In [1]:
```
#COMMENT IF NOT USING COLAB VM

# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'DeepLearning/assignments/assignment5/'
FOLDERNAME = "CS6353/Assignments/assignment5/assignment5/"
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd /content/drive/My\ Drive/$FOLDERNAME/cs6353/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5/cs6353/datasets
--2024-11-28 04:16:02--  http://supermoe.cs.umass.edu/682/asgns/coco_captioning.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 1035210391 (987M) [application/zip]
Saving to: ‘coco_captioning.zip’

coco_captioning.zip 100%[===================>] 987.25M  8.59MB/s    in 5m 8s

2024-11-28 04:21:10 (3.21 MB/s) - ‘coco_captioning.zip’ saved [1035210391/103521039
1]

Archive:  coco_captioning.zip
replace coco_captioning/coco2014_captions.h5? [y]es, [n]o, [A]ll, [N]one, [r]ename:
A
  inflating: coco_captioning/coco2014_captions.h5
  inflating: coco_captioning/coco2014_vocab.json
  inflating: coco_captioning/train2014_images.txt
  inflating: coco_captioning/train2014_urls.txt
  inflating: coco_captioning/train2014_vgg16_fc7.h5
  inflating: coco_captioning/train2014_vgg16_fc7_pca.h5
  inflating: coco_captioning/val2014_images.txt
  inflating: coco_captioning/val2014_urls.txt
  inflating: coco_captioning/val2014_vgg16_fc7.h5
  inflating: coco_captioning/val2014_vgg16_fc7_pca.h5
--2024-11-28 04:23:12--  http://supermoe.cs.umass.edu/682/asgns/squeezenet_tf.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 9202140 (8.8M) [application/zip]
Saving to: ‘squeezenet_tf.zip’

squeezenet_tf.zip   100%[===================>]   8.78M  2.46MB/s    in 4.3s

2024-11-28 04:23:16 (2.03 MB/s) - ‘squeezenet_tf.zip’ saved [9202140/9202140]

Archive:  squeezenet_tf.zip
replace squeezenet.ckpt.data-00000-of-00001? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: squeezenet.ckpt.data-00000-of-00001
  inflating: squeezenet.ckpt.index
  inflating: squeezenet.ckpt.meta
--2024-11-28 04:26:30--  http://supermoe.cs.umass.edu/682/asgns/imagenet_val_25.npz
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 3940548 (3.8M)
Saving to: ‘imagenet_val_25.npz.6’

imagenet_val_25.npz 100%[===================>]   3.76M  2.05MB/s    in 1.8s

2024-11-28 04:26:32 (2.05 MB/s) - ‘imagenet_val_25.npz.6’ saved [3940548/3940548]
```

```
/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5
```

In [2]:
```
# #UNCOMMENT IF USING CADE
# import os
# ##### Request a GPU #####
# ## This function locates an available gpu for usage. In addition, this function r
# ## memory space exclusively for your account. The memory reservation prevents the
# ## speed when other users try to allocate memory on the same gpu in the shared sy
# ## Note: If you use your own system which has a GPU with less than 4GB of memory,
# ## specified mimimum memory.
# def define_gpu_to_use(minimum_memory_mb = 3500):
#     thres_memory = 600 #
#     gpu_to_use = None
#     try:
#         os.environ['CUDA_VISIBLE_DEVICES']
#         print('GPU already assigned before: ' + str(os.environ['CUDA_VISIBLE_DEVI
#         return
#     except:
#         pass

#     for i in range(16):
#         free_memory = !nvidia-smi --query-gpu=memory.free -i $i --format=csv,noun
#         if free_memory[0] == 'No devices were found':
#             break
#         free_memory = int(free_memory[0])

#         if free_memory>minimum_memory_mb-thres_memory:
#             gpu_to_use = i
#             break

#     if gpu_to_use is None:
#         print('Could not find any GPU available with the required free memory of
#               + 'MB. Please use a different system for this assignment.')
#     else:
#         os.environ['CUDA_VISIBLE_DEVICES'] = str(gpu_to_use)
#         print('Chosen GPU: ' + str(gpu_to_use))

# ## Request a gpu and reserve the memory space
# define_gpu_to_use(4000)
```

Image Captioning with RNNs

In this exercise you will implement a vanilla recurrent neural networks and use them it to train a model that can generate novel captions for images.

In [3]:
```
# As usual, a bit of setup
import time, os, json
import numpy as np
import matplotlib.pyplot as plt

from cs6353.gradient_check import eval_numerical_gradient, eval_numerical_gradient_
from cs6353.rnn_layers import *
```

```
from cs6353.captioning_solver import CaptioningSolver
from cs6353.classifiers.rnn import CaptioningRNN
from cs6353.coco_utils import load_coco_data, sample_coco_minibatch, decode_caption
from cs6353.image_utils import image_from_url

%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

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

Install h5py

The COCO dataset we will be using is stored in HDF5 format. To load HDF5 files, we will need to install the `h5py` Python package. Check if h5py is already installed:

In [4]:
```
import h5py
```

If the modual is not found, you will need to install it now. From the command line, run:
`pip install h5py`
If you receive a permissions error, you may need to run the command as root:
`sudo pip install h5py`

You can also run commands directly from the Jupyter notebook by prefixing the command with the "!" character:

In [5]:
```
!pip install h5py
```

```
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages (3.1
2.1)
Requirement already satisfied: numpy>=1.19.3 in /usr/local/lib/python3.10/dist-packa
ges (from h5py) (1.26.4)
```

Microsoft COCO

For this exercise we will use the 2014 release of the Microsoft COCO dataset which has become the standard testbed for image captioning. The dataset consists of 80,000 training images and 40,000 validation images, each annotated with 5 captions written by workers on Amazon Mechanical Turk.

You should have already downloaded the data by changing to the `cs6353/datasets` directory and running the script `get_assignment3_data.sh`. If you haven't yet done so, run that script now. Warning: the COCO data download is ~1GB.

We have preprocessed the data and extracted features for you already. For all images we have extracted features from the fc7 layer of the VGG-16 network pretrained on ImageNet; these features are stored in the files `train2014_vgg16_fc7.h5` and `val2014_vgg16_fc7.h5` respectively. To cut down on processing time and memory requirements, we have reduced the dimensionality of the features from 4096 to 512; these features can be found in the files `train2014_vgg16_fc7_pca.h5` and `val2014_vgg16_fc7_pca.h5`.

The raw images take up a lot of space (nearly 20GB) so we have not included them in the download. However all images are taken from Flickr, and URLs of the training and validation images are stored in the files `train2014_urls.txt` and `val2014_urls.txt` respectively. This allows you to download images on the fly for visualization. Since images are downloaded on-the-fly, **you must be connected to the internet to view images**.

Dealing with strings is inefficient, so we will work with an encoded version of the captions. Each word is assigned an integer ID, allowing us to represent a caption by a sequence of integers. The mapping between integer IDs and words is in the file `coco2014_vocab.json`, and you can use the function `decode_captions` from the file `cs6353/coco_utils.py` to convert numpy arrays of integer IDs back into strings.

There are a couple special tokens that we add to the vocabulary. We prepend a special `<START>` token and append an `<END>` token to the beginning and end of each caption respectively. Rare words are replaced with a special `<UNK>` token (for "unknown"). In addition, since we want to train with minibatches containing captions of different lengths, we pad short captions with a special `<NULL>` token after the `<END>` token and don't compute loss or gradient for `<NULL>` tokens. Since they are a bit of a pain, we have taken care of all implementation details around special tokens for you.

You can load all of the MS-COCO data (captions, features, URLs, and vocabulary) using the `load_coco_data` function from the file `cs6353/coco_utils.py`. Run the following cell to do so:

In [6]:
```
# Load COCO data from disk; this returns a dictionary
# We'll work with dimensionality-reduced features for this notebook, but feel
# free to experiment with the original features by changing the flag below.
data = load_coco_data(pca_features=True)

# Print out all the keys and values from the data dictionary
for k, v in data.items():
    if type(v) == np.ndarray:
        print(k, type(v), v.shape, v.dtype)
    else:
        print(k, type(v), len(v))
```

```
train_captions <class 'numpy.ndarray'> (400135, 17) int32
train_image_idxs <class 'numpy.ndarray'> (400135,) int32
val_captions <class 'numpy.ndarray'> (195954, 17) int32
val_image_idxs <class 'numpy.ndarray'> (195954,) int32
train_features <class 'numpy.ndarray'> (82783, 512) float32
val_features <class 'numpy.ndarray'> (40504, 512) float32
idx_to_word <class 'list'> 1004
word_to_idx <class 'dict'> 1004
train_urls <class 'numpy.ndarray'> (82783,) <U63
val_urls <class 'numpy.ndarray'> (40504,) <U63
```

Look at the data

It is always a good idea to look at examples from the dataset before working with it.

You can use the `sample_coco_minibatch` function from the file `cs6353/coco_utils.py` to sample minibatches of data from the data structure returned from `load_coco_data`. Run the following to sample a small minibatch of training data and show the images and their captions. Running it multiple times and looking at the results helps you to get a sense of the dataset.

Note that we decode the captions using the `decode_captions` function and that we download the images on-the-fly using their Flickr URL, so **you must be connected to the internet to view images**.

In [7]:
```
# Sample a minibatch and show the images and captions
batch_size = 3

captions, features, urls = sample_coco_minibatch(data, batch_size=batch_size)
for i, (caption, url) in enumerate(zip(captions, urls)):
    plt.imshow(image_from_url(url))
    plt.axis('off')
    caption_str = decode_captions(caption, data['idx_to_word'])
    plt.title(caption_str)
    plt.show()
```

<START> three zebras are standing on a <UNK> grass plain <END>

<START> a zebra grazing in a field eating grass <END>

<START> a man is cutting a cake to <UNK> <UNK> <UNK> <END>

Recurrent Neural Networks

As discussed in lecture, we will use recurrent neural network (RNN) language models for image captioning. The file `cs6353/rnn_layers.py` contains implementations of different layer types that are needed for recurrent neural networks, and the file `cs6353/classifiers/rnn.py` uses these layers to implement an image captioning model.

We will first implement different types of RNN layers in `cs6353/rnn_layers.py`.

Vanilla RNN: step forward

Open the file `cs6353/rnn_layers.py`. This file implements the forward and backward passes for different types of layers that are commonly used in recurrent neural networks.

First implement the function `rnn_step_forward` which implements the forward pass for a single timestep of a vanilla recurrent neural network. After doing so run the following to check your implementation. You should see errors on the order of e-8 or less.

In [8]:
```
N, D, H = 3, 10, 4

x = np.linspace(-0.4, 0.7, num=N*D).reshape(N, D)
```

```
prev_h = np.linspace(-0.2, 0.5, num=N*H).reshape(N, H)
Wx = np.linspace(-0.1, 0.9, num=D*H).reshape(D, H)
Wh = np.linspace(-0.3, 0.7, num=H*H).reshape(H, H)
b = np.linspace(-0.2, 0.4, num=H)

next_h, _ = rnn_step_forward(x, prev_h, Wx, Wh, b)
expected_next_h = np.asarray([
  [-0.58172089, -0.50182032, -0.41232771, -0.31410098],
  [ 0.66854692,  0.79562378,  0.87755553,  0.92795967],
  [ 0.97934501,  0.99144213,  0.99646691,  0.99854353]])

print('next_h error: ', rel_error(expected_next_h, next_h))
```

```
next_h error:  6.292421426471037e-09
```

Vanilla RNN: step backward

In the file `cs6353/rnn_layers.py` implement the `rnn_step_backward` function. After doing so run the following to numerically gradient check your implementation. You should see errors on the order of `e-8` or less.

In [9]:
```
from cs6353.rnn_layers import rnn_step_forward, rnn_step_backward
np.random.seed(231)
N, D, H = 4, 5, 6
x = np.random.randn(N, D)
h = np.random.randn(N, H)
Wx = np.random.randn(D, H)
Wh = np.random.randn(H, H)
b = np.random.randn(H)

out, cache = rnn_step_forward(x, h, Wx, Wh, b)

dnext_h = np.random.randn(*out.shape)

fx = lambda x: rnn_step_forward(x, h, Wx, Wh, b)[0]
fh = lambda prev_h: rnn_step_forward(x, h, Wx, Wh, b)[0]
fWx = lambda Wx: rnn_step_forward(x, h, Wx, Wh, b)[0]
fWh = lambda Wh: rnn_step_forward(x, h, Wx, Wh, b)[0]
fb = lambda b: rnn_step_forward(x, h, Wx, Wh, b)[0]

dx_num = eval_numerical_gradient_array(fx, x, dnext_h)
dprev_h_num = eval_numerical_gradient_array(fh, h, dnext_h)
dWx_num = eval_numerical_gradient_array(fWx, Wx, dnext_h)
dWh_num = eval_numerical_gradient_array(fWh, Wh, dnext_h)
db_num = eval_numerical_gradient_array(fb, b, dnext_h)

dx, dprev_h, dWx, dWh, db = rnn_step_backward(dnext_h, cache)

print('dx error: ', rel_error(dx_num, dx))
print('dprev_h error: ', rel_error(dprev_h_num, dprev_h))
print('dWx error: ', rel_error(dWx_num, dWx))
print('dWh error: ', rel_error(dWh_num, dWh))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  2.7795541640745535e-10
dprev_h error:  2.732467428030486e-10
dWx error:  9.709219069305414e-10
dWh error:  5.034262638717296e-10
db error:  1.708752322503098e-11
```

Vanilla RNN: forward

Now that you have implemented the forward and backward passes for a single timestep of a vanilla RNN, you will combine these pieces to implement a RNN that processes an entire sequence of data.

In the file `cs6353/rnn_layers.py`, implement the function `rnn_forward`. This should be implemented using the `rnn_step_forward` function that you defined above. After doing so run the following to check your implementation. You should see errors on the order of `e-7` or less.

In [10]:
```
N, T, D, H = 2, 3, 4, 5

x = np.linspace(-0.1, 0.3, num=N*T*D).reshape(N, T, D)
h0 = np.linspace(-0.3, 0.1, num=N*H).reshape(N, H)
Wx = np.linspace(-0.2, 0.4, num=D*H).reshape(D, H)
Wh = np.linspace(-0.4, 0.1, num=H*H).reshape(H, H)
b = np.linspace(-0.7, 0.1, num=H)

h, _ = rnn_forward(x, h0, Wx, Wh, b)
expected_h = np.asarray([
  [
    [-0.42070749, -0.27279261, -0.11074945,  0.05740409,  0.22236251],
    [-0.39525808, -0.22554661, -0.0409454,   0.14649412,  0.32397316],
    [-0.42305111, -0.24223728, -0.04287027,  0.15997045,  0.35014525],
  ],
  [
    [-0.55857474, -0.39065825, -0.19198182,  0.02378408,  0.23735671],
    [-0.27150199, -0.07088804,  0.13562939,  0.33099728,  0.50158768],
    [-0.51014825, -0.30524429, -0.06755202,  0.17806392,  0.40333043]]])
print('h error: ', rel_error(expected_h, h))
```

```
h error:  7.728466151011529e-08
```

Vanilla RNN: backward

In the file `cs6353/rnn_layers.py`, implement the backward pass for a vanilla RNN in the function `rnn_backward`. This should run back-propagation over the entire sequence, making calls to the `rnn_step_backward` function that you defined earlier. You should see errors on the order of e-6 or less.

In [11]:
```
np.random.seed(231)
```

```
N, D, T, H = 2, 5, 10, 5

x = np.random.randn(N, T, D)
h0 = np.random.randn(N, H)
Wx = np.random.randn(D, H)
Wh = np.random.randn(H, H)
b = np.random.randn(H)

out, cache = rnn_forward(x, h0, Wx, Wh, b)

dout = np.random.randn(*out.shape)

dx, dh0, dWx, dWh, db = rnn_backward(dout, cache)

fx = lambda x: rnn_forward(x, h0, Wx, Wh, b)[0]
fh0 = lambda h0: rnn_forward(x, h0, Wx, Wh, b)[0]
fWx = lambda Wx: rnn_forward(x, h0, Wx, Wh, b)[0]
fWh = lambda Wh: rnn_forward(x, h0, Wx, Wh, b)[0]
fb = lambda b: rnn_forward(x, h0, Wx, Wh, b)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
dh0_num = eval_numerical_gradient_array(fh0, h0, dout)
dWx_num = eval_numerical_gradient_array(fWx, Wx, dout)
dWh_num = eval_numerical_gradient_array(fWh, Wh, dout)
db_num = eval_numerical_gradient_array(fb, b, dout)

print('dx error: ', rel_error(dx_num, dx))
print('dh0 error: ', rel_error(dh0_num, dh0))
print('dWx error: ', rel_error(dWx_num, dWx))
print('dWh error: ', rel_error(dWh_num, dWh))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  3.84928063719157e-09
dh0 error:  1.020473174359301e-10
dWx error:  1.7230110684806883e-10
dWh error:  2.4102509807628146e-09
db error:  7.937656148540516e-09
```

Word embedding: forward

In deep learning systems, we commonly represent words using vectors. Each word of the vocabulary will be associated with a vector, and these vectors will be learned jointly with the rest of the system.

In the file `cs6353/rnn_layers.py`, implement the function `word_embedding_forward` to convert words (represented by integers) into vectors. Run the following to check your implementation. You should see an error on the order of `e-8` or less.

In [12]:
```
N, T, V, D = 2, 4, 5, 3

x = np.asarray([[0, 3, 1, 2], [2, 1, 0, 3]])
W = np.linspace(0, 1, num=V*D).reshape(V, D)
```

```
out, _ = word_embedding_forward(x, W)
expected_out = np.asarray([
 [[ 0.,          0.07142857,  0.14285714],
  [ 0.64285714,  0.71428571,  0.78571429],
  [ 0.21428571,  0.28571429,  0.35714286],
  [ 0.42857143,  0.5,         0.57142857]],
 [[ 0.42857143,  0.5,         0.57142857],
  [ 0.21428571,  0.28571429,  0.35714286],
  [ 0.,          0.07142857,  0.14285714],
  [ 0.64285714,  0.71428571,  0.78571429]]])

print('out error: ', rel_error(expected_out, out))
```

```
out error:  1.0000000094736443e-08
```

Word embedding: backward

Implement the backward pass for the word embedding function in the function `word_embedding_backward`. After doing so run the following to numerically gradient check your implementation. You should see an error on the order of `e-11` or less.

In [13]:
```
np.random.seed(231)

