	d_loss: 1
Epoch 2/2: batch 785/936:	time/batch: 0.52s	remaining time: 79s	d_loss: 0
Epoch 2/2: batch 790/936:	time/batch: 0.52s	remaining time: 76s	d_loss: 1
Epoch 2/2: batch 795/936:	time/batch: 0.52s	remaining time: 73s	d_loss: 0
Epoch 2/2: batch 800/936:	time/batch: 0.52s	remaining time: 71s	d_loss: 1



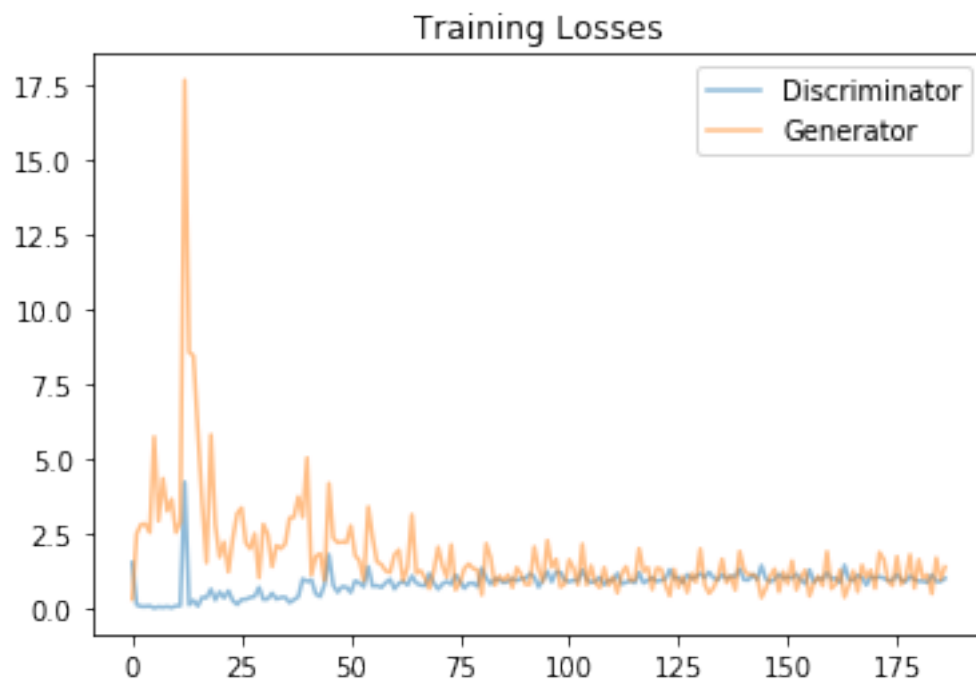
Epoch 2/2: batch 805/936:	time/batch: 0.52s	remaining time: 68s	d_loss: 1
Epoch 2/2: batch 810/936:	time/batch: 0.52s	remaining time: 65s	d_loss: 1
Epoch 2/2: batch 815/936:	time/batch: 0.52s	remaining time: 63s	d_loss: 0
Epoch 2/2: batch 820/936:	time/batch: 0.52s	remaining time: 60s	d_loss: 1
Epoch 2/2: batch 825/936:	time/batch: 0.52s	remaining time: 57s	d_loss: 0
Epoch 2/2: batch 830/936:	time/batch: 0.52s	remaining time: 55s	d_loss: 0
Epoch 2/2: batch 835/936:	time/batch: 0.52s	remaining time: 52s	d_loss: 1
Epoch 2/2: batch 840/936:	time/batch: 0.52s	remaining time: 50s	d_loss: 1
Epoch 2/2: batch 845/936:	time/batch: 0.52s	remaining time: 47s	d_loss: 0
Epoch 2/2: batch 850/936:	time/batch: 0.52s	remaining time: 44s	d_loss: 1
Epoch 2/2: batch 855/936:	time/batch: 0.52s	remaining time: 42s	d_loss: 1
Epoch 2/2: batch 860/936:	time/batch: 0.52s	remaining time: 39s	d_loss: 1
Epoch 2/2: batch 865/936:	time/batch: 0.52s	remaining time: 36s	d_loss: 1
Epoch 2/2: batch 870/936:	time/batch: 0.52s	remaining time: 34s	d_loss: 0
Epoch 2/2: batch 875/936:	time/batch: 0.52s	remaining time: 31s	d_loss: 0
Epoch 2/2: batch 880/936:	time/batch: 0.52s	remaining time: 29s	d_loss: 1
Epoch 2/2: batch 885/936:	time/batch: 0.52s	remaining time: 26s	d_loss: 0
Epoch 2/2: batch 890/936:	time/batch: 0.52s	remaining time: 23s	d_loss: 0
Epoch 2/2: batch 895/936:	time/batch: 0.52s	remaining time: 21s	d_loss: 1
Epoch 2/2: batch 900/936:	time/batch: 0.52s	remaining time: 18s	d_loss: 0



Epoch 2/2: batch 905/936:	time/batch: 0.52s	remaining time: 16s	d_loss: 0
Epoch 2/2: batch 910/936:	time/batch: 0.52s	remaining time: 13s	d_loss: 0
Epoch 2/2: batch 915/936:	time/batch: 0.52s	remaining time: 10s	d_loss: 0
Epoch 2/2: batch 920/936:	time/batch: 0.52s	remaining time: 8s	d_loss: 1.
Epoch 2/2: batch 925/936:	time/batch: 0.52s	remaining time: 5s	d_loss: 0.
Epoch 2/2: batch 930/936:	time/batch: 0.52s	remaining time: 3s	d_loss: 0.
Epoch 2/2: batch 935/936:	time/batch: 0.52s	remaining time: 0s	d_loss: 1.



```
In [14]: plot_losses(d_losses, g_losses)
```



1.3.5 MNIST Run 2

Generator shape: - layer 1: 4x4x512 with LRELU activation - layer 2: 7x7x256 with LRELU - layer 3: 14x14x128 with LRELU - layer 4: 28x28xOutput_Channel with TANH

```
In [17]: batch_size = 128
         z_dim = 100
         learning_rate = 0.0002
         beta1 = 0.5

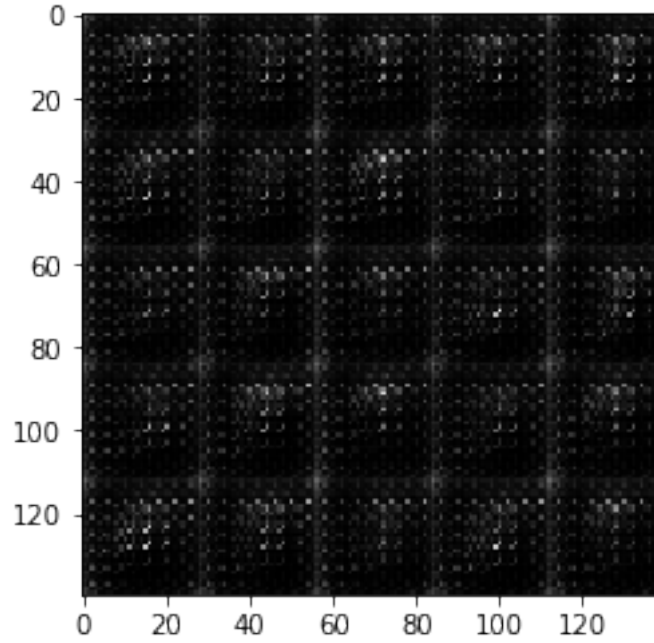
         d_losses = []
         g_losses = []

         """
         DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
         """

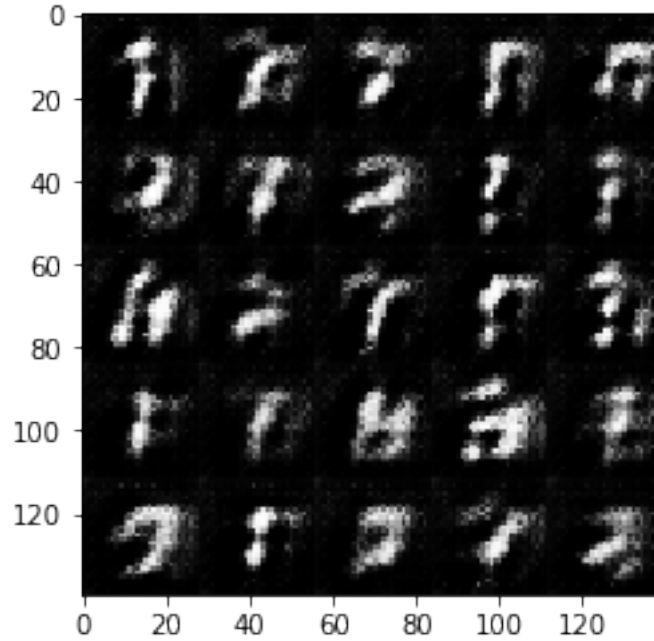
         epochs = 2

         mnist_dataset = helper.Dataset('mnist', glob(os.path.join(data_dir, 'mnist/*.jpg')))
         with tf.Graph().as_default():
             # jcc: added lists for plotting discriminator and generator losses
             d_losses, g_losses = train(epochs, batch_size, z_dim, learning_rate, beta1, mnist_d,
                                         mnist_dataset.shape, mnist_dataset.image_mode)

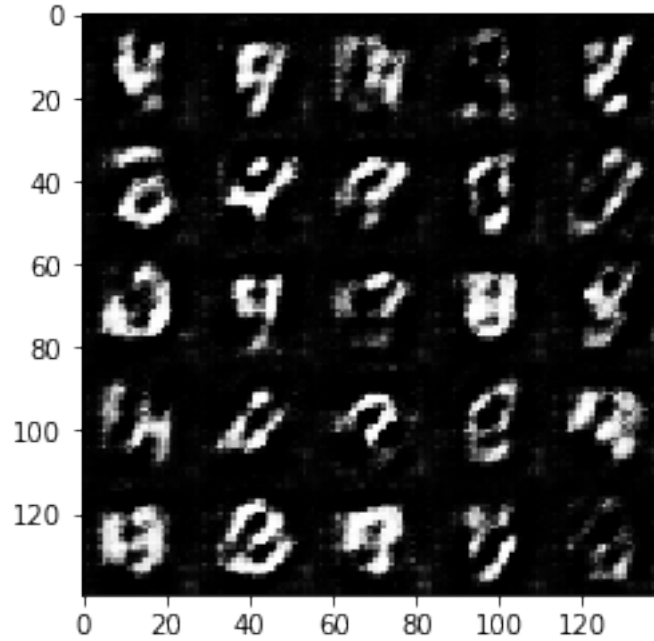
Epoch 1/2: batch 5/936:      time/batch: 0.40s      remaining time: 369s      d_loss: 0.
Epoch 1/2: batch 10/936:     time/batch: 0.31s      remaining time: 291s      d_loss: 0.
Epoch 1/2: batch 15/936:     time/batch: 0.28s      remaining time: 262s      d_loss: 0.
Epoch 1/2: batch 20/936:     time/batch: 0.27s      remaining time: 246s      d_loss: 0.
Epoch 1/2: batch 25/936:     time/batch: 0.26s      remaining time: 236s      d_loss: 0.
Epoch 1/2: batch 30/936:     time/batch: 0.25s      remaining time: 230s      d_loss: 0.
Epoch 1/2: batch 35/936:     time/batch: 0.25s      remaining time: 224s      d_loss: 2.
Epoch 1/2: batch 40/936:     time/batch: 0.25s      remaining time: 220s      d_loss: 0.
Epoch 1/2: batch 45/936:     time/batch: 0.24s      remaining time: 217s      d_loss: 0.
Epoch 1/2: batch 50/936:     time/batch: 0.24s      remaining time: 214s      d_loss: 2.
Epoch 1/2: batch 55/936:     time/batch: 0.24s      remaining time: 211s      d_loss: 0.
Epoch 1/2: batch 60/936:     time/batch: 0.24s      remaining time: 209s      d_loss: 0.
Epoch 1/2: batch 65/936:     time/batch: 0.24s      remaining time: 206s      d_loss: 0.
Epoch 1/2: batch 70/936:     time/batch: 0.24s      remaining time: 204s      d_loss: 0.
Epoch 1/2: batch 75/936:     time/batch: 0.24s      remaining time: 202s      d_loss: 0.
Epoch 1/2: batch 80/936:     time/batch: 0.24s      remaining time: 201s      d_loss: 0.
Epoch 1/2: batch 85/936:     time/batch: 0.23s      remaining time: 199s      d_loss: 1.
Epoch 1/2: batch 90/936:     time/batch: 0.23s      remaining time: 197s      d_loss: 0.
Epoch 1/2: batch 95/936:     time/batch: 0.23s      remaining time: 196s      d_loss: 0.
Epoch 1/2: batch 100/936:    time/batch: 0.23s      remaining time: 194s      d_loss:
```



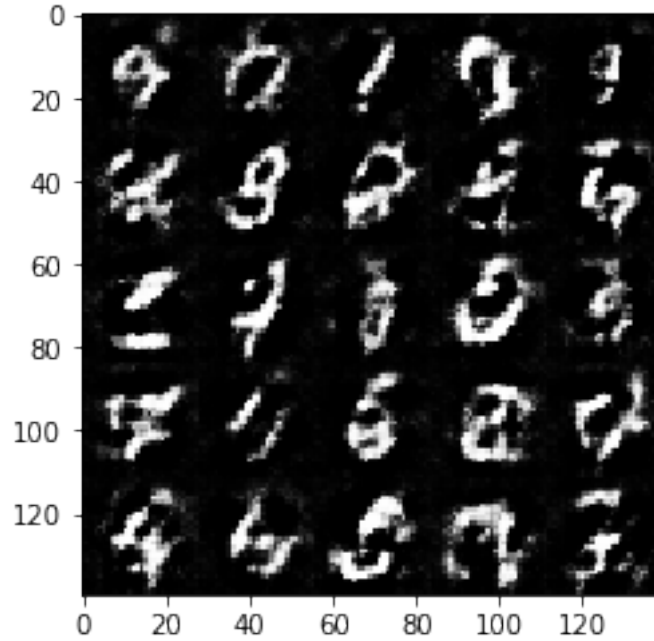
Epoch 1/2: batch 105/936:	time/batch: 0.24s	remaining time: 196s	d_loss:
Epoch 1/2: batch 110/936:	time/batch: 0.24s	remaining time: 194s	d_loss:
Epoch 1/2: batch 115/936:	time/batch: 0.23s	remaining time: 192s	d_loss:
Epoch 1/2: batch 120/936:	time/batch: 0.23s	remaining time: 191s	d_loss:
Epoch 1/2: batch 125/936:	time/batch: 0.23s	remaining time: 189s	d_loss:
Epoch 1/2: batch 130/936:	time/batch: 0.23s	remaining time: 188s	d_loss:
Epoch 1/2: batch 135/936:	time/batch: 0.23s	remaining time: 186s	d_loss:
Epoch 1/2: batch 140/936:	time/batch: 0.23s	remaining time: 185s	d_loss:
Epoch 1/2: batch 145/936:	time/batch: 0.23s	remaining time: 184s	d_loss:
Epoch 1/2: batch 150/936:	time/batch: 0.23s	remaining time: 182s	d_loss:
Epoch 1/2: batch 155/936:	time/batch: 0.23s	remaining time: 181s	d_loss:
Epoch 1/2: batch 160/936:	time/batch: 0.23s	remaining time: 179s	d_loss:
Epoch 1/2: batch 165/936:	time/batch: 0.23s	remaining time: 178s	d_loss:
Epoch 1/2: batch 170/936:	time/batch: 0.23s	remaining time: 177s	d_loss:
Epoch 1/2: batch 175/936:	time/batch: 0.23s	remaining time: 175s	d_loss:
Epoch 1/2: batch 180/936:	time/batch: 0.23s	remaining time: 174s	d_loss:
Epoch 1/2: batch 185/936:	time/batch: 0.23s	remaining time: 173s	d_loss:
Epoch 1/2: batch 190/936:	time/batch: 0.23s	remaining time: 172s	d_loss:
Epoch 1/2: batch 195/936:	time/batch: 0.23s	remaining time: 170s	d_loss:
Epoch 1/2: batch 200/936:	time/batch: 0.23s	remaining time: 169s	d_loss:



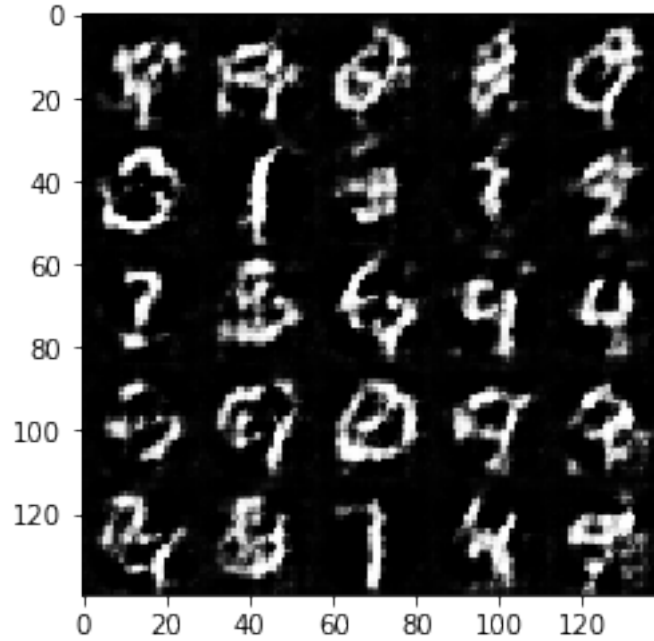
Epoch 1/2: batch 205/936:	time/batch: 0.23s	remaining time: 169s	d_loss:
Epoch 1/2: batch 210/936:	time/batch: 0.23s	remaining time: 168s	d_loss:
Epoch 1/2: batch 215/936:	time/batch: 0.23s	remaining time: 166s	d_loss:
Epoch 1/2: batch 220/936:	time/batch: 0.23s	remaining time: 165s	d_loss:
Epoch 1/2: batch 225/936:	time/batch: 0.23s	remaining time: 164s	d_loss:
Epoch 1/2: batch 230/936:	time/batch: 0.23s	remaining time: 163s	d_loss:
Epoch 1/2: batch 235/936:	time/batch: 0.23s	remaining time: 161s	d_loss:
Epoch 1/2: batch 240/936:	time/batch: 0.23s	remaining time: 160s	d_loss:
Epoch 1/2: batch 245/936:	time/batch: 0.23s	remaining time: 159s	d_loss:
Epoch 1/2: batch 250/936:	time/batch: 0.23s	remaining time: 158s	d_loss:
Epoch 1/2: batch 255/936:	time/batch: 0.23s	remaining time: 156s	d_loss:
Epoch 1/2: batch 260/936:	time/batch: 0.23s	remaining time: 155s	d_loss:
Epoch 1/2: batch 265/936:	time/batch: 0.23s	remaining time: 154s	d_loss:
Epoch 1/2: batch 270/936:	time/batch: 0.23s	remaining time: 153s	d_loss:
Epoch 1/2: batch 275/936:	time/batch: 0.23s	remaining time: 152s	d_loss:
Epoch 1/2: batch 280/936:	time/batch: 0.23s	remaining time: 150s	d_loss:
Epoch 1/2: batch 285/936:	time/batch: 0.23s	remaining time: 149s	d_loss:
Epoch 1/2: batch 290/936:	time/batch: 0.23s	remaining time: 148s	d_loss:
Epoch 1/2: batch 295/936:	time/batch: 0.23s	remaining time: 147s	d_loss:
Epoch 1/2: batch 300/936:	time/batch: 0.23s	remaining time: 146s	d_loss:



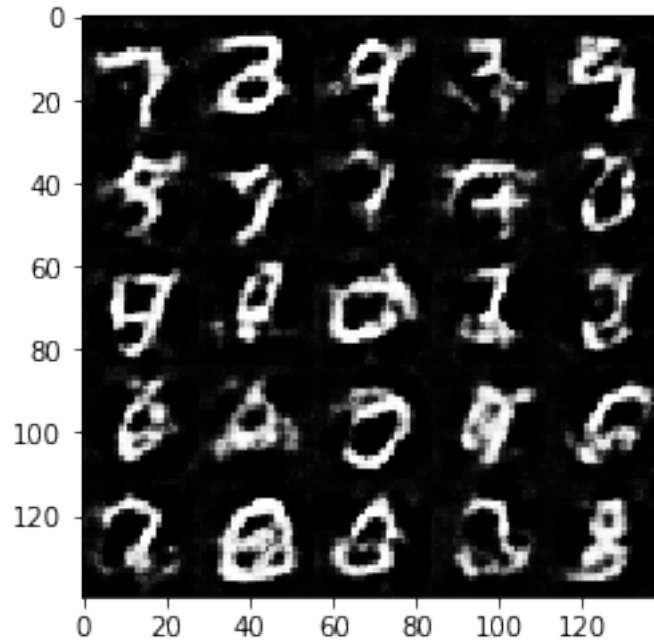
Epoch 1/2: batch 305/936:	time/batch: 0.23s	remaining time: 145s	d_loss:
Epoch 1/2: batch 310/936:	time/batch: 0.23s	remaining time: 144s	d_loss:
Epoch 1/2: batch 315/936:	time/batch: 0.23s	remaining time: 143s	d_loss:
Epoch 1/2: batch 320/936:	time/batch: 0.23s	remaining time: 142s	d_loss:
Epoch 1/2: batch 325/936:	time/batch: 0.23s	remaining time: 140s	d_loss:
Epoch 1/2: batch 330/936:	time/batch: 0.23s	remaining time: 139s	d_loss:
Epoch 1/2: batch 335/936:	time/batch: 0.23s	remaining time: 138s	d_loss:
Epoch 1/2: batch 340/936:	time/batch: 0.23s	remaining time: 137s	d_loss:
Epoch 1/2: batch 345/936:	time/batch: 0.23s	remaining time: 136s	d_loss:
Epoch 1/2: batch 350/936:	time/batch: 0.23s	remaining time: 134s	d_loss:
Epoch 1/2: batch 355/936:	time/batch: 0.23s	remaining time: 133s	d_loss:
Epoch 1/2: batch 360/936:	time/batch: 0.23s	remaining time: 132s	d_loss:
Epoch 1/2: batch 365/936:	time/batch: 0.23s	remaining time: 131s	d_loss:
Epoch 1/2: batch 370/936:	time/batch: 0.23s	remaining time: 130s	d_loss:
Epoch 1/2: batch 375/936:	time/batch: 0.23s	remaining time: 128s	d_loss:
Epoch 1/2: batch 380/936:	time/batch: 0.23s	remaining time: 127s	d_loss:
Epoch 1/2: batch 385/936:	time/batch: 0.23s	remaining time: 126s	d_loss:
Epoch 1/2: batch 390/936:	time/batch: 0.23s	remaining time: 125s	d_loss:
Epoch 1/2: batch 395/936:	time/batch: 0.23s	remaining time: 124s	d_loss:
Epoch 1/2: batch 400/936:	time/batch: 0.23s	remaining time: 123s	d_loss:



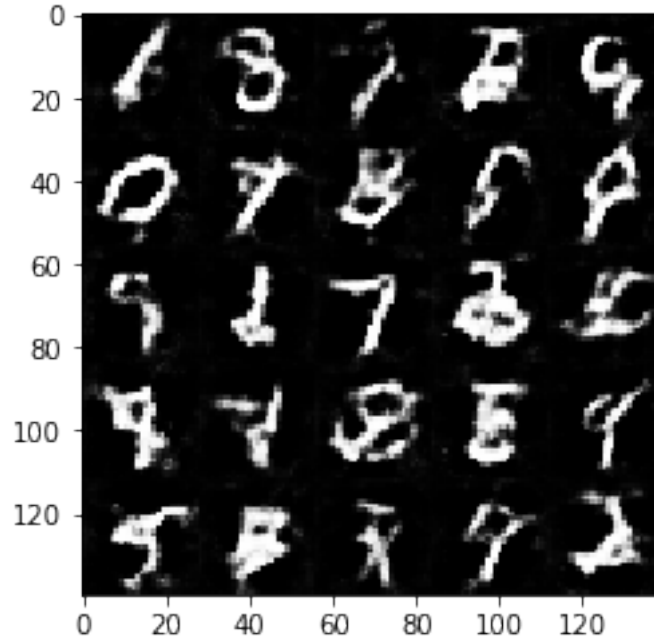
Epoch 1/2: batch 405/936:	time/batch: 0.23s	remaining time: 122s	d_loss:
Epoch 1/2: batch 410/936:	time/batch: 0.23s	remaining time: 121s	d_loss:
Epoch 1/2: batch 415/936:	time/batch: 0.23s	remaining time: 119s	d_loss:
Epoch 1/2: batch 420/936:	time/batch: 0.23s	remaining time: 118s	d_loss:
Epoch 1/2: batch 425/936:	time/batch: 0.23s	remaining time: 117s	d_loss:
Epoch 1/2: batch 430/936:	time/batch: 0.23s	remaining time: 116s	d_loss:
Epoch 1/2: batch 435/936:	time/batch: 0.23s	remaining time: 115s	d_loss:
Epoch 1/2: batch 440/936:	time/batch: 0.23s	remaining time: 114s	d_loss:
Epoch 1/2: batch 445/936:	time/batch: 0.23s	remaining time: 112s	d_loss:
Epoch 1/2: batch 450/936:	time/batch: 0.23s	remaining time: 111s	d_loss:
Epoch 1/2: batch 455/936:	time/batch: 0.23s	remaining time: 110s	d_loss:
Epoch 1/2: batch 460/936:	time/batch: 0.23s	remaining time: 109s	d_loss:
Epoch 1/2: batch 465/936:	time/batch: 0.23s	remaining time: 108s	d_loss:
Epoch 2/2: batch 470/936:	time/batch: 0.23s	remaining time: 106s	d_loss:
Epoch 2/2: batch 475/936:	time/batch: 0.23s	remaining time: 105s	d_loss:
Epoch 2/2: batch 480/936:	time/batch: 0.23s	remaining time: 104s	d_loss:
Epoch 2/2: batch 485/936:	time/batch: 0.23s	remaining time: 103s	d_loss:
Epoch 2/2: batch 490/936:	time/batch: 0.23s	remaining time: 102s	d_loss:
Epoch 2/2: batch 495/936:	time/batch: 0.23s	remaining time: 101s	d_loss:
Epoch 2/2: batch 500/936:	time/batch: 0.23s	remaining time: 99s	d_loss: 0



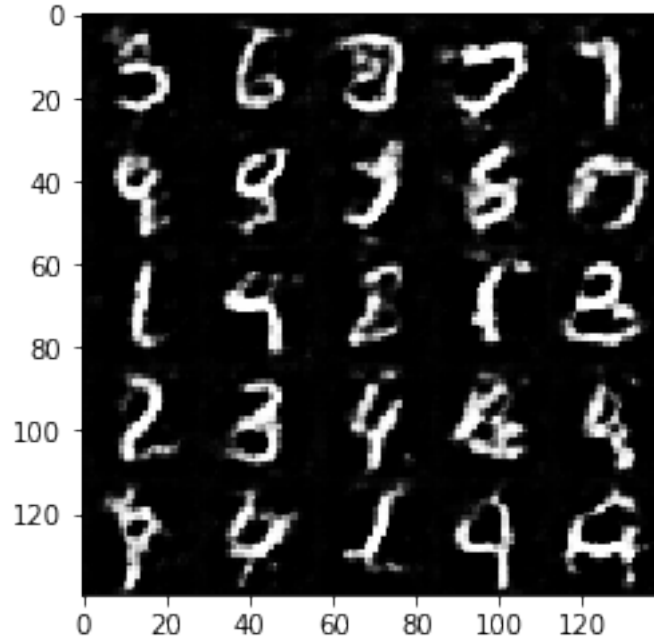
Epoch 2/2: batch 505/936:	time/batch: 0.23s	remaining time: 99s	d_loss: 0
Epoch 2/2: batch 510/936:	time/batch: 0.23s	remaining time: 97s	d_loss: 1
Epoch 2/2: batch 515/936:	time/batch: 0.23s	remaining time: 96s	d_loss: 0
Epoch 2/2: batch 520/936:	time/batch: 0.23s	remaining time: 95s	d_loss: 0
Epoch 2/2: batch 525/936:	time/batch: 0.23s	remaining time: 94s	d_loss: 0
Epoch 2/2: batch 530/936:	time/batch: 0.23s	remaining time: 93s	d_loss: 1
Epoch 2/2: batch 535/936:	time/batch: 0.23s	remaining time: 92s	d_loss: 0
Epoch 2/2: batch 540/936:	time/batch: 0.23s	remaining time: 90s	d_loss: 0
Epoch 2/2: batch 545/936:	time/batch: 0.23s	remaining time: 89s	d_loss: 0
Epoch 2/2: batch 550/936:	time/batch: 0.23s	remaining time: 88s	d_loss: 1
Epoch 2/2: batch 555/936:	time/batch: 0.23s	remaining time: 87s	d_loss: 0
Epoch 2/2: batch 560/936:	time/batch: 0.23s	remaining time: 86s	d_loss: 0
Epoch 2/2: batch 565/936:	time/batch: 0.23s	remaining time: 85s	d_loss: 0
Epoch 2/2: batch 570/936:	time/batch: 0.23s	remaining time: 83s	d_loss: 0
Epoch 2/2: batch 575/936:	time/batch: 0.23s	remaining time: 82s	d_loss: 0
Epoch 2/2: batch 580/936:	time/batch: 0.23s	remaining time: 81s	d_loss: 0
Epoch 2/2: batch 585/936:	time/batch: 0.23s	remaining time: 80s	d_loss: 1
Epoch 2/2: batch 590/936:	time/batch: 0.23s	remaining time: 79s	d_loss: 0
Epoch 2/2: batch 595/936:	time/batch: 0.23s	remaining time: 78s	d_loss: 1
Epoch 2/2: batch 600/936:	time/batch: 0.23s	remaining time: 76s	d_loss: 0



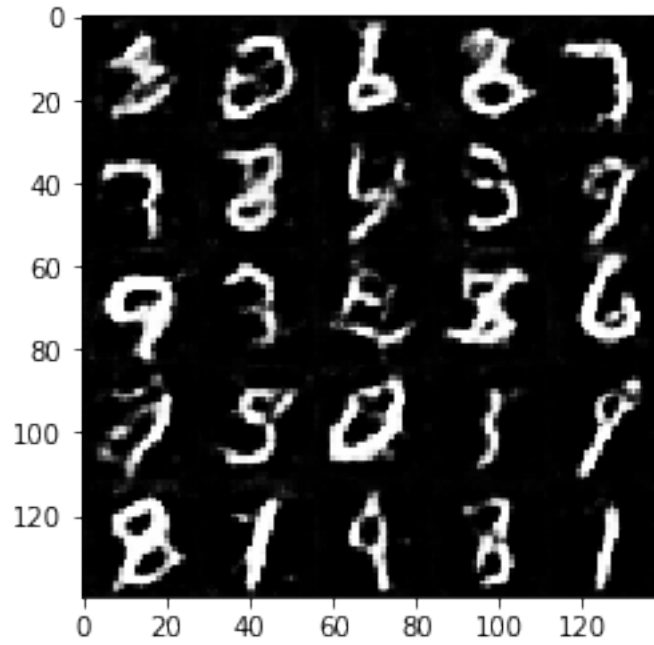
Epoch 2/2: batch 605/936:	time/batch: 0.23s	remaining time: 75s	d_loss: 0
Epoch 2/2: batch 610/936:	time/batch: 0.23s	remaining time: 74s	d_loss: 0
Epoch 2/2: batch 615/936:	time/batch: 0.23s	remaining time: 73s	d_loss: 1
Epoch 2/2: batch 620/936:	time/batch: 0.23s	remaining time: 72s	d_loss: 0
Epoch 2/2: batch 625/936:	time/batch: 0.23s	remaining time: 71s	d_loss: 1
Epoch 2/2: batch 630/936:	time/batch: 0.23s	remaining time: 70s	d_loss: 0
Epoch 2/2: batch 635/936:	time/batch: 0.23s	remaining time: 68s	d_loss: 0
Epoch 2/2: batch 640/936:	time/batch: 0.23s	remaining time: 67s	d_loss: 0
Epoch 2/2: batch 645/936:	time/batch: 0.23s	remaining time: 66s	d_loss: 0
Epoch 2/2: batch 650/936:	time/batch: 0.23s	remaining time: 65s	d_loss: 1
Epoch 2/2: batch 655/936:	time/batch: 0.23s	remaining time: 64s	d_loss: 0
Epoch 2/2: batch 660/936:	time/batch: 0.23s	remaining time: 63s	d_loss: 0
Epoch 2/2: batch 665/936:	time/batch: 0.23s	remaining time: 62s	d_loss: 1
Epoch 2/2: batch 670/936:	time/batch: 0.23s	remaining time: 60s	d_loss: 0
Epoch 2/2: batch 675/936:	time/batch: 0.23s	remaining time: 59s	d_loss: 0
Epoch 2/2: batch 680/936:	time/batch: 0.23s	remaining time: 58s	d_loss: 0
Epoch 2/2: batch 685/936:	time/batch: 0.23s	remaining time: 57s	d_loss: 0
Epoch 2/2: batch 690/936:	time/batch: 0.23s	remaining time: 56s	d_loss: 1
Epoch 2/2: batch 695/936:	time/batch: 0.23s	remaining time: 55s	d_loss: 0
Epoch 2/2: batch 700/936:	time/batch: 0.23s	remaining time: 53s	d_loss: 0



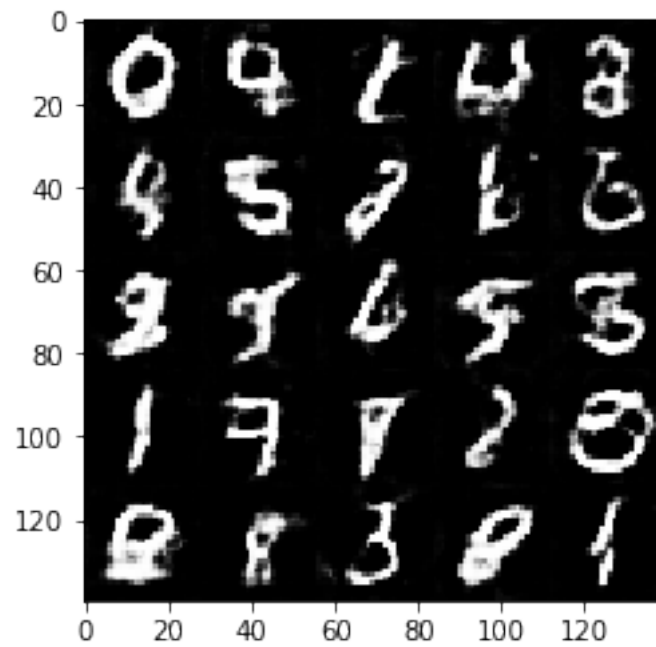
Epoch 2/2: batch 705/936:	time/batch: 0.23s	remaining time: 52s	d_loss: 0
Epoch 2/2: batch 710/936:	time/batch: 0.23s	remaining time: 51s	d_loss: 0
Epoch 2/2: batch 715/936:	time/batch: 0.23s	remaining time: 50s	d_loss: 1
Epoch 2/2: batch 720/936:	time/batch: 0.23s	remaining time: 49s	d_loss: 0
Epoch 2/2: batch 725/936:	time/batch: 0.23s	remaining time: 48s	d_loss: 0
Epoch 2/2: batch 730/936:	time/batch: 0.23s	remaining time: 47s	d_loss: 0
Epoch 2/2: batch 735/936:	time/batch: 0.23s	remaining time: 46s	d_loss: 0
Epoch 2/2: batch 740/936:	time/batch: 0.23s	remaining time: 44s	d_loss: 0
Epoch 2/2: batch 745/936:	time/batch: 0.23s	remaining time: 43s	d_loss: 0
Epoch 2/2: batch 750/936:	time/batch: 0.23s	remaining time: 42s	d_loss: 0
Epoch 2/2: batch 755/936:	time/batch: 0.23s	remaining time: 41s	d_loss: 0
Epoch 2/2: batch 760/936:	time/batch: 0.23s	remaining time: 40s	d_loss: 1
Epoch 2/2: batch 765/936:	time/batch: 0.23s	remaining time: 39s	d_loss: 0
Epoch 2/2: batch 770/936:	time/batch: 0.23s	remaining time: 37s	d_loss: 0
Epoch 2/2: batch 775/936:	time/batch: 0.23s	remaining time: 36s	d_loss: 0
Epoch 2/2: batch 780/936:	time/batch: 0.23s	remaining time: 35s	d_loss: 0
Epoch 2/2: batch 785/936:	time/batch: 0.23s	remaining time: 34s	d_loss: 0
Epoch 2/2: batch 790/936:	time/batch: 0.23s	remaining time: 33s	d_loss: 0
Epoch 2/2: batch 795/936:	time/batch: 0.23s	remaining time: 32s	d_loss: 0
Epoch 2/2: batch 800/936:	time/batch: 0.23s	remaining time: 31s	d_loss: 1



