In [52]:
```python
import warnings
warnings.filterwarnings('ignore')
```

Generative Adversarial Networks (GANs)

So far in class, all the applications of neural networks that we have explored have been **discriminative models** that take an input and are trained to produce a labeled output. This has ranged from straightforward classification of image categories to sentence generation (which was still phrased as a classification problem, our labels were in vocabulary space and we'd learned a recurrence to capture multi-word labels). In this notebook, we will expand our repetoire, and build **generative models** using neural networks. Specifically, we will learn how to build models which generate novel images that resemble a set of training images.

What is a GAN?

In 2014, Goodfellow et al. presented a method for training generative models called Generative Adversarial Networks (GANs for short). In a GAN, we build two different neural networks. Our first network is a traditional classification network, called the **discriminator**. We will train the discriminator to take images, and classify them as being real (belonging to the training set) or fake (not present in the training set). Our other network, called the **generator**, will take random noise as input and transform it using a neural network to produce images. The goal of the generator is to fool the discriminator into thinking the images it produced are real.

We can think of this back and forth process of the generator (G) trying to fool the discriminator (D), and the discriminator trying to correctly classify real vs. fake as a minimax game:

$$\underset{G}{\text{minimize}}\; \underset{D}{\text{maximize}}\; \mathbb{E}_{x \sim p_\text{data}}\left[\log D(x)\right] + \mathbb{E}_{z \sim p(z)}\left[\log \left(1-D(G(z))\right)\right]$$

where $x \sim p_\text{data}$ are samples from the input data, $z \sim p(z)$ are the random noise samples, $G(z)$ are the generated images using the neural network generator G, and D is the output of the discriminator, specifying the probability of an input being real. In Goodfellow et al., they analyze this minimax game and show how it relates to minimizing the Jensen-Shannon divergence between the training data distribution and the generated samples from G.

To optimize this minimax game, we will aternate between taking gradient *descent* steps on the objective for G, and gradient *ascent* steps on the objective for D:

1. update the **generator** (G) to minimize the probability of the **discriminator making the correct choice**.
2. update the **discriminator** (D) to maximize the probability of the **discriminator making the correct choice**.

While these updates are useful for analysis, they do not perform well in practice. Instead, we will use a different objective when we update the generator: maximize the probability of the **discriminator making the incorrect choice**. This small change helps to allevaiate problems with the generator gradient vanishing when the discriminator is confident. This is the standard update used in most GAN papers, and was used in the original paper from Goodfellow et al..

In this assignment, we will alternate the following updates:

1. Update the generator (G) to maximize the probability of the discriminator making the incorrect choice on generated data:
$$\underset{G}{\text{maximize}}\; \mathbb{E}_{z \sim p(z)}\left[\log D(G(z))\right]$$
2. Update the discriminator (D), to maximize the probability of the discriminator making the correct choice on real and generated data:
$$\underset{D}{\text{maximize}}\; \mathbb{E}_{x \sim p_\text{data}}\left[\log D(x)\right] + \mathbb{E}_{z \sim p(z)}\left[\log \left(1-D(G(z))\right)\right]$$

What else is there?

Since 2014, GANs have exploded into a huge research area, with massive workshops, and hundreds of new papers. Compared to other approaches for generative models, they often produce the highest quality samples but are some of the most difficult and finicky models to train (see this github repo that contains a set of 17 hacks that are useful for getting models working). Improving the stabiilty and robustness of GAN training is an open research question, with new papers coming out every day! For a more recent tutorial on GANs, see here. There is also some even more recent exciting work that changes the objective function to Wasserstein distance and yields much more stable results across model architectures: WGAN, WGAN-GP.

GANs are not the only way to train a generative model! For other approaches to generative modeling check out the deep generative model chapter of the Deep Learning book. Another popular way of training neural networks as generative models is Variational Autoencoders (co-discovered here and here). Variational autoencoders combine neural networks with variational inference to train deep generative models. These models tend to be far more stable and easier to train but currently don't produce samples that are as pretty as GANs.