N, T, V, D = 50, 3, 5, 6
x = np.random.randint(V, size=(N, T))
W = np.random.randn(V, D)

out, cache = word_embedding_forward(x, W)
dout = np.random.randn(*out.shape)
dW = word_embedding_backward(dout, cache)

f = lambda W: word_embedding_forward(x, W)[0]
dW_num = eval_numerical_gradient_array(f, W, dout)

print('dW error: ', rel_error(dW, dW_num))
```

```
dW error:  3.2774595693100364e-12
```

Temporal Affine layer

At every timestep we use an affine function to transform the RNN hidden vector at that timestep into scores for each word in the vocabulary. Because this is very similar to the affine layer that you implemented in assignment 3, we have provided this function for you in the `temporal_affine_forward` and `temporal_affine_backward` functions in the file `cs6353/rnn_layers.py`. Run the following to perform numeric gradient checking on the implementation. You should see errors on the order of e-9 or less.

In [14]:
```
np.random.seed(231)

# Gradient check for temporal affine layer
```

```
N, T, D, M = 2, 3, 4, 5
x = np.random.randn(N, T, D)
w = np.random.randn(D, M)
b = np.random.randn(M)

out, cache = temporal_affine_forward(x, w, b)

dout = np.random.randn(*out.shape)

fx = lambda x: temporal_affine_forward(x, w, b)[0]
fw = lambda w: temporal_affine_forward(x, w, b)[0]
fb = lambda b: temporal_affine_forward(x, w, b)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
dw_num = eval_numerical_gradient_array(fw, w, dout)
db_num = eval_numerical_gradient_array(fb, b, dout)

dx, dw, db = temporal_affine_backward(dout, cache)

print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  2.9215945034030545e-10
dw error:  1.5772088618663602e-10
db error:  3.252200556967514e-11
```

Temporal Softmax loss

In an RNN language model, at every timestep we produce a score for each word in the vocabulary. We know the ground-truth word at each timestep, so we use a softmax loss function to compute loss and gradient at each timestep. We sum the losses over time and average them over the minibatch.

However there is one wrinkle: since we operate over minibatches and different captions may have different lengths, we append `<NULL>` tokens to the end of each caption so they all have the same length. We don't want these `<NULL>` tokens to count toward the loss or gradient, so in addition to scores and ground-truth labels our loss function also accepts a `mask` array that tells it which elements of the scores count towards the loss.

Since this is very similar to the softmax loss function you implemented in assignment 2, we have implemented this loss function for you; look at the `temporal_softmax_loss` function in the file `cs6353/rnn_layers.py`.

Run the following cell to sanity check the loss and perform numeric gradient checking on the function. You should see an error for dx on the order of e-7 or less.

In [15]:
```
# Sanity check for temporal softmax loss
from cs6353.rnn_layers import temporal_softmax_loss
```

```
N, T, V = 100, 1, 10

def check_loss(N, T, V, p):
    x = 0.001 * np.random.randn(N, T, V)
    y = np.random.randint(V, size=(N, T))
    mask = np.random.rand(N, T) <= p
    print(temporal_softmax_loss(x, y, mask)[0])

check_loss(100, 1, 10, 1.0)   # Should be about 2.3
check_loss(100, 10, 10, 1.0)  # Should be about 23
check_loss(5000, 10, 10, 0.1) # Should be about 2.3

# Gradient check for temporal softmax loss
N, T, V = 7, 8, 9

x = np.random.randn(N, T, V)
y = np.random.randint(V, size=(N, T))
mask = (np.random.rand(N, T) > 0.5)

loss, dx = temporal_softmax_loss(x, y, mask, verbose=False)

dx_num = eval_numerical_gradient(lambda x: temporal_softmax_loss(x, y, mask)[0], x,

print('dx error: ', rel_error(dx, dx_num))
```

```
2.3027781774290146
23.025985953127226
2.2643611790293394
dx error:  2.583585303524283e-08
```

RNN for image captioning

Now that you have implemented the necessary layers, you can combine them to build an image captioning model. Open the file `cs6353/classifiers/rnn.py` and look at the `CaptioningRNN` class.

Implement the forward and backward pass of the model in the `loss` function. For now you only need to implement the case where `cell_type='rnn'` for vanialla RNNs; you will implement the LSTM case later. After doing so, run the following to check your forward pass using a small test case; You should see an error of about `0.02` or less.

In [16]:
```
N, D, W, H = 10, 20, 40, 40
word_to_idx = {'<NULL>': 0, 'cat': 2, 'dog': 3}
V = len(word_to_idx)
T = 13

model = CaptioningRNN(word_to_idx,
          input_dim=D,
          wordvec_dim=W,
          hidden_dim=H,
          cell_type='rnn',
          dtype=np.float64)
```

```
# Set all model parameters to fixed values
for k, v in model.params.items():
    model.params[k] = np.linspace(-1.4, 1.3, num=v.size).reshape(*v.shape)

features = np.linspace(-1.5, 0.3, num=(N * D)).reshape(N, D)
captions = (np.arange(N * T) % V).reshape(N, T)

loss, grads = model.loss(features, captions)
expected_loss = 9.83235591003

print('loss: ', loss)
print('expected loss: ', expected_loss)
print('difference: ', abs(loss - expected_loss))
```

```
loss:  9.809174730925443
expected loss:  9.83235591003
difference:  0.023181179104556193
```

Run the following cell to perform numeric gradient checking on the `CaptioningRNN` class; you should see errors around the order of `e-6` or less.

In [17]:
```
np.random.seed(231)

batch_size = 2
timesteps = 3
input_dim = 4
wordvec_dim = 6
hidden_dim = 6
word_to_idx = {'<NULL>': 0, 'cat': 2, 'dog': 3}
vocab_size = len(word_to_idx)

captions = np.random.randint(vocab_size, size=(batch_size, timesteps))
features = np.random.randn(batch_size, input_dim)

model = CaptioningRNN(word_to_idx,
          input_dim=input_dim,
          wordvec_dim=wordvec_dim,
          hidden_dim=hidden_dim,
          cell_type='rnn',
          dtype=np.float64,
        )

loss, grads = model.loss(features, captions)

for param_name in sorted(grads):
    f = lambda _: model.loss(features, captions)[0]
    param_grad_num = eval_numerical_gradient(f, model.params[param_name], verbose=F
    e = rel_error(param_grad_num, grads[param_name])
    print('%s relative error: %e' % (param_name, e))
```

```
W_embed relative error: 1.350162e-09
W_proj relative error: 7.760852e-09
W_vocab relative error: 1.879471e-09
Wh relative error: 8.772596e-09
Wx relative error: 4.146389e-07
b relative error: 5.270458e-10
b_proj relative error: 4.936156e-09
b_vocab relative error: 3.619788e-10
```

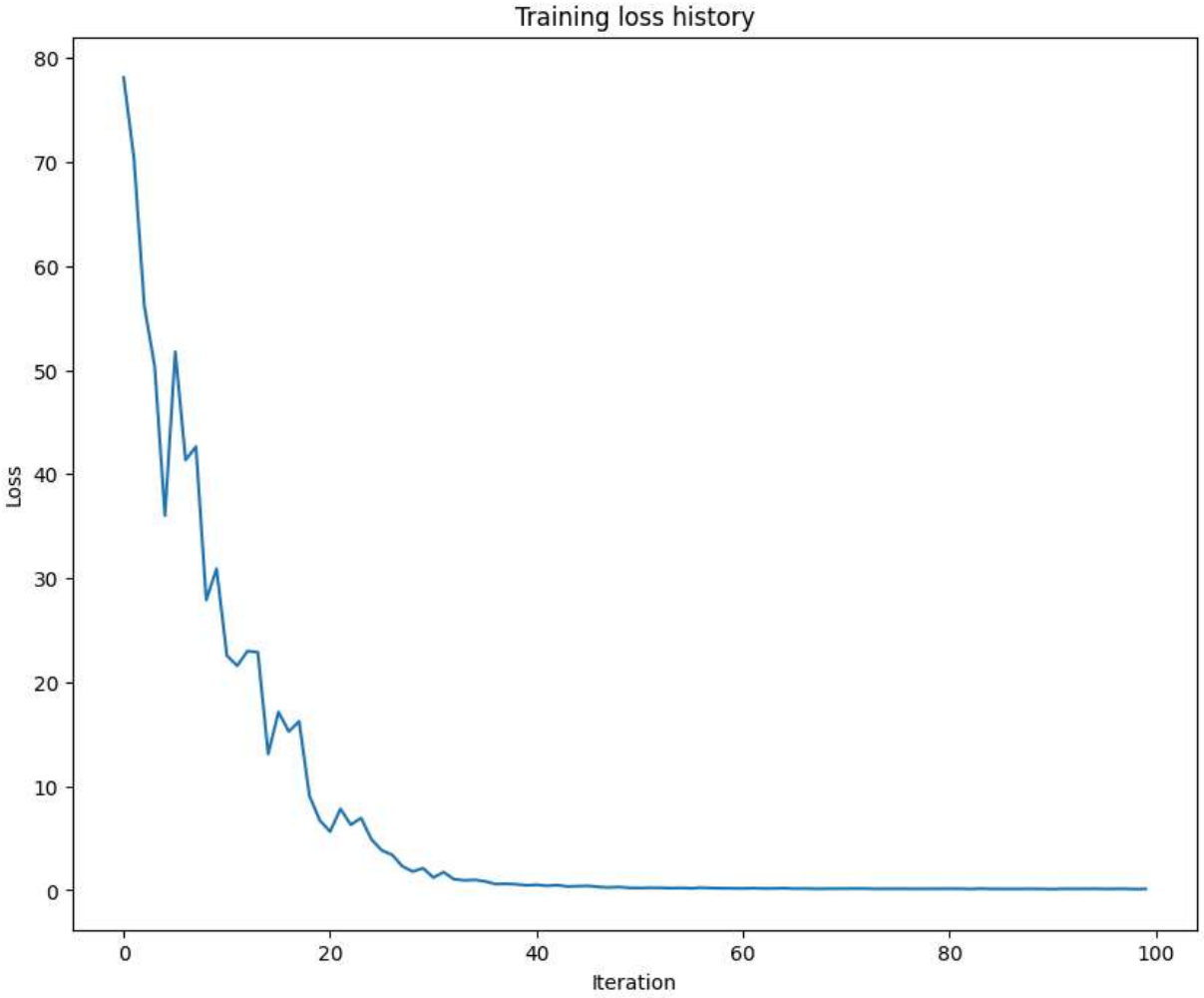
Overfit small data

Similar to the `Solver` class that we used to train image classification models on the previous assignment, on this assignment we use a `CaptioningSolver` class to train image captioning models. Open the file `cs6353/captioning_solver.py` and read through the `CaptioningSolver` class; it should look very familiar.

Once you have familiarized yourself with the API, run the following to make sure your model overfits a small sample of 100 training examples. You should see a final loss very close to 0.1

In [18]:
```
np.random.seed(231)

small_data = load_coco_data(max_train=50)

small_rnn_model = CaptioningRNN(
          cell_type='rnn',
          word_to_idx=data['word_to_idx'],
          input_dim=data['train_features'].shape[1],
          hidden_dim=512,
          wordvec_dim=512,
        )

small_rnn_solver = CaptioningSolver(small_rnn_model, small_data,
           update_rule='adam',
           num_epochs=50,
           batch_size=25,
           optim_config={
             'learning_rate': 5e-3,
           },
           lr_decay=0.95,
           verbose=True, print_every=10,
         )

small_rnn_solver.train()

# Plot the training losses
plt.plot(small_rnn_solver.loss_history)
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Training loss history')
plt.show()
```

```
(Iteration 1 / 100) loss: 78.117267
(Iteration 11 / 100) loss: 22.548865
(Iteration 21 / 100) loss: 5.637183
(Iteration 31 / 100) loss: 1.219399
(Iteration 41 / 100) loss: 0.518500
(Iteration 51 / 100) loss: 0.217734
(Iteration 61 / 100) loss: 0.170852
(Iteration 71 / 100) loss: 0.156351
(Iteration 81 / 100) loss: 0.145743
(Iteration 91 / 100) loss: 0.102868
```



Test-time sampling

Unlike classification models, image captioning models behave very differently at training time and at test time. At training time, we have access to the ground-truth caption, so we feed ground-truth words as input to the RNN at each timestep. At test time, we sample from the distribution over the vocabulary at each timestep, and feed the sample as input to the RNN at the next timestep.

In the file `cs6353/classifiers/rnn.py`, implement the `sample` method for test-time sampling. After doing so, run the following to sample from your overfitted model on both

training and validation data. The samples on training data should be very good; the samples on validation data probably won't make sense.

In [19]:
```
for split in ['train', 'val']:
    minibatch = sample_coco_minibatch(small_data, split=split, batch_size=2)
    gt_captions, features, urls = minibatch
    gt_captions = decode_captions(gt_captions, data['idx_to_word'])

    sample_captions = small_rnn_model.sample(features)
    sample_captions = decode_captions(sample_captions, data['idx_to_word'])

    for gt_caption, sample_caption, url in zip(gt_captions, sample_captions, urls):
        plt.imshow(image_from_url(url))
        plt.title('%s\n%s\nGT:%s' % (split, sample_caption, gt_caption))
        plt.axis('off')
        plt.show()
```

train
a large truck parked on the cement in front of a building <END>
GT:<START> a large truck parked on the cement in front of a building <END>

train
a man is taking a bite of his food while having his picture taken <END>
GT:<START> a man is taking a bite of his food while having his picture taken <END>

val
a <UNK> up of a cat on the ground near a table <END>
GT:<START> a black cat in a tie laying on a <UNK> next to <UNK> <END>

INLINE QUESTION 1

In our current image captioning setup, our RNN language model produces a word at every timestep as its output. However, an alternate way to pose the problem is to train the network to operate over *characters* (e.g. 'a', 'b', etc.) as opposed to words, so that at it every timestep, it receives the previous character as input and tries to predict the next character in the sequence. For example, the network might generate a caption like

'A', ' ', 'c', 'a', 't', ' ', 'o', 'n', ' ', 'a', ' ', 'b', 'e', 'd'

Can you describe one advantage of an image-captioning model that uses a character-level RNN? Can you also describe one disadvantage? HINT: there are several valid answers, but it might be useful to compare the parameter space of word-level and character-level models.

Answer:

Advantage: Flexibility in Generating New Words

- A character-level RNN can create words it has never seen before because it works with individual letters instead of whole words. This is useful when the model needs to handle rare or completely new words, like names or technical terms, that a word-based model might not know.

Disadvantage: Longer Sequences and Slower Training

- Since it generates text one letter at a time, the sequences are much longer than word-based models, making training slower and more difficult for the RNN to learn meaningful patterns. This means that the RNN might require more number of layers and a larger recurrent neural network to understand the dependencies between each character.

In [ ]:
```
#COMMENT IF NOT USING COLAB VM

# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'DeepLearning/assignments/assignment5/'
FOLDERNAME = "CS6353/Assignments/assignment5/assignment5/"
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd /content/drive/My\ Drive/$FOLDERNAME/cs6353/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5/cs6353/datasets
--2024-11-27 09:53:35--  http://supermoe.cs.umass.edu/682/asgns/coco_captioning.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 1035210391 (987M) [application/zip]
Saving to: ‘coco_captioning.zip’

coco_captioning.zip 100%[===================>] 987.25M  3.66MB/s    in 4m 50s

2024-11-27 09:58:25 (3.40 MB/s) - ‘coco_captioning.zip’ saved [1035210391/103521039
1]

Archive:  coco_captioning.zip
replace coco_captioning/coco2014_captions.h5? [y]es, [n]o, [A]ll, [N]one, [r]ename:
y
  inflating: coco_captioning/coco2014_captions.h5
replace coco_captioning/coco2014_vocab.json? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: coco_captioning/coco2014_vocab.json
replace coco_captioning/train2014_images.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename:
y
  inflating: coco_captioning/train2014_images.txt
replace coco_captioning/train2014_urls.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: coco_captioning/train2014_urls.txt
replace coco_captioning/train2014_vgg16_fc7.h5? [y]es, [n]o, [A]ll, [N]one, [r]enam
e: y
  inflating: coco_captioning/train2014_vgg16_fc7.h5  y

replace coco_captioning/train2014_vgg16_fc7_pca.h5? [y]es, [n]o, [A]ll, [N]one, [r]e
name:   inflating: coco_captioning/train2014_vgg16_fc7_pca.h5
replace coco_captioning/val2014_images.txt? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: coco_captioning/val2014_images.txt
  inflating: coco_captioning/val2014_urls.txt
  inflating: coco_captioning/val2014_vgg16_fc7.h5
  inflating: coco_captioning/val2014_vgg16_fc7_pca.h5
--2024-11-27 10:03:51--  http://supermoe.cs.umass.edu/682/asgns/squeezenet_tf.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 9202140 (8.8M) [application/zip]
Saving to: ‘squeezenet_tf.zip’

squeezenet_tf.zip   100%[===================>]   8.78M  3.57MB/s    in 2.5s

2024-11-27 10:03:53 (3.57 MB/s) - ‘squeezenet_tf.zip’ saved [9202140/9202140]

Archive:  squeezenet_tf.zip
replace squeezenet.ckpt.data-00000-of-00001? [y]es, [n]o, [A]ll, [N]one, [r]ename: y
  inflating: squeezenet.ckpt.data-00000-of-00001
replace squeezenet.ckpt.index? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: squeezenet.ckpt.index
  inflating: squeezenet.ckpt.meta
--2024-11-27 10:04:40--  http://supermoe.cs.umass.edu/682/asgns/imagenet_val_25.npz
```

```
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 3940548 (3.8M)
Saving to: ‘imagenet_val_25.npz.2’

imagenet_val_25.npz 100%[===================>]   3.76M  4.07MB/s    in 0.9s

2024-11-27 10:04:42 (4.07 MB/s) - ‘imagenet_val_25.npz.2’ saved [3940548/3940548]

/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5
```

In [ ]:
```
# #UNCOMMENT IF USING CADE
# import os
# ##### Request a GPU #####
# ## This function locates an available gpu for usage. In addition, this function r
# ## memory space exclusively for your account. The memory reservation prevents the
# ## speed when other users try to allocate memory on the same gpu in the shared sy
# ## Note: If you use your own system which has a GPU with less than 4GB of memory,
# ## specified mimimum memory.
# def define_gpu_to_use(minimum_memory_mb = 3500):
#     thres_memory = 600 #
#     gpu_to_use = None
#     try:
#         os.environ['CUDA_VISIBLE_DEVICES']
#         print('GPU already assigned before: ' + str(os.environ['CUDA_VISIBLE_DEVI
#         return
#     except:
#         pass