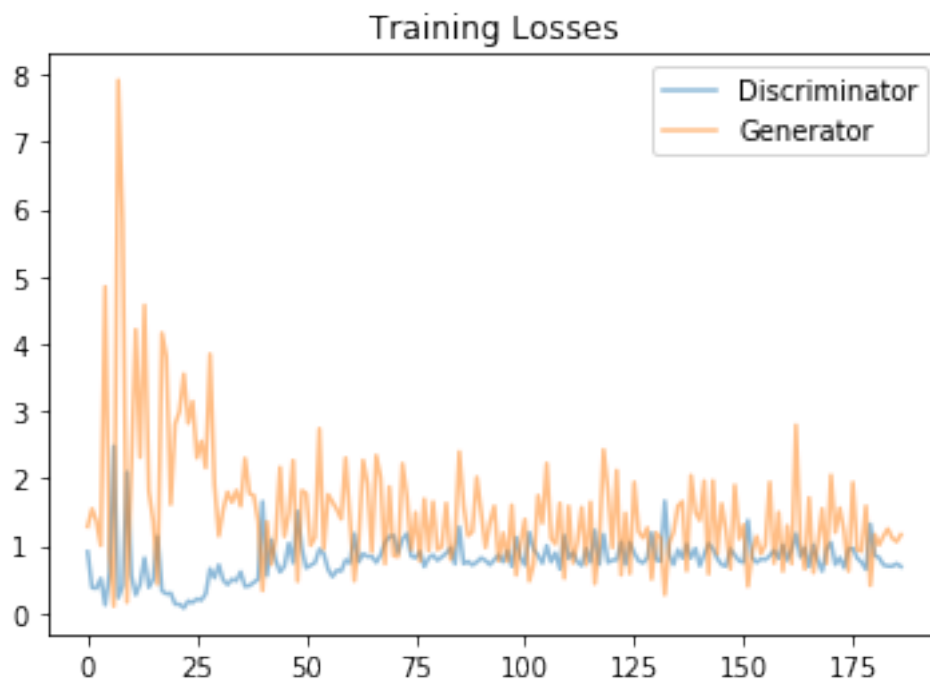
Epoch 2/2: batch 805/936:	time/batch: 0.23s	remaining time: 29s	d_loss: 0
Epoch 2/2: batch 810/936:	time/batch: 0.23s	remaining time: 28s	d_loss: 0
Epoch 2/2: batch 815/936:	time/batch: 0.23s	remaining time: 27s	d_loss: 1
Epoch 2/2: batch 820/936:	time/batch: 0.23s	remaining time: 26s	d_loss: 0
Epoch 2/2: batch 825/936:	time/batch: 0.23s	remaining time: 25s	d_loss: 0
Epoch 2/2: batch 830/936:	time/batch: 0.23s	remaining time: 24s	d_loss: 0
Epoch 2/2: batch 835/936:	time/batch: 0.23s	remaining time: 23s	d_loss: 1
Epoch 2/2: batch 840/936:	time/batch: 0.23s	remaining time: 21s	d_loss: 0
Epoch 2/2: batch 845/936:	time/batch: 0.23s	remaining time: 20s	d_loss: 0
Epoch 2/2: batch 850/936:	time/batch: 0.23s	remaining time: 19s	d_loss: 0
Epoch 2/2: batch 855/936:	time/batch: 0.23s	remaining time: 18s	d_loss: 1
Epoch 2/2: batch 860/936:	time/batch: 0.23s	remaining time: 17s	d_loss: 0
Epoch 2/2: batch 865/936:	time/batch: 0.23s	remaining time: 16s	d_loss: 0
Epoch 2/2: batch 870/936:	time/batch: 0.23s	remaining time: 15s	d_loss: 0
Epoch 2/2: batch 875/936:	time/batch: 0.23s	remaining time: 13s	d_loss: 0
Epoch 2/2: batch 880/936:	time/batch: 0.23s	remaining time: 12s	d_loss: 0
Epoch 2/2: batch 885/936:	time/batch: 0.23s	remaining time: 11s	d_loss: 0
Epoch 2/2: batch 890/936:	time/batch: 0.23s	remaining time: 10s	d_loss: 0
Epoch 2/2: batch 895/936:	time/batch: 0.23s	remaining time: 9s	d_loss: 0
Epoch 2/2: batch 900/936:	time/batch: 0.23s	remaining time: 8s	d_loss: 1



Epoch 2/2: batch 905/936:	time/batch: 0.23s	remaining time: 7s	d_loss: 0.
Epoch 2/2: batch 910/936:	time/batch: 0.23s	remaining time: 5s	d_loss: 0.
Epoch 2/2: batch 915/936:	time/batch: 0.23s	remaining time: 4s	d_loss: 0.
Epoch 2/2: batch 920/936:	time/batch: 0.23s	remaining time: 3s	d_loss: 0.
Epoch 2/2: batch 925/936:	time/batch: 0.23s	remaining time: 2s	d_loss: 0.
Epoch 2/2: batch 930/936:	time/batch: 0.23s	remaining time: 1s	d_loss: 0.
Epoch 2/2: batch 935/936:	time/batch: 0.23s	remaining time: 0s	d_loss: 0.



```
In [18]: plot_losses(d_losses, g_losses)
```



1.3.6 MNIST Run 3: decrease learning rate

Generator - layer 1: 4x4x512 with LRELU - layer 2: 7x7x256 with LRELU - layer 3: 14x14x128 with LRELU - layer 4: 28x28xOutput_Channel with TANH

```
In [21]: batch_size = 128
        z_dim = 100
        learning_rate = 0.0001
        beta1 = 0.5

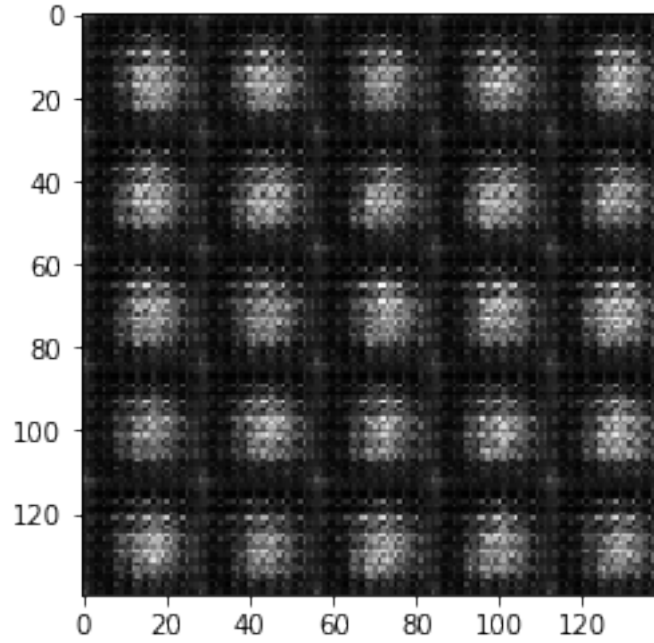
        d_losses = []
        g_losses = []

        """
        DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
        """

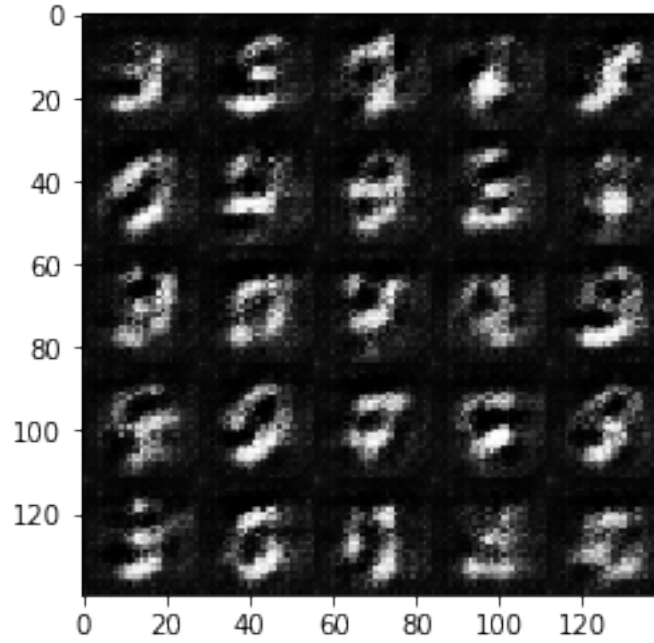
        epochs = 2

        mnist_dataset = helper.Dataset('mnist', glob(os.path.join(data_dir, 'mnist/*.jpg')))
        with tf.Graph().as_default():
            # jcc: added lists for plotting discriminator and generator losses
            d_losses, g_losses = train(epochs, batch_size, z_dim, learning_rate, beta1, mnist_d
                                     mnist_dataset.shape, mnist_dataset.image_mode)

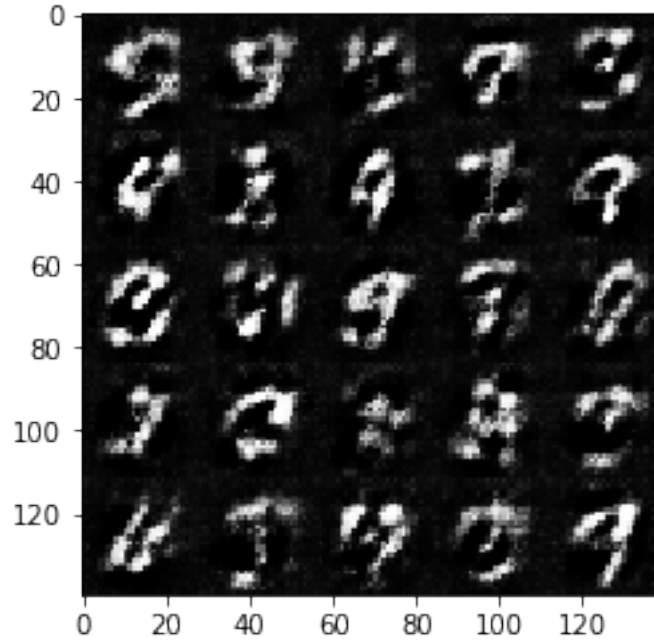
Epoch 1/2: batch 5/936:      time/batch: 0.32s      remaining time: 294s      d_loss: 1.
Epoch 1/2: batch 10/936:     time/batch: 0.27s      remaining time: 253s      d_loss: 0
Epoch 1/2: batch 15/936:     time/batch: 0.26s      remaining time: 236s      d_loss: 0
Epoch 1/2: batch 20/936:     time/batch: 0.25s      remaining time: 228s      d_loss: 0
Epoch 1/2: batch 25/936:     time/batch: 0.24s      remaining time: 222s      d_loss: 0
Epoch 1/2: batch 30/936:     time/batch: 0.24s      remaining time: 217s      d_loss: 0
Epoch 1/2: batch 35/936:     time/batch: 0.24s      remaining time: 214s      d_loss: 1
Epoch 1/2: batch 40/936:     time/batch: 0.24s      remaining time: 211s      d_loss: 0
Epoch 1/2: batch 45/936:     time/batch: 0.23s      remaining time: 209s      d_loss: 0
Epoch 1/2: batch 50/936:     time/batch: 0.23s      remaining time: 207s      d_loss: 1
Epoch 1/2: batch 55/936:     time/batch: 0.23s      remaining time: 205s      d_loss: 0
Epoch 1/2: batch 60/936:     time/batch: 0.23s      remaining time: 203s      d_loss: 0
Epoch 1/2: batch 65/936:     time/batch: 0.23s      remaining time: 201s      d_loss: 0
Epoch 1/2: batch 70/936:     time/batch: 0.23s      remaining time: 200s      d_loss: 0
Epoch 1/2: batch 75/936:     time/batch: 0.23s      remaining time: 198s      d_loss: 0
Epoch 1/2: batch 80/936:     time/batch: 0.23s      remaining time: 197s      d_loss: 0
Epoch 1/2: batch 85/936:     time/batch: 0.23s      remaining time: 195s      d_loss: 0
Epoch 1/2: batch 90/936:     time/batch: 0.23s      remaining time: 194s      d_loss: 0
Epoch 1/2: batch 95/936:     time/batch: 0.23s      remaining time: 192s      d_loss: 0
Epoch 1/2: batch 100/936:    time/batch: 0.23s      remaining time: 191s      d_loss:
```



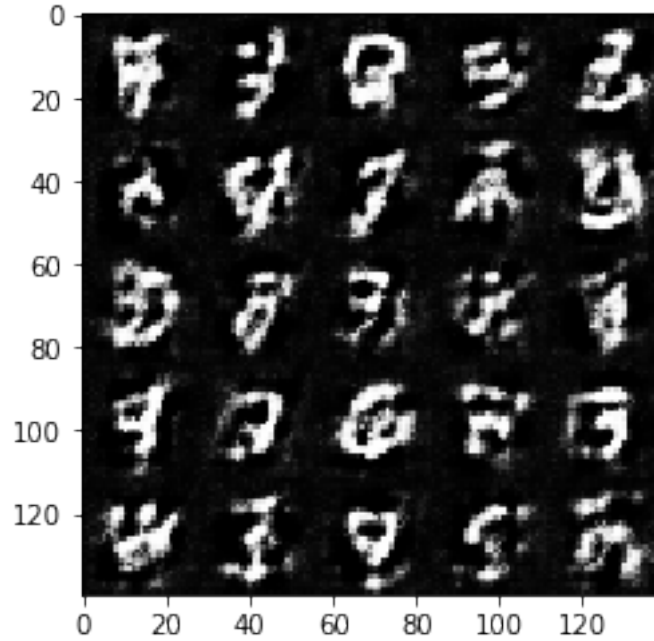
Epoch 1/2: batch 105/936:	time/batch: 0.23s	remaining time: 192s	d_loss:
Epoch 1/2: batch 110/936:	time/batch: 0.23s	remaining time: 191s	d_loss:
Epoch 1/2: batch 115/936:	time/batch: 0.23s	remaining time: 189s	d_loss:
Epoch 1/2: batch 120/936:	time/batch: 0.23s	remaining time: 188s	d_loss:
Epoch 1/2: batch 125/936:	time/batch: 0.23s	remaining time: 186s	d_loss:
Epoch 1/2: batch 130/936:	time/batch: 0.23s	remaining time: 185s	d_loss:
Epoch 1/2: batch 135/936:	time/batch: 0.23s	remaining time: 184s	d_loss:
Epoch 1/2: batch 140/936:	time/batch: 0.23s	remaining time: 182s	d_loss:
Epoch 1/2: batch 145/936:	time/batch: 0.23s	remaining time: 181s	d_loss:
Epoch 1/2: batch 150/936:	time/batch: 0.23s	remaining time: 180s	d_loss:
Epoch 1/2: batch 155/936:	time/batch: 0.23s	remaining time: 179s	d_loss:
Epoch 1/2: batch 160/936:	time/batch: 0.23s	remaining time: 177s	d_loss:
Epoch 1/2: batch 165/936:	time/batch: 0.23s	remaining time: 176s	d_loss:
Epoch 1/2: batch 170/936:	time/batch: 0.23s	remaining time: 175s	d_loss:
Epoch 1/2: batch 175/936:	time/batch: 0.23s	remaining time: 174s	d_loss:
Epoch 1/2: batch 180/936:	time/batch: 0.23s	remaining time: 172s	d_loss:
Epoch 1/2: batch 185/936:	time/batch: 0.23s	remaining time: 171s	d_loss:
Epoch 1/2: batch 190/936:	time/batch: 0.23s	remaining time: 170s	d_loss:
Epoch 1/2: batch 195/936:	time/batch: 0.23s	remaining time: 169s	d_loss:
Epoch 1/2: batch 200/936:	time/batch: 0.23s	remaining time: 168s	d_loss:



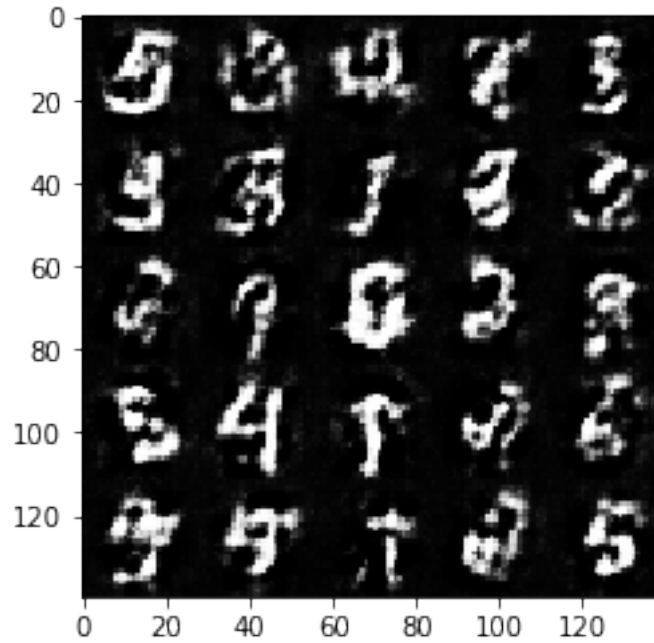
Epoch 1/2: batch 205/936:	time/batch: 0.23s	remaining time: 167s	d_loss:
Epoch 1/2: batch 210/936:	time/batch: 0.23s	remaining time: 166s	d_loss:
Epoch 1/2: batch 215/936:	time/batch: 0.23s	remaining time: 165s	d_loss:
Epoch 1/2: batch 220/936:	time/batch: 0.23s	remaining time: 164s	d_loss:
Epoch 1/2: batch 225/936:	time/batch: 0.23s	remaining time: 162s	d_loss:
Epoch 1/2: batch 230/936:	time/batch: 0.23s	remaining time: 161s	d_loss:
Epoch 1/2: batch 235/936:	time/batch: 0.23s	remaining time: 160s	d_loss:
Epoch 1/2: batch 240/936:	time/batch: 0.23s	remaining time: 159s	d_loss:
Epoch 1/2: batch 245/936:	time/batch: 0.23s	remaining time: 158s	d_loss:
Epoch 1/2: batch 250/936:	time/batch: 0.23s	remaining time: 156s	d_loss:
Epoch 1/2: batch 255/936:	time/batch: 0.23s	remaining time: 155s	d_loss:
Epoch 1/2: batch 260/936:	time/batch: 0.23s	remaining time: 154s	d_loss:
Epoch 1/2: batch 265/936:	time/batch: 0.23s	remaining time: 153s	d_loss:
Epoch 1/2: batch 270/936:	time/batch: 0.23s	remaining time: 152s	d_loss:
Epoch 1/2: batch 275/936:	time/batch: 0.23s	remaining time: 150s	d_loss:
Epoch 1/2: batch 280/936:	time/batch: 0.23s	remaining time: 149s	d_loss:
Epoch 1/2: batch 285/936:	time/batch: 0.23s	remaining time: 148s	d_loss:
Epoch 1/2: batch 290/936:	time/batch: 0.23s	remaining time: 147s	d_loss:
Epoch 1/2: batch 295/936:	time/batch: 0.23s	remaining time: 146s	d_loss:
Epoch 1/2: batch 300/936:	time/batch: 0.23s	remaining time: 145s	d_loss:



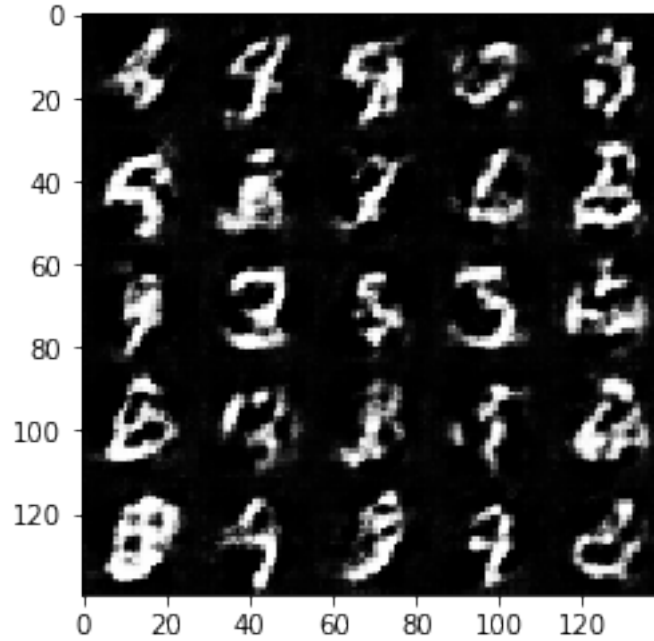
Epoch 1/2: batch 305/936:	time/batch: 0.23s	remaining time: 144s	d_loss:
Epoch 1/2: batch 310/936:	time/batch: 0.23s	remaining time: 143s	d_loss:
Epoch 1/2: batch 315/936:	time/batch: 0.23s	remaining time: 142s	d_loss:
Epoch 1/2: batch 320/936:	time/batch: 0.23s	remaining time: 141s	d_loss:
Epoch 1/2: batch 325/936:	time/batch: 0.23s	remaining time: 140s	d_loss:
Epoch 1/2: batch 330/936:	time/batch: 0.23s	remaining time: 138s	d_loss:
Epoch 1/2: batch 335/936:	time/batch: 0.23s	remaining time: 137s	d_loss:
Epoch 1/2: batch 340/936:	time/batch: 0.23s	remaining time: 136s	d_loss:
Epoch 1/2: batch 345/936:	time/batch: 0.23s	remaining time: 135s	d_loss:
Epoch 1/2: batch 350/936:	time/batch: 0.23s	remaining time: 134s	d_loss:
Epoch 1/2: batch 355/936:	time/batch: 0.23s	remaining time: 132s	d_loss:
Epoch 1/2: batch 360/936:	time/batch: 0.23s	remaining time: 131s	d_loss:
Epoch 1/2: batch 365/936:	time/batch: 0.23s	remaining time: 130s	d_loss:
Epoch 1/2: batch 370/936:	time/batch: 0.23s	remaining time: 129s	d_loss:
Epoch 1/2: batch 375/936:	time/batch: 0.23s	remaining time: 128s	d_loss:
Epoch 1/2: batch 380/936:	time/batch: 0.23s	remaining time: 127s	d_loss:
Epoch 1/2: batch 385/936:	time/batch: 0.23s	remaining time: 125s	d_loss:
Epoch 1/2: batch 390/936:	time/batch: 0.23s	remaining time: 124s	d_loss:
Epoch 1/2: batch 395/936:	time/batch: 0.23s	remaining time: 123s	d_loss:
Epoch 1/2: batch 400/936:	time/batch: 0.23s	remaining time: 122s	d_loss:



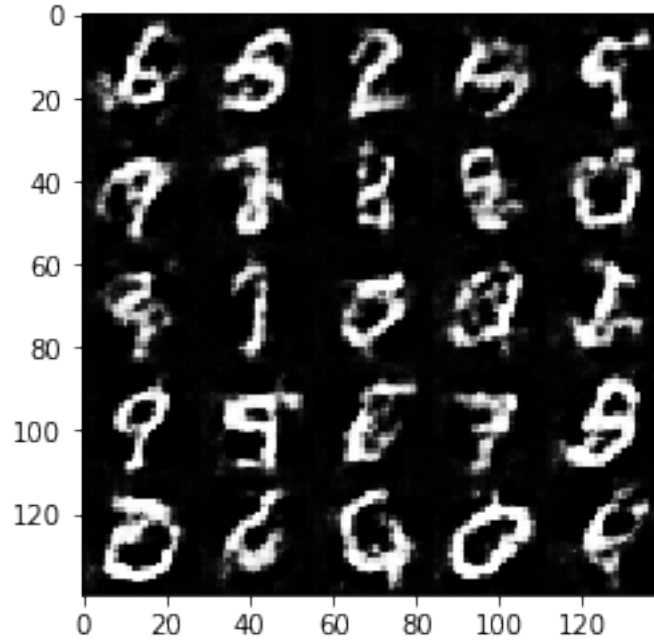
Epoch 1/2: batch 405/936:	time/batch: 0.23s	remaining time: 121s	d_loss:
Epoch 1/2: batch 410/936:	time/batch: 0.23s	remaining time: 120s	d_loss:
Epoch 1/2: batch 415/936:	time/batch: 0.23s	remaining time: 119s	d_loss:
Epoch 1/2: batch 420/936:	time/batch: 0.23s	remaining time: 118s	d_loss:
Epoch 1/2: batch 425/936:	time/batch: 0.23s	remaining time: 116s	d_loss:
Epoch 1/2: batch 430/936:	time/batch: 0.23s	remaining time: 115s	d_loss:
Epoch 1/2: batch 435/936:	time/batch: 0.23s	remaining time: 114s	d_loss:
Epoch 1/2: batch 440/936:	time/batch: 0.23s	remaining time: 113s	d_loss:
Epoch 1/2: batch 445/936:	time/batch: 0.23s	remaining time: 112s	d_loss:
Epoch 1/2: batch 450/936:	time/batch: 0.23s	remaining time: 111s	d_loss:
Epoch 1/2: batch 455/936:	time/batch: 0.23s	remaining time: 109s	d_loss:
Epoch 1/2: batch 460/936:	time/batch: 0.23s	remaining time: 108s	d_loss:
Epoch 1/2: batch 465/936:	time/batch: 0.23s	remaining time: 107s	d_loss:
Epoch 2/2: batch 470/936:	time/batch: 0.23s	remaining time: 106s	d_loss:
Epoch 2/2: batch 475/936:	time/batch: 0.23s	remaining time: 105s	d_loss:
Epoch 2/2: batch 480/936:	time/batch: 0.23s	remaining time: 104s	d_loss:
Epoch 2/2: batch 485/936:	time/batch: 0.23s	remaining time: 102s	d_loss:
Epoch 2/2: batch 490/936:	time/batch: 0.23s	remaining time: 101s	d_loss:
Epoch 2/2: batch 495/936:	time/batch: 0.23s	remaining time: 100s	d_loss:
Epoch 2/2: batch 500/936:	time/batch: 0.23s	remaining time: 99s	d_loss: 0



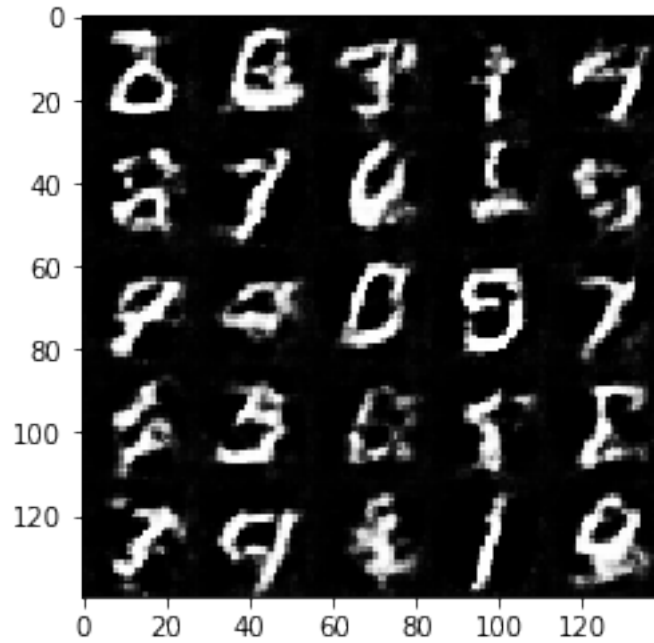
Epoch 2/2: batch 505/936:	time/batch: 0.23s	remaining time: 98s	d_loss: 0
Epoch 2/2: batch 510/936:	time/batch: 0.23s	remaining time: 97s	d_loss: 0
Epoch 2/2: batch 515/936:	time/batch: 0.23s	remaining time: 96s	d_loss: 0
Epoch 2/2: batch 520/936:	time/batch: 0.23s	remaining time: 95s	d_loss: 0
Epoch 2/2: batch 525/936:	time/batch: 0.23s	remaining time: 94s	d_loss: 0
Epoch 2/2: batch 530/936:	time/batch: 0.23s	remaining time: 92s	d_loss: 0
Epoch 2/2: batch 535/936:	time/batch: 0.23s	remaining time: 91s	d_loss: 0
Epoch 2/2: batch 540/936:	time/batch: 0.23s	remaining time: 90s	d_loss: 0
Epoch 2/2: batch 545/936:	time/batch: 0.23s	remaining time: 89s	d_loss: 0
Epoch 2/2: batch 550/936:	time/batch: 0.23s	remaining time: 88s	d_loss: 0
Epoch 2/2: batch 555/936:	time/batch: 0.23s	remaining time: 87s	d_loss: 0
Epoch 2/2: batch 560/936:	time/batch: 0.23s	remaining time: 85s	d_loss: 0
Epoch 2/2: batch 565/936:	time/batch: 0.23s	remaining time: 84s	d_loss: 0
Epoch 2/2: batch 570/936:	time/batch: 0.23s	remaining time: 83s	d_loss: 0
Epoch 2/2: batch 575/936:	time/batch: 0.23s	remaining time: 82s	d_loss: 0
Epoch 2/2: batch 580/936:	time/batch: 0.23s	remaining time: 81s	d_loss: 0
Epoch 2/2: batch 585/936:	time/batch: 0.23s	remaining time: 80s	d_loss: 0
Epoch 2/2: batch 590/936:	time/batch: 0.23s	remaining time: 78s	d_loss: 0
Epoch 2/2: batch 595/936:	time/batch: 0.23s	remaining time: 77s	d_loss: 0
Epoch 2/2: batch 600/936:	time/batch: 0.23s	remaining time: 76s	d_loss: 0



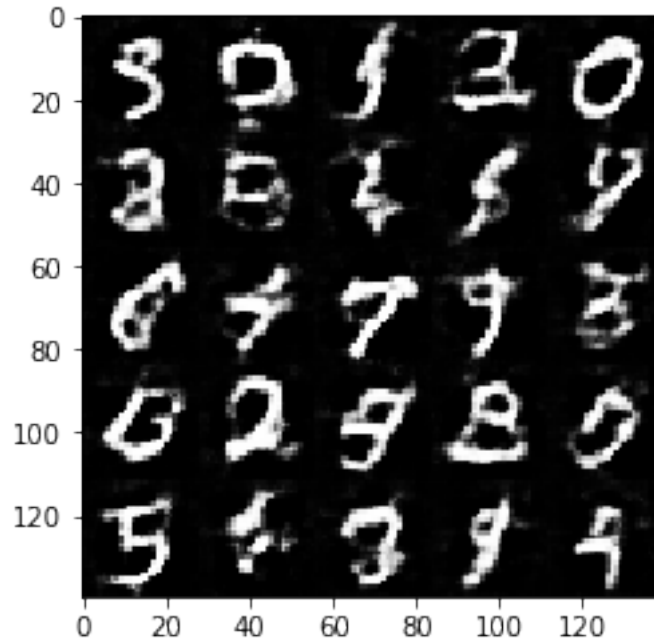
Epoch 2/2: batch 605/936:	time/batch: 0.23s	remaining time: 75s	d_loss: 0
Epoch 2/2: batch 610/936:	time/batch: 0.23s	remaining time: 74s	d_loss: 0
Epoch 2/2: batch 615/936:	time/batch: 0.23s	remaining time: 73s	d_loss: 0
Epoch 2/2: batch 620/936:	time/batch: 0.23s	remaining time: 72s	d_loss: 0
Epoch 2/2: batch 625/936:	time/batch: 0.23s	remaining time: 71s	d_loss: 0
Epoch 2/2: batch 630/936:	time/batch: 0.23s	remaining time: 69s	d_loss: 0
Epoch 2/2: batch 635/936:	time/batch: 0.23s	remaining time: 68s	d_loss: 0
Epoch 2/2: batch 640/936:	time/batch: 0.23s	remaining time: 67s	d_loss: 0
Epoch 2/2: batch 645/936:	time/batch: 0.23s	remaining time: 66s	d_loss: 1
Epoch 2/2: batch 650/936:	time/batch: 0.23s	remaining time: 65s	d_loss: 0
Epoch 2/2: batch 655/936:	time/batch: 0.23s	remaining time: 64s	d_loss: 0
Epoch 2/2: batch 660/936:	time/batch: 0.23s	remaining time: 63s	d_loss: 0
Epoch 2/2: batch 665/936:	time/batch: 0.23s	remaining time: 61s	d_loss: 0
Epoch 2/2: batch 670/936:	time/batch: 0.23s	remaining time: 60s	d_loss: 0
Epoch 2/2: batch 675/936:	time/batch: 0.23s	remaining time: 59s	d_loss: 0
Epoch 2/2: batch 680/936:	time/batch: 0.23s	remaining time: 58s	d_loss: 0
Epoch 2/2: batch 685/936:	time/batch: 0.23s	remaining time: 57s	d_loss: 0
Epoch 2/2: batch 690/936:	time/batch: 0.23s	remaining time: 56s	d_loss: 0
Epoch 2/2: batch 695/936:	time/batch: 0.23s	remaining time: 55s	d_loss: 0
Epoch 2/2: batch 700/936:	time/batch: 0.23s	remaining time: 53s	d_loss: 0



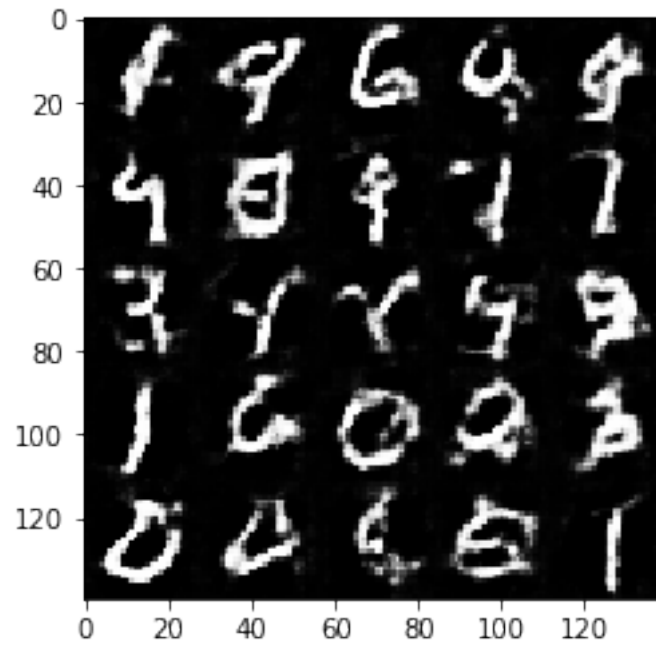
Epoch 2/2: batch 705/936:	time/batch: 0.23s	remaining time: 52s	d_loss: 0
Epoch 2/2: batch 710/936:	time/batch: 0.23s	remaining time: 51s	d_loss: 0
Epoch 2/2: batch 715/936:	time/batch: 0.23s	remaining time: 50s	d_loss: 0
Epoch 2/2: batch 720/936:	time/batch: 0.23s	remaining time: 49s	d_loss: 0
Epoch 2/2: batch 725/936:	time/batch: 0.23s	remaining time: 48s	d_loss: 0
Epoch 2/2: batch 730/936:	time/batch: 0.23s	remaining time: 47s	d_loss: 0
Epoch 2/2: batch 735/936:	time/batch: 0.23s	remaining time: 45s	d_loss: 0
Epoch 2/2: batch 740/936:	time/batch: 0.23s	remaining time: 44s	d_loss: 0
Epoch 2/2: batch 745/936:	time/batch: 0.23s	remaining time: 43s	d_loss: 0
Epoch 2/2: batch 750/936:	time/batch: 0.23s	remaining time: 42s	d_loss: 0
Epoch 2/2: batch 755/936:	time/batch: 0.23s	remaining time: 41s	d_loss: 0
Epoch 2/2: batch 760/936:	time/batch: 0.23s	remaining time: 40s	d_loss: 1
Epoch 2/2: batch 765/936:	time/batch: 0.23s	remaining time: 39s	d_loss: 1
Epoch 2/2: batch 770/936:	time/batch: 0.23s	remaining time: 37s	d_loss: 0
Epoch 2/2: batch 775/936:	time/batch: 0.23s	remaining time: 36s	d_loss: 0
Epoch 2/2: batch 780/936:	time/batch: 0.23s	remaining time: 35s	d_loss: 0
Epoch 2/2: batch 785/936:	time/batch: 0.23s	remaining time: 34s	d_loss: 0
Epoch 2/2: batch 790/936:	time/batch: 0.23s	remaining time: 33s	d_loss: 0
Epoch 2/2: batch 795/936:	time/batch: 0.23s	remaining time: 32s	d_loss: 0
Epoch 2/2: batch 800/936:	time/batch: 0.23s	remaining time: 31s	d_loss: 0



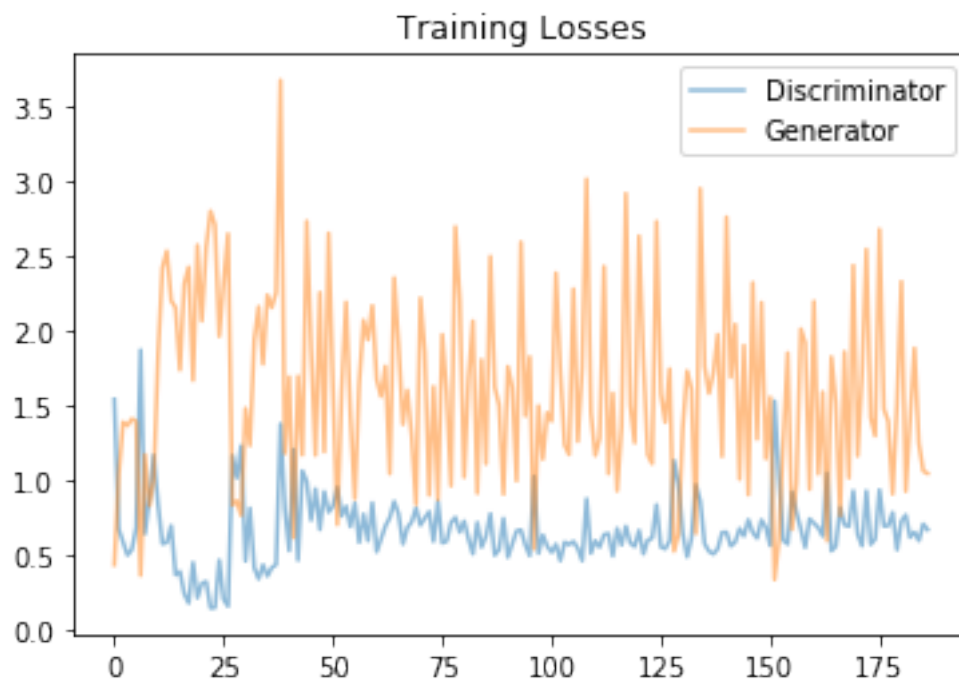
Epoch 2/2: batch 805/936:	time/batch: 0.23s	remaining time: 29s	d_loss: 0
Epoch 2/2: batch 810/936:	time/batch: 0.23s	remaining time: 28s	d_loss: 0
Epoch 2/2: batch 815/936:	time/batch: 0.23s	remaining time: 27s	d_loss: 0
Epoch 2/2: batch 820/936:	time/batch: 0.23s	remaining time: 26s	d_loss: 1
Epoch 2/2: batch 825/936:	time/batch: 0.23s	remaining time: 25s	d_loss: 0
Epoch 2/2: batch 830/936:	time/batch: 0.23s	remaining time: 24s	d_loss: 0
Epoch 2/2: batch 835/936:	time/batch: 0.23s	remaining time: 23s	d_loss: 0
Epoch 2/2: batch 840/936:	time/batch: 0.23s	remaining time: 21s	d_loss: 0
Epoch 2/2: batch 845/936:	time/batch: 0.23s	remaining time: 20s	d_loss: 0
Epoch 2/2: batch 850/936:	time/batch: 0.23s	remaining time: 19s	d_loss: 0
Epoch 2/2: batch 855/936:	time/batch: 0.23s	remaining time: 18s	d_loss: 0
Epoch 2/2: batch 860/936:	time/batch: 0.23s	remaining time: 17s	d_loss: 0
Epoch 2/2: batch 865/936:	time/batch: 0.23s	remaining time: 16s	d_loss: 0
Epoch 2/2: batch 870/936:	time/batch: 0.23s	remaining time: 15s	d_loss: 0
Epoch 2/2: batch 875/936:	time/batch: 0.23s	remaining time: 13s	d_loss: 0
Epoch 2/2: batch 880/936:	time/batch: 0.23s	remaining time: 12s	d_loss: 0
Epoch 2/2: batch 885/936:	time/batch: 0.23s	remaining time: 11s	d_loss: 0
Epoch 2/2: batch 890/936:	time/batch: 0.23s	remaining time: 10s	d_loss: 0
Epoch 2/2: batch 895/936:	time/batch: 0.23s	remaining time: 9s	d_loss: 0
Epoch 2/2: batch 900/936:	time/batch: 0.23s	remaining time: 8s	d_loss: 0



Epoch 2/2: batch 905/936:	time/batch: 0.23s	remaining time: 7s	d_loss: 0.
Epoch 2/2: batch 910/936:	time/batch: 0.23s	remaining time: 5s	d_loss: 0.
Epoch 2/2: batch 915/936:	time/batch: 0.23s	remaining time: 4s	d_loss: 0.
Epoch 2/2: batch 920/936:	time/batch: 0.23s	remaining time: 3s	d_loss: 0.
Epoch 2/2: batch 925/936:	time/batch: 0.23s	remaining time: 2s	d_loss: 0.
Epoch 2/2: batch 930/936:	time/batch: 0.23s	remaining time: 1s	d_loss: 0.
Epoch 2/2: batch 935/936:	time/batch: 0.23s	remaining time: 0s	d_loss: 0.



```
In [22]: plot_losses(d_losses, g_losses)
```



1.3.7 MNIST Run 4

The Generator defined in Run 1 seems to give the best results so far. We return to it and experiment with some of the other hyperparameters.