Example pictures of what you should expect (yours might look slightly different):

caption

Setup

In [1]:
```python
import tensorflow.compat.v1 as tf
# I am using tensorflow version 1.14. If there are any discrepencies due to tensorflow versions please
# install tensorflow version 1.14 for this assignment.
import numpy as np
import os

import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

# A bunch of utility functions

def show_images(images):
    images = np.reshape(images, [images.shape[0], -1])  # images reshape to (batch_size, D)
    sqrtn = int(np.ceil(np.sqrt(images.shape[0])))
    sqrtimg = int(np.ceil(np.sqrt(images.shape[1])))

    fig = plt.figure(figsize=(sqrtn, sqrtn))
    gs = gridspec.GridSpec(sqrtn, sqrtn)
    gs.update(wspace=0.05, hspace=0.05)

    for i, img in enumerate(images):
        ax = plt.subplot(gs[i])
        plt.axis('off')
        ax.set_xticklabels([])
        ax.set_yticklabels([])
        ax.set_aspect('equal')
        plt.imshow(img.reshape([sqrtimg,sqrtimg]))
    return

def preprocess_img(x):
    return 2 * x - 1.0

def deprocess_img(x):
    return (x + 1.0) / 2.0

def rel_error(x,y):
    return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))

def count_params():
    """Count the number of parameters in the current TensorFlow graph """
    param_count = np.sum([np.prod(x.get_shape().as_list()) for x in tf.global_variables()])
    return param_count


def get_session():
    config = tf.ConfigProto()
    config.gpu_options.allow_growth = True
    session = tf.Session(config=config)
    return session

answers = np.load('gan-checks-tf.npz')

NOISE_DIM = 96

print(tf.__version__)
```

```
2.7.0
```

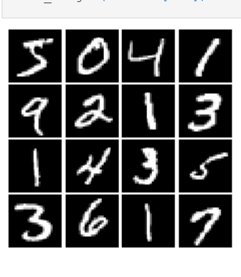
Dataset

GANs are notoriously finicky with hyperparameters, and also require many training epochs. In order to make this assignment approachable without a GPU, we will be working on the MNIST dataset, which is 60,000 training and 10,000 test images. Each picture contains a centered image of white digit on black background (0 through 9). This was one of the first datasets used to train convolutional neural networks and it is fairly easy -- a standard CNN model can easily exceed 99% accuracy.

Heads-up: Our MNIST wrapper returns images as vectors. That is, they're size (batch, 784). If you want to treat them as images, we have to resize them to (batch,28,28) or (batch,28,28,1). They are also type np.float32 and bounded [0,1].

In [2]:
```python
class MNIST(object):
    def __init__(self, batch_size, shuffle=False):
        """
        Construct an iterator object over the MNIST data

        Inputs:
        - batch_size: Integer giving number of elements per minibatch
        - shuffle: (optional) Boolean, whether to shuffle the data on each epoch
        """
        train, _ = tf.keras.datasets.mnist.load_data()
        X, y = train
        X = X.astype(np.float32)/255
        X = X.reshape((X.shape[0], -1))
        self.X, self.y = X, y
        self.batch_size, self.shuffle = batch_size, shuffle

    def __iter__(self):
        N, B = self.X.shape[0], self.batch_size
        idxs = np.arange(N)
        if self.shuffle:
            np.random.shuffle(idxs)
        return iter((self.X[i:i+B], self.y[i:i+B]) for i in range(0, N, B))
```

In [3]:
```python
# show a batch
mnist = MNIST(batch_size=16)
show_images(mnist.X[:16])
```



LeakyReLU

In the cell below, you should implement a LeakyReLU. See the class notes (where alpha is small number) or equation (3) in this paper. LeakyReLUs keep ReLU units from dying and are often used in GAN methods (as are maxout units, however those increase model size and therefore are not used in this notebook).