#     for i in range(16):
#         free_memory = !nvidia-smi --query-gpu=memory.free -i $i --format=csv,noun
#         if free_memory[0] == 'No devices were found':
#             break
#         free_memory = int(free_memory[0])

#         if free_memory>minimum_memory_mb-thres_memory:
#             gpu_to_use = i
#             break

#     if gpu_to_use is None:
#         print('Could not find any GPU available with the required free memory of
#               + 'MB. Please use a different system for this assignment.')
#     else:
#         os.environ['CUDA_VISIBLE_DEVICES'] = str(gpu_to_use)
#         print('Chosen GPU: ' + str(gpu_to_use))

# ## Request a gpu and reserve the memory space
# define_gpu_to_use(4000)
```

Network Visualization (PyTorch)

In this notebook we will explore the use of *image gradients* for generating new images.

When training a model, we define a loss function which measures our current unhappiness with the model's performance; we then use backpropagation to compute the gradient of the loss with respect to the model parameters, and perform gradient descent on the model parameters to minimize the loss.

Here we will do something slightly different. We will start from a convolutional neural network model which has been pretrained to perform image classification on the ImageNet dataset. We will use this model to define a loss function which quantifies our current unhappiness with our image, then use backpropagation to compute the gradient of this loss with respect to the pixels of the image. We will then keep the model fixed, and perform gradient descent *on the image* to synthesize a new image which minimizes the loss.

In this notebook we will explore three techniques for image generation:

1. **Saliency Maps**: Saliency maps are a quick way to tell which part of the image influenced the classification decision made by the network.
2. **Fooling Images**: We can perturb an input image so that it appears the same to humans, but will be misclassified by the pretrained network.
3. **Class Visualization**: We can synthesize an image to maximize the classification score of a particular class; this can give us some sense of what the network is looking for when it classifies images of that class.

This notebook uses **PyTorch**;

In [ ]:
```
import torch
import torchvision
import torchvision.transforms as T
import random
import numpy as np
from scipy.ndimage import gaussian_filter1d
import matplotlib.pyplot as plt
from cs6353.image_utils import SQUEEZENET_MEAN, SQUEEZENET_STD
from PIL import Image

%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'
```

Helper Functions

Our pretrained model was trained on images that had been preprocessed by subtracting the per-color mean and dividing by the per-color standard deviation. We define a few helper functions for performing and undoing this preprocessing. You don't need to do anything in this cell.

In [ ]:
```
def preprocess(img, size=224):
    transform = T.Compose([
        T.Resize(size),
        T.ToTensor(),
        T.Normalize(mean=SQUEEZENET_MEAN.tolist(),
                    std=SQUEEZENET_STD.tolist()),
        T.Lambda(lambda x: x[None]),
    ])
    return transform(img)

def deprocess(img, should_rescale=True):
    transform = T.Compose([
        T.Lambda(lambda x: x[0]),
        T.Normalize(mean=[0, 0, 0], std=(1.0 / SQUEEZENET_STD).tolist()),
        T.Normalize(mean=(-SQUEEZENET_MEAN).tolist(), std=[1, 1, 1]),
        T.Lambda(rescale) if should_rescale else T.Lambda(lambda x: x),
        T.ToPILImage(),
    ])
    return transform(img)

def rescale(x):
    low, high = x.min(), x.max()
    x_rescaled = (x - low) / (high - low)
    return x_rescaled

def blur_image(X, sigma=1):
    X_np = X.cpu().clone().numpy()
    X_np = gaussian_filter1d(X_np, sigma, axis=2)
    X_np = gaussian_filter1d(X_np, sigma, axis=3)
    X.copy_(torch.Tensor(X_np).type_as(X))
    return X
```

Pretrained Model

For all of our image generation experiments, we will start with a convolutional neural network which was pretrained to perform image classification on ImageNet. We can use any model here, but for the purposes of this assignment we will use SqueezeNet [1], which achieves accuracies comparable to AlexNet but with a significantly reduced parameter count and computational complexity.

Using SqueezeNet rather than AlexNet or VGG or ResNet means that we can easily perform all image generation experiments on CPU.

[1] Iandola et al, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and < 0.5MB model size", arXiv 2016

In [ ]:
```
# Download and load the pretrained SqueezeNet model.
model = torchvision.models.squeezenet1_1(pretrained=True)

# We don't want to train the model, so tell PyTorch not to compute gradients
```

```
# with respect to model parameters.
for param in model.parameters():
    param.requires_grad = False

# you may see warning regarding initialization deprecated, that's fine, please cont
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWarnin
g: The parameter 'pretrained' is deprecated since 0.13 and may be removed in the fut
ure, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWarnin
g: Arguments other than a weight enum or `None` for 'weights' are deprecated since
0.13 and may be removed in the future. The current behavior is equivalent to passing
`weights=SqueezeNet1_1_Weights.IMAGENET1K_V1`. You can also use `weights=SqueezeNet1
_1_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/squeezenet1_1-b8a52dc0.pth" to /ro
ot/.cache/torch/hub/checkpoints/squeezenet1_1-b8a52dc0.pth
100%|██████████| 4.73M/4.73M [00:00<00:00, 26.5MB/s]
```

Load some ImageNet images

We have provided a few example images from the validation set of the ImageNet ILSVRC 2012 Classification dataset. To download these images, descend into `cs6353/datasets/` and run `get_imagenet_val.sh`.

Since they come from the validation set, our pretrained model did not see these images during training.

Run the following cell to visualize some of these images, along with their ground-truth labels.

In [ ]:
```
from cs6353.data_utils import load_imagenet_val
X, y, class_names = load_imagenet_val(num=5)

plt.figure(figsize=(12, 6))
for i in range(5):
    plt.subplot(1, 5, i + 1)
    plt.imshow(X[i])
    plt.title(class_names[y[i]])
    plt.axis('off')
plt.gcf().tight_layout()
```

Saliency Maps

Using this pretrained model, we will compute class saliency maps as described in Section 3.1 of [2].

A **saliency map** tells us the degree to which each pixel in the image affects the classification score for that image. To compute it, we compute the gradient of the unnormalized score corresponding to the correct class (which is a scalar) with respect to the pixels of the image. If the image has shape `(3, H, W)` then this gradient will also have shape `(3, H, W)`; for each pixel in the image, this gradient tells us the amount by which the classification score will change if the pixel changes by a small amount. To compute the saliency map, we take the absolute value of this gradient, then take the maximum value over the 3 input channels; the final saliency map thus has shape `(H, W)` and all entries are nonnegative.

[2] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

Hint: PyTorch `gather` method

Recall in Assignment 1 you needed to select one element from each row of a matrix; if `s` is an numpy array of shape `(N, C)` and `y` is a numpy array of shape `(N,)` containing integers `0 <= y[i] < C`, then `s[np.arange(N), y]` is a numpy array of shape `(N,)` which selects one element from each element in `s` using the indices in `y`.

In PyTorch you can perform the same operation using the `gather()` method. If `s` is a PyTorch Tensor of shape `(N, C)` and `y` is a PyTorch Tensor of shape `(N,)` containing longs in the range `0 <= y[i] < C`, then

`s.gather(1, y.view(-1, 1)).squeeze()`

will be a PyTorch Tensor of shape `(N,)` containing one entry from each row of `s`, selected according to the indices in `y`.

run the following cell to see an example.

You can also read the documentation for the gather method and the squeeze method.

In [ ]:
```
# Example of using gather to select one entry from each row in PyTorch
def gather_example():
    N, C = 4, 5
    s = torch.randn(N, C)
    y = torch.LongTensor([1, 2, 1, 3])
    print(s)
    print(y)
```

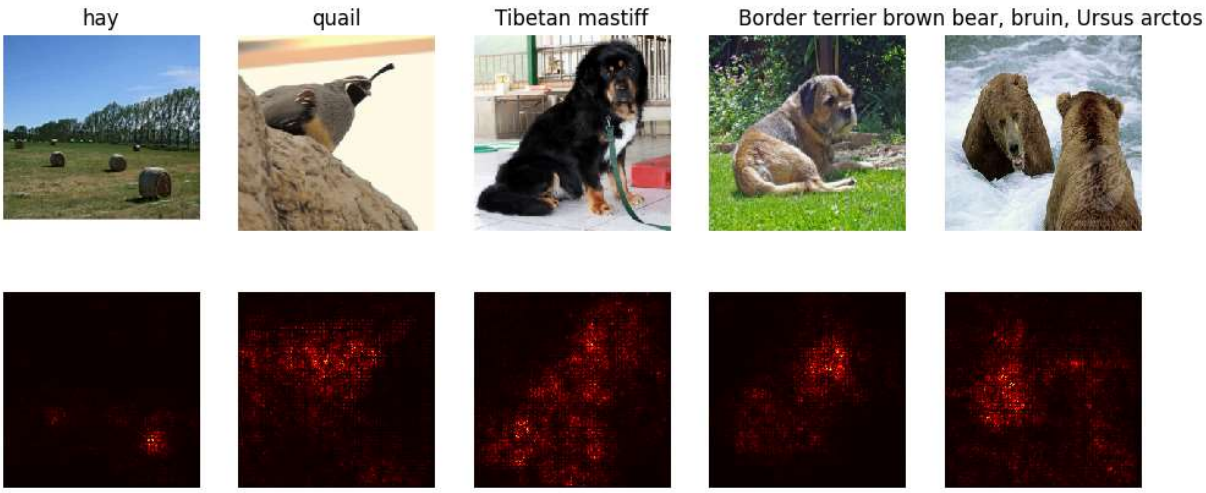
```
    print(s.gather(1, y.view(-1, 1)).squeeze())
gather_example()
```

```
tensor([[-0.3255, -0.4475,  1.6392,  1.8355,  0.1879],
        [-1.6643, -1.8245, -1.1639,  0.3177,  0.1512],
        [-1.0997, -1.6267,  0.1507, -0.1027,  0.3247],
        [-0.6965,  1.6366,  0.0670,  1.6660,  0.1202]])
tensor([1, 2, 1, 3])
tensor([-0.4475, -1.1639, -1.6267,  1.6660])
```

In [ ]:
```
def compute_saliency_maps(X, y, model):
    """
    Compute a class saliency map using the model for images X and labels y.

    Input:
    - X: Input images; Tensor of shape (N, 3, H, W)
    - y: Labels for X; LongTensor of shape (N,)
    - model: A pretrained CNN that will be used to compute the saliency map.

    Returns:
    - saliency: A Tensor of shape (N, H, W) giving the saliency maps for the input
    images.
    """
    # Make sure the model is in "test" mode
    model.eval()

    # Make input tensor require gradient
    X.requires_grad_()

    saliency = None
    ##############################################################################
    # TODO: Implement this function. Perform a forward and backward pass through #
    # the model to compute the gradient of the correct class score with respect  #
    # to each input image. You first want to compute the loss over the correct   #
    # scores (we'll combine losses across a batch by summing), and then compute  #
    # the gradients with a backward pass.                                        #
    ##############################################################################
    # Forward pass
    scores = model(X)
    target_scores = scores.gather(dim=1, index=y.view(-1, 1)).squeeze()

    # Backward pass
    gradient_weights = torch.ones_like(target_scores)
    target_scores.backward(gradient_weights)

    gradients = X.grad.data
    absolute_gradients = gradients.abs()
    saliency, _ = absolute_gradients.max(dim=1)
    ##############################################################################
    #                               END OF YOUR CODE                             #
    ##############################################################################
    return saliency
```

Once you have completed the implementation in the cell above, run the following to visualize some class saliency maps on our example images from the ImageNet validation set:

In [ ]:
```
def show_saliency_maps(X, y):
    # Convert X and y from numpy arrays to Torch Tensors
    X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
    y_tensor = torch.LongTensor(y)

    # Compute saliency maps for images in X
    saliency = compute_saliency_maps(X_tensor, y_tensor, model)

    # Convert the saliency map from Torch Tensor to numpy array and show images
    # and saliency maps together.
    saliency = saliency.numpy()
    N = X.shape[0]
    for i in range(N):
        plt.subplot(2, N, i + 1)
        plt.imshow(X[i])
        plt.axis('off')
        plt.title(class_names[y[i]])
        plt.subplot(2, N, N + i + 1)
        plt.imshow(saliency[i], cmap=plt.cm.hot)
        plt.axis('off')
        plt.gcf().set_size_inches(12, 5)
    plt.show()

show_saliency_maps(X, y)
```



INLINE QUESTION

A friend of yours suggests that in order to find an image that maximizes the correct score, we can perform gradient ascent on the input image, but instead of the gradient we can actually use the saliency map in each step to update the image. Is this assertion true? Why or why not?

Answer:

No, using the saliency map for gradient ascent instead of the raw gradient won't work because the saliency map loses important information needed for optimization. The raw

gradient tells us the exact direction (positive or negative) to change each pixel in every channel (red, green, blue) to maximize the score for a specific class. On the other hand, the saliency map collapses this information into a single channel by taking the absolute value and the maximum across the RGB channels, which means it doesn't know which way (positive or negative) to update each pixel. If we used the saliency map, the updates would all be positive and biased toward just one channel per pixel, which would lead to unbalanced changes and likely cause pixel values to blow up without achieving the desired outcome. To properly generate images, we must use the raw gradient, which has the full directional information for all three channels.

Fooling Images

We can also use image gradients to generate "fooling images" as discussed in [3]. Given an image and a target class, we can perform gradient **ascent** over the image to maximize the target class, stopping when the network classifies the image as the target class. Implement the following function to generate fooling images.

[3] Szegedy et al, "Intriguing properties of neural networks", ICLR 2014

In [ ]:
```
def make_fooling_image(X, target_y, model):
    """
    Generate a fooling image that is close to X, but that the model classifies
    as target_y.

    Inputs:
    - X: Input image; Tensor of shape (1, 3, 224, 224)
    - target_y: An integer in the range [0, 1000)
    - model: A pretrained CNN

    Returns:
    - X_fooling: An image that is close to X, but that is classifed as target_y
    by the model.
    """
    # Initialize our fooling image to the input image, and make it require gradient
    X_fooling = X.clone()
    X_fooling = X_fooling.requires_grad_()

    learning_rate = 1
    ##############################################################################
    # TODO: Generate a fooling image X_fooling that the model will classify as   #
    # the class target_y. You should perform gradient ascent on the score of the #
    # target class, stopping when the model is fooled.                           #
    # When computing an update step, first normalize the gradient:               #
    #   dX = learning_rate * g / ||g||_2                                         #
    #                                                                            #
    # You should write a training loop.                                          #
    #                                                                            #
    # HINT: For most examples, you should be able to generate a fooling image    #
    # in fewer than 100 iterations of gradient ascent.                           #
```

```
    # You can print your progress over iterations to check your algorithm.       #
    ##############################################################################
    for iteration in range(100):
        scores = model(X_fooling)
        predicted_class = torch.argmax(scores, dim=1)

        if predicted_class == target_y:
            print(f"Model fooled at iteration {iteration}: Predicted {predicted_cla
            break
        else:
            scores[:, target_y].backward()
            gradient_norm = torch.norm(X_fooling.grad.data)
            normalized_gradient = X_fooling.grad.data / gradient_norm
            update_step = learning_rate * normalized_gradient
            X_fooling.data += update_step
            X_fooling.grad.data.zero_()
    ##############################################################################
    #                             END OF YOUR CODE                               #
    ##############################################################################
    return X_fooling
```

Run the following cell to generate a fooling image. You should ideally see at first glance no major difference between the original and fooling images, and the network should now make an incorrect prediction on the fooling one. However you should see a bit of random noise if you look at the 10x magnified difference between the original and fooling images. Feel free to change the `idx` variable to explore other images.

In [ ]:
```
idx = 0
target_y = 6

X_tensor = torch.cat([preprocess(Image.fromarray(x)) for x in X], dim=0)
X_fooling = make_fooling_image(X_tensor[idx:idx+1], target_y, model)

scores = model(X_fooling)
assert target_y == scores.data.max(1)[1][0].item(), 'The model is not fooled!'
```

```
Model fooled at iteration 9: Predicted 6, Target 6
```

After generating a fooling image, run the following cell to visualize the original image, the fooling image, as well as the difference between them.

In [ ]:
```
X_fooling_np = deprocess(X_fooling.clone())
X_fooling_np = np.asarray(X_fooling_np).astype(np.uint8)

plt.subplot(1, 4, 1)
plt.imshow(X[idx])
plt.title(class_names[y[idx]])
plt.axis('off')

plt.subplot(1, 4, 2)
plt.imshow(X_fooling_np)
plt.title(class_names[target_y])
plt.axis('off')
```

```
plt.subplot(1, 4, 3)
X_pre = preprocess(Image.fromarray(X[idx]))
diff = np.asarray(deprocess(X_fooling - X_pre, should_rescale=False))
plt.imshow(diff)
plt.title('Difference')
plt.axis('off')

plt.subplot(1, 4, 4)
diff = np.asarray(deprocess(10 * (X_fooling - X_pre), should_rescale=False))
plt.imshow(diff)
plt.title('Magnified difference (10x)')
plt.axis('off')

plt.gcf().set_size_inches(12, 5)
plt.show()
```

Class visualization

By starting with a random noise image and performing gradient ascent on a target class, we can generate an image that the network will recognize as the target class. This idea was first presented in [2]; [3] extended this idea by suggesting several regularization techniques that can improve the quality of the generated image.

Concretely, let I be an image and let y be a target class. Let $s_y(I)$ be the score that a convolutional network assigns to the image I for class y; note that these are raw unnormalized scores, not class probabilities. We wish to generate an image I^* that achieves a high score for the class y by solving the problem

$$I^* = \arg\max_I (s_y(I) - R(I))$$

where R is a (possibly implicit) regularizer (note the sign of $R(I)$ in the argmax: we want to minimize this regularization term). We can solve this optimization problem using gradient ascent, computing gradients with respect to the generated image. We will use (explicit) L2 regularization of the form

$$R(I) = \lambda \|I\|_2^2$$

and implicit regularization as suggested by [3] by periodically blurring the generated image. We can solve this problem using gradient ascent on the generated image.

In the cell below, complete the implementation of the `create_class_visualization` function.

[2] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

[3] Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML 2015 Deep Learning Workshop

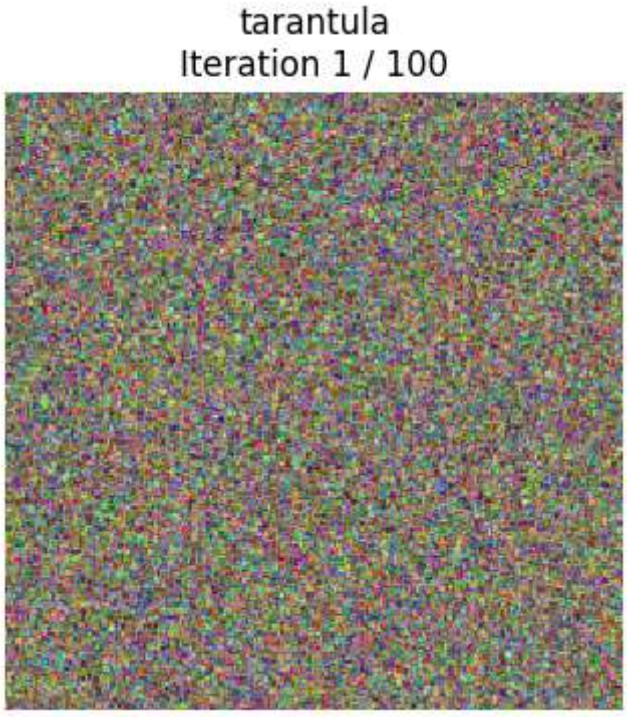
In [ ]:
```
def jitter(X, ox, oy):
    """
    Helper function to randomly jitter an image.