Generator shape: - layer 1: 4x4x1024 with LRELU activation - layer 2: 7x7x512 with LRELU - layer 3: 14x14x256 with LRELU - layer 4: 28x28xOutput_Channel with TANH

```
In [25]: batch_size = 256
         z_dim = 100
         learning_rate = 0.0002
         beta1 = 0.5

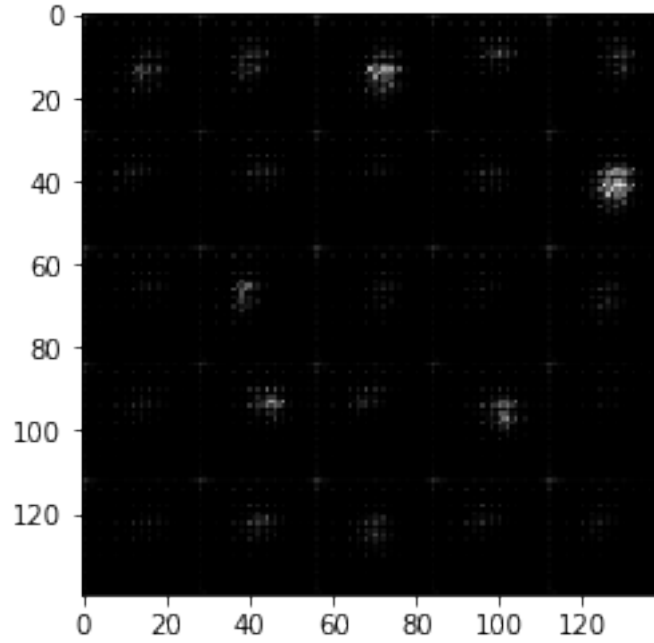
         d_losses = []
         g_losses = []

         """
         DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
         """

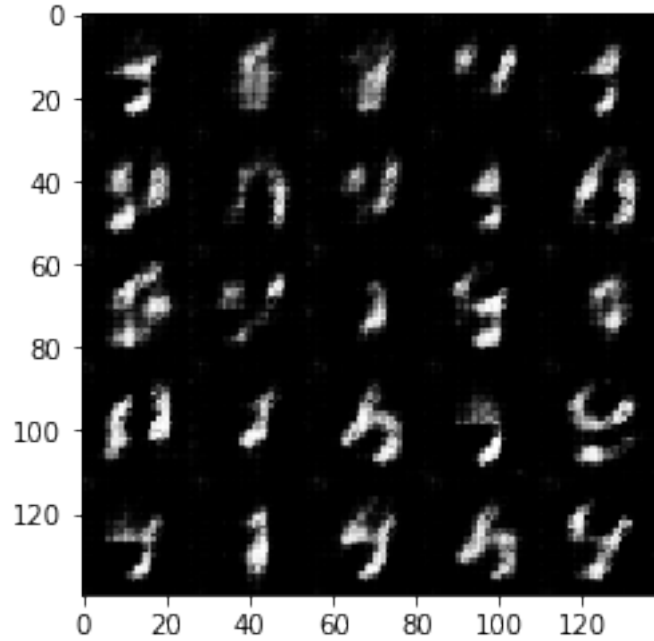
         epochs = 2

         mnist_dataset = helper.Dataset('mnist', glob(os.path.join(data_dir, 'mnist/*.jpg')))
         with tf.Graph().as_default():
             # jcc: added lists for plotting discriminator and generator losses
             d_losses, g_losses = train(epochs, batch_size, z_dim, learning_rate, beta1, mnist_d
                                     mnist_dataset.shape, mnist_dataset.image_mode)

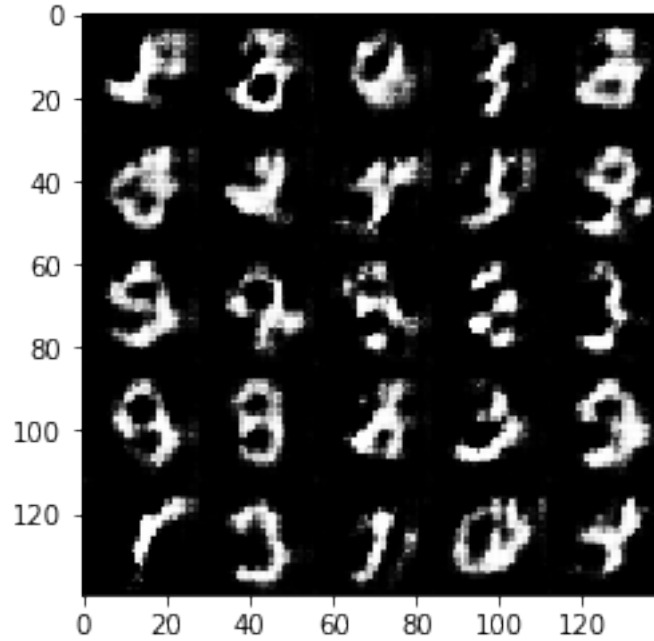
Epoch 1/2: batch 5/468:      time/batch: 1.61s      remaining time: 744s      d_loss: 1.
Epoch 1/2: batch 10/468:     time/batch: 1.24s      remaining time: 568s      d_loss: 0
Epoch 1/2: batch 15/468:     time/batch: 1.12s      remaining time: 506s      d_loss: 0
Epoch 1/2: batch 20/468:     time/batch: 1.06s      remaining time: 472s      d_loss: 0
Epoch 1/2: batch 25/468:     time/batch: 1.02s      remaining time: 450s      d_loss: 0
Epoch 1/2: batch 30/468:     time/batch: 0.99s      remaining time: 434s      d_loss: 0
Epoch 1/2: batch 35/468:     time/batch: 0.97s      remaining time: 421s      d_loss: 0
Epoch 1/2: batch 40/468:     time/batch: 0.96s      remaining time: 411s      d_loss: 0
Epoch 1/2: batch 45/468:     time/batch: 0.95s      remaining time: 402s      d_loss: 0
Epoch 1/2: batch 50/468:     time/batch: 0.94s      remaining time: 393s      d_loss: 0
Epoch 1/2: batch 55/468:     time/batch: 0.94s      remaining time: 386s      d_loss: 0
Epoch 1/2: batch 60/468:     time/batch: 0.93s      remaining time: 379s      d_loss: 1
Epoch 1/2: batch 65/468:     time/batch: 0.93s      remaining time: 373s      d_loss: 1
Epoch 1/2: batch 70/468:     time/batch: 0.92s      remaining time: 366s      d_loss: 0
Epoch 1/2: batch 75/468:     time/batch: 0.92s      remaining time: 360s      d_loss: 0
Epoch 1/2: batch 80/468:     time/batch: 0.92s      remaining time: 355s      d_loss: 0
Epoch 1/2: batch 85/468:     time/batch: 0.91s      remaining time: 349s      d_loss: 0
Epoch 1/2: batch 90/468:     time/batch: 0.91s      remaining time: 344s      d_loss: 0
Epoch 1/2: batch 95/468:     time/batch: 0.91s      remaining time: 338s      d_loss: 0
Epoch 1/2: batch 100/468:    time/batch: 0.91s      remaining time: 333s      d_loss:
```



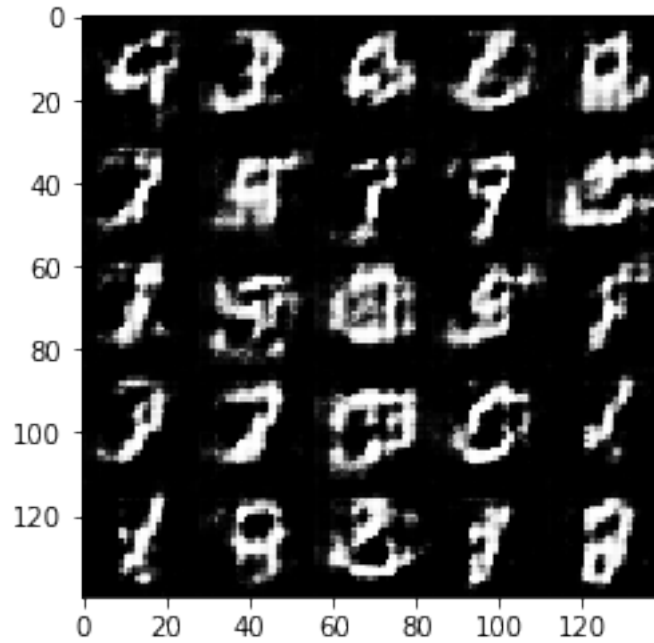
Epoch 1/2: batch 105/468:	time/batch: 0.91s	remaining time: 329s	d_loss:
Epoch 1/2: batch 110/468:	time/batch: 0.91s	remaining time: 324s	d_loss:
Epoch 1/2: batch 115/468:	time/batch: 0.90s	remaining time: 319s	d_loss:
Epoch 1/2: batch 120/468:	time/batch: 0.90s	remaining time: 314s	d_loss:
Epoch 1/2: batch 125/468:	time/batch: 0.90s	remaining time: 309s	d_loss:
Epoch 1/2: batch 130/468:	time/batch: 0.90s	remaining time: 304s	d_loss:
Epoch 1/2: batch 135/468:	time/batch: 0.90s	remaining time: 299s	d_loss:
Epoch 1/2: batch 140/468:	time/batch: 0.90s	remaining time: 294s	d_loss:
Epoch 1/2: batch 145/468:	time/batch: 0.90s	remaining time: 290s	d_loss:
Epoch 1/2: batch 150/468:	time/batch: 0.90s	remaining time: 285s	d_loss:
Epoch 1/2: batch 155/468:	time/batch: 0.90s	remaining time: 280s	d_loss:
Epoch 1/2: batch 160/468:	time/batch: 0.90s	remaining time: 275s	d_loss:
Epoch 1/2: batch 165/468:	time/batch: 0.89s	remaining time: 271s	d_loss:
Epoch 1/2: batch 170/468:	time/batch: 0.89s	remaining time: 266s	d_loss:
Epoch 1/2: batch 175/468:	time/batch: 0.89s	remaining time: 261s	d_loss:
Epoch 1/2: batch 180/468:	time/batch: 0.89s	remaining time: 257s	d_loss:
Epoch 1/2: batch 185/468:	time/batch: 0.89s	remaining time: 252s	d_loss:
Epoch 1/2: batch 190/468:	time/batch: 0.89s	remaining time: 248s	d_loss:
Epoch 1/2: batch 195/468:	time/batch: 0.89s	remaining time: 243s	d_loss:
Epoch 1/2: batch 200/468:	time/batch: 0.89s	remaining time: 238s	d_loss:



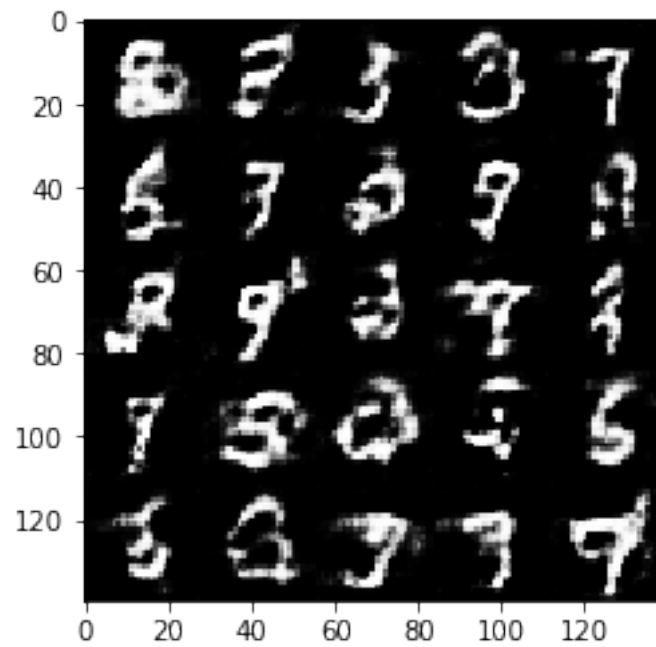
Epoch 1/2: batch 205/468:	time/batch: 0.89s	remaining time: 234s	d_loss:
Epoch 1/2: batch 210/468:	time/batch: 0.89s	remaining time: 230s	d_loss:
Epoch 1/2: batch 215/468:	time/batch: 0.89s	remaining time: 225s	d_loss:
Epoch 1/2: batch 220/468:	time/batch: 0.89s	remaining time: 220s	d_loss:
Epoch 1/2: batch 225/468:	time/batch: 0.89s	remaining time: 216s	d_loss:
Epoch 1/2: batch 230/468:	time/batch: 0.89s	remaining time: 211s	d_loss:
Epoch 2/2: batch 235/468:	time/batch: 0.89s	remaining time: 207s	d_loss:
Epoch 2/2: batch 240/468:	time/batch: 0.89s	remaining time: 202s	d_loss:
Epoch 2/2: batch 245/468:	time/batch: 0.89s	remaining time: 198s	d_loss:
Epoch 2/2: batch 250/468:	time/batch: 0.89s	remaining time: 193s	d_loss:
Epoch 2/2: batch 255/468:	time/batch: 0.89s	remaining time: 189s	d_loss:
Epoch 2/2: batch 260/468:	time/batch: 0.89s	remaining time: 184s	d_loss:
Epoch 2/2: batch 265/468:	time/batch: 0.89s	remaining time: 180s	d_loss:
Epoch 2/2: batch 270/468:	time/batch: 0.89s	remaining time: 175s	d_loss:
Epoch 2/2: batch 275/468:	time/batch: 0.89s	remaining time: 171s	d_loss:
Epoch 2/2: batch 280/468:	time/batch: 0.89s	remaining time: 166s	d_loss:
Epoch 2/2: batch 285/468:	time/batch: 0.89s	remaining time: 162s	d_loss:
Epoch 2/2: batch 290/468:	time/batch: 0.89s	remaining time: 157s	d_loss:
Epoch 2/2: batch 295/468:	time/batch: 0.89s	remaining time: 153s	d_loss:
Epoch 2/2: batch 300/468:	time/batch: 0.89s	remaining time: 148s	d_loss:



Epoch 2/2: batch 305/468:	time/batch: 0.89s	remaining time: 144s	d_loss:
Epoch 2/2: batch 310/468:	time/batch: 0.89s	remaining time: 140s	d_loss:
Epoch 2/2: batch 315/468:	time/batch: 0.89s	remaining time: 135s	d_loss:
Epoch 2/2: batch 320/468:	time/batch: 0.89s	remaining time: 131s	d_loss:
Epoch 2/2: batch 325/468:	time/batch: 0.89s	remaining time: 126s	d_loss:
Epoch 2/2: batch 330/468:	time/batch: 0.89s	remaining time: 122s	d_loss:
Epoch 2/2: batch 335/468:	time/batch: 0.89s	remaining time: 117s	d_loss:
Epoch 2/2: batch 340/468:	time/batch: 0.89s	remaining time: 113s	d_loss:
Epoch 2/2: batch 345/468:	time/batch: 0.89s	remaining time: 108s	d_loss:
Epoch 2/2: batch 350/468:	time/batch: 0.89s	remaining time: 104s	d_loss:
Epoch 2/2: batch 355/468:	time/batch: 0.89s	remaining time: 100s	d_loss:
Epoch 2/2: batch 360/468:	time/batch: 0.89s	remaining time: 95s	d_loss: 0
Epoch 2/2: batch 365/468:	time/batch: 0.89s	remaining time: 91s	d_loss: 1
Epoch 2/2: batch 370/468:	time/batch: 0.89s	remaining time: 86s	d_loss: 0
Epoch 2/2: batch 375/468:	time/batch: 0.88s	remaining time: 82s	d_loss: 0
Epoch 2/2: batch 380/468:	time/batch: 0.88s	remaining time: 77s	d_loss: 1
Epoch 2/2: batch 385/468:	time/batch: 0.88s	remaining time: 73s	d_loss: 0
Epoch 2/2: batch 390/468:	time/batch: 0.88s	remaining time: 68s	d_loss: 0
Epoch 2/2: batch 395/468:	time/batch: 0.88s	remaining time: 64s	d_loss: 1
Epoch 2/2: batch 400/468:	time/batch: 0.88s	remaining time: 60s	d_loss: 0



Epoch 2/2: batch 405/468:	time/batch: 0.88s	remaining time: 55s	d_loss: 0
Epoch 2/2: batch 410/468:	time/batch: 0.88s	remaining time: 51s	d_loss: 1
Epoch 2/2: batch 415/468:	time/batch: 0.88s	remaining time: 46s	d_loss: 0
Epoch 2/2: batch 420/468:	time/batch: 0.88s	remaining time: 42s	d_loss: 0
Epoch 2/2: batch 425/468:	time/batch: 0.88s	remaining time: 38s	d_loss: 1
Epoch 2/2: batch 430/468:	time/batch: 0.88s	remaining time: 33s	d_loss: 1
Epoch 2/2: batch 435/468:	time/batch: 0.88s	remaining time: 29s	d_loss: 0
Epoch 2/2: batch 440/468:	time/batch: 0.88s	remaining time: 24s	d_loss: 1
Epoch 2/2: batch 445/468:	time/batch: 0.88s	remaining time: 20s	d_loss: 1
Epoch 2/2: batch 450/468:	time/batch: 0.88s	remaining time: 15s	d_loss: 0
Epoch 2/2: batch 455/468:	time/batch: 0.88s	remaining time: 11s	d_loss: 1
Epoch 2/2: batch 460/468:	time/batch: 0.88s	remaining time: 7s	d_loss: 0
Epoch 2/2: batch 465/468:	time/batch: 0.88s	remaining time: 2s	d_loss: 1



In [26]: plot_losses(d_losses, g_losses)



1.3.8 Results:

Use parameters from MNIST run no. 1 as the starting point for CelebA dataset.