HINT: You should be able to use `tf.maximum`

Test your leaky ReLU implementation. You should get errors < 1e-10

In [54]:
```python
def leaky_relu(x, alpha=0.01):
    """Compute the leaky ReLU activation function.

    Inputs:
    - x: TensorFlow Tensor with arbitrary shape
    - alpha: leak parameter for leaky ReLU

    Returns:
    TensorFlow Tensor with the same shape as x
    """
    # TODO: implement leaky ReLU
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    return tf.maximum(alpha*x, x)

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

In [55]:
```python
def test_leaky_relu(x, y_true):
    tf.reset_default_graph()
    with get_session() as sess:
        y_tf = leaky_relu(tf.constant(x))
        y = sess.run(y_tf)
        print('Maximum error: %g'%rel_error(y_true, y))

test_leaky_relu(answers['lrelu_x'], answers['lrelu_y'])
```

```
Maximum error: 0
```

Random Noise

Generate a TensorFlow `Tensor` containing uniform noise from -1 to 1 with shape `[batch_size, dim]`.

Make sure noise is the correct shape and type:

In [56]:
```python
def sample_noise(batch_size, dim, seed=None):
    """Generate random uniform noise from -1 to 1.

    Inputs:
    - batch_size: integer giving the batch size of noise to generate
    - dim: integer giving the dimension of the noise to generate

    Returns:
    TensorFlow Tensor containing uniform noise in [-1, 1] with shape [batch_size, dim]
    """
    if seed is not None:
        tf.random.set_seed(seed)
    # TODO: sample and return noise
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    return tf.random_uniform([batch_size,dim], -1, 1)

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

In [57]:
```python
def test_sample_noise():
    batch_size = 3
    dim = 4
    tf.reset_default_graph()
    with get_session() as sess:
        z = sample_noise(batch_size, dim)
        # Check z has the correct shape
        assert z.get_shape().as_list() == [batch_size, dim]
        # Make sure z is a Tensor and not a numpy array
        assert isinstance(z, tf.Tensor)
        # Check that we get different noise for different evaluations
        z1 = sess.run(z)
        z2 = sess.run(z)
        assert not np.array_equal(z1, z2)
        # Check that we get the correct range
        assert np.all(z1 >= -1.0) and np.all(z1 <= 1.0)
        print("All tests passed!")

test_sample_noise()
```

```
All tests passed!
```

Discriminator

Our first step is to build a discriminator. **Hint:** You should use the layers in `tf.keras.layers` to build the model. All fully connected layers should include bias terms. For initialization, just use the default initializer used by the `tf.keras.layers` functions.

Architecture:

- Fully connected layer with input size 784 and output size 256
- LeakyReLU with alpha 0.01
- Fully connected layer with output size 256
- LeakyReLU with alpha 0.01
- Fully connected layer with output size 1

The output of the discriminator should thus have shape `[batch_size, 1]`, and contain real numbers corresponding to the scores that each of the `batch_size` inputs is a real image.

Test to make sure the number of parameters in the discriminator is correct:

In [58]:
```python
def discriminator(x):
    """Compute discriminator score for a batch of input images.

    Inputs:
    - x: TensorFlow Tensor of flattened input images, shape [batch_size, 784]

    Returns:
    TensorFlow Tensor with shape [batch_size, 1], containing the score
    for an image being real for each input image.
    """

    ##############################################################################
    # TODO: Implement architecture                                               #
    #                                                                            #
    # HINT: tf.keras.models.Sequential might be helpful.                         #
    ##############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    with tf.variable_scope("discriminator"):
        f_c_layer = tf.layers.dense(x, 256)
        logic_r = leaky_relu(f_c_layer)
        f_c_layer_2 = tf.layers.dense(logic_r, 256)
        logic_r_2 = leaky_relu(f_c_layer_2)
        scores = tf.layers.dense(logic_r_2, 1)

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ##############################################################################
    #                               END OF YOUR CODE                             #
    ##############################################################################
    return scores
```

In [59]:
```python
def test_discriminator(true_count=267009):
    tf.reset_default_graph()
    with get_session() as sess:
        y = discriminator(tf.ones((2, 784)))
        cur_count = count_params()
        if cur_count != true_count:
            print('Incorrect number of parameters in discriminator. {0} instead of {1}. Check your achitecture.
        else:
            print('Correct number of parameters in discriminator.')

test_discriminator()
```

```
Correct number of parameters in discriminator.
```

Generator

Now to build a generator. You should use the layers in `tf.keras.layers` to construct the model. All fully connected layers should include bias terms. Note that you can use the tf.nn module to access activation functions. Once again, use the default initializers for parameters.