    Inputs
    - X: PyTorch Tensor of shape (N, C, H, W)
    - ox, oy: Integers giving number of pixels to jitter along W and H axes

    Returns: A new PyTorch Tensor of shape (N, C, H, W)
    """
    if ox != 0:
        left = X[:, :, :, :-ox]
        right = X[:, :, :, -ox:]
        X = torch.cat([right, left], dim=3)
    if oy != 0:
        top = X[:, :, :-oy]
        bottom = X[:, :, -oy:]
        X = torch.cat([bottom, top], dim=2)
    return X
```

In [ ]:
```
def create_class_visualization(target_y, model, dtype, **kwargs):
    """
    Generate an image to maximize the score of target_y under a pretrained model.

    Inputs:
    - target_y: Integer in the range [0, 1000) giving the index of the class
    - model: A pretrained CNN that will be used to generate the image
    - dtype: Torch datatype to use for computations

    Keyword arguments:
    - l2_reg: Strength of L2 regularization on the image
    - learning_rate: How big of a step to take
    - num_iterations: How many iterations to use
    - blur_every: How often to blur the image as an implicit regularizer
    - max_jitter: How much to gjitter the image as an implicit regularizer
    - show_every: How often to show the intermediate result
    """
    model.type(dtype)
    l2_reg = kwargs.pop('l2_reg', 1e-3)
    learning_rate = kwargs.pop('learning_rate', 25)
    num_iterations = kwargs.pop('num_iterations', 100)
    blur_every = kwargs.pop('blur_every', 10)
    max_jitter = kwargs.pop('max_jitter', 16)
    show_every = kwargs.pop('show_every', 25)
```

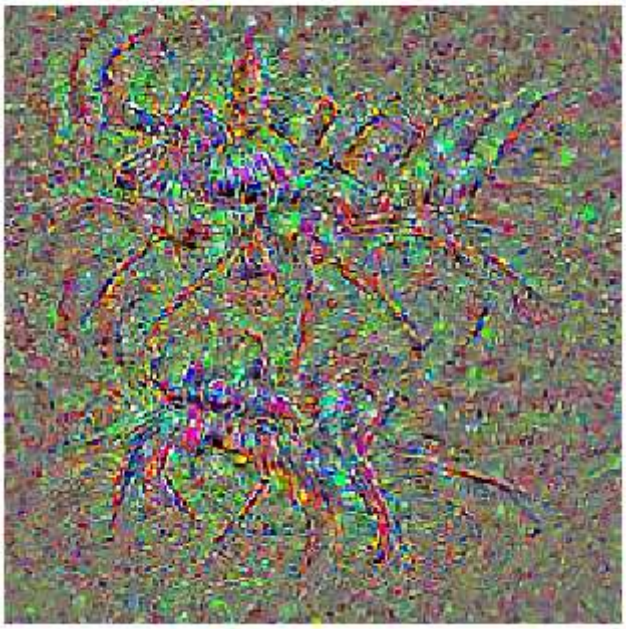
```
    # Randomly initialize the image as a PyTorch Tensor, and make it requires gradi
    img = torch.randn(1, 3, 224, 224).mul_(1.0).type(dtype).requires_grad_()

    for t in range(num_iterations):
        # Randomly jitter the image a bit; this gives slightly nicer results
        ox, oy = random.randint(0, max_jitter), random.randint(0, max_jitter)
        img.data.copy_(jitter(img.data, ox, oy))

        ########################################################################
        # TODO: Use the model to compute the gradient of the score for the     #
        # class target_y with respect to the pixels of the image, and make a   #
        # gradient step on the image using the learning rate. Don't forget the #
        # L2 regularization term!                                              #
        # Be very careful about the signs of elements in your code.            #
        ########################################################################
        scores = model(img)

        img_norm = torch.norm(img)
        img_norm_squared = torch.square(img_norm)
        l2_penalty = l2_reg * img_norm_squared

        target_score = scores[:, target_y] - l2_penalty

        target_score.backward()

        img.data += learning_rate * img.grad.data

        img.grad.data.zero_()
        ########################################################################
        #                             END OF YOUR CODE                         #
        ########################################################################

        # Undo the random jitter
        img.data.copy_(jitter(img.data, -ox, -oy))

        # As regularizer, clamp and periodically blur the image
        for c in range(3):
            lo = float(-SQUEEZENET_MEAN[c] / SQUEEZENET_STD[c])
            hi = float((1.0 - SQUEEZENET_MEAN[c]) / SQUEEZENET_STD[c])
            img.data[:, c].clamp_(min=lo, max=hi)
        if t % blur_every == 0:
            blur_image(img.data, sigma=0.5)

        # Periodically show the image
        if t == 0 or (t + 1) % show_every == 0 or t == num_iterations - 1:
            plt.imshow(deprocess(img.data.clone().cpu()))
            class_name = class_names[target_y]
            plt.title('%s\nIteration %d / %d' % (class_name, t + 1, num_iterations)
            plt.gcf().set_size_inches(4, 4)
            plt.axis('off')
            plt.show()

    return deprocess(img.data.cpu())
```

Once you have completed the implementation in the cell above, run the following cell to generate an image of a Tarantula:

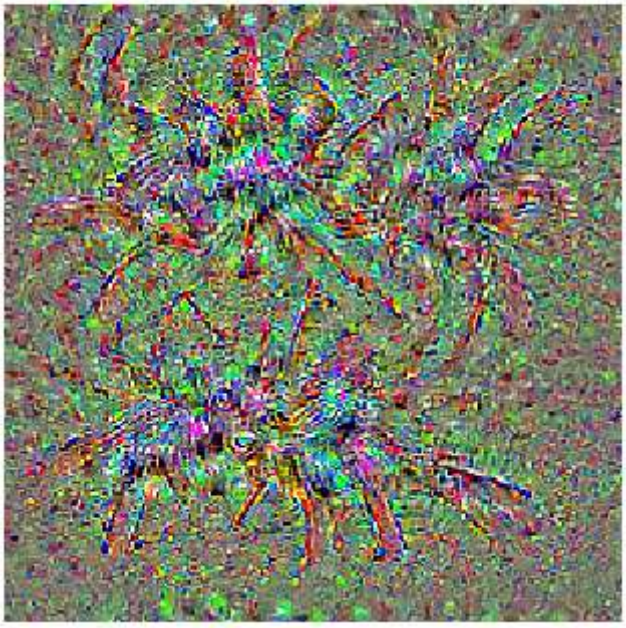
In [ ]:
```
dtype = torch.FloatTensor
# dtype = torch.cuda.FloatTensor # Uncomment this to use GPU
model.type(dtype)

target_y = 76 # Tarantula
# target_y = 78 # Tick
# target_y = 187 # Yorkshire Terrier
# target_y = 683 # Oboe
# target_y = 366 # Gorilla
# target_y = 604 # Hourglass
out = create_class_visualization(target_y, model, dtype)
```

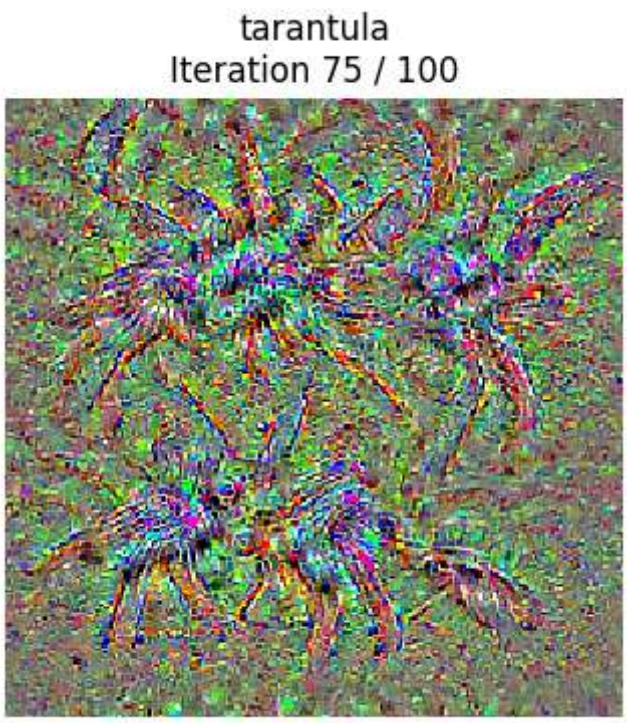


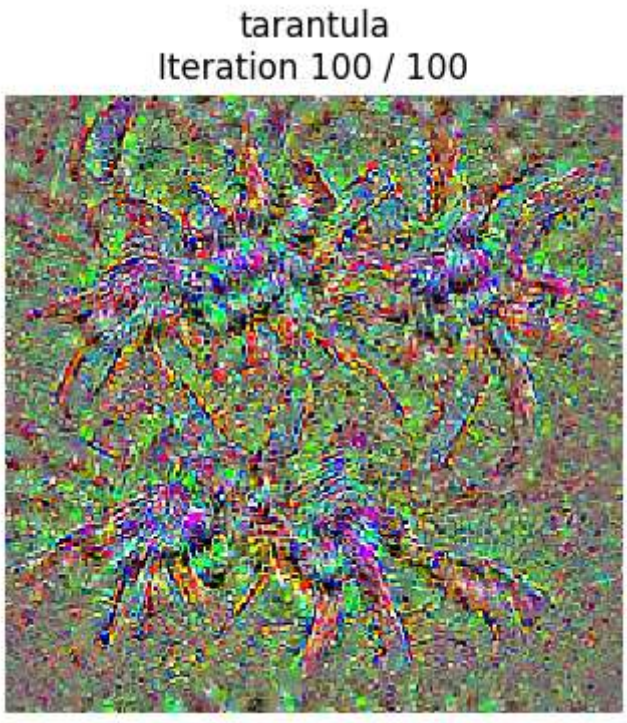
tarantula
Iteration 25 / 100



tarantula
Iteration 50 / 100





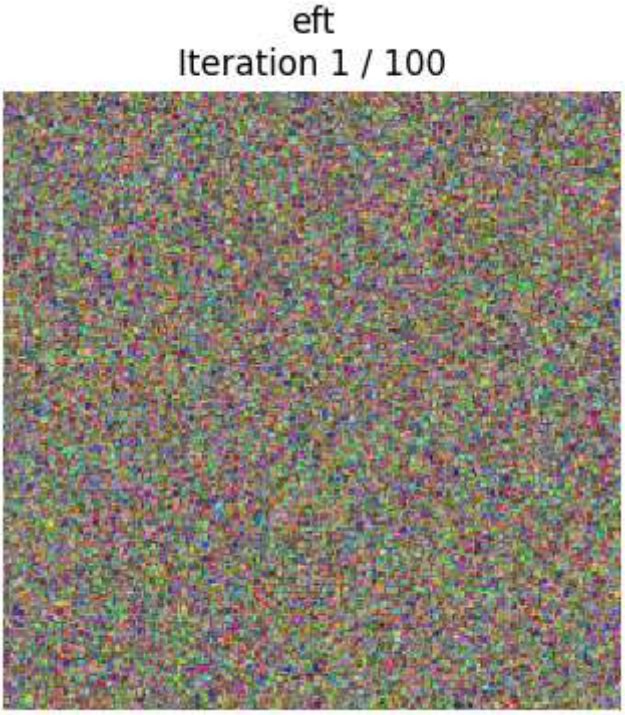


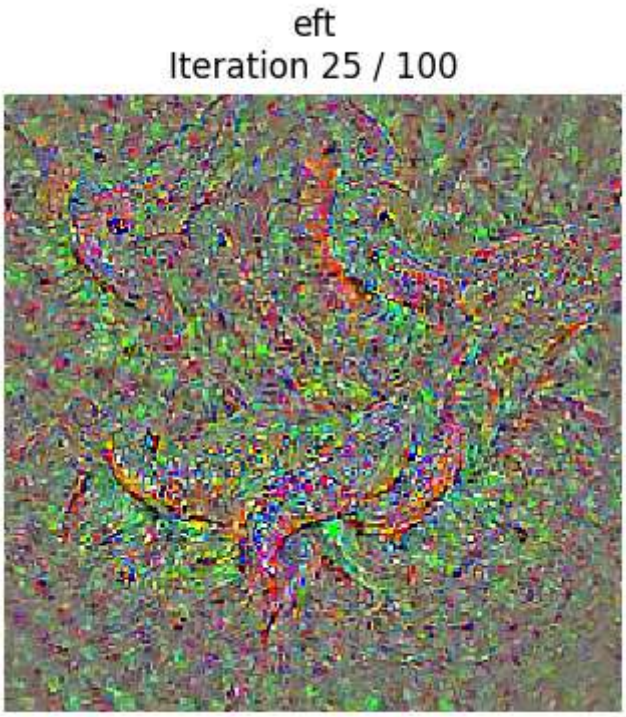
Try out your class visualization on other classes! You should also feel free to play with various hyperparameters to try and improve the quality of the generated image, but this is not required.

In [ ]:
```
# target_y = 78 # Tick
# target_y = 187 # Yorkshire Terrier
# target_y = 683 # Oboe
# target_y = 366 # Gorilla
target_y = 604 # Hourglass
target_y = np.random.randint(1000)
```

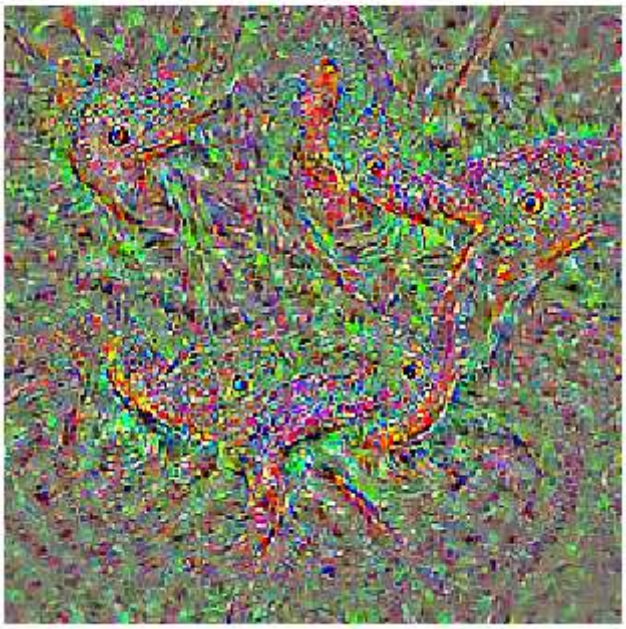
```
print(class_names[target_y])
X = create_class_visualization(target_y, model, dtype)
```

```
eft
```

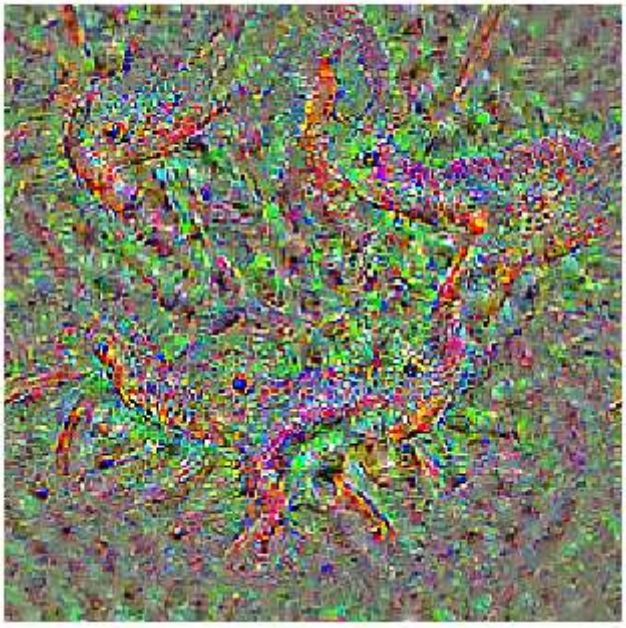


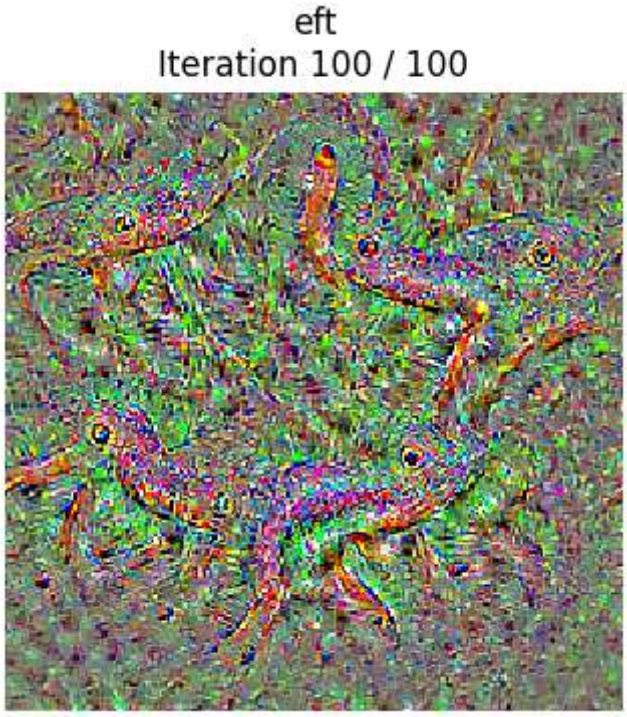


eft
Iteration 50 / 100



eft
Iteration 75 / 100




eft
Iteration 100 / 100

In [3]:
```
#COMMENT IF NOT USING COLAB VM

# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'DeepLearning/assignments/assignment5/'
FOLDERNAME = "CS6353/Assignments/assignment5/assignment5/"
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd /content/drive/My\ Drive/$FOLDERNAME/cs6353/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.
mount("/content/drive", force_remount=True).
/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5/cs6353/datasets
--2024-11-27 23:10:04--  http://supermoe.cs.umass.edu/682/asgns/coco_captioning.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 1035210391 (987M) [application/zip]
Saving to: ‘coco_captioning.zip.1’

coco_captioning.zip 100%[===================>] 987.25M  5.01MB/s    in 3m 58s

2024-11-27 23:14:02 (4.14 MB/s) - ‘coco_captioning.zip.1’ saved [1035210391/10352103
91]

Archive:  coco_captioning.zip
replace coco_captioning/coco2014_captions.h5? [y]es, [n]o, [A]ll, [N]one, [r]ename:
A
  inflating: coco_captioning/coco2014_captions.h5
  inflating: coco_captioning/coco2014_vocab.json
  inflating: coco_captioning/train2014_images.txt
  inflating: coco_captioning/train2014_urls.txt
  inflating: coco_captioning/train2014_vgg16_fc7.h5
  inflating: coco_captioning/train2014_vgg16_fc7_pca.h5
  inflating: coco_captioning/val2014_images.txt
  inflating: coco_captioning/val2014_urls.txt
  inflating: coco_captioning/val2014_vgg16_fc7.h5
  inflating: coco_captioning/val2014_vgg16_fc7_pca.h5
--2024-11-27 23:19:06--  http://supermoe.cs.umass.edu/682/asgns/squeezenet_tf.zip
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 9202140 (8.8M) [application/zip]
Saving to: ‘squeezenet_tf.zip’

squeezenet_tf.zip   100%[===================>]   8.78M  3.56MB/s    in 2.5s

2024-11-27 23:19:09 (3.56 MB/s) - ‘squeezenet_tf.zip’ saved [9202140/9202140]

Archive:  squeezenet_tf.zip
replace squeezenet.ckpt.data-00000-of-00001? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: squeezenet.ckpt.data-00000-of-00001
  inflating: squeezenet.ckpt.index
  inflating: squeezenet.ckpt.meta
--2024-11-27 23:19:13--  http://supermoe.cs.umass.edu/682/asgns/imagenet_val_25.npz
Resolving supermoe.cs.umass.edu (supermoe.cs.umass.edu)... 128.119.244.95
Connecting to supermoe.cs.umass.edu (supermoe.cs.umass.edu)|128.119.244.95|:80... co
nnected.
HTTP request sent, awaiting response... 200 OK
Length: 3940548 (3.8M)
Saving to: ‘imagenet_val_25.npz.5’

imagenet_val_25.npz 100%[===================>]   3.76M  3.52MB/s    in 1.1s
```

```
2024-11-27 23:19:14 (3.52 MB/s) - ‘imagenet_val_25.npz.5’ saved [3940548/3940548]

/content/drive/My Drive/CS6353/Assignments/assignment5/assignment5
```

In [ ]:
```
# #UNCOMMENT IF USING CADE
# import os
# ##### Request a GPU #####
# ## This function locates an available gpu for usage. In addition, this function r
# ## memory space exclusively for your account. The memory reservation prevents the
# ## speed when other users try to allocate memory on the same gpu in the shared sy
# ## Note: If you use your own system which has a GPU with less than 4GB of memory,
# ## specified mimimum memory.
# def define_gpu_to_use(minimum_memory_mb = 3500):
#     thres_memory = 600 #
#     gpu_to_use = None
#     try:
#         os.environ['CUDA_VISIBLE_DEVICES']
#         print('GPU already assigned before: ' + str(os.environ['CUDA_VISIBLE_DEVI
#         return
#     except:
#         pass

#     for i in range(16):
#         free_memory = !nvidia-smi --query-gpu=memory.free -i $i --format=csv,noun
#         if free_memory[0] == 'No devices were found':
#             break
#         free_memory = int(free_memory[0])

#         if free_memory>minimum_memory_mb-thres_memory:
#             gpu_to_use = i
#             break

#     if gpu_to_use is None:
#         print('Could not find any GPU available with the required free memory of
#               + 'MB. Please use a different system for this assignment.')
#     else:
#         os.environ['CUDA_VISIBLE_DEVICES'] = str(gpu_to_use)
#         print('Chosen GPU: ' + str(gpu_to_use))

# ## Request a gpu and reserve the memory space
# define_gpu_to_use(4000)
```

Generative Adversarial Networks (GANs)

So far in cs6353, 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:

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

where $z \sim p(z)$ 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:

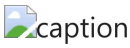
$$\underset{D}{\text{maximize}}\ \mathbb{E}_{x\sim p_{\text{data}}}\left[\log D(x)\right] + \mathbb{E}_{z\sim p(z)}\left[\log(1-D(G(z)))\right]$$

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). Variatonal autoencoders combine neural networks with variationl 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.

Here's an example of what your outputs from the 3 different models you're going to train should look like... note that GANs are sometimes finicky, so your outputs might not look exactly like this... this is just meant to be a *rough* guideline of the kind of quality you can expect:

 caption

Setup

In [4]:
```
import torch
import torch.nn as nn
from torch.nn import init
import torchvision
import torchvision.transforms as T
import torch.optim as optim
from torch.utils.data import DataLoader
from torch.utils.data import sampler
import torchvision.datasets as dset

import numpy as np

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'

def show_images(images):
    images = np.reshape(images, [images.shape[0], -1])  # images reshape to (batch_
    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(model):
    """Count the number of parameters"""
    param_count = np.sum([np.prod(p.size()) for p in model.parameters()])
    return param_count

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

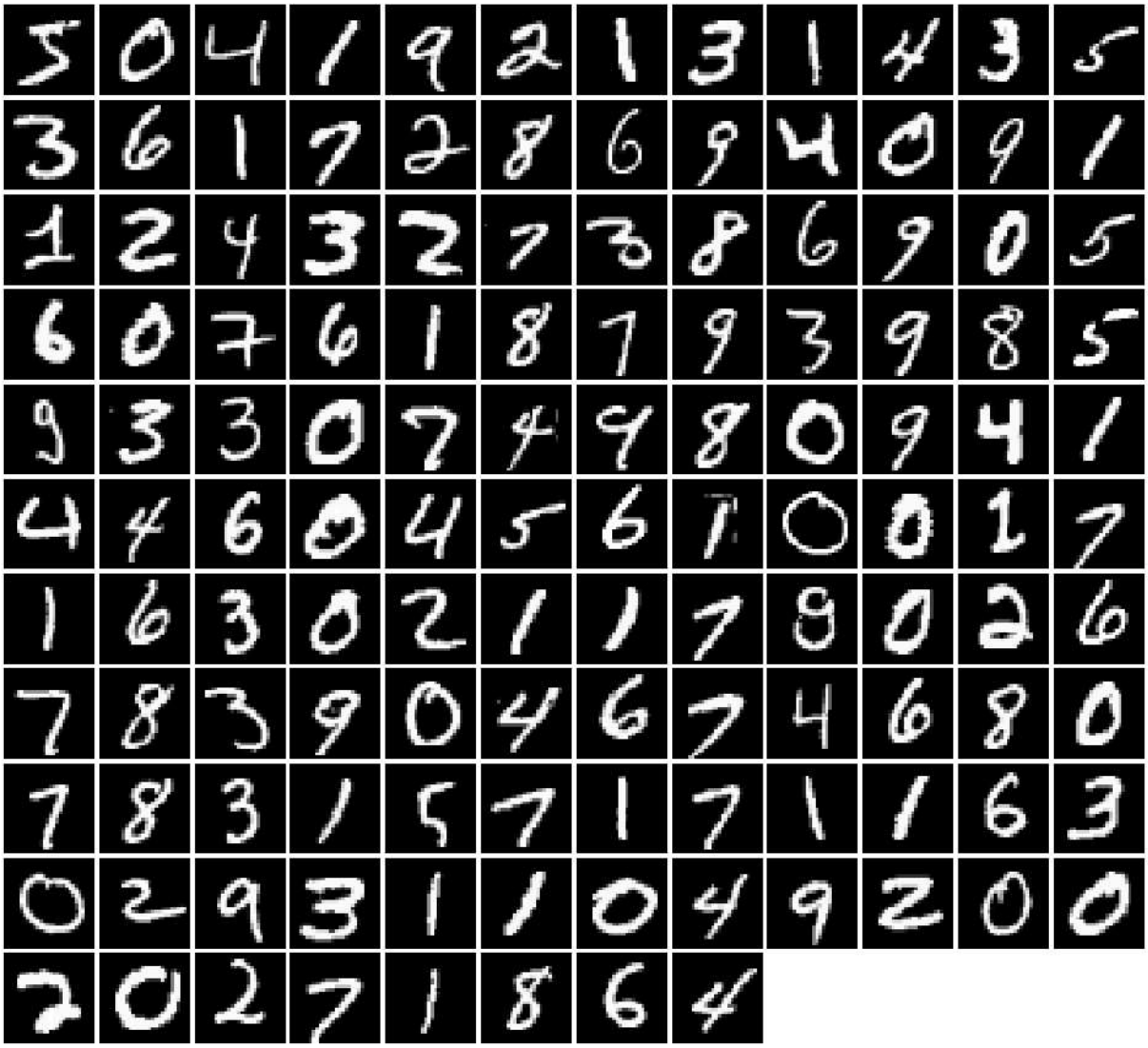
Dataset

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.

To simplify our code here, we will use the PyTorch MNIST wrapper, which downloads and loads the MNIST dataset. See the documentation for more information about the interface.

The default parameters will take 5,000 of the training examples and place them into a validation dataset. The data will be saved into a folder called `MNIST_data`.

In [5]:
```
class ChunkSampler(sampler.Sampler):
    """Samples elements sequentially from some offset.
    Arguments:
        num_samples: # of desired datapoints
        start: offset where we should start selecting from
    """
    def __init__(self, num_samples, start=0):
        self.num_samples = num_samples
        self.start = start

    def __iter__(self):
        return iter(range(self.start, self.start + self.num_samples))

    def __len__(self):
        return self.num_samples

NUM_TRAIN = 50000
NUM_VAL = 5000

NOISE_DIM = 96
batch_size = 128

mnist_train = dset.MNIST('./cs6353/datasets/MNIST_data', train=True, download=True,
                           transform=T.ToTensor())
loader_train = DataLoader(mnist_train, batch_size=batch_size,
                          sampler=ChunkSampler(NUM_TRAIN, 0))

mnist_val = dset.MNIST('./cs6353/datasets/MNIST_data', train=True, download=True,
                           transform=T.ToTensor())
loader_val = DataLoader(mnist_val, batch_size=batch_size,
                        sampler=ChunkSampler(NUM_VAL, NUM_TRAIN))


imgs = next(loader_train.__iter__())[0].view(batch_size, 784).numpy().squeeze()
show_images(imgs)
```



Random Noise

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

Hint: use `torch.rand`.

In [6]:
```
def sample_noise(batch_size, dim):
    """
    Generate a PyTorch Tensor of uniform random noise.

    Input:
    - batch_size: Integer giving the batch size of noise to generate.
    - dim: Integer giving the dimension of noise to generate.

    Output:
    - A PyTorch Tensor of shape (batch_size, dim) containing uniform
      random noise in the range (-1, 1).
    """
    noise = torch.rand(batch_size, dim)
```

```
    noise = noise * 2 - 1
    return noise
```

Make sure noise is the correct shape and type:

In [7]:
```
def test_sample_noise():
    batch_size = 3
    dim = 4
    torch.manual_seed(231)
    z = sample_noise(batch_size, dim)
    np_z = z.cpu().numpy()
    assert np_z.shape == (batch_size, dim)
    assert torch.is_tensor(z)
    assert np.all(np_z >= -1.0) and np.all(np_z <= 1.0)
    assert np.any(np_z < 0.0) and np.any(np_z > 0.0)
    print('All tests passed!')

test_sample_noise()
```

```
All tests passed!
```

Flatten

Recall our Flatten operation from previous notebooks... this time we also provide an Unflatten, which you might want to use when implementing the convolutional generator. We also provide a weight initializer (and call it for you) that uses Xavier initialization instead of PyTorch's uniform default.

In [8]:
```
class Flatten(nn.Module):
    def forward(self, x):
        N, C, H, W = x.size() # read in N, C, H, W
        return x.view(N, -1)  # "flatten" the C * H * W values into a single vector

class Unflatten(nn.Module):
    """
    An Unflatten module receives an input of shape (N, C*H*W) and reshapes it
    to produce an output of shape (N, C, H, W).
    """
    def __init__(self, N=-1, C=128, H=7, W=7):
        super(Unflatten, self).__init__()
        self.N = N
        self.C = C
        self.H = H
        self.W = W
    def forward(self, x):
        return x.view(self.N, self.C, self.H, self.W)

def initialize_weights(m):
    if isinstance(m, nn.Linear) or isinstance(m, nn.ConvTranspose2d):
        init.xavier_uniform_(m.weight.data)
```

CPU / GPU

By default all code will run on CPU. GPUs are not needed for this assignment, but will help you to train your models faster. If you do want to run the code on a GPU, then change the `dtype` variable in the following cell.

In [21]:
```
dtype = torch.FloatTensor
# dtype = torch.cuda.FloatTensor ## UNCOMMENT THIS LINE IF YOU'RE ON A GPU!
```

Discriminator

Our first step is to build a discriminator. Fill in the architecture as part of the `nn.Sequential` constructor in the function below. All fully connected layers should include bias terms. The architecture is:

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

Recall that the Leaky ReLU nonlinearity computes $f(x) = \max(\alpha x, x)$ for some fixed constant α; for the LeakyReLU nonlinearities in the architecture above we set $\alpha = 0.01$.

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

In [22]:
```
def discriminator():
    """
    Build and return a PyTorch model implementing the architecture above.
    """
    model = nn.Sequential(
              nn.Flatten(),
              nn.Linear(784, 256),
              nn.LeakyReLU(negative_slope=0.01, inplace=True),
              nn.Linear(256, 256),
              nn.LeakyReLU(negative_slope=0.01, inplace=True),
              nn.Linear(256, 1)
    )
    return model
```

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

In [23]:
```
def test_discriminator(true_count=267009):
    model = discriminator()
    cur_count = count_params(model)
    if cur_count != true_count:
        print('Incorrect number of parameters in discriminator. Check your achitect
    else:
        print('Correct number of parameters in discriminator.')
```

```
test_discriminator()
```

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

Generator

Now to build the generator network:

- Fully connected layer from noise_dim to 1024
- `ReLU`
- Fully connected layer with size 1024
- `ReLU`
- Fully connected layer with size 784
- `TanH` (to clip the image to be in the range of [-1,1])

In [24]:
```
def generator(noise_dim=NOISE_DIM):
    """
    Build and return a PyTorch model implementing the architecture above.
    """
    model = nn.Sequential(
              nn.Linear(noise_dim, 1024),
              nn.ReLU(inplace=True),
              nn.Linear(1024, 1024),
              nn.ReLU(inplace=True),
              nn.Linear(1024, 784),
              nn.Tanh()
    )
    return model
```

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

In [25]:
```
def test_generator(true_count=1858320):
    model = generator(4)
    cur_count = count_params(model)
    if cur_count != true_count:
        print('Incorrect number of parameters in generator. Check your achitecture.
    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:

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

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

HINTS: You should use the `bce_loss` function defined below to compute the binary cross entropy loss which is needed to compute the log probability of the true label given the logits output from the discriminator. Given a score $s \in \mathbb{R}$ and a label $y \in \{0, 1\}$, the binary cross entropy loss is

$$bce(s, y) = -y * \log(s) - (1 - y) * \log(1 - s)$$

A naive implementation of this formula can be numerically unstable, so we have provided a numerically stable implementation for you below.

You will also need to compute labels corresponding to real or fake and use the logit arguments to determine their size. Make sure you cast these labels to the correct data type using the global `dtype` variable, for example:

`true_labels = torch.ones(size).type(dtype)`

Instead of computing the expectation of $\log D(G(z))$, $\log D(x)$ and $\log(1 - D(G(z)))$, we will be averaging over elements of the minibatch, so make sure to combine the loss by averaging instead of summing.

In [26]:
```
def bce_loss(input, target):
    """
    Numerically stable version of the binary cross-entropy loss function.

    As per https://github.com/pytorch/pytorch/issues/751

    Inputs:
    - input: PyTorch Tensor of shape (N, ) giving scores.
    - target: PyTorch Tensor of shape (N,) containing 0 and 1 giving targets.

    Returns:
    - A PyTorch Tensor containing the mean BCE loss over the minibatch of input dat
    """
    neg_abs = - input.abs()
    loss = input.clamp(min=0) - input * target + (1 + neg_abs.exp()).log()
    return loss.mean()
```

In [27]:
```
def discriminator_loss(logits_real, logits_fake):
    """
    Computes the discriminator loss described above.

    Inputs:
    - logits_real: PyTorch Tensor of shape (N,) giving scores for the real data.
    - logits_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
```

```
    Returns:
    - loss: PyTorch Tensor containing (scalar) the loss for the discriminator.
    """
    loss = None
    N = logits_real.size(0)
    real_loss = bce_loss(logits_real, torch.ones(N, device=logits_real.device, dtyp
    fake_loss = bce_loss(logits_fake, torch.zeros(N, device=logits_fake.device, dty
    loss = real_loss + fake_loss
    return loss

def generator_loss(logits_fake):
    """
    Computes the generator loss described above.

    Inputs:
    - logits_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.

    Returns:
    - loss: PyTorch Tensor containing the (scalar) loss for the generator.
    """
    loss = None
    N = logits_fake.size(0)

    loss = bce_loss(
        logits_fake,
        torch.ones(N, device=logits_fake.device, dtype=logits_fake.dtype)
    )
    return loss
```

Test your generator and discriminator loss. You should see errors < 1e-7.

In [28]:
```
def test_discriminator_loss(logits_real, logits_fake, d_loss_true):
    d_loss = discriminator_loss(torch.Tensor(logits_real).type(dtype),
                                torch.Tensor(logits_fake).type(dtype)).cpu().numpy(
    print("Maximum error in d_loss: %g"%rel_error(d_loss_true, d_loss))

test_discriminator_loss(answers['logits_real'], answers['logits_fake'],
                        answers['d_loss_true'])
```

```
Maximum error in d_loss: 3.97058e-09
```

In [29]:
```
def test_generator_loss(logits_fake, g_loss_true):
    g_loss = generator_loss(torch.Tensor(logits_fake).type(dtype)).cpu().numpy()
    print("Maximum error in g_loss: %g"%rel_error(g_loss_true, g_loss))

test_generator_loss(answers['logits_fake'], answers['g_loss_true'])
```

```
Maximum error in g_loss: 4.4518e-09
```

Optimizing our loss

Make a function that returns an `optim.Adam` optimizer for the given model with a 1e-3 learning rate, beta1=0.5, beta2=0.999. You'll use this to construct optimizers for the

generators and discriminators for the rest of the notebook.

In [30]:
```
def get_optimizer(model):
    """
    Construct and return an Adam optimizer for the model with learning rate 1e-3,
    beta1=0.5, and beta2=0.999.

    Input:
    - model: A PyTorch model that we want to optimize.

    Returns:
    - An Adam optimizer for the model with the desired hyperparameters.
    """
    optimizer = None
    learning_rate = 1e-3
    beta1, beta2 = 0.5, 0.999

    optimizer = optim.Adam(
        model.parameters(),
        lr=learning_rate,
        betas=(beta1, beta2)
    )
    return optimizer
```

Training a GAN!

We provide you the main training loop... you won't need to change this function, but we encourage you to read through and understand it.

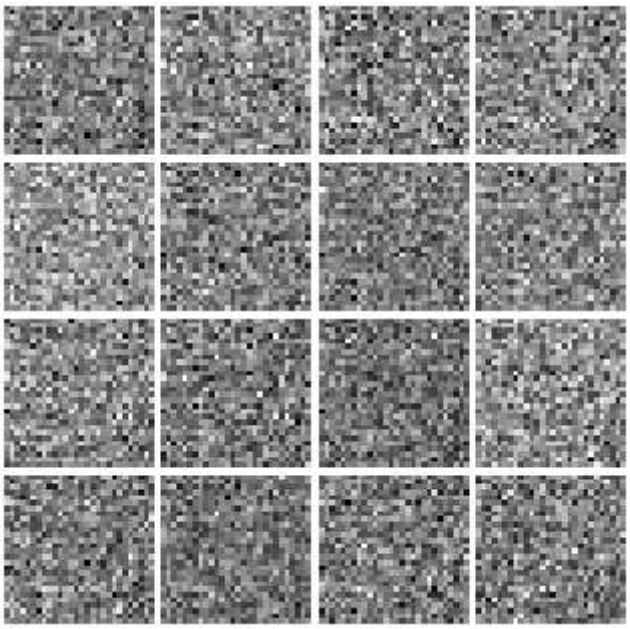
In [31]:
```
def run_a_gan(D, G, D_solver, G_solver, discriminator_loss, generator_loss, show_ev
              batch_size=128, noise_size=96, num_epochs=10):
    """
    Train a GAN!

    Inputs:
    - D, G: PyTorch models for the discriminator and generator
    - D_solver, G_solver: torch.optim Optimizers to use for training the
      discriminator and generator.
    - discriminator_loss, generator_loss: Functions to use for computing the genera
      discriminator loss, respectively.
    - show_every: Show samples after every show_every iterations.
    - batch_size: Batch size to use for training.
    - noise_size: Dimension of the noise to use as input to the generator.
    - num_epochs: Number of epochs over the training dataset to use for training.
    """
    iter_count = 0
    for epoch in range(num_epochs):
        for x, _ in loader_train:
            if len(x) != batch_size:
                continue
            D_solver.zero_grad()
            real_data = x.type(dtype)
```

```
            logits_real = D(2* (real_data - 0.5)).type(dtype)

            g_fake_seed = sample_noise(batch_size, noise_size).type(dtype)
            fake_images = G(g_fake_seed).detach()
            logits_fake = D(fake_images.view(batch_size, 1, 28, 28))

            d_total_error = discriminator_loss(logits_real, logits_fake)
            d_total_error.backward()
            D_solver.step()

            G_solver.zero_grad()
            g_fake_seed = sample_noise(batch_size, noise_size).type(dtype)
            fake_images = G(g_fake_seed)

            gen_logits_fake = D(fake_images.view(batch_size, 1, 28, 28))
            g_error = generator_loss(gen_logits_fake)
            g_error.backward()
            G_solver.step()

            if (iter_count % show_every == 0):
                print('Iter: {}, D: {:.4}, G:{:.4}'.format(iter_count,d_total_error
                imgs_numpy = fake_images.data.cpu().numpy()
                show_images(imgs_numpy[0:16])
                plt.show()
                print()
            iter_count += 1
```

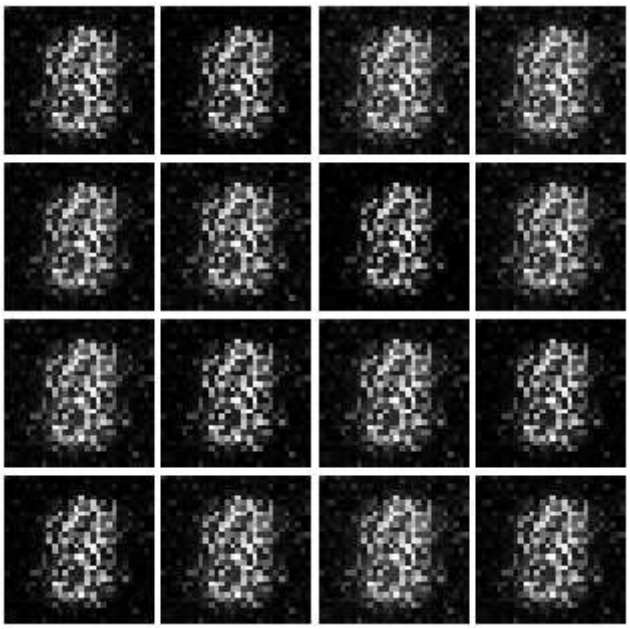
In [32]:

```
# Make the discriminator
D = discriminator().type(dtype)

# Make the generator
G = generator().type(dtype)

# Use the function you wrote earlier to get optimizers for the Discriminator and th
D_solver = get_optimizer(D)
G_solver = get_optimizer(G)
# Run it!
run_a_gan(D, G, D_solver, G_solver, discriminator_loss, generator_loss)
```

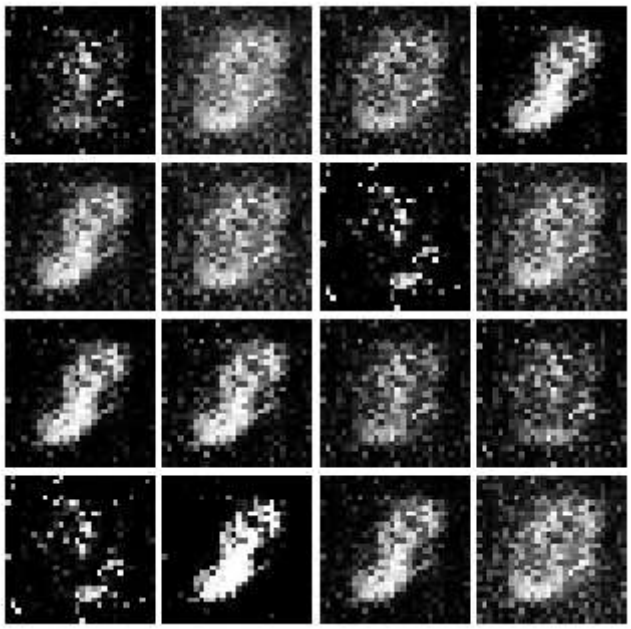
```
Iter: 0, D: 1.432, G:0.6993
```



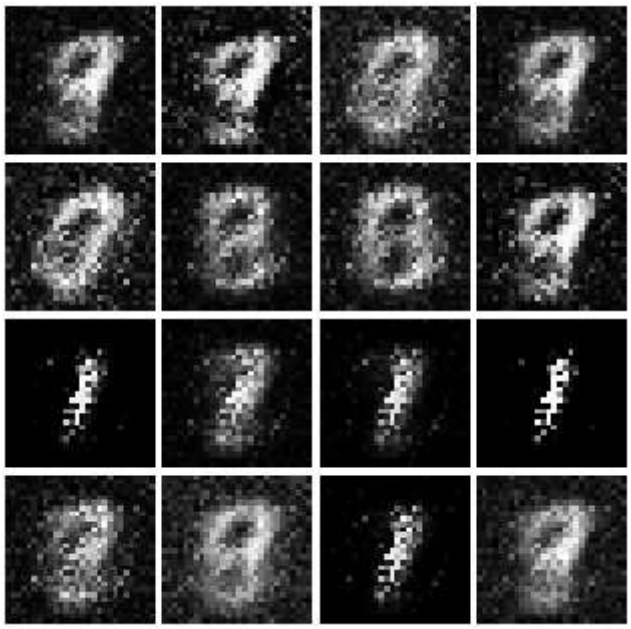
```
Iter: 250, D: 1.477, G:0.9675
```



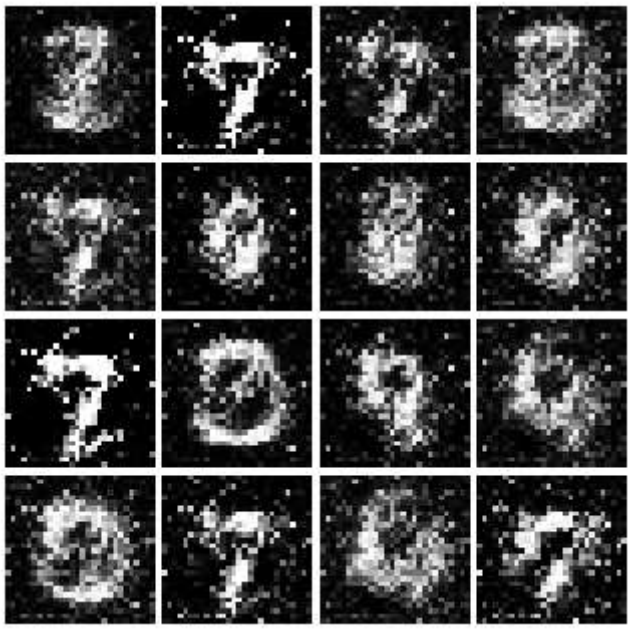
```
Iter: 500, D: 1.213, G:1.208
```



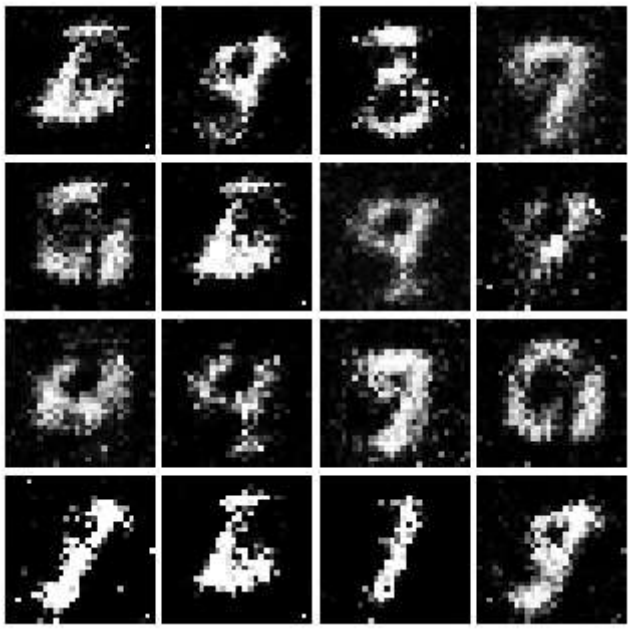
Iter: 750, D: 1.903, G:1.082



Iter: 1000, D: 1.104, G:1.297



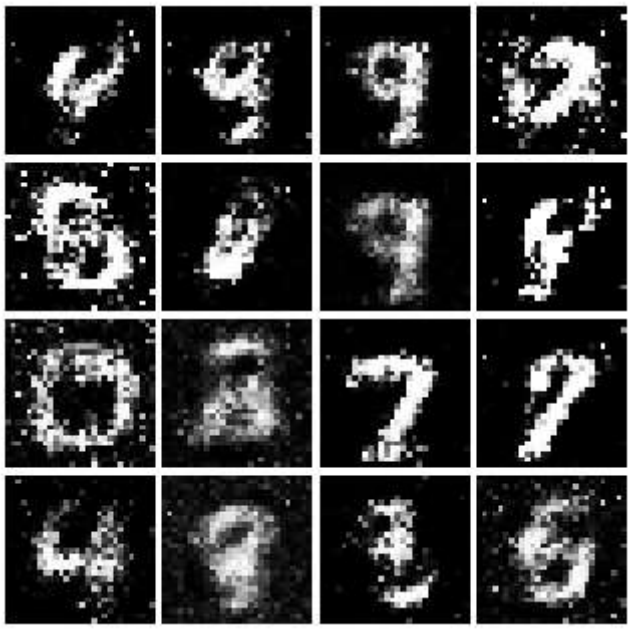
Iter: 1250, D: 1.201, G:0.7782



Iter: 1500, D: 1.334, G:0.8746

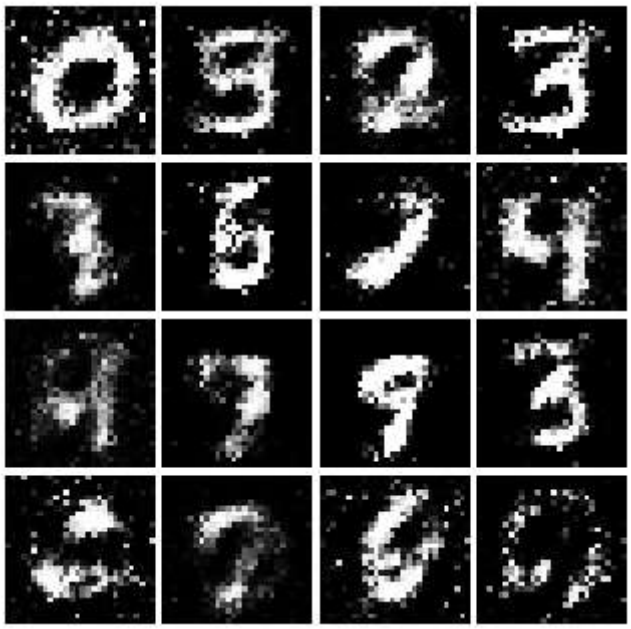
```
Iter: 1750, D: 1.351, G:1.061
```

```
Iter: 2000, D: 1.318, G:0.9285
```

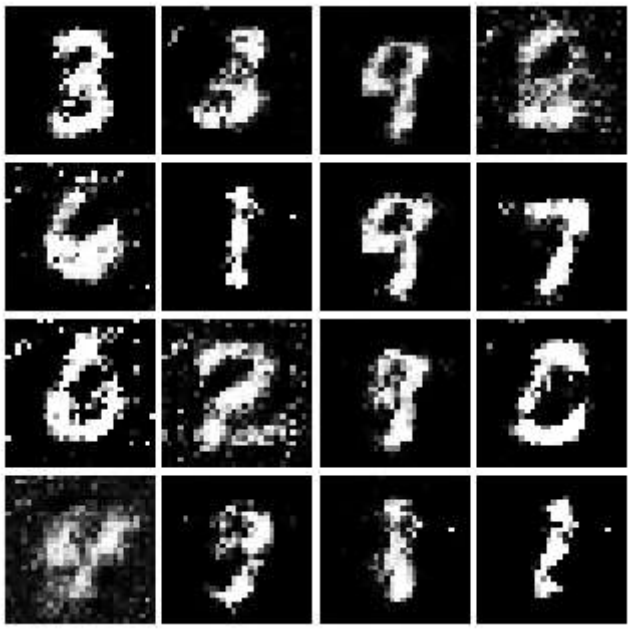


Iter: 2250, D: 1.414, G:0.7856

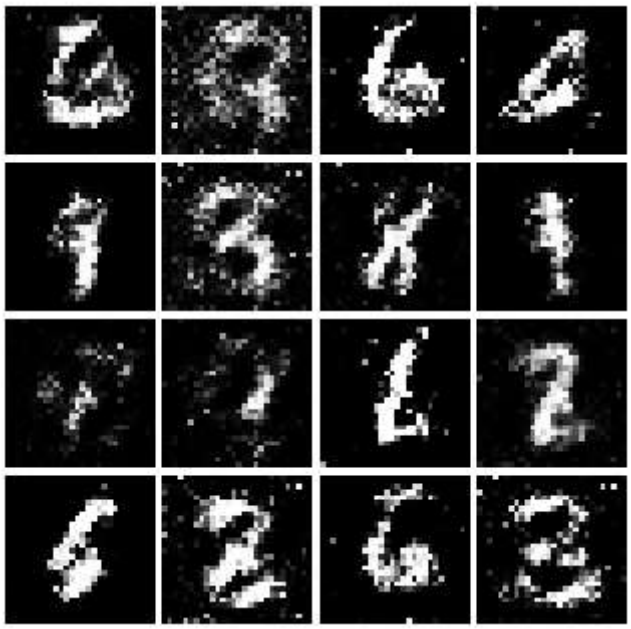
Iter: 2500, D: 1.21, G:1.029



Iter: 2750, D: 1.288, G:0.8027

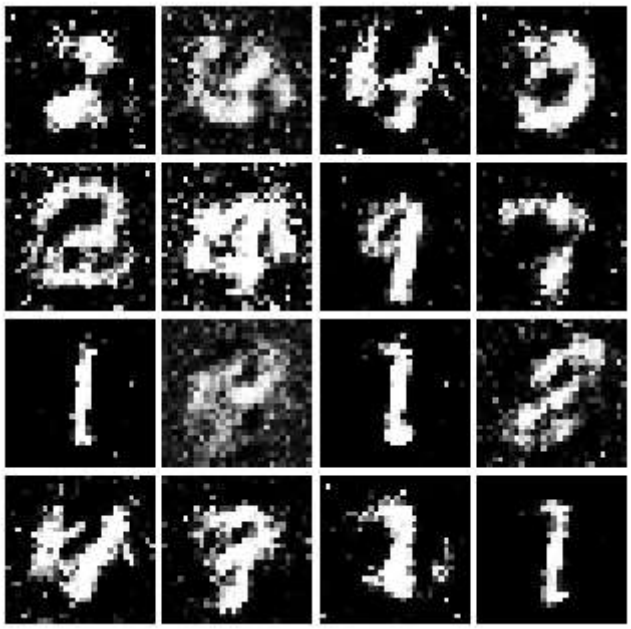


Iter: 3000, D: 1.331, G:0.9361



Iter: 3250, D: 1.258, G:0.8425

Iter: 3500, D: 1.302, G:0.8387



```
Iter: 3750, D: 1.354, G:0.9072
```

Well that wasn't so hard, was it? In the iterations in the low 100s you should see black backgrounds, fuzzy shapes as you approach iteration 1000, and decent shapes, about half of which will be sharp and clearly recognizable as we pass 3000.

Least Squares GAN

We'll now look at Least Squares GAN, a newer, more stable alernative to the original GAN loss function. For this part, all we have to do is change the loss function and retrain the model. We'll implement equation (9) in the paper, with the generator loss:

$$\ell_G = \frac{1}{2}\mathbb{E}_{z\sim p(z)}\left[\left(D(G(z))-1\right)^2\right]$$

and the discriminator loss:

$$\ell_D = \frac{1}{2}\mathbb{E}_{x\sim p_{\text{data}}}\left[\left(D(x)-1\right)^2\right] + \frac{1}{2}\mathbb{E}_{z\sim p(z)}\left[\left(D(G(z))\right)^2\right]$$

HINTS: Instead of computing the expectation, we will be averaging over elements of the minibatch, so make sure to combine the loss by averaging instead of summing. When plugging in for $D(x)$ and $D(G(z))$ use the direct output from the discriminator (`scores_real` and `scores_fake`).

In [40]:
```
def ls_discriminator_loss(scores_real, scores_fake):
    """
    Compute the Least-Squares GAN loss for the discriminator.

    Inputs:
    - scores_real: PyTorch Tensor of shape (N,) giving scores for the real data.
    - scores_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.

    Outputs:
    - loss: A PyTorch Tensor containing the loss.
    """
    loss = None
    batch_size = scores_real.size(0)

    real_loss = 0.5 * torch.mean((scores_real - torch.ones(batch_size, device=score
    fake_loss = 0.5 * torch.mean(scores_fake ** 2)

    loss = real_loss + fake_loss
    return loss

def ls_generator_loss(scores_fake):
    """
    Computes the Least-Squares GAN loss for the generator.

    Inputs:
    - scores_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.

    Outputs:
    - loss: A PyTorch Tensor containing the loss.
    """
    loss = None
    batch_size = scores_fake.size(0)
    loss = 0.5 * torch.mean((scores_fake - torch.ones(batch_size, device=scores_fak
    return loss
```

Before running a GAN with our new loss function, let's check it:

In [41]:
```
def test_lsgan_loss(score_real, score_fake, d_loss_true, g_loss_true):
    score_real = torch.Tensor(score_real).type(dtype)
    score_fake = torch.Tensor(score_fake).type(dtype)
    d_loss = ls_discriminator_loss(score_real, score_fake).cpu().numpy()
```

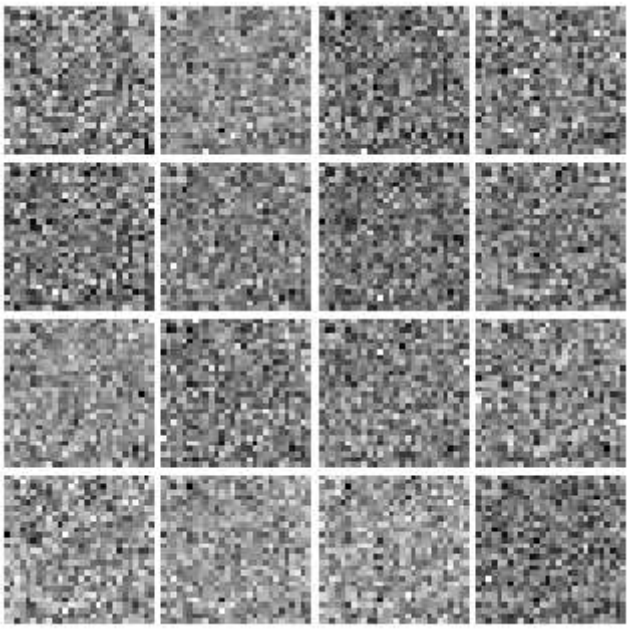
```
    g_loss = ls_generator_loss(score_fake).cpu().numpy()
    print("Maximum error in d_loss: %g"%rel_error(d_loss_true, d_loss))
    print("Maximum error in g_loss: %g"%rel_error(g_loss_true, g_loss))

test_lsgan_loss(answers['logits_real'], answers['logits_fake'],
                answers['d_loss_lsgan_true'], answers['g_loss_lsgan_true'])
```

```
Maximum error in d_loss: 1.53171e-08
Maximum error in g_loss: 2.7837e-09
```

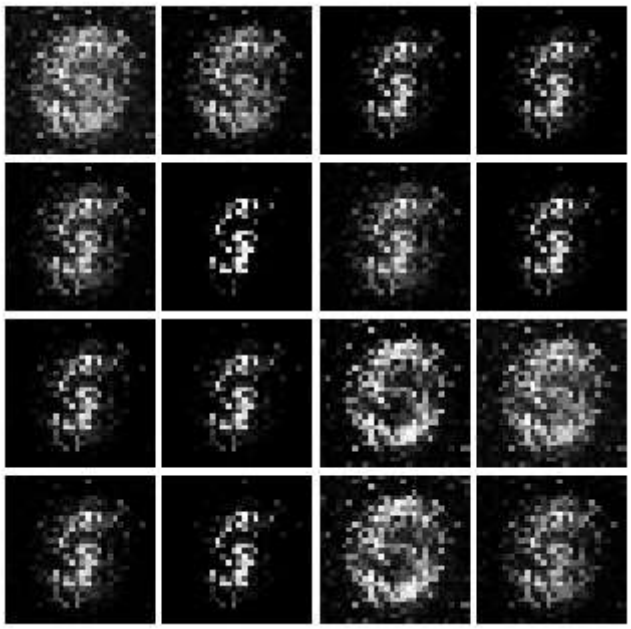
Run the following cell to train your model!

In [39]:
```
D_LS = discriminator().type(dtype)
G_LS = generator().type(dtype)

D_LS_solver = get_optimizer(D_LS)
G_LS_solver = get_optimizer(G_LS)

run_a_gan(D_LS, G_LS, D_LS_solver, G_LS_solver, ls_discriminator_loss, ls_generator
```

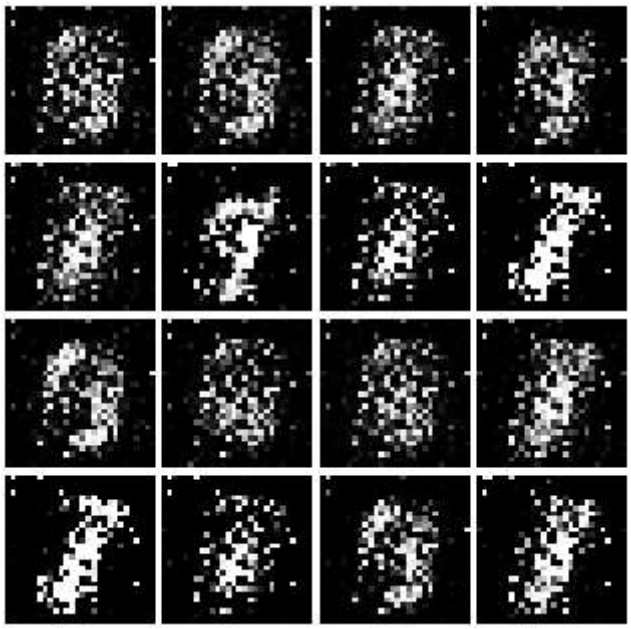
```
Iter: 0, D: 0.5766, G:0.4739
```



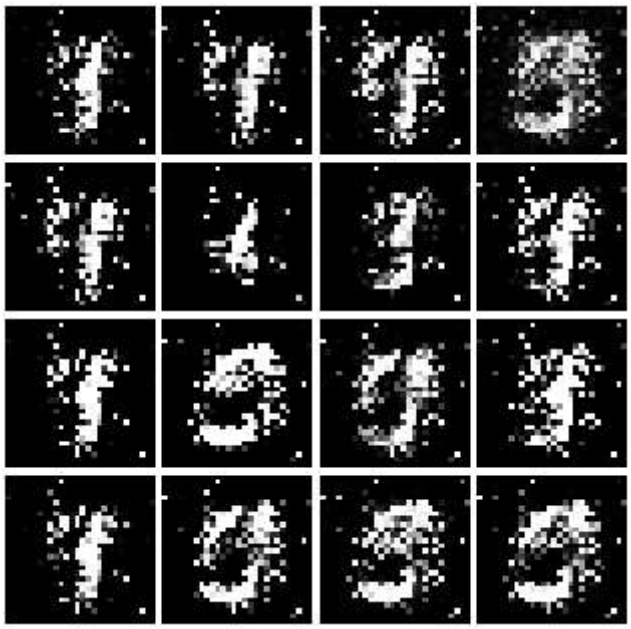
```
Iter: 250, D: 0.1978, G:0.6615
```



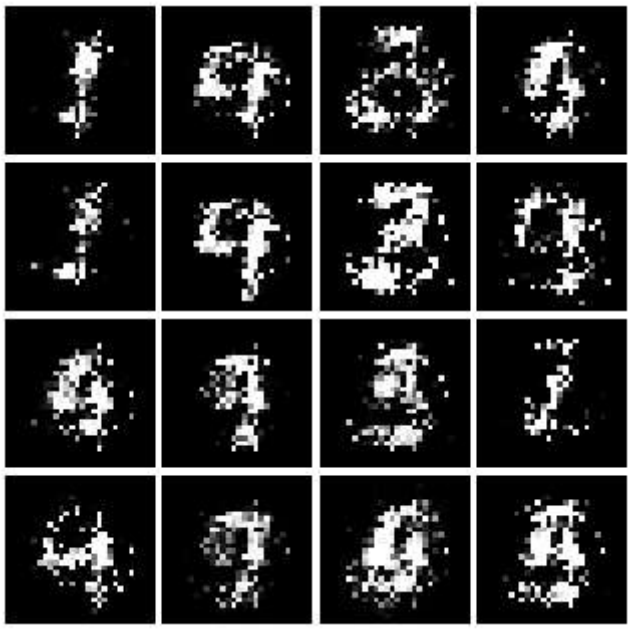
Iter: 500, D: 0.196, G:0.2661



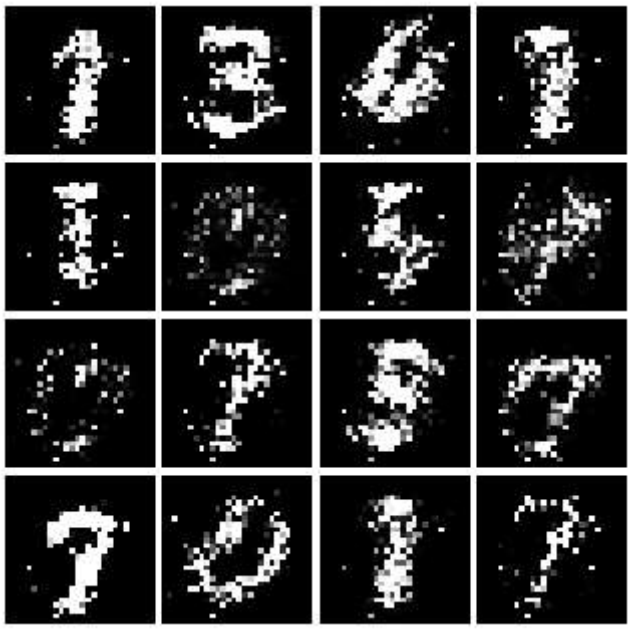
Iter: 750, D: 0.1144, G:0.4098



Iter: 1000, D: 0.3679, G:0.3311



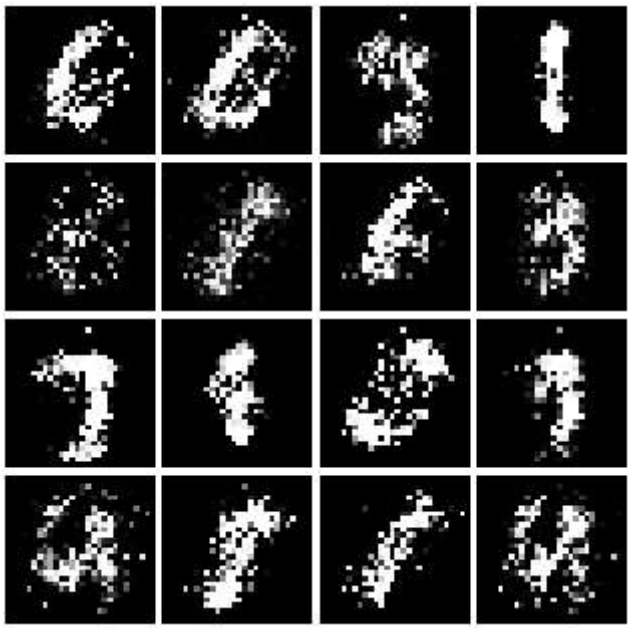
Iter: 1250, D: 0.198, G:0.2582



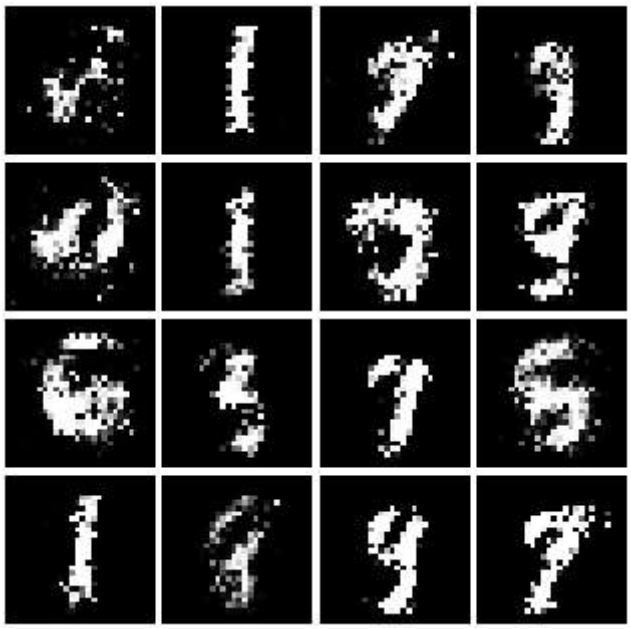
Iter: 1500, D: 0.2318, G:0.1525

Iter: 1750, D: 0.2096, G:0.1648

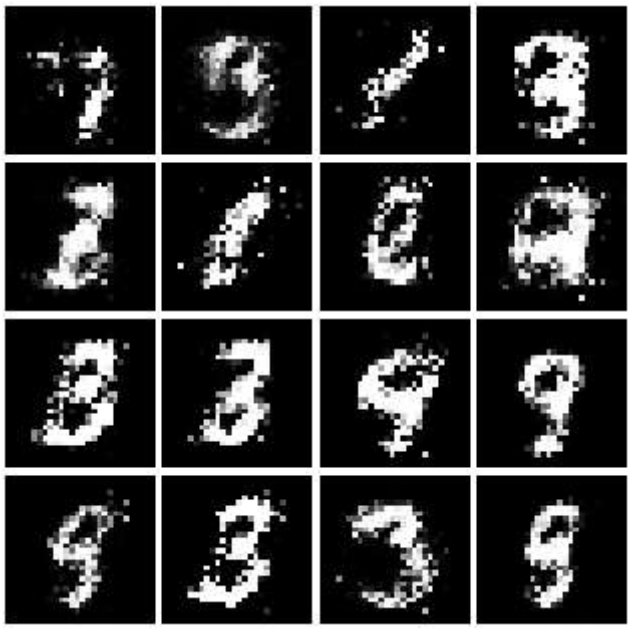
Iter: 2000, D: 0.2067, G:0.2041



Iter: 2250, D: 0.2114, G:0.1544

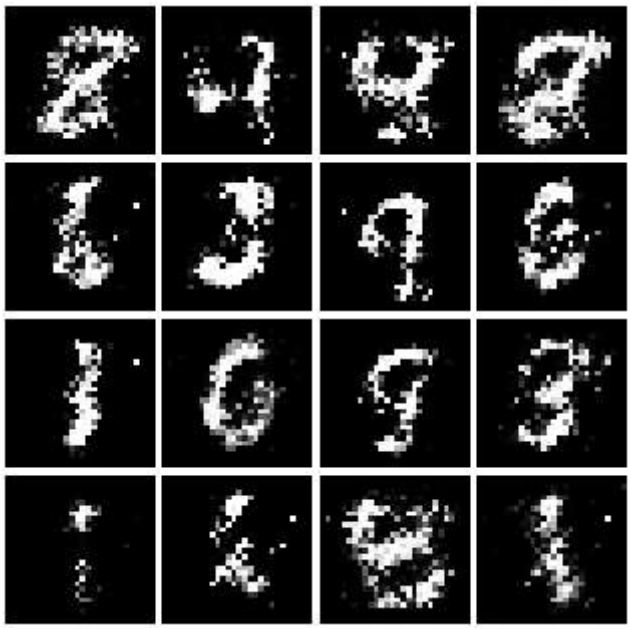


Iter: 2500, D: 0.2133, G:0.1805

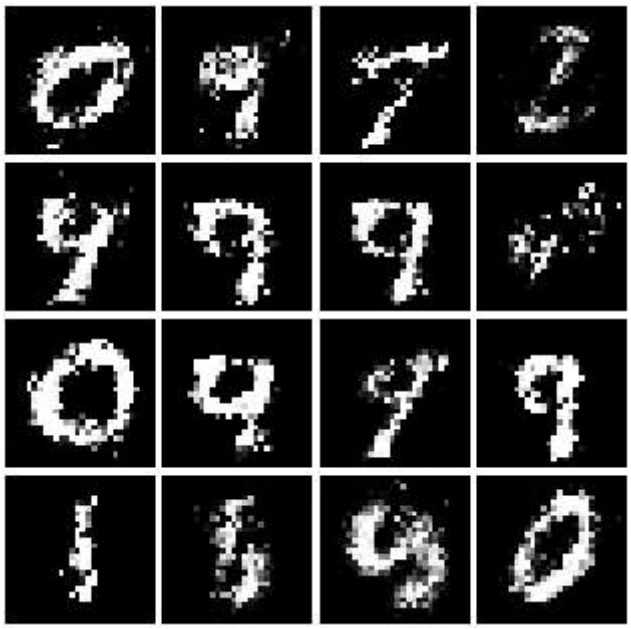


Iter: 2750, D: 0.2336, G:0.1599

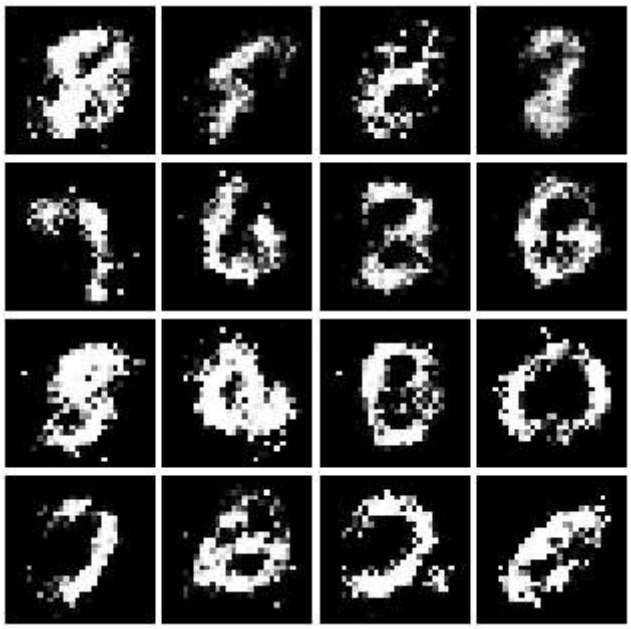
Iter: 3000, D: 0.2462, G:0.1556



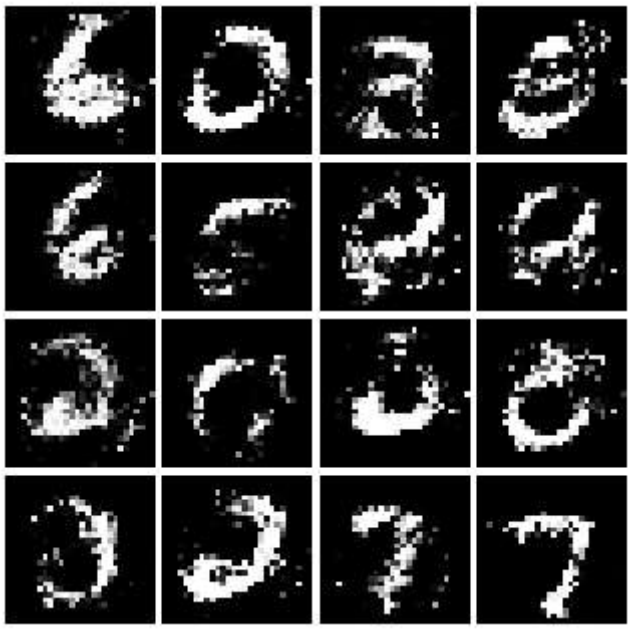
Iter: 3250, D: 0.2289, G:0.1608



Iter: 3500, D: 0.2072, G:0.1534



Iter: 3750, D: 0.2401, G:0.1723



Deeply 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

Discriminator

- Reshape into image tensor (Use Unflatten!)
- Conv2D: 32 Filters, 5x5, Stride 1
- Leaky ReLU(alpha=0.01)
- Max Pool 2x2, Stride 2
- Conv2D: 64 Filters, 5x5, Stride 1
- 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

In [50]:
```
def build_dc_classifier():
    """
    Build and return a PyTorch model for the DCGAN discriminator implementing
    the architecture above.
    """
    return nn.Sequential(
```

```
        Unflatten(N=batch_size, C=1, H=28, W=28),

        nn.Conv2d(in_channels=1, out_channels=32, kernel_size=5, stride=1),
        nn.LeakyReLU(negative_slope=0.01, inplace=True),
        nn.MaxPool2d(kernel_size=2, stride=2),

        nn.Conv2d(in_channels=32, out_channels=64, kernel_size=5, stride=1),
        nn.LeakyReLU(negative_slope=0.01, inplace=True),
        nn.MaxPool2d(kernel_size=2, stride=2),

        Flatten(),

        nn.Linear(in_features=4 * 4 * 64, out_features=4 * 4 * 64),
        nn.LeakyReLU(negative_slope=0.01, inplace=True),
        nn.Linear(in_features=4 * 4 * 64, out_features=1),
    )

data = next(enumerate(loader_train))[-1][0].type(dtype)
b = build_dc_classifier().type(dtype)
out = b(data)
print(out.size())
```

```
torch.Size([128, 1])
```

Check the number of parameters in your classifier as a sanity check:

In [51]:
```
def test_dc_classifer(true_count=1102721):
    model = build_dc_classifier()
    cur_count = count_params(model)
    if cur_count != true_count:
        print('Incorrect number of parameters in generator. Check your achitecture.
    else:
        print('Correct number of parameters in generator.')

test_dc_classifer()
```

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

Generator

For the generator, we will copy the architecture exactly from the InfoGAN paper. See Appendix C.1 MNIST. See the documentation for tf.nn.conv2d_transpose. We are always "training" in GAN mode.

- Fully connected with output size 1024
- `ReLU`
- BatchNorm
- Fully connected with output size 7 x 7 x 128
- ReLU
- BatchNorm
- Reshape into Image Tensor of shape 7, 7, 128
- Conv2D^T (Transpose): 64 filters of 4x4, stride 2, 'same' padding
- `ReLU`

- BatchNorm
- Conv2D^T (Transpose): 1 filter of 4x4, stride 2, 'same' padding
- `TanH`
- Should have a 28x28x1 image, reshape back into 784 vector

In [54]:
```
def build_dc_generator(noise_dim=NOISE_DIM):
    """
    Build and return a PyTorch model implementing the DCGAN generator using
    the architecture described above.
    """
    return nn.Sequential(
        nn.Linear(in_features=noise_dim, out_features=1024),
        nn.ReLU(inplace=True),
        nn.BatchNorm1d(num_features=1024),

        nn.Linear(in_features=1024, out_features=7 * 7 * 128),
        nn.ReLU(inplace=True),
        nn.BatchNorm1d(num_features=7 * 7 * 128),

        Unflatten(C=128, H=7, W=7),

        nn.ConvTranspose2d(in_channels=128, out_channels=64, kernel_size=4, stride=
        nn.ReLU(inplace=True),
        nn.BatchNorm2d(num_features=64),

        nn.ConvTranspose2d(in_channels=64, out_channels=1, kernel_size=4, stride=2,
        nn.Tanh(),

        Flatten(),
    )

test_g_gan = build_dc_generator().type(dtype)
test_g_gan.apply(initialize_weights)

fake_seed = torch.randn(batch_size, NOISE_DIM).type(dtype)
fake_images = test_g_gan.forward(fake_seed)
fake_images.size()
```

Out[54]:
```
torch.Size([128, 784])
```

Check the number of parameters in your generator as a sanity check:

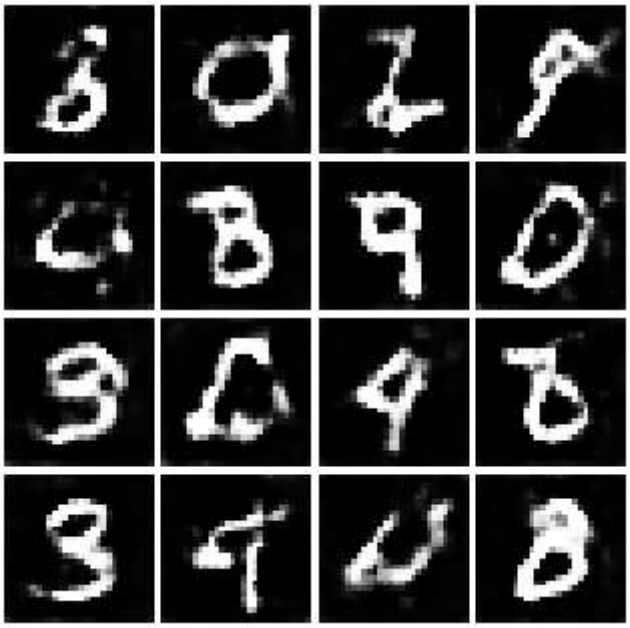
In [57]:
```
def test_dc_generator(true_count=6580801):
    model = build_dc_generator(4)
    cur_count = count_params(model)
    if cur_count != true_count:
        print('Incorrect number of parameters in generator. Check your achitecture.
    else:
        print('Correct number of parameters in generator.')

test_dc_generator()
```

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

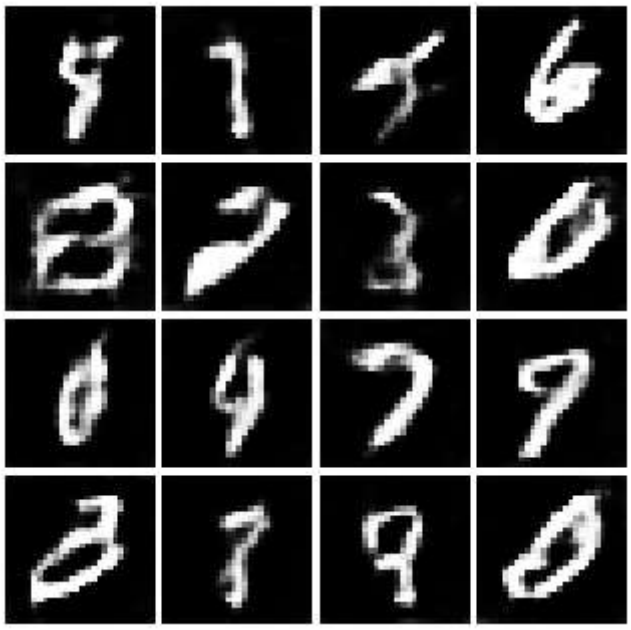
In [58]:
```
D_DC = build_dc_classifier().type(dtype)
D_DC.apply(initialize_weights)
G_DC = build_dc_generator().type(dtype)
G_DC.apply(initialize_weights)

D_DC_solver = get_optimizer(D_DC)
G_DC_solver = get_optimizer(G_DC)

run_a_gan(D_DC, G_DC, D_DC_solver, G_DC_solver, discriminator_loss, generator_loss,
```

```
Iter: 0, D: 1.321, G:1.415
```

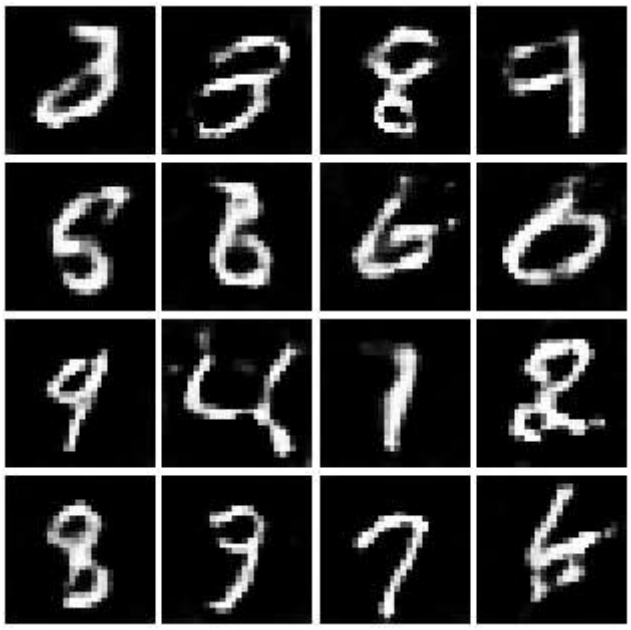
```
Iter: 250, D: 1.21, G:0.9267
```



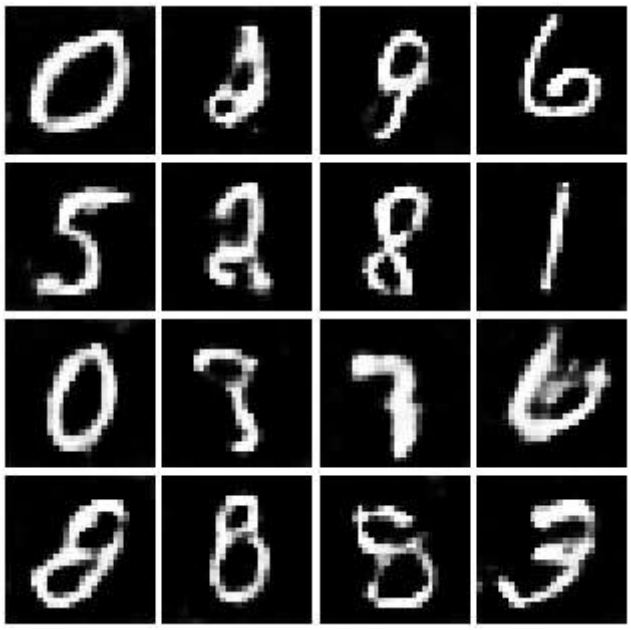
```
Iter: 500, D: 1.189, G:1.006
```



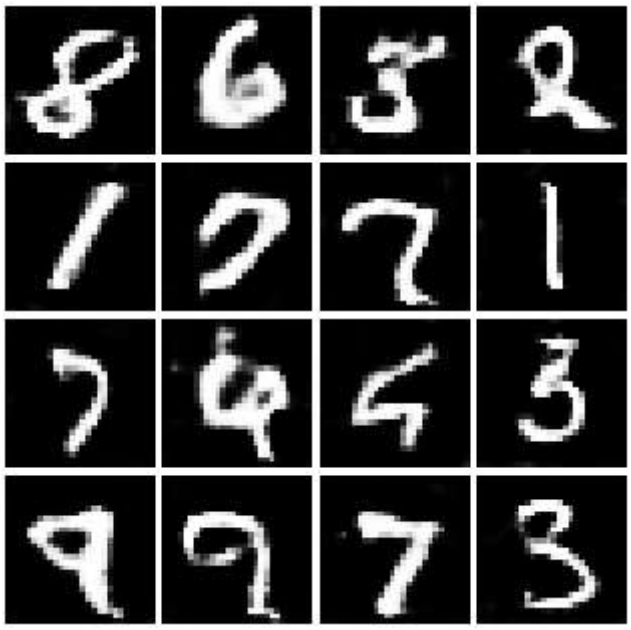
Iter: 750, D: 1.179, G:1.092



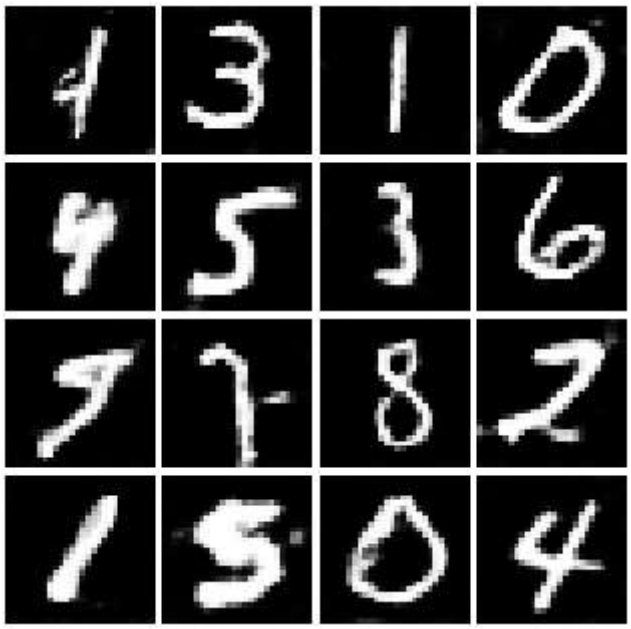
Iter: 1000, D: 1.277, G:1.011



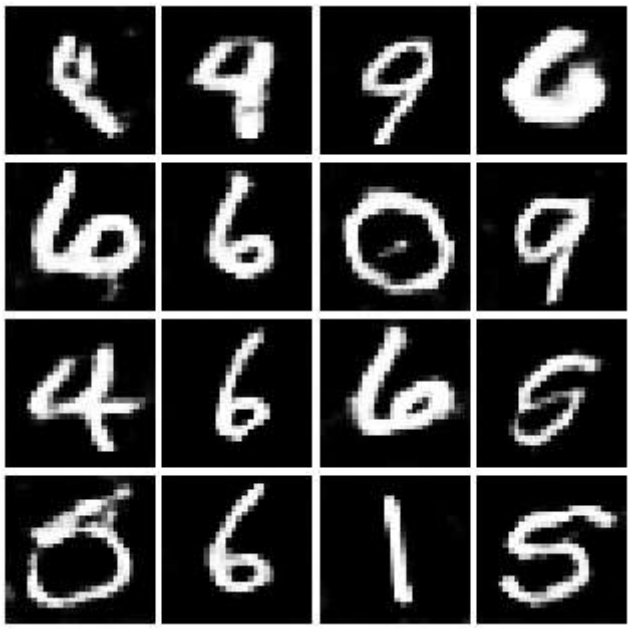
Iter: 1250, D: 1.222, G:0.9037



Iter: 1500, D: 2.043, G:1.008



```
Iter: 1750, D: 1.135, G:0.8847
```



INLINE QUESTION 1

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, this is not a good sign. If the discriminator's loss stays high throughout training, it means the discriminator is struggling to distinguish between real and fake images, likely because it has not learned the real data's patterns properly. This could happen if the discriminator is

too simple and is unable to understand the data. Even though the generator's loss decreases, it does not necessarily mean the generator is producing good images, instead it could just mean that the generator is easily fooling a weak discriminator. In this case, the generator might still be creating low-quality images, but the discriminator is too poor to recognize them as fake, so the generator's loss drops without any real improvement.