1.3.9 CelebA

Run your GANs on CelebA. It will take around 20 minutes on the average GPU to run one epoch. You can run the whole epoch or stop when it starts to generate realistic faces.

```
In [27]: batch_size = 128
         z_dim = 100
         learning_rate = 0.0002
         beta1 = 0.5

         d_losses = []
         g_losses = []

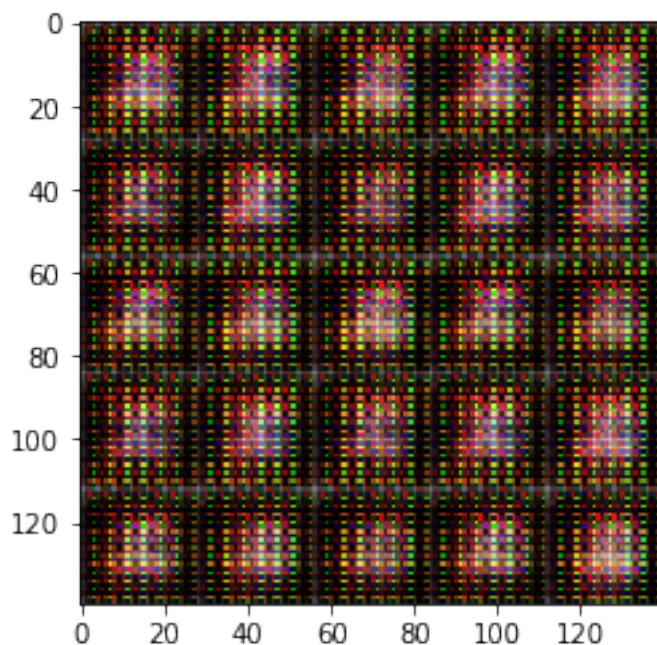
         """
         DON'T MODIFY ANYTHING IN THIS CELL THAT IS BELOW THIS LINE
         """

         epochs = 1

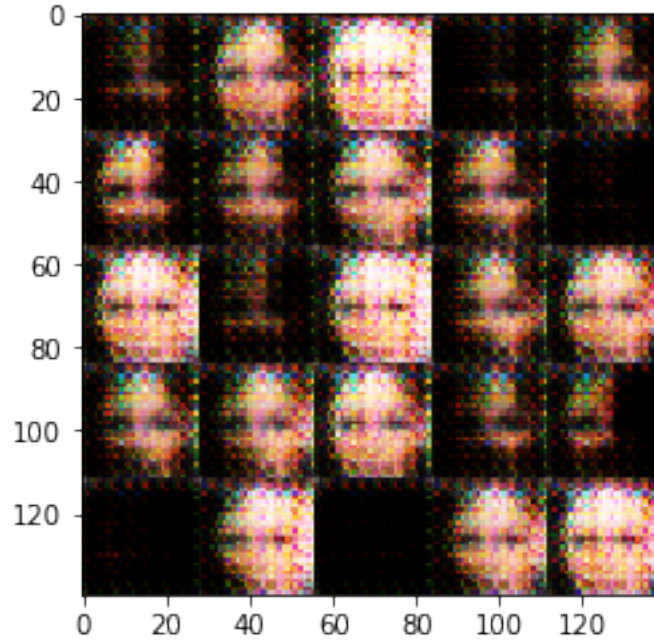
         celeba_dataset = helper.Dataset('celeba', glob(os.path.join(data_dir, 'img_align_celeba_*')))
         with tf.Graph().as_default():
             # jcc: added lists for plotting discriminator and generator losses
             d_losses, g_losses = train(epochs, batch_size, z_dim, learning_rate, beta1, celeba_dataset,
                                       celeba_dataset.shape, celeba_dataset.image_mode)

Epoch 1/1: batch 5/1582:      time/batch: 0.97s      remaining time: 1524s      d_loss:
Epoch 1/1: batch 10/1582:    time/batch: 0.83s      remaining time: 1306s      d_loss:
Epoch 1/1: batch 15/1582:    time/batch: 0.78s      remaining time: 1220s      d_loss:
Epoch 1/1: batch 20/1582:    time/batch: 0.75s      remaining time: 1174s      d_loss:
Epoch 1/1: batch 25/1582:    time/batch: 0.73s      remaining time: 1143s      d_loss:
Epoch 1/1: batch 30/1582:    time/batch: 0.72s      remaining time: 1124s      d_loss:
Epoch 1/1: batch 35/1582:    time/batch: 0.72s      remaining time: 1108s      d_loss:
Epoch 1/1: batch 40/1582:    time/batch: 0.71s      remaining time: 1095s      d_loss:
Epoch 1/1: batch 45/1582:    time/batch: 0.71s      remaining time: 1085s      d_loss:
Epoch 1/1: batch 50/1582:    time/batch: 0.70s      remaining time: 1075s      d_loss:
Epoch 1/1: batch 55/1582:    time/batch: 0.70s      remaining time: 1067s      d_loss:
Epoch 1/1: batch 60/1582:    time/batch: 0.70s      remaining time: 1060s      d_loss:
Epoch 1/1: batch 65/1582:    time/batch: 0.69s      remaining time: 1052s      d_loss:
Epoch 1/1: batch 70/1582:    time/batch: 0.69s      remaining time: 1046s      d_loss:
Epoch 1/1: batch 75/1582:    time/batch: 0.69s      remaining time: 1040s      d_loss:
Epoch 1/1: batch 80/1582:    time/batch: 0.69s      remaining time: 1034s      d_loss:
Epoch 1/1: batch 85/1582:    time/batch: 0.69s      remaining time: 1029s      d_loss:
Epoch 1/1: batch 90/1582:    time/batch: 0.69s      remaining time: 1025s      d_loss:
Epoch 1/1: batch 95/1582:    time/batch: 0.69s      remaining time: 1020s      d_loss:
```

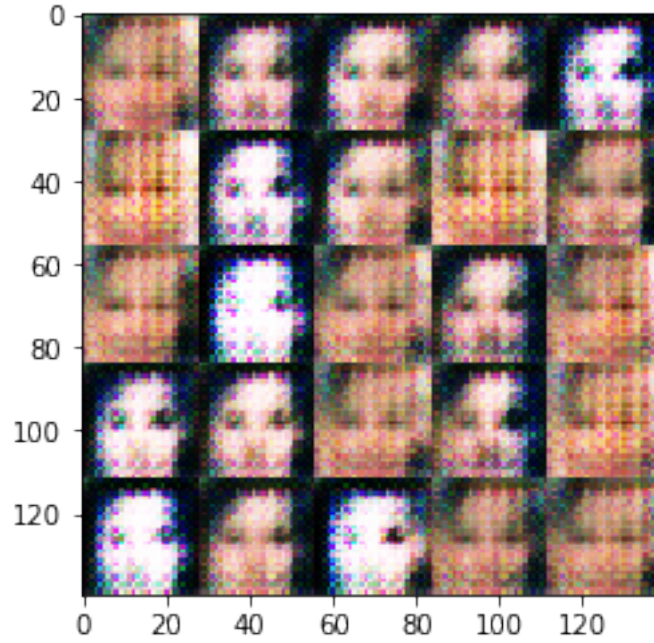
Epoch 1/1: batch 100/1582: time/batch: 0.69s remaining time: 1015s d_loss



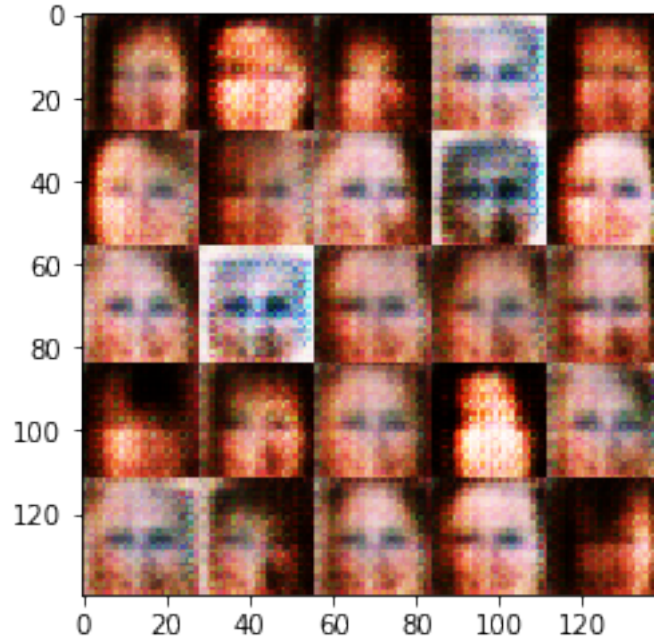
Epoch 1/1: batch 105/1582:	time/batch: 0.69s	remaining time: 1016s	d_loss
Epoch 1/1: batch 110/1582:	time/batch: 0.69s	remaining time: 1011s	d_loss
Epoch 1/1: batch 115/1582:	time/batch: 0.69s	remaining time: 1007s	d_loss
Epoch 1/1: batch 120/1582:	time/batch: 0.69s	remaining time: 1002s	d_loss
Epoch 1/1: batch 125/1582:	time/batch: 0.69s	remaining time: 998s	d_loss:
Epoch 1/1: batch 130/1582:	time/batch: 0.68s	remaining time: 994s	d_loss:
Epoch 1/1: batch 135/1582:	time/batch: 0.68s	remaining time: 989s	d_loss:
Epoch 1/1: batch 140/1582:	time/batch: 0.68s	remaining time: 985s	d_loss:
Epoch 1/1: batch 145/1582:	time/batch: 0.68s	remaining time: 981s	d_loss:
Epoch 1/1: batch 150/1582:	time/batch: 0.68s	remaining time: 977s	d_loss:
Epoch 1/1: batch 155/1582:	time/batch: 0.68s	remaining time: 973s	d_loss:
Epoch 1/1: batch 160/1582:	time/batch: 0.68s	remaining time: 969s	d_loss:
Epoch 1/1: batch 165/1582:	time/batch: 0.68s	remaining time: 966s	d_loss:
Epoch 1/1: batch 170/1582:	time/batch: 0.68s	remaining time: 962s	d_loss:
Epoch 1/1: batch 175/1582:	time/batch: 0.68s	remaining time: 958s	d_loss:
Epoch 1/1: batch 180/1582:	time/batch: 0.68s	remaining time: 954s	d_loss:
Epoch 1/1: batch 185/1582:	time/batch: 0.68s	remaining time: 950s	d_loss:
Epoch 1/1: batch 190/1582:	time/batch: 0.68s	remaining time: 946s	d_loss:
Epoch 1/1: batch 195/1582:	time/batch: 0.68s	remaining time: 943s	d_loss:
Epoch 1/1: batch 200/1582:	time/batch: 0.68s	remaining time: 939s	d_loss:



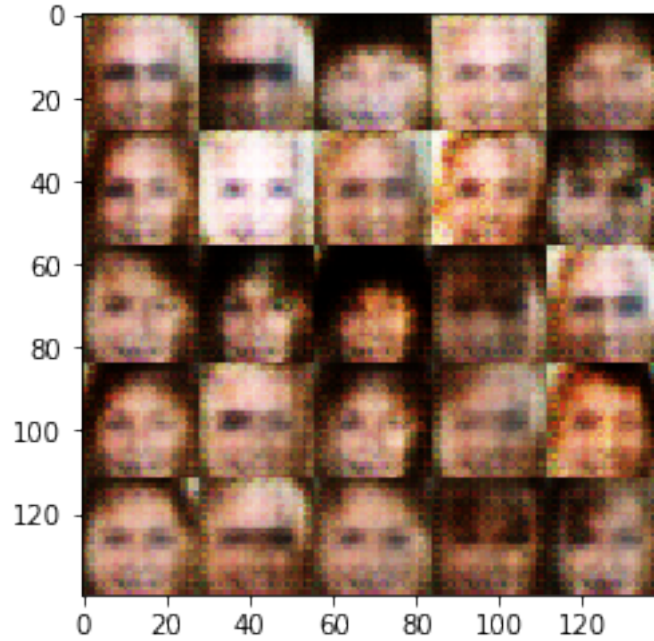
Epoch 1/1: batch 205/1582:	time/batch: 0.68s	remaining time: 937s	d_loss:
Epoch 1/1: batch 210/1582:	time/batch: 0.68s	remaining time: 934s	d_loss:
Epoch 1/1: batch 215/1582:	time/batch: 0.68s	remaining time: 930s	d_loss:
Epoch 1/1: batch 220/1582:	time/batch: 0.68s	remaining time: 926s	d_loss:
Epoch 1/1: batch 225/1582:	time/batch: 0.68s	remaining time: 922s	d_loss:
Epoch 1/1: batch 230/1582:	time/batch: 0.68s	remaining time: 919s	d_loss:
Epoch 1/1: batch 235/1582:	time/batch: 0.68s	remaining time: 915s	d_loss:
Epoch 1/1: batch 240/1582:	time/batch: 0.68s	remaining time: 911s	d_loss:
Epoch 1/1: batch 245/1582:	time/batch: 0.68s	remaining time: 908s	d_loss:
Epoch 1/1: batch 250/1582:	time/batch: 0.68s	remaining time: 904s	d_loss:
Epoch 1/1: batch 255/1582:	time/batch: 0.68s	remaining time: 901s	d_loss:
Epoch 1/1: batch 260/1582:	time/batch: 0.68s	remaining time: 897s	d_loss:
Epoch 1/1: batch 265/1582:	time/batch: 0.68s	remaining time: 893s	d_loss:
Epoch 1/1: batch 270/1582:	time/batch: 0.68s	remaining time: 889s	d_loss:
Epoch 1/1: batch 275/1582:	time/batch: 0.68s	remaining time: 886s	d_loss:
Epoch 1/1: batch 280/1582:	time/batch: 0.68s	remaining time: 882s	d_loss:
Epoch 1/1: batch 285/1582:	time/batch: 0.68s	remaining time: 879s	d_loss:
Epoch 1/1: batch 290/1582:	time/batch: 0.68s	remaining time: 875s	d_loss:
Epoch 1/1: batch 295/1582:	time/batch: 0.68s	remaining time: 871s	d_loss:
Epoch 1/1: batch 300/1582:	time/batch: 0.68s	remaining time: 868s	d_loss:



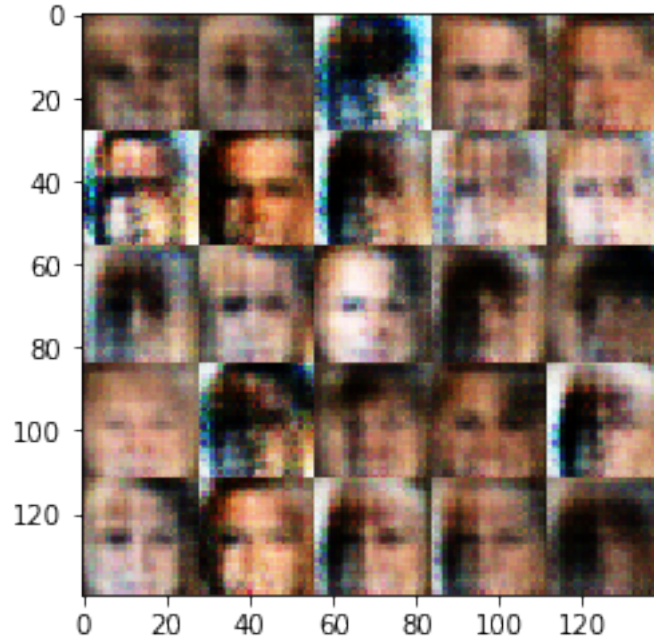
Epoch 1/1: batch 305/1582:	time/batch: 0.68s	remaining time: 866s	d_loss:
Epoch 1/1: batch 310/1582:	time/batch: 0.68s	remaining time: 863s	d_loss:
Epoch 1/1: batch 315/1582:	time/batch: 0.68s	remaining time: 859s	d_loss:
Epoch 1/1: batch 320/1582:	time/batch: 0.68s	remaining time: 856s	d_loss:
Epoch 1/1: batch 325/1582:	time/batch: 0.68s	remaining time: 852s	d_loss:
Epoch 1/1: batch 330/1582:	time/batch: 0.68s	remaining time: 849s	d_loss:
Epoch 1/1: batch 335/1582:	time/batch: 0.68s	remaining time: 845s	d_loss:
Epoch 1/1: batch 340/1582:	time/batch: 0.68s	remaining time: 842s	d_loss:
Epoch 1/1: batch 345/1582:	time/batch: 0.68s	remaining time: 838s	d_loss:
Epoch 1/1: batch 350/1582:	time/batch: 0.68s	remaining time: 835s	d_loss:
Epoch 1/1: batch 355/1582:	time/batch: 0.68s	remaining time: 831s	d_loss:
Epoch 1/1: batch 360/1582:	time/batch: 0.68s	remaining time: 827s	d_loss:
Epoch 1/1: batch 365/1582:	time/batch: 0.68s	remaining time: 824s	d_loss:
Epoch 1/1: batch 370/1582:	time/batch: 0.68s	remaining time: 821s	d_loss:
Epoch 1/1: batch 375/1582:	time/batch: 0.68s	remaining time: 817s	d_loss:
Epoch 1/1: batch 380/1582:	time/batch: 0.68s	remaining time: 814s	d_loss:
Epoch 1/1: batch 385/1582:	time/batch: 0.68s	remaining time: 810s	d_loss:
Epoch 1/1: batch 390/1582:	time/batch: 0.68s	remaining time: 807s	d_loss:
Epoch 1/1: batch 395/1582:	time/batch: 0.68s	remaining time: 803s	d_loss:
Epoch 1/1: batch 400/1582:	time/batch: 0.68s	remaining time: 800s	d_loss:



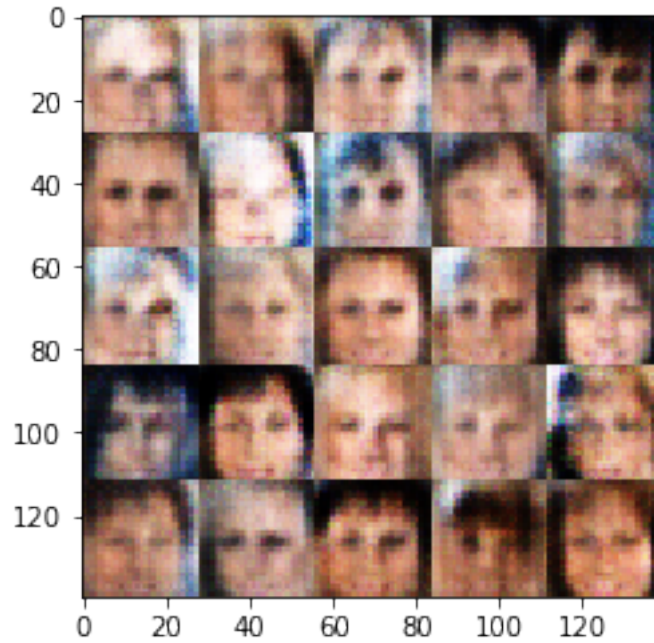
Epoch 1/1: batch 405/1582:	time/batch: 0.68s	remaining time: 797s	d_loss:
Epoch 1/1: batch 410/1582:	time/batch: 0.68s	remaining time: 794s	d_loss:
Epoch 1/1: batch 415/1582:	time/batch: 0.68s	remaining time: 790s	d_loss:
Epoch 1/1: batch 420/1582:	time/batch: 0.68s	remaining time: 787s	d_loss:
Epoch 1/1: batch 425/1582:	time/batch: 0.68s	remaining time: 783s	d_loss:
Epoch 1/1: batch 430/1582:	time/batch: 0.68s	remaining time: 780s	d_loss:
Epoch 1/1: batch 435/1582:	time/batch: 0.68s	remaining time: 776s	d_loss:
Epoch 1/1: batch 440/1582:	time/batch: 0.68s	remaining time: 773s	d_loss:
Epoch 1/1: batch 445/1582:	time/batch: 0.68s	remaining time: 769s	d_loss:
Epoch 1/1: batch 450/1582:	time/batch: 0.68s	remaining time: 766s	d_loss:
Epoch 1/1: batch 455/1582:	time/batch: 0.68s	remaining time: 762s	d_loss:
Epoch 1/1: batch 460/1582:	time/batch: 0.68s	remaining time: 759s	d_loss:
Epoch 1/1: batch 465/1582:	time/batch: 0.68s	remaining time: 755s	d_loss:
Epoch 1/1: batch 470/1582:	time/batch: 0.68s	remaining time: 752s	d_loss:
Epoch 1/1: batch 475/1582:	time/batch: 0.68s	remaining time: 748s	d_loss:
Epoch 1/1: batch 480/1582:	time/batch: 0.68s	remaining time: 745s	d_loss:
Epoch 1/1: batch 485/1582:	time/batch: 0.68s	remaining time: 742s	d_loss:
Epoch 1/1: batch 490/1582:	time/batch: 0.68s	remaining time: 738s	d_loss:
Epoch 1/1: batch 495/1582:	time/batch: 0.68s	remaining time: 735s	d_loss:
Epoch 1/1: batch 500/1582:	time/batch: 0.68s	remaining time: 731s	d_loss:



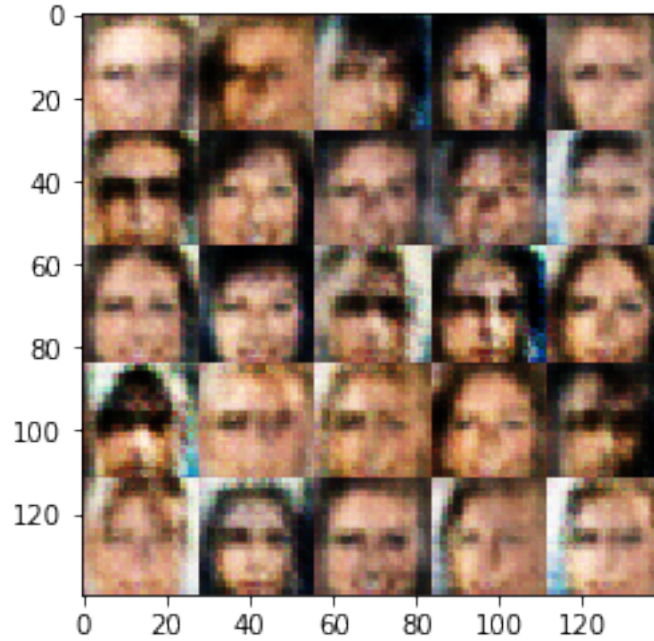
Epoch 1/1: batch 505/1582:	time/batch: 0.68s	remaining time: 729s	d_loss:
Epoch 1/1: batch 510/1582:	time/batch: 0.68s	remaining time: 725s	d_loss:
Epoch 1/1: batch 515/1582:	time/batch: 0.68s	remaining time: 722s	d_loss:
Epoch 1/1: batch 520/1582:	time/batch: 0.68s	remaining time: 718s	d_loss:
Epoch 1/1: batch 525/1582:	time/batch: 0.68s	remaining time: 715s	d_loss:
Epoch 1/1: batch 530/1582:	time/batch: 0.68s	remaining time: 711s	d_loss:
Epoch 1/1: batch 535/1582:	time/batch: 0.68s	remaining time: 708s	d_loss:
Epoch 1/1: batch 540/1582:	time/batch: 0.68s	remaining time: 704s	d_loss:
Epoch 1/1: batch 545/1582:	time/batch: 0.68s	remaining time: 701s	d_loss:
Epoch 1/1: batch 550/1582:	time/batch: 0.68s	remaining time: 697s	d_loss:
Epoch 1/1: batch 555/1582:	time/batch: 0.68s	remaining time: 694s	d_loss:
Epoch 1/1: batch 560/1582:	time/batch: 0.68s	remaining time: 691s	d_loss:
Epoch 1/1: batch 565/1582:	time/batch: 0.68s	remaining time: 687s	d_loss:
Epoch 1/1: batch 570/1582:	time/batch: 0.68s	remaining time: 684s	d_loss:
Epoch 1/1: batch 575/1582:	time/batch: 0.68s	remaining time: 680s	d_loss:
Epoch 1/1: batch 580/1582:	time/batch: 0.68s	remaining time: 677s	d_loss:
Epoch 1/1: batch 585/1582:	time/batch: 0.68s	remaining time: 674s	d_loss:
Epoch 1/1: batch 590/1582:	time/batch: 0.68s	remaining time: 670s	d_loss:
Epoch 1/1: batch 595/1582:	time/batch: 0.68s	remaining time: 667s	d_loss:
Epoch 1/1: batch 600/1582:	time/batch: 0.68s	remaining time: 663s	d_loss:



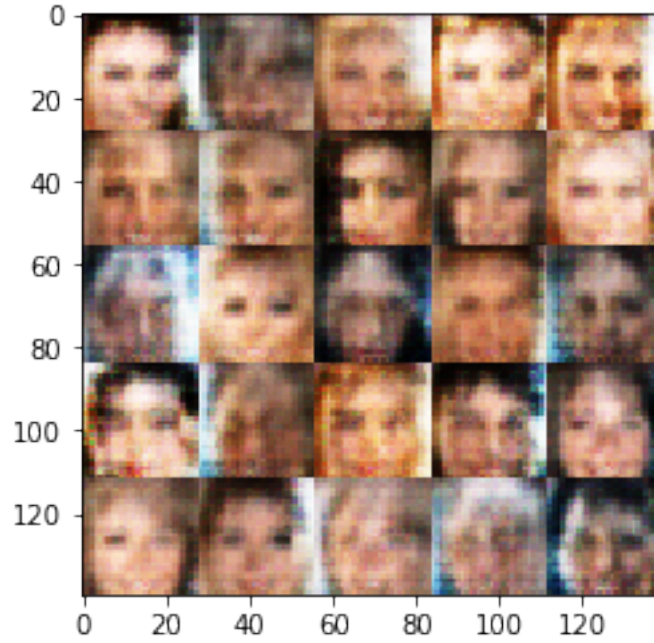
Epoch 1/1: batch 605/1582:	time/batch: 0.68s	remaining time: 660s	d_loss:
Epoch 1/1: batch 610/1582:	time/batch: 0.68s	remaining time: 657s	d_loss:
Epoch 1/1: batch 615/1582:	time/batch: 0.68s	remaining time: 654s	d_loss:
Epoch 1/1: batch 620/1582:	time/batch: 0.68s	remaining time: 650s	d_loss:
Epoch 1/1: batch 625/1582:	time/batch: 0.68s	remaining time: 647s	d_loss:
Epoch 1/1: batch 630/1582:	time/batch: 0.68s	remaining time: 643s	d_loss:
Epoch 1/1: batch 635/1582:	time/batch: 0.68s	remaining time: 640s	d_loss:
Epoch 1/1: batch 640/1582:	time/batch: 0.68s	remaining time: 636s	d_loss:
Epoch 1/1: batch 645/1582:	time/batch: 0.68s	remaining time: 633s	d_loss:
Epoch 1/1: batch 650/1582:	time/batch: 0.68s	remaining time: 629s	d_loss:
Epoch 1/1: batch 655/1582:	time/batch: 0.68s	remaining time: 626s	d_loss:
Epoch 1/1: batch 660/1582:	time/batch: 0.68s	remaining time: 623s	d_loss:
Epoch 1/1: batch 665/1582:	time/batch: 0.68s	remaining time: 619s	d_loss:
Epoch 1/1: batch 670/1582:	time/batch: 0.68s	remaining time: 616s	d_loss:
Epoch 1/1: batch 675/1582:	time/batch: 0.68s	remaining time: 612s	d_loss:
Epoch 1/1: batch 680/1582:	time/batch: 0.68s	remaining time: 609s	d_loss:
Epoch 1/1: batch 685/1582:	time/batch: 0.68s	remaining time: 606s	d_loss:
Epoch 1/1: batch 690/1582:	time/batch: 0.68s	remaining time: 602s	d_loss:
Epoch 1/1: batch 695/1582:	time/batch: 0.68s	remaining time: 599s	d_loss:
Epoch 1/1: batch 700/1582:	time/batch: 0.68s	remaining time: 595s	d_loss:



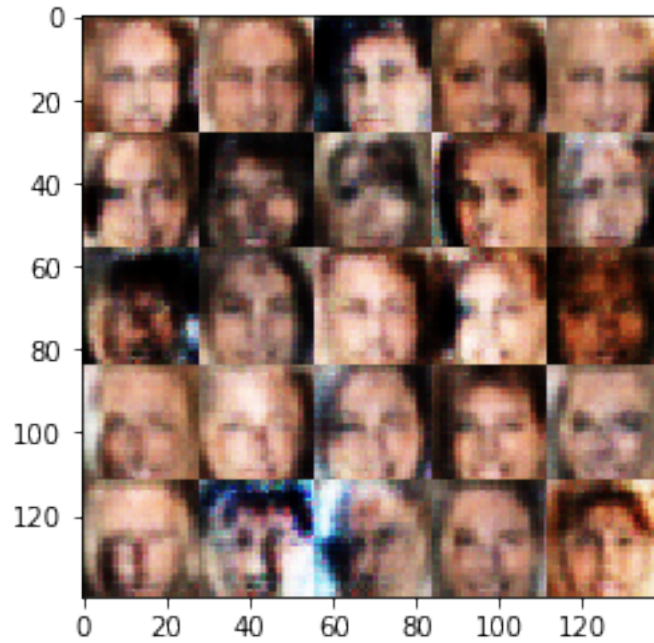
Epoch 1/1: batch 705/1582:	time/batch: 0.68s	remaining time: 592s	d_loss:
Epoch 1/1: batch 710/1582:	time/batch: 0.68s	remaining time: 589s	d_loss:
Epoch 1/1: batch 715/1582:	time/batch: 0.68s	remaining time: 586s	d_loss:
Epoch 1/1: batch 720/1582:	time/batch: 0.68s	remaining time: 582s	d_loss:
Epoch 1/1: batch 725/1582:	time/batch: 0.68s	remaining time: 579s	d_loss:
Epoch 1/1: batch 730/1582:	time/batch: 0.68s	remaining time: 575s	d_loss:
Epoch 1/1: batch 735/1582:	time/batch: 0.68s	remaining time: 572s	d_loss:
Epoch 1/1: batch 740/1582:	time/batch: 0.68s	remaining time: 568s	d_loss:
Epoch 1/1: batch 745/1582:	time/batch: 0.68s	remaining time: 565s	d_loss:
Epoch 1/1: batch 750/1582:	time/batch: 0.68s	remaining time: 562s	d_loss:
Epoch 1/1: batch 755/1582:	time/batch: 0.68s	remaining time: 558s	d_loss:
Epoch 1/1: batch 760/1582:	time/batch: 0.68s	remaining time: 555s	d_loss:
Epoch 1/1: batch 765/1582:	time/batch: 0.68s	remaining time: 551s	d_loss:
Epoch 1/1: batch 770/1582:	time/batch: 0.68s	remaining time: 548s	d_loss:
Epoch 1/1: batch 775/1582:	time/batch: 0.68s	remaining time: 545s	d_loss:
Epoch 1/1: batch 780/1582:	time/batch: 0.68s	remaining time: 541s	d_loss:
Epoch 1/1: batch 785/1582:	time/batch: 0.68s	remaining time: 538s	d_loss:
Epoch 1/1: batch 790/1582:	time/batch: 0.68s	remaining time: 534s	d_loss:
Epoch 1/1: batch 795/1582:	time/batch: 0.68s	remaining time: 531s	d_loss:
Epoch 1/1: batch 800/1582:	time/batch: 0.68s	remaining time: 528s	d_loss:



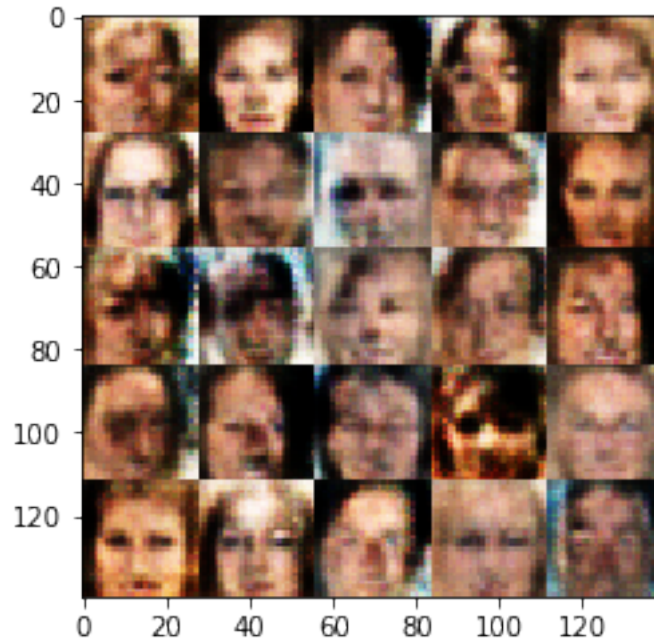
Epoch 1/1: batch 805/1582:	time/batch: 0.68s	remaining time: 524s	d_loss:
Epoch 1/1: batch 810/1582:	time/batch: 0.68s	remaining time: 521s	d_loss:
Epoch 1/1: batch 815/1582:	time/batch: 0.68s	remaining time: 518s	d_loss:
Epoch 1/1: batch 820/1582:	time/batch: 0.68s	remaining time: 514s	d_loss:
Epoch 1/1: batch 825/1582:	time/batch: 0.68s	remaining time: 511s	d_loss:
Epoch 1/1: batch 830/1582:	time/batch: 0.68s	remaining time: 507s	d_loss:
Epoch 1/1: batch 835/1582:	time/batch: 0.68s	remaining time: 504s	d_loss:
Epoch 1/1: batch 840/1582:	time/batch: 0.68s	remaining time: 501s	d_loss:
Epoch 1/1: batch 845/1582:	time/batch: 0.68s	remaining time: 497s	d_loss:
Epoch 1/1: batch 850/1582:	time/batch: 0.68s	remaining time: 494s	d_loss:
Epoch 1/1: batch 855/1582:	time/batch: 0.68s	remaining time: 490s	d_loss:
Epoch 1/1: batch 860/1582:	time/batch: 0.68s	remaining time: 487s	d_loss:
Epoch 1/1: batch 865/1582:	time/batch: 0.68s	remaining time: 484s	d_loss:
Epoch 1/1: batch 870/1582:	time/batch: 0.68s	remaining time: 480s	d_loss:
Epoch 1/1: batch 875/1582:	time/batch: 0.68s	remaining time: 477s	d_loss:
Epoch 1/1: batch 880/1582:	time/batch: 0.67s	remaining time: 473s	d_loss:
Epoch 1/1: batch 885/1582:	time/batch: 0.67s	remaining time: 470s	d_loss:
Epoch 1/1: batch 890/1582:	time/batch: 0.67s	remaining time: 467s	d_loss:
Epoch 1/1: batch 895/1582:	time/batch: 0.67s	remaining time: 463s	d_loss:
Epoch 1/1: batch 900/1582:	time/batch: 0.67s	remaining time: 460s	d_loss:



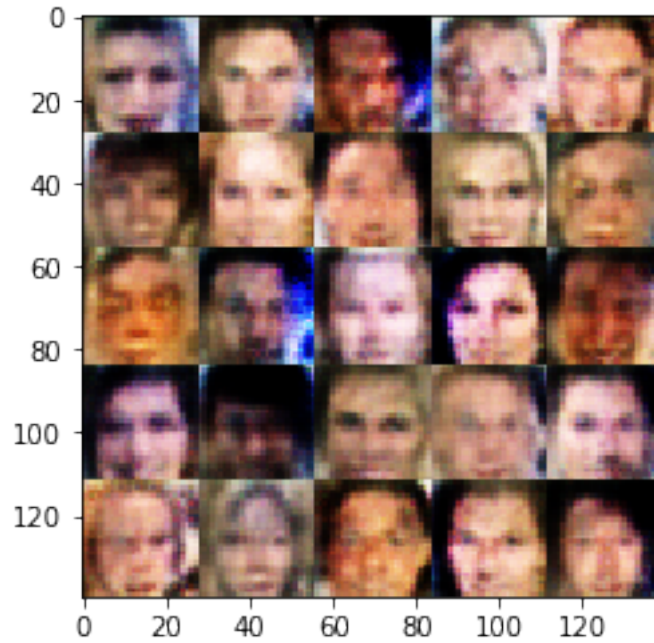
Epoch 1/1: batch 905/1582:	time/batch: 0.68s	remaining time: 457s	d_loss:
Epoch 1/1: batch 910/1582:	time/batch: 0.68s	remaining time: 453s	d_loss:
Epoch 1/1: batch 915/1582:	time/batch: 0.68s	remaining time: 450s	d_loss:
Epoch 1/1: batch 920/1582:	time/batch: 0.68s	remaining time: 446s	d_loss:
Epoch 1/1: batch 925/1582:	time/batch: 0.68s	remaining time: 443s	d_loss:
Epoch 1/1: batch 930/1582:	time/batch: 0.68s	remaining time: 440s	d_loss:
Epoch 1/1: batch 935/1582:	time/batch: 0.68s	remaining time: 436s	d_loss:
Epoch 1/1: batch 940/1582:	time/batch: 0.68s	remaining time: 433s	d_loss:
Epoch 1/1: batch 945/1582:	time/batch: 0.68s	remaining time: 430s	d_loss:
Epoch 1/1: batch 950/1582:	time/batch: 0.68s	remaining time: 426s	d_loss:
Epoch 1/1: batch 955/1582:	time/batch: 0.67s	remaining time: 423s	d_loss:
Epoch 1/1: batch 960/1582:	time/batch: 0.67s	remaining time: 419s	d_loss:
Epoch 1/1: batch 965/1582:	time/batch: 0.67s	remaining time: 416s	d_loss:
Epoch 1/1: batch 970/1582:	time/batch: 0.67s	remaining time: 413s	d_loss:
Epoch 1/1: batch 975/1582:	time/batch: 0.67s	remaining time: 409s	d_loss:
Epoch 1/1: batch 980/1582:	time/batch: 0.67s	remaining time: 406s	d_loss:
Epoch 1/1: batch 985/1582:	time/batch: 0.67s	remaining time: 402s	d_loss:
Epoch 1/1: batch 990/1582:	time/batch: 0.67s	remaining time: 399s	d_loss:
Epoch 1/1: batch 995/1582:	time/batch: 0.67s	remaining time: 396s	d_loss:
Epoch 1/1: batch 1000/1582:	time/batch: 0.67s	remaining time: 392s	d_loss:



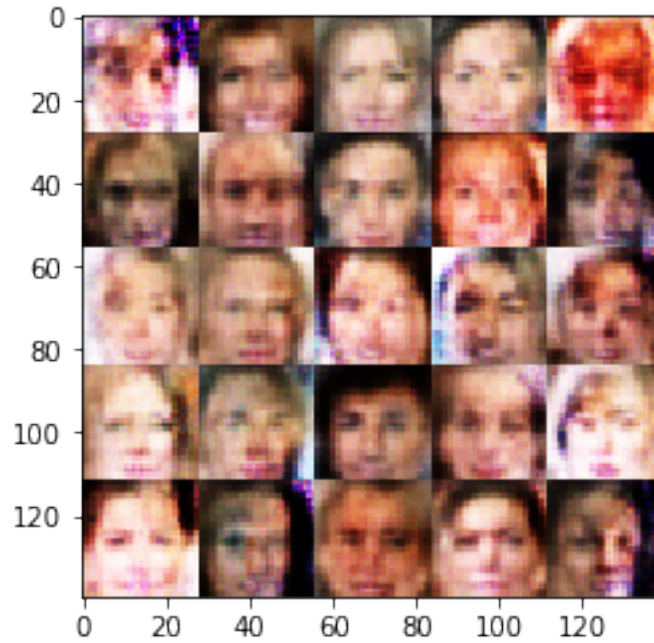
Epoch 1/1: batch 1005/1582:	time/batch: 0.68s	remaining time: 389s	d_loss
Epoch 1/1: batch 1010/1582:	time/batch: 0.67s	remaining time: 386s	d_loss
Epoch 1/1: batch 1015/1582:	time/batch: 0.67s	remaining time: 382s	d_loss
Epoch 1/1: batch 1020/1582:	time/batch: 0.67s	remaining time: 379s	d_loss
Epoch 1/1: batch 1025/1582:	time/batch: 0.67s	remaining time: 375s	d_loss
Epoch 1/1: batch 1030/1582:	time/batch: 0.67s	remaining time: 372s	d_loss
Epoch 1/1: batch 1035/1582:	time/batch: 0.67s	remaining time: 369s	d_loss
Epoch 1/1: batch 1040/1582:	time/batch: 0.67s	remaining time: 365s	d_loss
Epoch 1/1: batch 1045/1582:	time/batch: 0.67s	remaining time: 362s	d_loss
Epoch 1/1: batch 1050/1582:	time/batch: 0.67s	remaining time: 358s	d_loss
Epoch 1/1: batch 1055/1582:	time/batch: 0.67s	remaining time: 355s	d_loss
Epoch 1/1: batch 1060/1582:	time/batch: 0.67s	remaining time: 352s	d_loss
Epoch 1/1: batch 1065/1582:	time/batch: 0.67s	remaining time: 348s	d_loss
Epoch 1/1: batch 1070/1582:	time/batch: 0.67s	remaining time: 345s	d_loss
Epoch 1/1: batch 1075/1582:	time/batch: 0.67s	remaining time: 342s	d_loss
Epoch 1/1: batch 1080/1582:	time/batch: 0.67s	remaining time: 338s	d_loss
Epoch 1/1: batch 1085/1582:	time/batch: 0.67s	remaining time: 335s	d_loss
Epoch 1/1: batch 1090/1582:	time/batch: 0.67s	remaining time: 331s	d_loss
Epoch 1/1: batch 1095/1582:	time/batch: 0.67s	remaining time: 328s	d_loss
Epoch 1/1: batch 1100/1582:	time/batch: 0.67s	remaining time: 325s	d_loss



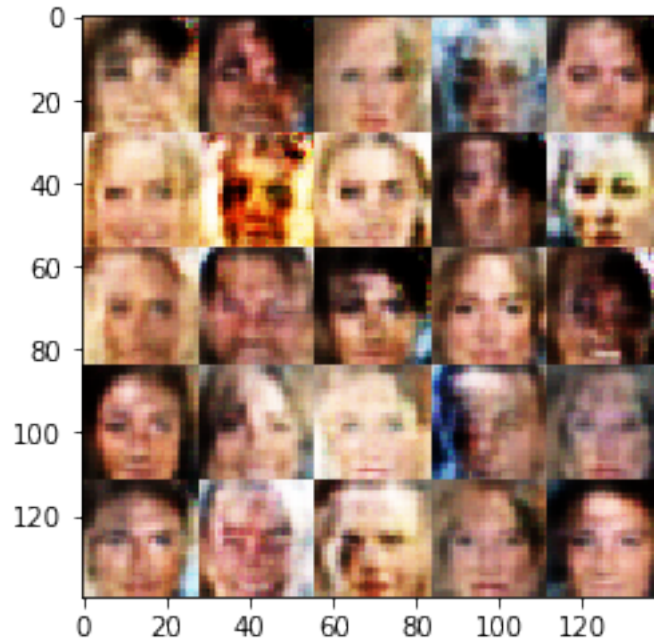
Epoch 1/1: batch 1105/1582:	time/batch: 0.67s	remaining time: 321s	d_loss
Epoch 1/1: batch 1110/1582:	time/batch: 0.67s	remaining time: 318s	d_loss
Epoch 1/1: batch 1115/1582:	time/batch: 0.67s	remaining time: 315s	d_loss
Epoch 1/1: batch 1120/1582:	time/batch: 0.67s	remaining time: 311s	d_loss
Epoch 1/1: batch 1125/1582:	time/batch: 0.67s	remaining time: 308s	d_loss
Epoch 1/1: batch 1130/1582:	time/batch: 0.67s	remaining time: 305s	d_loss
Epoch 1/1: batch 1135/1582:	time/batch: 0.67s	remaining time: 301s	d_loss
Epoch 1/1: batch 1140/1582:	time/batch: 0.67s	remaining time: 298s	d_loss
Epoch 1/1: batch 1145/1582:	time/batch: 0.67s	remaining time: 294s	d_loss
Epoch 1/1: batch 1150/1582:	time/batch: 0.67s	remaining time: 291s	d_loss
Epoch 1/1: batch 1155/1582:	time/batch: 0.67s	remaining time: 288s	d_loss
Epoch 1/1: batch 1160/1582:	time/batch: 0.67s	remaining time: 284s	d_loss
Epoch 1/1: batch 1165/1582:	time/batch: 0.67s	remaining time: 281s	d_loss
Epoch 1/1: batch 1170/1582:	time/batch: 0.67s	remaining time: 277s	d_loss
Epoch 1/1: batch 1175/1582:	time/batch: 0.67s	remaining time: 274s	d_loss
Epoch 1/1: batch 1180/1582:	time/batch: 0.67s	remaining time: 271s	d_loss
Epoch 1/1: batch 1185/1582:	time/batch: 0.67s	remaining time: 267s	d_loss
Epoch 1/1: batch 1190/1582:	time/batch: 0.67s	remaining time: 264s	d_loss
Epoch 1/1: batch 1195/1582:	time/batch: 0.67s	remaining time: 261s	d_loss
Epoch 1/1: batch 1200/1582:	time/batch: 0.67s	remaining time: 257s	d_loss



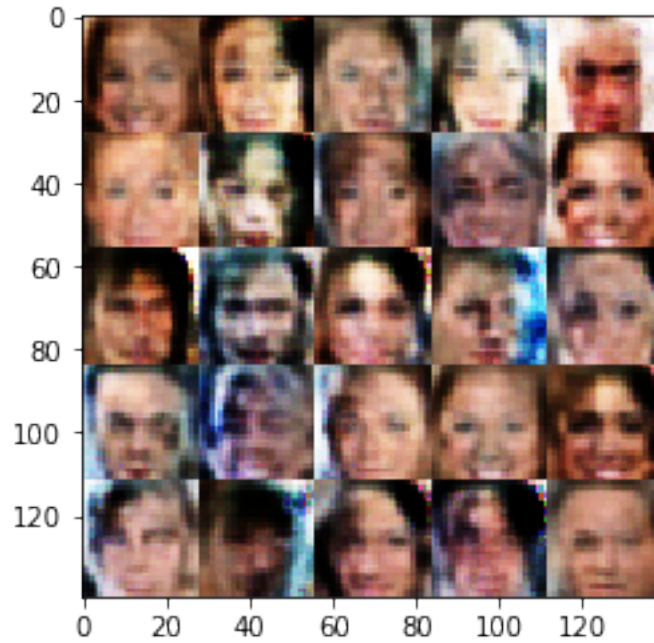
Epoch 1/1: batch 1205/1582:	time/batch: 0.67s	remaining time: 254s	d_loss
Epoch 1/1: batch 1210/1582:	time/batch: 0.67s	remaining time: 251s	d_loss
Epoch 1/1: batch 1215/1582:	time/batch: 0.67s	remaining time: 247s	d_loss
Epoch 1/1: batch 1220/1582:	time/batch: 0.67s	remaining time: 244s	d_loss
Epoch 1/1: batch 1225/1582:	time/batch: 0.67s	remaining time: 240s	d_loss
Epoch 1/1: batch 1230/1582:	time/batch: 0.67s	remaining time: 237s	d_loss
Epoch 1/1: batch 1235/1582:	time/batch: 0.67s	remaining time: 234s	d_loss
Epoch 1/1: batch 1240/1582:	time/batch: 0.67s	remaining time: 230s	d_loss
Epoch 1/1: batch 1245/1582:	time/batch: 0.67s	remaining time: 227s	d_loss
Epoch 1/1: batch 1250/1582:	time/batch: 0.67s	remaining time: 223s	d_loss
Epoch 1/1: batch 1255/1582:	time/batch: 0.67s	remaining time: 220s	d_loss
Epoch 1/1: batch 1260/1582:	time/batch: 0.67s	remaining time: 217s	d_loss
Epoch 1/1: batch 1265/1582:	time/batch: 0.67s	remaining time: 213s	d_loss
Epoch 1/1: batch 1270/1582:	time/batch: 0.67s	remaining time: 210s	d_loss
Epoch 1/1: batch 1275/1582:	time/batch: 0.67s	remaining time: 207s	d_loss
Epoch 1/1: batch 1280/1582:	time/batch: 0.67s	remaining time: 203s	d_loss
Epoch 1/1: batch 1285/1582:	time/batch: 0.67s	remaining time: 200s	d_loss
Epoch 1/1: batch 1290/1582:	time/batch: 0.67s	remaining time: 196s	d_loss
Epoch 1/1: batch 1295/1582:	time/batch: 0.67s	remaining time: 193s	d_loss
Epoch 1/1: batch 1300/1582:	time/batch: 0.67s	remaining time: 190s	d_loss



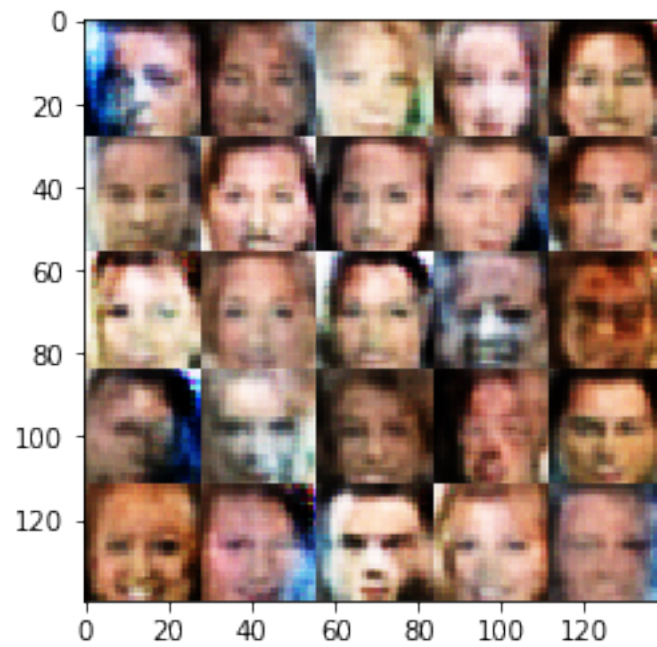
Epoch 1/1: batch 1305/1582:	time/batch: 0.67s	remaining time: 186s	d_loss
Epoch 1/1: batch 1310/1582:	time/batch: 0.67s	remaining time: 183s	d_loss
Epoch 1/1: batch 1315/1582:	time/batch: 0.67s	remaining time: 180s	d_loss
Epoch 1/1: batch 1320/1582:	time/batch: 0.67s	remaining time: 176s	d_loss
Epoch 1/1: batch 1325/1582:	time/batch: 0.67s	remaining time: 173s	d_loss
Epoch 1/1: batch 1330/1582:	time/batch: 0.67s	remaining time: 169s	d_loss
Epoch 1/1: batch 1335/1582:	time/batch: 0.67s	remaining time: 166s	d_loss
Epoch 1/1: batch 1340/1582:	time/batch: 0.67s	remaining time: 163s	d_loss
Epoch 1/1: batch 1345/1582:	time/batch: 0.67s	remaining time: 159s	d_loss
Epoch 1/1: batch 1350/1582:	time/batch: 0.67s	remaining time: 156s	d_loss
Epoch 1/1: batch 1355/1582:	time/batch: 0.67s	remaining time: 153s	d_loss
Epoch 1/1: batch 1360/1582:	time/batch: 0.67s	remaining time: 149s	d_loss
Epoch 1/1: batch 1365/1582:	time/batch: 0.67s	remaining time: 146s	d_loss
Epoch 1/1: batch 1370/1582:	time/batch: 0.67s	remaining time: 142s	d_loss
Epoch 1/1: batch 1375/1582:	time/batch: 0.67s	remaining time: 139s	d_loss
Epoch 1/1: batch 1380/1582:	time/batch: 0.67s	remaining time: 136s	d_loss
Epoch 1/1: batch 1385/1582:	time/batch: 0.67s	remaining time: 132s	d_loss
Epoch 1/1: batch 1390/1582:	time/batch: 0.67s	remaining time: 129s	d_loss
Epoch 1/1: batch 1395/1582:	time/batch: 0.67s	remaining time: 126s	d_loss
Epoch 1/1: batch 1400/1582:	time/batch: 0.67s	remaining time: 122s	d_loss



Epoch 1/1: batch 1405/1582:	time/batch: 0.67s	remaining time: 119s	d_loss:
Epoch 1/1: batch 1410/1582:	time/batch: 0.67s	remaining time: 116s	d_loss:
Epoch 1/1: batch 1415/1582:	time/batch: 0.67s	remaining time: 112s	d_loss:
Epoch 1/1: batch 1420/1582:	time/batch: 0.67s	remaining time: 109s	d_loss:
Epoch 1/1: batch 1425/1582:	time/batch: 0.67s	remaining time: 105s	d_loss:
Epoch 1/1: batch 1430/1582:	time/batch: 0.67s	remaining time: 102s	d_loss:
Epoch 1/1: batch 1435/1582:	time/batch: 0.67s	remaining time: 99s	d_loss:
Epoch 1/1: batch 1440/1582:	time/batch: 0.67s	remaining time: 95s	d_loss:
Epoch 1/1: batch 1445/1582:	time/batch: 0.67s	remaining time: 92s	d_loss:
Epoch 1/1: batch 1450/1582:	time/batch: 0.67s	remaining time: 89s	d_loss:
Epoch 1/1: batch 1455/1582:	time/batch: 0.67s	remaining time: 85s	d_loss:
Epoch 1/1: batch 1460/1582:	time/batch: 0.67s	remaining time: 82s	d_loss:
Epoch 1/1: batch 1465/1582:	time/batch: 0.67s	remaining time: 78s	d_loss:
Epoch 1/1: batch 1470/1582:	time/batch: 0.67s	remaining time: 75s	d_loss:
Epoch 1/1: batch 1475/1582:	time/batch: 0.67s	remaining time: 72s	d_loss:
Epoch 1/1: batch 1480/1582:	time/batch: 0.67s	remaining time: 68s	d_loss:
Epoch 1/1: batch 1485/1582:	time/batch: 0.67s	remaining time: 65s	d_loss:
Epoch 1/1: batch 1490/1582:	time/batch: 0.67s	remaining time: 62s	d_loss:
Epoch 1/1: batch 1495/1582:	time/batch: 0.67s	remaining time: 58s	d_loss:
Epoch 1/1: batch 1500/1582:	time/batch: 0.67s	remaining time: 55s	d_loss:



Epoch 1/1: batch 1505/1582:	time/batch: 0.67s	remaining time: 51s	d_loss:
Epoch 1/1: batch 1510/1582:	time/batch: 0.67s	remaining time: 48s	d_loss:
Epoch 1/1: batch 1515/1582:	time/batch: 0.67s	remaining time: 45s	d_loss:
Epoch 1/1: batch 1520/1582:	time/batch: 0.67s	remaining time: 41s	d_loss:
Epoch 1/1: batch 1525/1582:	time/batch: 0.67s	remaining time: 38s	d_loss:
Epoch 1/1: batch 1530/1582:	time/batch: 0.67s	remaining time: 35s	d_loss:
Epoch 1/1: batch 1535/1582:	time/batch: 0.67s	remaining time: 31s	d_loss:
Epoch 1/1: batch 1540/1582:	time/batch: 0.67s	remaining time: 28s	d_loss:
Epoch 1/1: batch 1545/1582:	time/batch: 0.67s	remaining time: 24s	d_loss:
Epoch 1/1: batch 1550/1582:	time/batch: 0.67s	remaining time: 21s	d_loss:
Epoch 1/1: batch 1555/1582:	time/batch: 0.67s	remaining time: 18s	d_loss:
Epoch 1/1: batch 1560/1582:	time/batch: 0.67s	remaining time: 14s	d_loss:
Epoch 1/1: batch 1565/1582:	time/batch: 0.67s	remaining time: 11s	d_loss:
Epoch 1/1: batch 1570/1582:	time/batch: 0.67s	remaining time: 8s	d_loss:
Epoch 1/1: batch 1575/1582:	time/batch: 0.67s	remaining time: 4s	d_loss:
Epoch 1/1: batch 1580/1582:	time/batch: 0.67s	remaining time: 1s	d_loss:



```
In [28]: plot_losses(d_losses, g_losses)
```



1.3.10 Submitting This Project

When submitting this project, make sure to run all the cells before saving the notebook. Save the notebook file as “dlnd_face_generation.ipynb” and save it as a HTML file under “File” -> “Download as”. Include the “helper.py” and “problem_unittests.py” files in your submission.