Architecture:

- Fully connected layer with inupt size tf.shape(z)[1] (the number of noise dimensions) and output size 1024
- `ReLU`
- Fully connected layer with output size 1024
- `ReLU`
- Fully connected layer with output size 784
- `TanH` (To restrict every element of the output to be in the range [-1,1])

Test to make sure the number of parameters in the generator is correct:

In [60]:
```python
def generator(z):
    """Generate images from a random noise vector.

    Inputs:
    - z: TensorFlow Tensor of random noise with shape [batch_size, noise_dim]

    Returns:
    TensorFlow Tensor of generated images, with shape [batch_size, 784].
    """

     ##############################################################################
    # TODO: Implement architecture                                               #
    #                                                                            #
    # HINT: tf.keras.models.Sequential might be helpful.                         #
    ##############################################################################
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    with tf.variable_scope("generator"):
            f_c_layer = tf.layers.dense(z, 1024, activation=tf.nn.relu)
            f_c_layer_2 = tf.layers.dense(f_c_layer, 1024, activation=tf.nn.relu)
            img = tf.layers.dense(f_c_layer_2, 784, activation=tf.nn.tanh)

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    ##############################################################################
    #                               END OF YOUR CODE                             #
    ##############################################################################
    return img
```

In [61]:
```python
def test_generator(true_count=1858320):
    tf.reset_default_graph()
    with get_session() as sess:
        y = generator(tf.ones((1, 4)))
        cur_count = count_params()
        if cur_count != true_count:
            print('Incorrect number of parameters in generator. {0} instead of {1}. Check your achitecture.'.fo
        else:
            print('Correct number of parameters in generator.')

test_generator()
```

```
Correct number of parameters in generator.
```

GAN Loss

Compute the generator and discriminator loss. The generator loss is:

$$\ell_G = -\mathbb{E}_{z \sim p(z)}\left[\log D(G(z))\right]$$

and the discriminator loss is:

$$\ell_D = -\mathbb{E}_{x \sim p_\text{data}}\left[\log D(x)\right] - \mathbb{E}_{z \sim p(z)}\left[\log \left(1-D(G(z))\right)\right]$$

Note that these are negated from the equations presented earlier as we will be *minimizing* these losses.

HINTS: Use tf.ones and tf.zeros to generate labels for your discriminator. Use tf.keras.losses.BinaryCrossentropy to help compute your loss function.

Test your GAN loss. Make sure both the generator and discriminator loss are correct. You should see errors less than 1e-8.

In [25]:
```python
def gan_loss(logits_real, logits_fake):
    """Compute the GAN loss.

    Inputs:
    - logits_real: Tensor, shape [batch_size, 1], output of discriminator
        Unnormalized score that the image is real for each real image
    - logits_fake: Tensor, shape[batch_size, 1], output of discriminator
        Unnormalized score that the image is real for each fake image

    Returns:
    - D_loss: discriminator loss scalar
    - G_loss: generator loss scalar

    HINT: for the discriminator loss, you'll want to do the averaging separately for
    its two components, and then add them together (instead of averaging once at the very end).
    """
    D_loss = None
    G_loss = None

    D_r_l = tf.nn.sigmoid_cross_entropy_with_logits(logits = logits_real, labels = tf.ones_like(logits_real))
    D_f_l = tf.nn.sigmoid_cross_entropy_with_logits(logits = logits_fake, labels = tf.zeros_like(logits_fake))
    G_l = tf.nn.sigmoid_cross_entropy_with_logits(logits = logits_fake, labels = tf.ones_like(logits_fake))

    D_loss = tf.reduce_mean(D_r_l) + tf.reduce_mean(D_f_l)
    G_loss = tf.reduce_mean(G_l)

    return D_loss, G_loss
```

In [15]:
```python
def test_gan_loss(logits_real, logits_fake, d_loss_true, g_loss_true):
    tf.reset_default_graph()
    with get_session() as sess:
        d_loss, g_loss = sess.run(gan_loss(tf.constant(logits_real), tf.constant(logits_fake)))
    print("Maximum error in d_loss: %g"%rel_error(d_loss_true, d_loss))
    print("Maximum error in g_loss: %g"%rel_error(g_loss_true, g_loss))

test_gan_loss(answers['logits_real'], answers['logits_fake'],
              answers['d_loss_true'], answers['g_loss_true'])
```

```
Maximum error in d_loss: 1.20519e-16
Maximum error in g_loss: 7.19722e-17
```

Optimizing our loss

Make an `Adam` optimizer with a 1e-3 learning rate, beta1=0.5 to mininize G_loss and D_loss separately. The trick of decreasing beta was shown to be effective in helping GANs converge in the Improved Techniques for Training GANs paper. In fact, with our current hyperparameters, if you set beta1 to the Tensorflow default of 0.9, there's a good chance your discriminator loss will go to zero and the generator will fail to learn entirely. In fact, this is a common failure mode in GANs; if your D(x) learns too fast (e.g. loss goes near zero), your G(z) is never able to learn. Often D(x) is trained with SGD with Momentum or RMSProp instead of Adam, but here we'll use Adam for both D(x) and G(z).

In [44]:
```python
def get_solvers(learning_rate=1e-3, beta1=0.5):
    """Create solvers for GAN training.

    Inputs:
    - learning_rate: learning rate to use for both solvers
    - beta1: beta1 parameter for both solvers (first moment decay)

    Returns:
    - D_solver: instance of tf.optimizers.Adam with correct learning_rate and beta1
    - G_solver: instance of tf.optimizers.Adam with correct learning_rate and beta1
    """
    # TODO: create an AdamOptimizer for D_solver and G_solver
#     D_solver = None
#     G_solver = None
    # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    D_solver = tf.train.AdamOptimizer(learning_rate = learning_rate, beta1 = beta1)
    G_solver = tf.train.AdamOptimizer(learning_rate = learning_rate, beta1 = beta1)

    # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
    return D_solver, G_solver
```

Putting it all together

In [62]:
```python
tf.reset_default_graph()

# number of images for each batch
batch_size = 128
# our noise dimension
noise_dim = 96

tf.compat.v1.disable_eager_execution()
# placeholder for images from the training dataset
x = tf.placeholder(tf.float32, [None, 784])
# random noise fed into our generator
z = sample_noise(batch_size, noise_dim)
# generated images
G_sample = generator(z)

with tf.variable_scope("") as scope:
    #scale images to be -1 to 1
    logits_real = discriminator(preprocess_img(x))
    # Re-use discriminator weights on new inputs
    scope.reuse_variables()
    logits_fake = discriminator(G_sample)

# Get the list of variables for the discriminator and generator
D_vars = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES, 'discriminator')
G_vars = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES, 'generator')

# get our solver
D_solver, G_solver = get_solvers()

# get our loss
D_loss, G_loss = gan_loss(logits_real, logits_fake)

# setup training steps
D_train_step = D_solver.minimize(D_loss, var_list=D_vars)
G_train_step = G_solver.minimize(G_loss, var_list=G_vars)
D_extra_step = tf.get_collection(tf.GraphKeys.UPDATE_OPS, 'discriminator')
G_extra_step = tf.get_collection(tf.GraphKeys.UPDATE_OPS, 'generator')
```

Training a GAN!

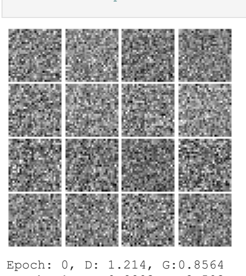
Well that wasn't so hard, was it? After the first epoch, you should see fuzzy outlines, clear shapes as you approach epoch 3, and decent shapes, about half of which will be sharp and clearly recognizable as we pass epoch 5. In our case, we'll simply train D(x) and G(z) with one batch each every iteration. However, papers often experiment with different schedules of training D(x) and G(z), sometimes doing one for more steps than the other, or even training each one until the loss gets "good enough" and then switching to training the other.

If you are a Colab user, it is recommeded to change colab runtime to GPU.

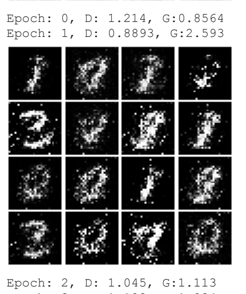
Train your GAN! This should take about 10 minutes on a CPU, or about 2 minutes on GPU.

In [46]:
```python
def run_a_gan(sess, G_train_step, G_loss, D_train_step, D_loss, G_extra_step, D_extra_step,\
              show_every=2, print_every=1, batch_size=128, num_epoch=10):
    """Train a GAN for a certain number of epochs.

    Inputs:
    - sess: A tf.Session that we want to use to run our data
    - G_train_step: A training step for the Generator
    - G_loss: Generator loss
    - D_train_step: A training step for the Generator
    - D_loss: Discriminator loss
    - G_extra_step: A collection of tf.GraphKeys.UPDATE_OPS for generator
    - D_extra_step: A collection of tf.GraphKeys.UPDATE_OPS for discriminator
    Returns:
        Nothing
    """
    # compute the number of iterations we need
    mnist = MNIST(batch_size=batch_size, shuffle=True)
    for epoch in range(num_epoch):
        # every show often, show a sample result
        if epoch % show_every == 0:
            samples = sess.run(G_sample)
            fig = show_images(samples[:16])
            plt.show()
            print()
        for (minibatch, minbatch_y) in mnist:
            # run a batch of data through the network
            _, D_loss_curr = sess.run([D_train_step, D_loss], feed_dict={x: minibatch})
            _, G_loss_curr = sess.run([G_train_step, G_loss])

        # print loss every so often.
        # We want to make sure D_loss doesn't go to 0
        if epoch % print_every == 0:
            print('Epoch: {}, D: {:.4}, G:{:.4}'.format(epoch,D_loss_curr,G_loss_curr))
    print('Final images')
    samples = sess.run(G_sample)

    fig = show_images(samples[:16])
    plt.show()
```

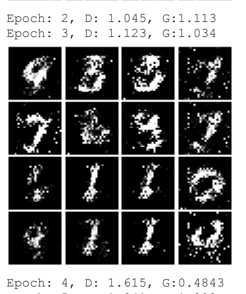
In [29]:
```python
with get_session() as sess:
    sess.run(tf.global_variables_initializer())
    run_a_gan(sess,G_train_step,G_loss,D_train_step,D_loss,G_extra_step,D_extra_step)

#     The output is shown for your reference
```



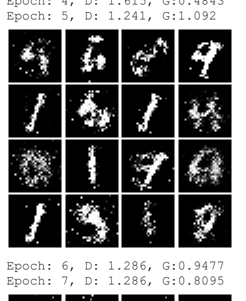
```
Epoch: 0, D: 1.214, G:0.8564
Epoch: 1, D: 0.8893, G:2.593
```



```
Epoch: 2, D: 1.045, G:1.113
Epoch: 3, D: 1.123, G:1.034
```

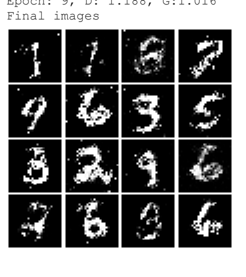


```
Epoch: 4, D: 1.615, G:0.4843
Epoch: 5, D: 1.241, G:1.092
```



```
Epoch: 6, D: 1.286, G:0.9477
Epoch: 7, D: 1.286, G:0.8095
```

```
Epoch: 8, D: 1.259, G:0.8469
Epoch: 9, D: 1.188, G:1.016
Final images
```



Deep Convolutional GANs

In the first part of the notebook, we implemented an almost direct copy of the original GAN network from Ian Goodfellow. However, this network architecture allows no real spatial reasoning. It is unable to reason about things like "sharp edges" in general because it lacks any convolutional layers. Thus, in this section, we will implement some of the ideas from DCGAN, where we use convolutional networks as our discriminators and generators.

Discriminator

We will use a discriminator inspired by the TensorFlow MNIST classification tutorial, which is able to get above 99% accuracy on the MNIST dataset fairly quickly. *Be sure to check the dimensions of x and reshape when needed*, fully connected blocks expect [N,D] Tensors while conv2d blocks expect [N,H,W,C] Tensors. Please use `tf.keras.layers` to define the following architecture:

Architecture:

- Conv2D: 32 Filters, 5x5, Stride 1, padding 0
- Leaky ReLU(alpha=0.01)
- Max Pool 2x2, Stride 2
- Conv2D: 64 Filters, 5x5, Stride 1, padding 0
- Leaky ReLU(alpha=0.01)
- Max Pool 2x2, Stride 2
- Flatten
- Fully Connected with output size 4 x 4 x 64
- Leaky ReLU(alpha=0.01)
- Fully Connected with output size 1

Once again, please use biases for all convolutional and fully connected layers, and use the default parameter initializers. Note that a padding of 0 can be accomplished with the 'VALID' padding option.

In [63]:
```python
def discriminator(x):
    """Compute discriminator score for a batch of input images.

    Inputs:
    - x: TensorFlow Tensor of flattened input images, shape [batch_size, 784]

    Returns:
    TensorFlow Tensor with shape [batch_size, 1], containing the score
    for an image being real for each input image.
    """
    with tf.variable_scope("discriminator"):
        # TODO: implement architecture
        x = tf.reshape(x, [-1, 28, 28, 1])
        conv = tf.layers.conv2d(x, 32, 5, 1, padding='valid', activation=leaky_relu)
        pool = tf.layers.max_pooling2d(conv, 2, 2)
        conv_2 = tf.layers.conv2d(pool, 64, 5, 1, padding='valid', activation=leaky_relu)
        pool_2 = tf.layers.max_pooling2d(conv_2, 2, 2)
        flat_2 = tf.layers.flatten(pool_2)
        f_c_l = tf.layers.dense(flat_2, 4*4*64, activation=leaky_relu)
        logits = tf.layers.dense(f_c_l, 1)

        return logits
test_discriminator(1102721)
```

```
Correct number of parameters in discriminator.
```

Generator

For the generator, we will copy the architecture exactly from the InfoGAN paper. See Appendix C.1 MNIST. Please use `tf.keras.layers` for your implementation. You might find the documentation for tf.keras.layers.Conv2DTranspose useful. The architecture is as follows.

Architecture:

- Fully connected with output size 1024
- `ReLU`
- BatchNorm
- Fully connected with output size 7 x 7 x 128
- `ReLU`
- BatchNorm
- Resize into Image Tensor of size 7, 7, 128
- Conv2D^T (transpose): 64 filters of 4x4, stride 2
- `ReLU`
- BatchNorm
- Conv2d^T (transpose): 1 filter of 4x4, stride 2
- `TanH`

Once again, use biases for the fully connected and transpose convolutional layers. Please use the default initializers for your parameters. For padding, choose the 'same' option for transpose convolutions. For Batch Normalization, assume we are always in 'training' mode.

In [64]:
```python
def generator(z):
    """Generate images from a random noise vector.

    Inputs:
    - z: TensorFlow Tensor of random noise with shape [batch_size, noise_dim]

    Returns:
    TensorFlow Tensor of generated images, with shape [batch_size, 784].
    """
    with tf.variable_scope("generator"):
        # TODO: implement architecture
        f_c_l = tf.layers.dense(z, 1024, activation=tf.nn.relu)
        b_n = tf.layers.batch_normalization(f_c_l, training=True)
        f_c_l_2 = tf.layers.dense(b_n, 7*7*128, activation=tf.nn.relu)
        b_n_2 = tf.layers.batch_normalization(f_c_l_2, training=True)
        reshaped_b_n_2 = tf.reshape(b_n_2, [-1,7,7,128])
        conv = tf.layers.conv2d_transpose(reshaped_b_n_2, 64, 4, 2, padding='same', activation=tf.nn.relu)
        b_n_3 = tf.layers.batch_normalization(conv, training=True)
        img = tf.layers.conv2d_transpose(b_n_3, 1, 4, 2, padding='same', activation=tf.nn.tanh)

        return img

test_generator(6595521)
```

```
Correct number of parameters in generator.
```

We have to recreate our network since we've changed our functions.

In [65]:
```python
tf.reset_default_graph()

batch_size = 128
# our noise dimension
noise_dim = 96

# placeholders for images from the training dataset
x = tf.placeholder(tf.float32, [None, 784])
z = sample_noise(batch_size, noise_dim)
# generated images
G_sample = generator(z)

with tf.variable_scope("") as scope:
    #scale images to be -1 to 1
    logits_real = discriminator(preprocess_img(x))
    # Re-use discriminator weights on new inputs
    scope.reuse_variables()
    logits_fake = discriminator(G_sample)

# Get the list of variables for the discriminator and generator
D_vars = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES,'discriminator')
G_vars = tf.get_collection(tf.GraphKeys.TRAINABLE_VARIABLES,'generator')

D_solver,G_solver = get_solvers()
D_loss, G_loss = gan_loss(logits_real, logits_fake)
D_train_step = D_solver.minimize(D_loss, var_list=D_vars)
G_train_step = G_solver.minimize(G_loss, var_list=G_vars)
D_extra_step = tf.get_collection(tf.GraphKeys.UPDATE_OPS,'discriminator')
G_extra_step = tf.get_collection(tf.GraphKeys.UPDATE_OPS,'generator')
```

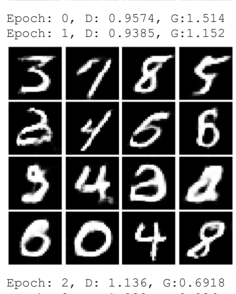
Train and evaluate a DCGAN

This is the one part of A3 that significantly benefits from using a GPU. It takes 3 minutes on a GPU for the requested five epochs. Or about 50 minutes on a dual core laptop on CPU (feel free to use 3 epochs if you do it on CPU).

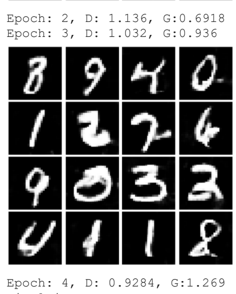
In [33]:

```
with get_session() as sess:
    sess.run(tf.global_variables_initializer())
    run_a_gan(sess,G_train_step,G_loss,D_train_step,D_loss,G_extra_step,D_extra_step,num_epoch=5)
    print('check')
```

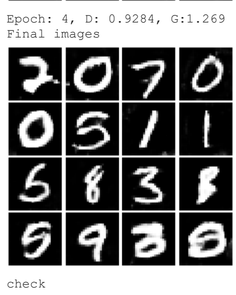
```
Epoch: 0, D: 0.9574, G:1.514
Epoch: 1, D: 0.9385, G:1.152
```



```
Epoch: 2, D: 1.136, G:0.6918
Epoch: 3, D: 1.032, G:0.936
```



```
Epoch: 4, D: 0.9284, G:1.269
Final images
```



```
check
```

In [ ]:

INLINE QUESTION

If the generator loss decreases during training while the discriminator loss stays at a constant high value from the start, is this a good sign? Why or why not? A qualitative answer is sufficient.

Your answer:

No, it is not a good sign.

If the loss of generator is decreasing while loss of discriminator is high, which means the discriminator is too bad that it can hardly correctly classify our real img, and it is continuing classifying noisy img as real img by cheating the computer.

In [ ]: