In [ ]:
```
# from google.colab import drive
# drive.mount('/content/drive')
```

change to whatever your path is to the part1-GANs folder

In [ ]:
```
# %cd "drive/MyDrive/homework4/part1-GANs"
```

In [ ]:
```
%load_ext autoreload
%autoreload 2
```

Homework 4: Part 1 - Generative Adversarial Networks (GANs) [9 pts]

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, there are 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 alternate 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:

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

In [ ]:
```
# Setup cell.
import numpy as np
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 dataset
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec

import sys
sys.path.append("part1_GANS")

# # # import os
# # # # home_dir = os.path.dirname(os.path.abspath('hw4-part1.ipynb'))
# # # home_dir = '/home/anascimento7/CS7643/Assignments/hw4_code_student_
# # # print(home_dir)
# # # # gans_dir = os.path.join(home_dir, 'part1-GANs')
# # # sys.path.append(home_dir)
# # # print(home_dir)

from part1_GANs.gan_pytorch import preprocess_img, deprocess_img, rel_err

dtype = torch.cuda.FloatTensor if torch.cuda.is_available() else torch.Fl

%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):
    sqrtn = int(np.ceil(np.sqrt(images.shape[0])))
    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')
        # If the image is in the shape (3, 32, 32), use transpose to chan
        if img.shape[0] == 3:
            img = np.transpose(img, (1, 2, 0))
        plt.imshow(img)
        # plt.show()

    return
```

Dataset

We are going to be using SVHN (Street View and House Number Dataset)

Link: http://ufldl.stanford.edu/housenumbers/

In [ ]:
```
# NUM_TRAIN = 73257
# NUM_VAL = 26032

NOISE_DIM = 96
batch_size = 128
val_batch_size = 128

svhn_train = dataset.SVHN(
    'datasets/svhn',
    split="train",
    download=True,
    transform=T.ToTensor()
)
```

```
loader_train = DataLoader(
    svhn_train,
    batch_size=batch_size,
    sampler=ChunkSampler(len(svhn_train), 0)
)

print(len(svhn_train))

svhn_val = dataset.SVHN(
    'datasets/svhn',
    split="test",
    download=True,
    transform=T.ToTensor()
)

print(len(svhn_val))

loader_val = DataLoader(
    svhn_val,
    batch_size=val_batch_size,
    sampler=ChunkSampler(len(svhn_val), 0)
)

iterator = iter(loader_train)
imgs, labels = next(iterator)
print(imgs.shape)
# imgs = imgs.view(batch_size, 3072).numpy().squeeze()
show_images(imgs[0:99])
```

```
Using downloaded and verified file: datasets/svhn/train_32x32.mat
73257
Using downloaded and verified file: datasets/svhn/test_32x32.mat
26032
torch.Size([128, 3, 32, 32])
```

TODO: Random Noise [1pts]

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

Implement `sample_noise` in `gan_pytorch.py`.

Hint: use `torch.rand`.

Make sure noise is the correct shape and type:

In [ ]:
```
from part1_GANs.gan_pytorch import sample_noise
from part1_GANs.gan_pytorch import Flatten, Unflatten, initialize_weights

def test_sample_noise():
    batch_size = 3
    dim = 4
    torch.manual_seed(6476)
    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!
```

TODO: Discriminator [0.5 pts]

GAN is composed of a discriminator and generator. The discriminator differentiates between a real and fake image. Let us create the architecture for it. In `gan_pytorch.py`, fill in the architecture as part of the `nn.Sequential` constructor in the function below. All fully connected layers should include bias terms.

The recommendation for discriminator architecture is to have 1-2 Conv2D blocks, and a fully connected layer after that.

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 [ ]:
```
from part1_GANs.gan_pytorch import discriminator

def test_discriminator():
    model = discriminator()
    cur_count = count_params(model)
    print('Number of parameters in discriminator: ', cur_count)

test_discriminator()
```

```
Number of parameters in discriminator:  142529
```

TODO: Generator [0.5 pts]

Recommendation for the generator is to have some fully connected layer followed by 1-2 ConvTranspose2D (It is also known as a fractionally-strided convolution). Remeber to use activation functions such as ReLU, Leaky RelU, etc. Finally use nn.Tanh() to finally output between [-1, 1].

The output of a generator should be the image. Therefore the shape will be `[batch_size, 3, 32, 32]`.

In [ ]:
```
from part1_GANs.gan_pytorch import generator

def test_generator():
    model = generator()
    cur_count = count_params(model)
    print('Number of parameters in generator: ', cur_count)
```

```
test_generator()
```

```
Number of parameters in generator:  2119811
```

TODO: Implement the Discriminator and Generator Loss Function [3 pts]

This will be the Vanilla GAN loss function which involves the Binary Cross Entropy Loss. Fill the `bce_loss`, `discriminator_loss`, and `generator_loss`. The errors should be less than 5e-5.

In [ ]:
```
from part1_GANs.gan_pytorch import bce_loss, discriminator_loss, generato

# import os
# print(os.getcwd())

# answers = dict(np.load('../test_resources/gan-checks.npz')) #ORIGINAL
answers = dict(np.load('test_resources/gan-checks.npz'))

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)).cp
    # print(d_loss, d_loss_true)
    assert torch.allclose(torch.Tensor(d_loss_true), torch.Tensor(d_loss)
    print("Maximum error in d_loss: %g"%rel_error(d_loss_true, d_loss.num

def test_generator_loss():
    sample_logits = torch.tensor([0.0, 0.5, 0.4, 0.1])
    g_loss = generator_loss(torch.Tensor(sample_logits).type(dtype)).cpu(
    assert torch.allclose(torch.Tensor([0.581159]), torch.Tensor(g_loss),
    print("Maximum error in d_loss: %g"%rel_error(0.581159, g_loss.item()

def test_bce_loss():
    input = torch.tensor([0.4, 0.1, 0.2, 0.3])
    target = torch.tensor([0.3, 0.25, 0.25, 0.2])
    bc_loss = bce_loss(input, target).item()
    # print('BC LOSS', bc_loss)
    assert torch.allclose(torch.Tensor([0.7637264728546143]), torch.Tenso
    print("Maximum error in d_loss: %g"%rel_error(0.7637264728546143, bc_

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

test_generator_loss()

test_bce_loss()
```

```
Maximum error in d_loss: 3.97058e-09
Maximum error in d_loss: 3.76114e-09
Maximum error in d_loss: 0
```

In [ ]:
```
## All imports done in the test cells

from part1_GANs.gan_pytorch import sample_noise
```

```
from part1_GANs.gan_pytorch import Flatten, Unflatten, initialize_weights
from part1_GANs.gan_pytorch import discriminator
from part1_GANs.gan_pytorch import generator
from part1_GANs.gan_pytorch import bce_loss, discriminator_loss, generato
```

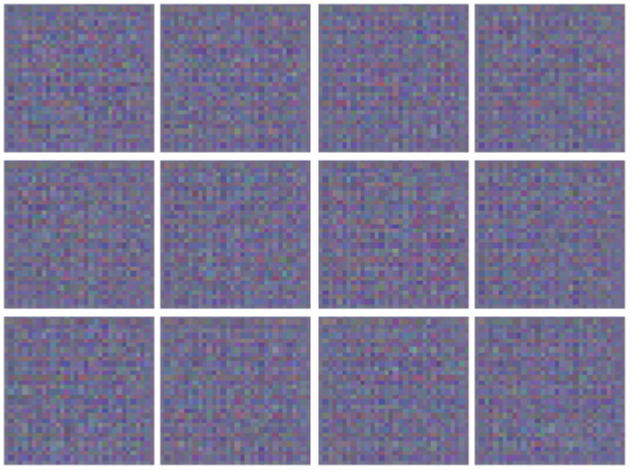
Now let's complete the GAN

Fill the training function `train_gan` and make sure to complete the `get_optimizer`. Adam is a good recommendation for the optimizer.

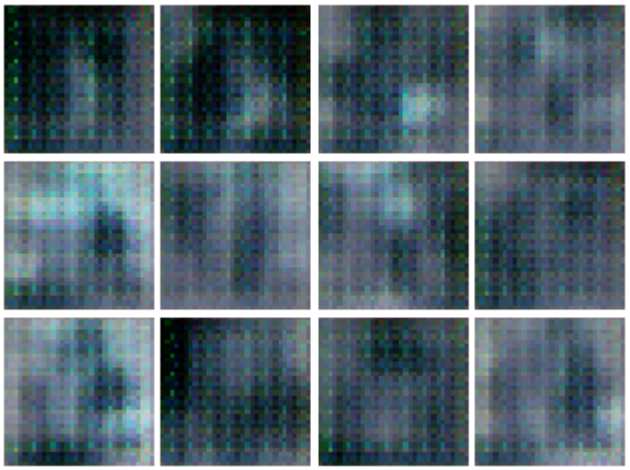
The top batch of images shown are the outputs from your generator. The bottom batch of images are the real inputs that the discriminator recieves along with your generated images.

In [ ]:
```
from part1_GANs.gan_pytorch import get_optimizer, train_gan

# 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 Discrimina
D_solver = get_optimizer(D)
G_solver = get_optimizer(G)

batch_size = 256

loader_train = DataLoader(
    svhn_train,
    batch_size=batch_size,
    sampler=ChunkSampler(len(svhn_train), 0)
)

# Run it!
images = train_gan(
    D,
    G,
    D_solver,
    G_solver,
    discriminator_loss,
    generator_loss,
    loader_train,
    batch_size = batch_size,
    noise_size=96,
    num_epochs=100
)
```

```
Iter: 0, D: 1.406, G:0.6583
```

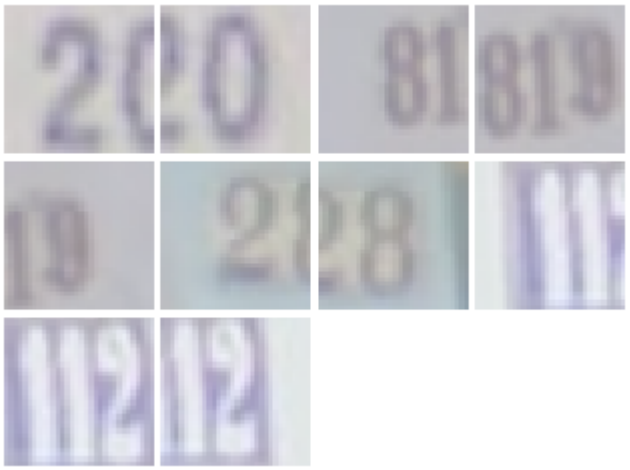


Iter: 250, D: 1.179, G:1.959



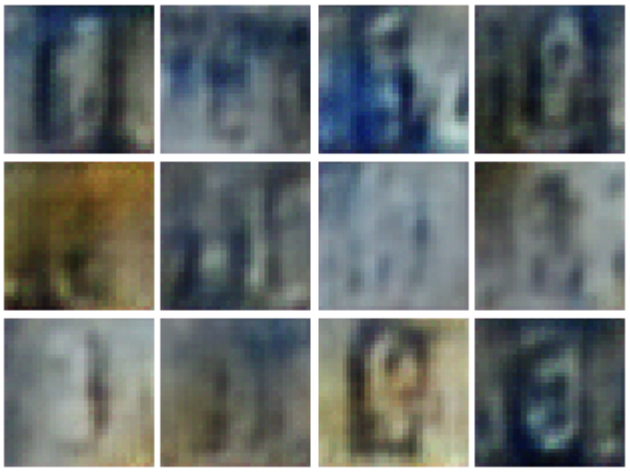
Iter: 500, D: 1.414, G:0.6468

Iter: 750, D: 1.377, G:0.807

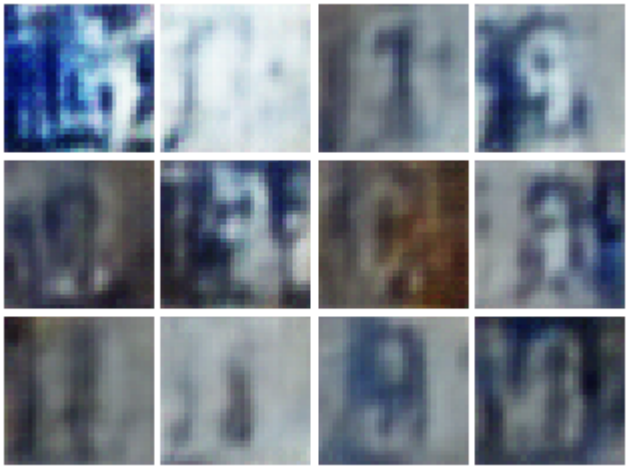


Iter: 1000, D: 1.349, G:0.7401

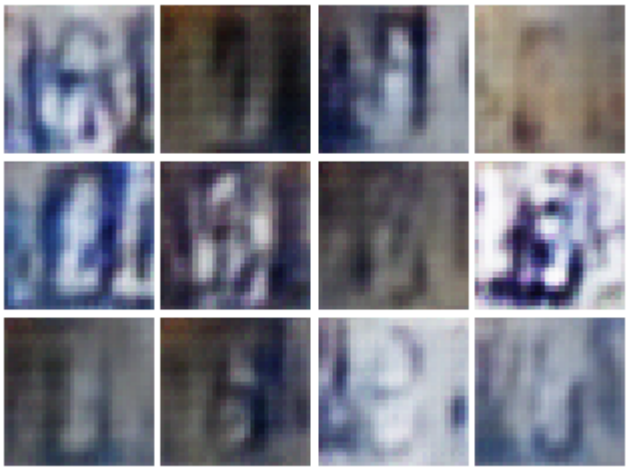
Iter: 1250, D: 1.363, G:0.6993



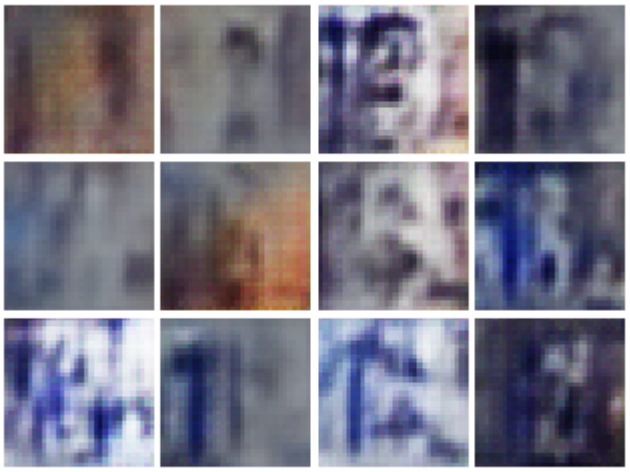
Iter: 1500, D: 1.376, G:0.6824



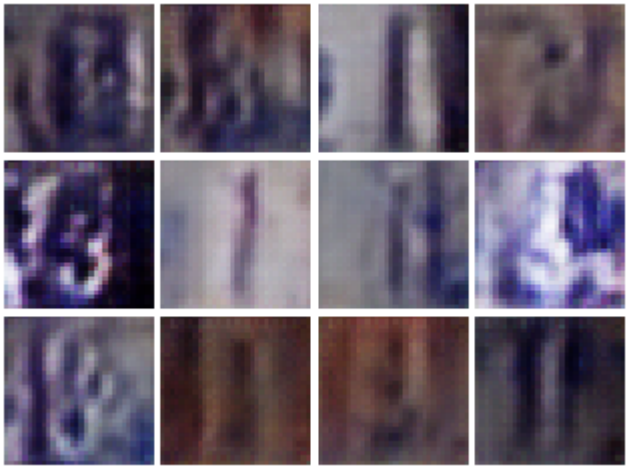
Iter: 1750, D: 1.355, G:0.7176



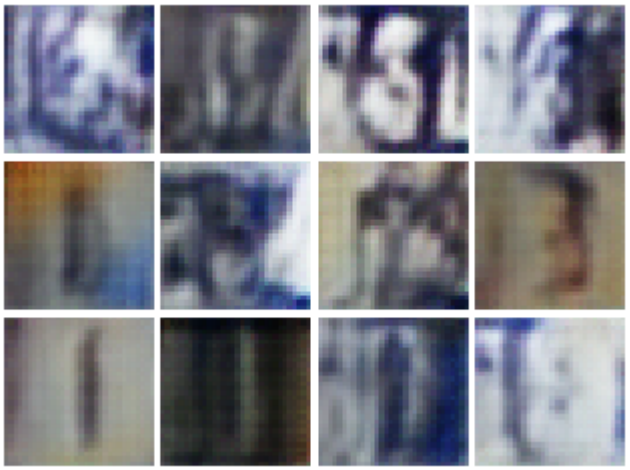
Iter: 2000, D: 1.378, G:0.7773



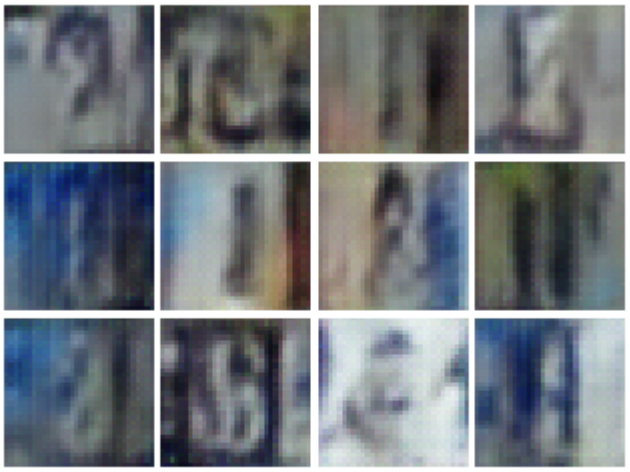
Iter: 2250, D: 1.371, G:0.8752



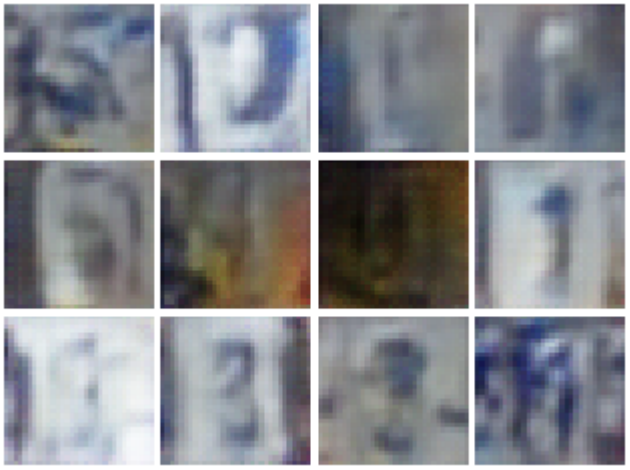
Iter: 2500, D: 1.327, G:0.8104



Iter: 2750, D: 1.399, G:0.8146

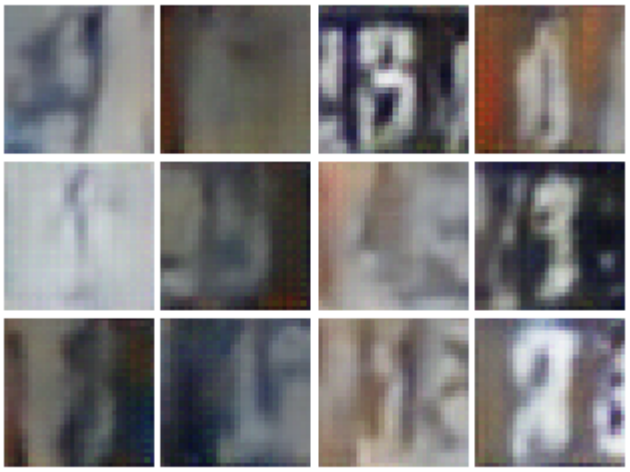


Iter: 3000, D: 1.361, G:0.7172



Iter: 3250, D: 1.344, G:0.8159

Iter: 3500, D: 1.338, G:0.6952

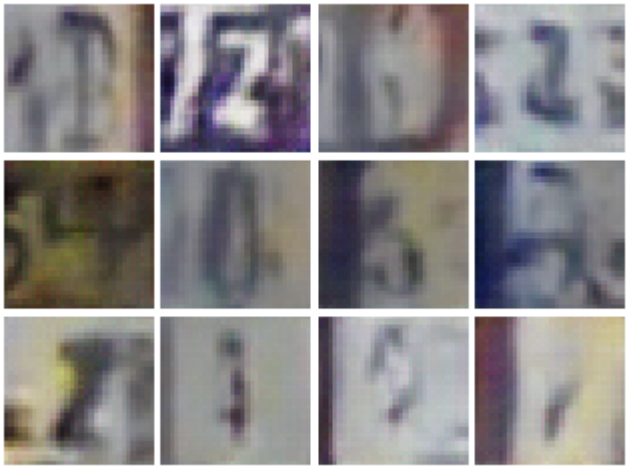


Iter: 3750, D: 1.286, G:0.8664

Iter: 4000, D: 1.324, G:0.8503

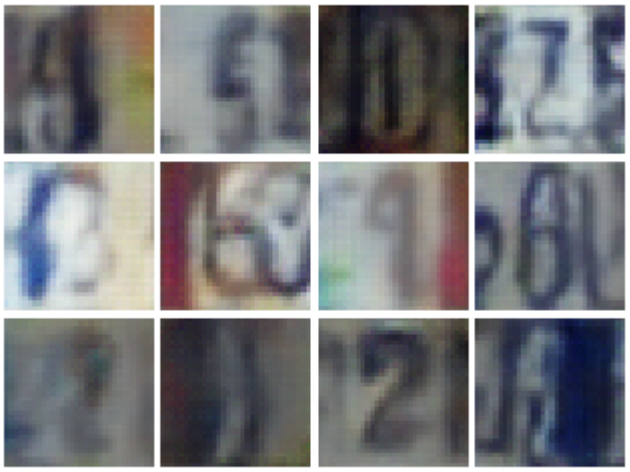
Iter: 4250, D: 1.377, G:0.8462

Iter: 4500, D: 1.312, G:0.85



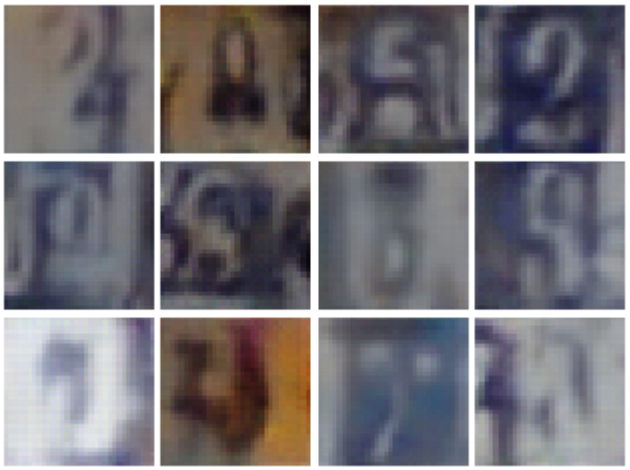
Iter: 4750, D: 1.344, G:0.7998

Iter: 5000, D: 1.361, G:0.915



Iter: 5250, D: 1.368, G:0.8965

Iter: 5500, D: 1.291, G:0.8306



Iter: 5750, D: 1.313, G:0.7721

Iter: 6000, D: 1.369, G:0.7824

Iter: 6250, D: 1.357, G:0.6901

Iter: 6500, D: 1.258, G:0.907

Iter: 6750, D: 1.332, G:0.8968

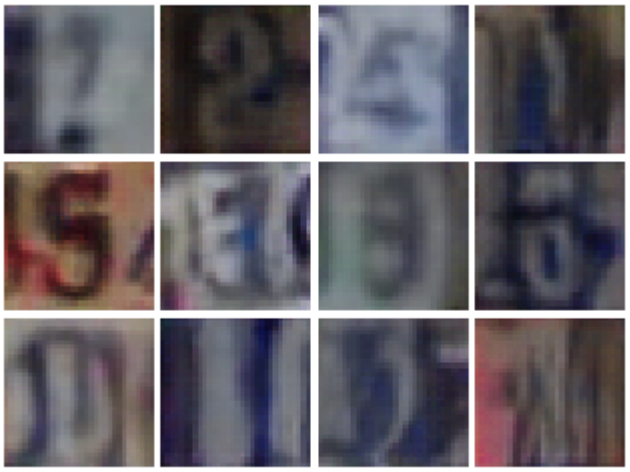
Iter: 7000, D: 1.293, G:0.8181

Iter: 7250, D: 1.264, G:0.8648

Iter: 7500, D: 1.275, G:0.7945

Iter: 7750, D: 1.27, G:0.7771

Iter: 8000, D: 1.271, G:0.8519



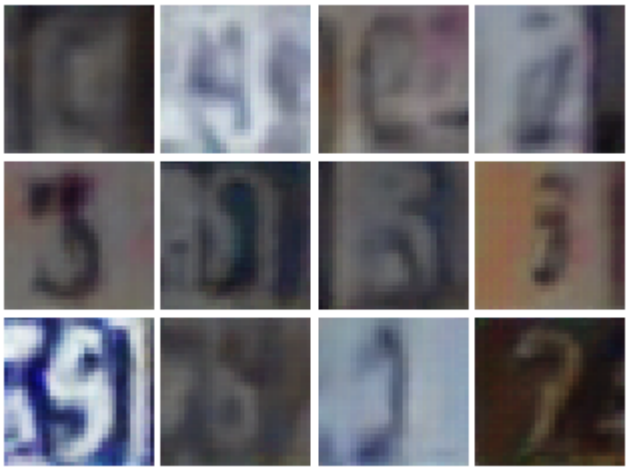
Iter: 8250, D: 1.318, G:0.799

Iter: 8500, D: 1.226, G:1.007

Iter: 8750, D: 1.298, G:0.81

Iter: 9000, D: 1.279, G:0.8775

Iter: 9250, D: 1.312, G:0.7987



Iter: 9500, D: 1.187, G:0.8791

Iter: 9750, D: 1.34, G:0.8476

Iter: 10000, D: 1.188, G:1.092

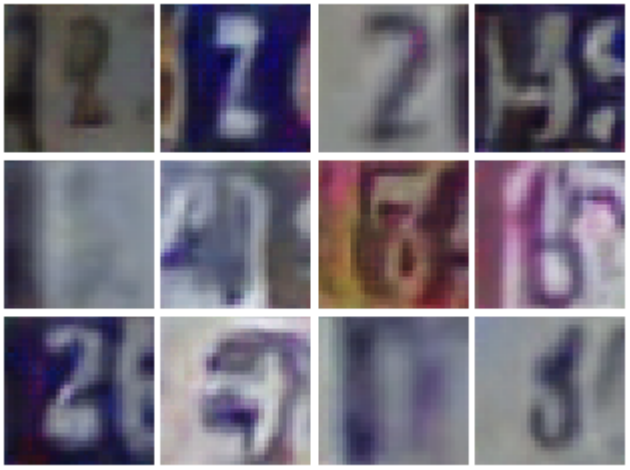
Iter: 10250, D: 1.329, G:0.7354

Iter: 10500, D: 1.148, G:0.9445

Iter: 10750, D: 1.235, G:0.7695

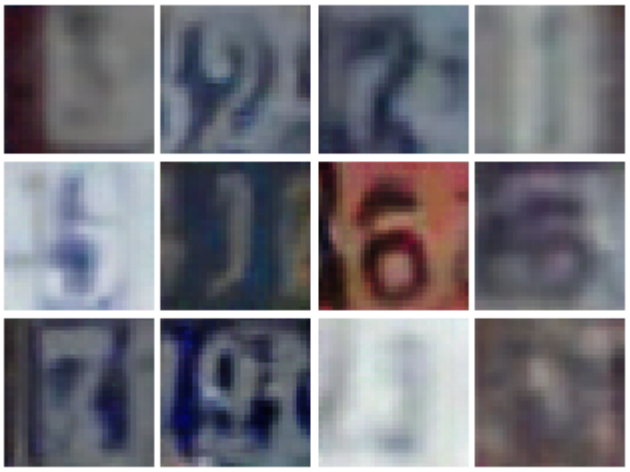
Iter: 11000, D: 1.216, G:1.365

Iter: 11250, D: 1.234, G:0.8879



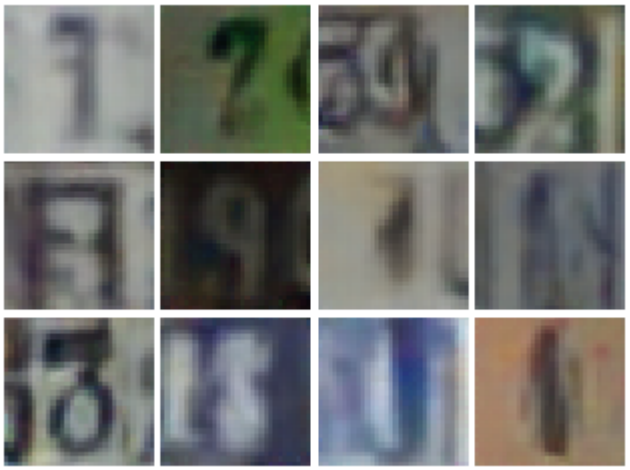
Iter: 11500, D: 1.167, G:0.9297

Iter: 11750, D: 1.243, G:0.9439



Iter: 12000, D: 1.269, G:0.9028

Iter: 12250, D: 1.241, G:0.8992

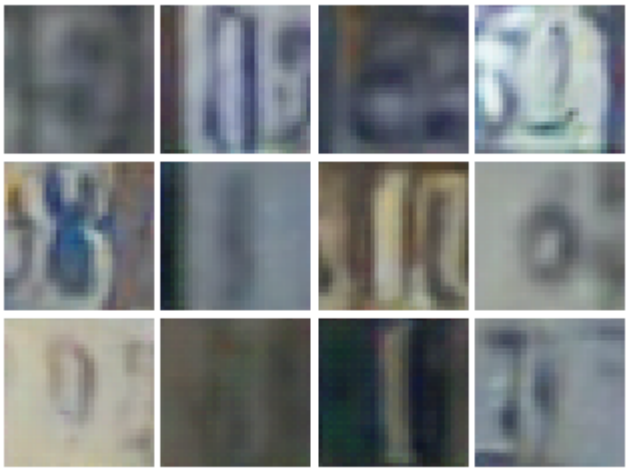


Iter: 12500, D: 1.177, G:1.036

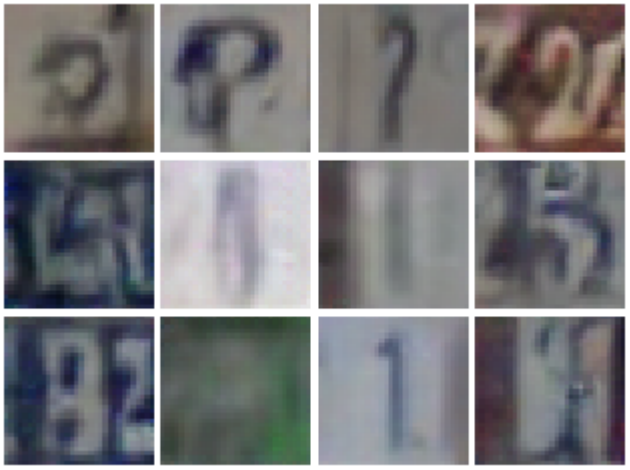
Iter: 12750, D: 1.282, G:0.9237

Iter: 13000, D: 1.316, G:0.8535

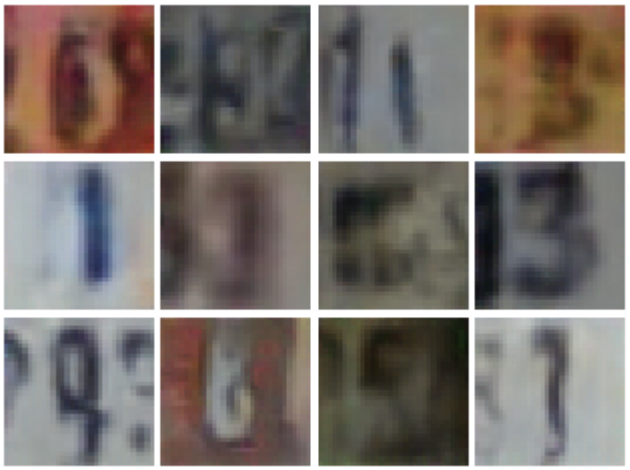
Iter: 13250, D: 1.317, G:0.9666



Iter: 13500, D: 1.279, G:0.879

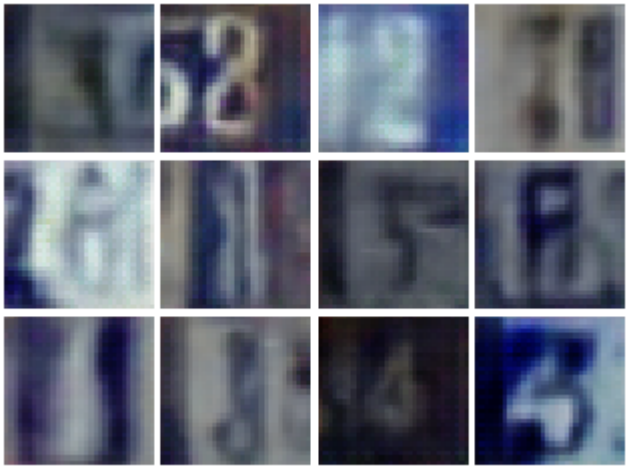


Iter: 13750, D: 1.234, G:0.8873



Iter: 14000, D: 1.16, G:0.9272

Iter: 14250, D: 1.438, G:0.8887



Iter: 14500, D: 1.233, G:0.9248

Iter: 14750, D: 1.19, G:0.8669

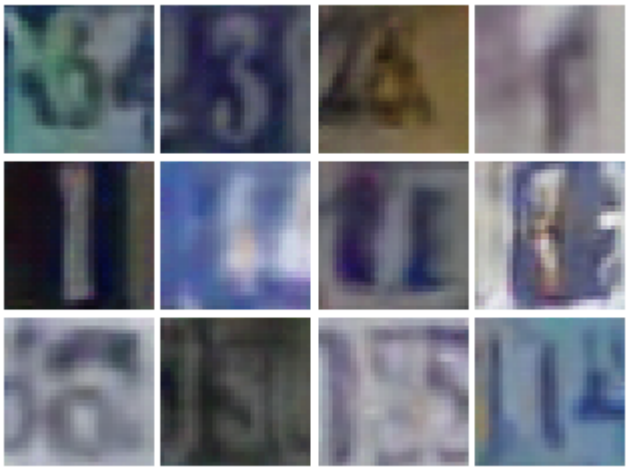
Iter: 15000, D: 1.304, G:1.002

```
Iter: 15250, D: 1.255, G:0.905
```

Iter: 15500, D: 1.204, G:1.011

Iter: 15750, D: 1.212, G:0.9114

Iter: 16000, D: 1.152, G:0.9947

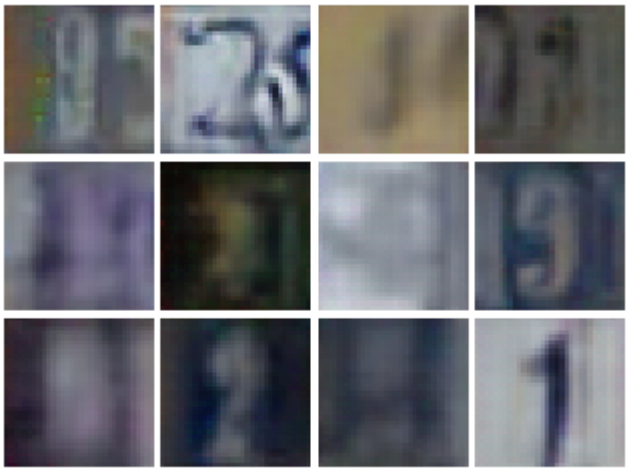


Iter: 16250, D: 1.211, G:1.014

Iter: 16500, D: 1.2, G:0.9297

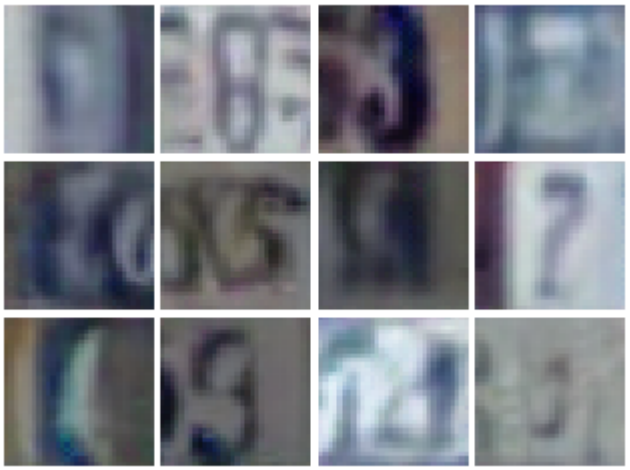
Iter: 16750, D: 1.21, G:0.9168

Iter: 17000, D: 1.255, G:0.9419

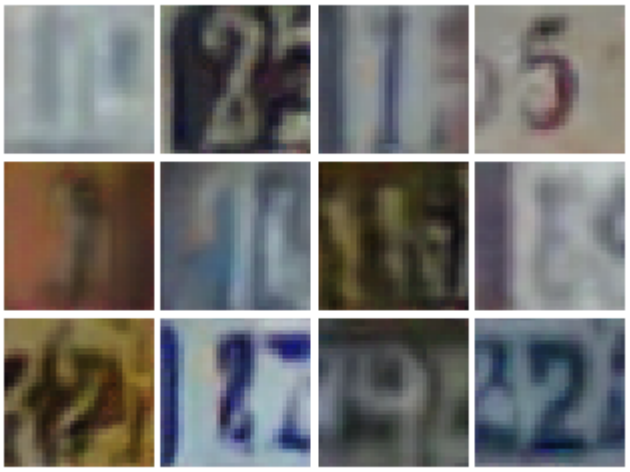


Iter: 17250, D: 1.279, G:0.8876

Iter: 17500, D: 1.141, G:1.02

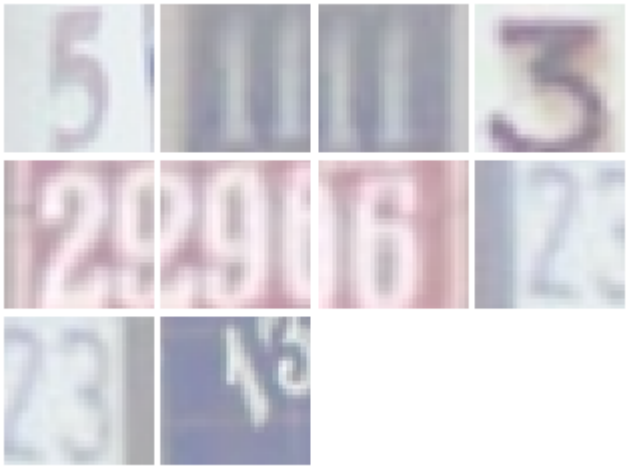


Iter: 17750, D: 1.208, G:0.9403



Iter: 18000, D: 1.183, G:0.9539

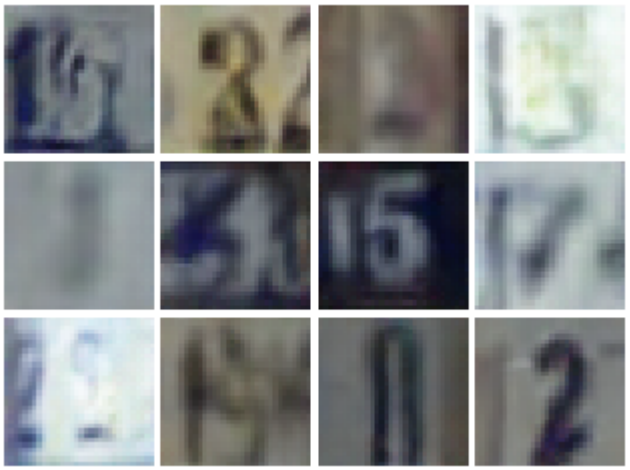
Iter: 18250, D: 1.166, G:2.503



Iter: 18500, D: 1.139, G:0.9401

Iter: 18750, D: 1.168, G:0.9265

Iter: 19000, D: 1.128, G:0.8735



Iter: 19250, D: 0.997, G:1.035

Iter: 19500, D: 0.9675, G:1.131

Iter: 19750, D: 0.8818, G:1.341

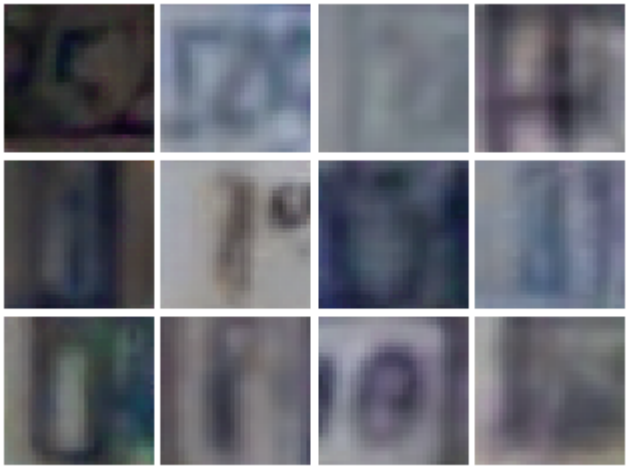
Iter: 20000, D: 1.206, G:0.9386

Iter: 20250, D: 1.198, G:1.721

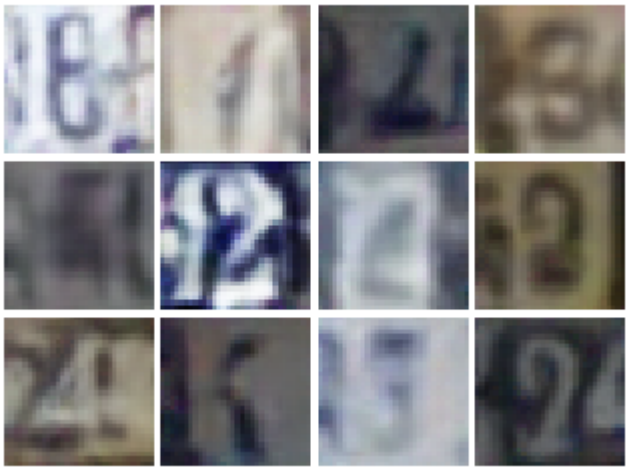
Iter: 20500, D: 1.255, G:1.083

Iter: 20750, D: 1.002, G:1.044

Iter: 21000, D: 1.079, G:1.219



Iter: 21250, D: 1.13, G:1.031

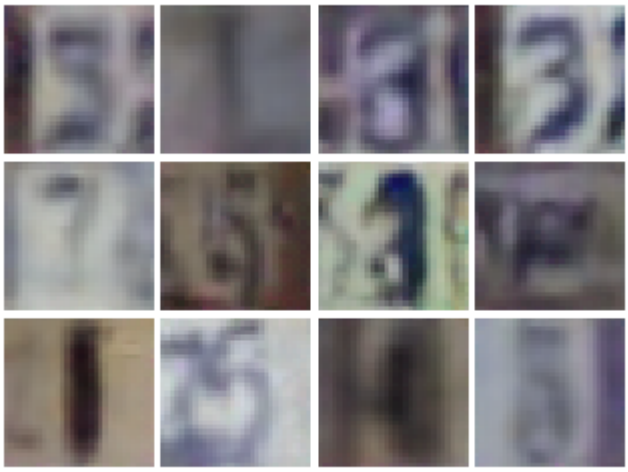


Iter: 21500, D: 1.066, G:1.352

Iter: 21750, D: 1.201, G:1.02

Iter: 22000, D: 1.163, G:1.014

Iter: 22250, D: 1.234, G:0.9257



Iter: 22500, D: 1.186, G:0.9466

```
Iter: 22750, D: 1.117, G:0.9053
```

Iter: 23000, D: 1.189, G:1.017

Iter: 23250, D: 1.186, G:0.997

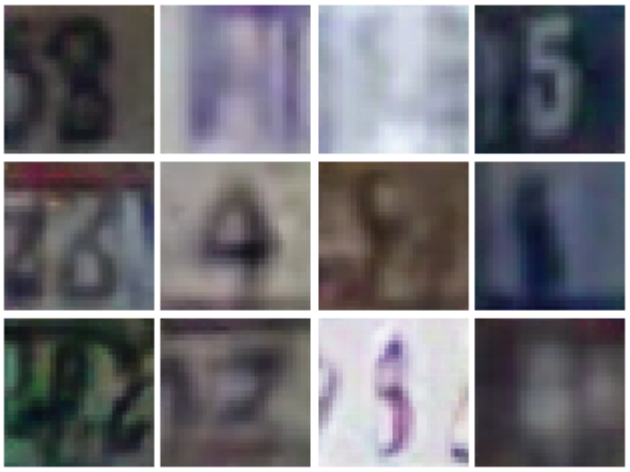
Iter: 23500, D: 0.9303, G:1.638

Iter: 23750, D: 1.174, G:0.9272

Iter: 24000, D: 0.925, G:1.148

Iter: 24250, D: 1.213, G:0.9479

Iter: 24500, D: 1.201, G:1.031

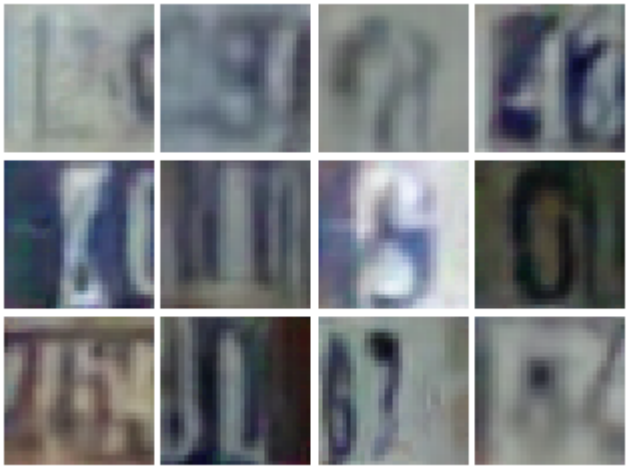


Iter: 24750, D: 1.043, G:1.229

Iter: 25000, D: 1.01, G:1.16

Iter: 25250, D: 1.162, G:0.9737

Iter: 25500, D: 1.119, G:1.046



Iter: 25750, D: 0.9775, G:1.329

Iter: 26000, D: 1.979, G:2.785

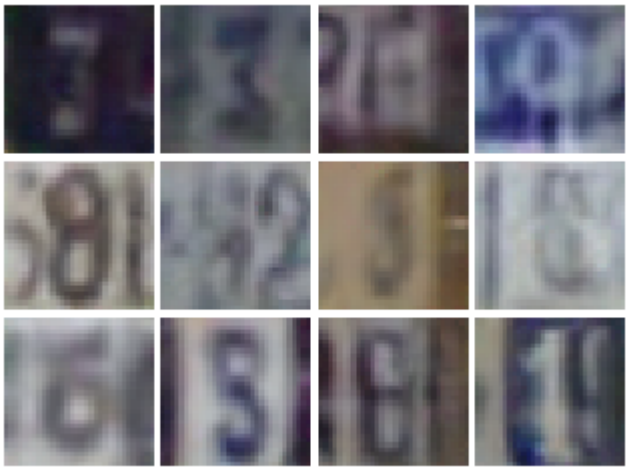
Iter: 26250, D: 0.8196, G:1.45

Iter: 26500, D: 0.8369, G:1.927

Iter: 26750, D: 1.13, G:1.076

Iter: 27000, D: 1.019, G:1.118

Iter: 27250, D: 0.8785, G:1.159



Iter: 27500, D: 0.9562, G:1.489

Iter: 27750, D: 1.068, G:1.339

Iter: 28000, D: 1.295, G:0.905

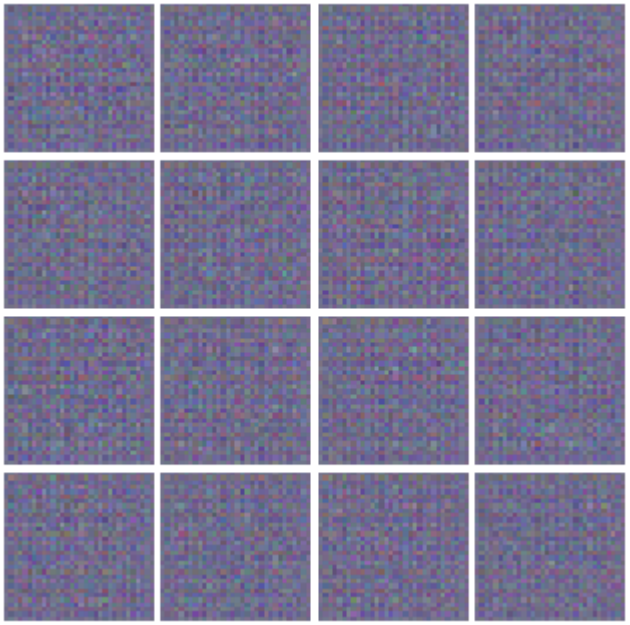
Iter: 28250, D: 0.8853, G:1.188

Iter: 28500, D: 1.189, G:1.071

You do not have to save the above training images for your final report, please just save the images generated by the cell below

In [ ]:
```
numIter = 0
if len(images) > 8:
    step = len(images) // 8
else:
    step = 1

for i in range(0, len(images), step):
    img = images[i]
    numIter = 250 * i * step
    print("Iter: {}".format(numIter))
    img = (img)/2 + 0.5
    show_images(img.reshape(-1, 3, 32, 32))
    plt.show()
```

```
Iter: 0
```



Iter: 49000

Iter: 98000

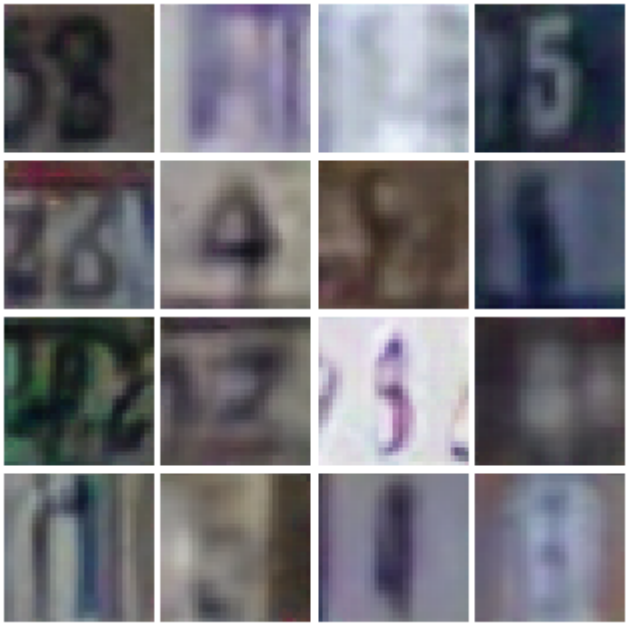
Iter: 147000

Iter: 196000

Iter: 245000

Iter: 294000

Iter: 343000



Iter: 392000

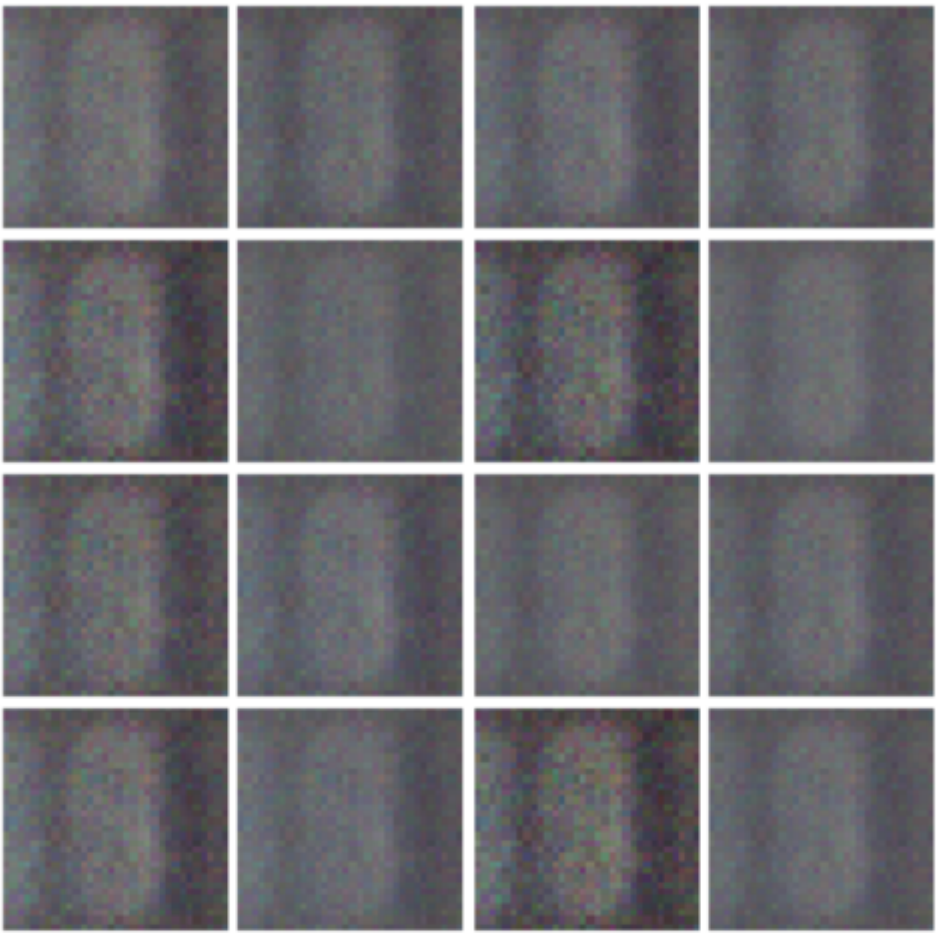
[TODO] GAN Output Visual Evaluation [2pts (Report)]

The main deliverable for this notebook is the final GAN generations! Run the cells in this section to show your final output. If you are unhappy with the generation, feel free to train for longer. Keep in mind we are not expecting perfect outputs, especially considering your limited computation resources. Below we have shown a few example images of what acceptable and unacceptable outputs are. Make sure your final image displays and is included in the report.

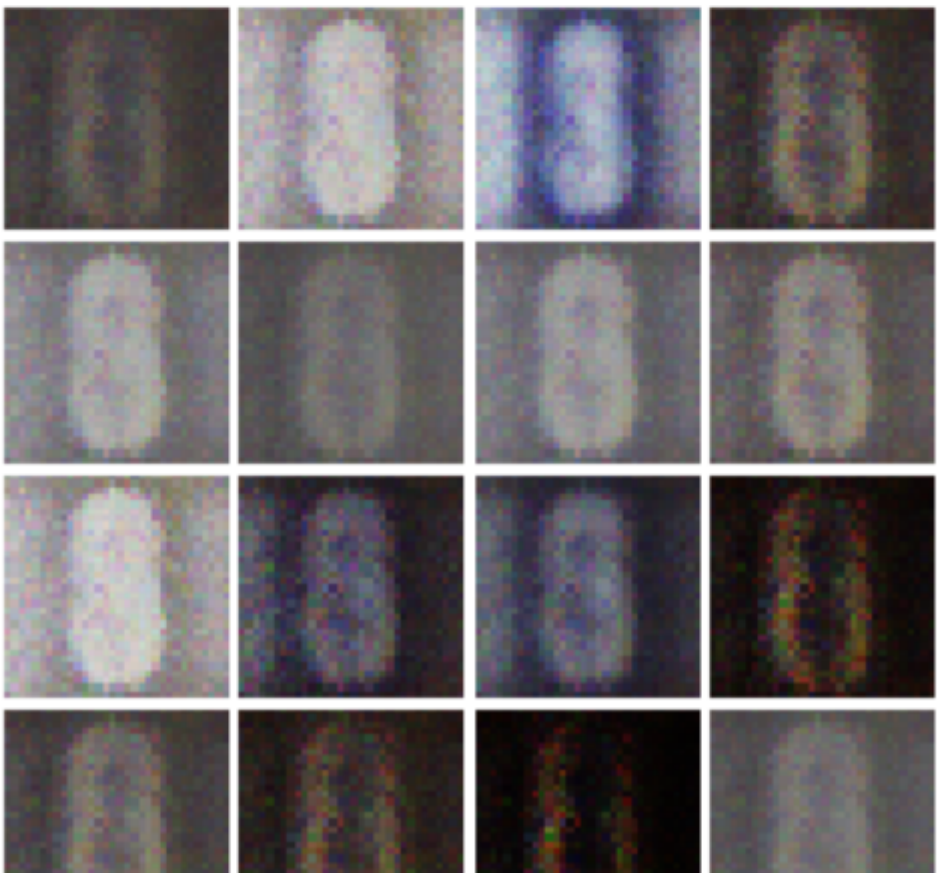
Acceptable Output:

Unreasonable Output:

Iter: 500



Iter: 750



In [ ]:
```
# This output is your answer - please include in the final report
print("Vanilla GAN final image:")
fin = (images[-1] - images[-1].min()) / (images[-1].max() - images[-1].mi
show_images(fin.reshape(-1, 3, 32, 32))
plt.show()
```

```
Vanilla GAN final image:
```

Reflections (2 Points)

[TODO]: Reflect on the GAN Training Process. What were some of the difficulties? How good were the generated outputs?

After understanding the structure of how the training should happen, the difficulties were a matter of tuning (although I relied on the suggested hyperparameters in the notebook, the network's architecture was still flexible).

For my first try, I just followed the suggestions for both discriminator and generator, and after knowing that my code was running smooth I experimented with the addition of batchnorm layers (following hte guidelines of https://arxiv.org/pdf/1511.06434.pdf).

The outputs were not perfect, but not bad. In a qualitative look, some generated images are very similar to the ones from the training set, and could even fool me.

[TODO] What is a mode collapse in GAN training, can you find any examples in your training?

Mode collapse in GAN training is when the outputs of the generator is not reflective of the actual dataset in the sense of not being as diverse. The symptoms are not being able to generate all the available "labels", or only being able to output that is very close to the training set. It basically means that the generator was not able to learn the "meaning" of all of the data.

Yes. Despite not having quantitative results, I can see that the generator tends to output certain numbers more than others. For example, the numbers 7 and 9 are barely seen. Moreover, on different runs I saw this phenomena with other numbers (almost always in pairs).

[TODO] Talk about the trends that you see in the losses for the generator and the discriminator. Explain why those values might make sense given the quality of the images generated after a given number of itterations.

I see a cyclic trend that the losses follow: in an iteration where the discriminator loss goes down, the generator loss goes up; when the generator loss goes down, the discriminator loss goes up. It makes sense because they are two competing networks. The way I see it, as the discriminator gets better, the generator has a harder time to fool it, and when it does, then the discriminator will fight against that.

Because of that it makes sense that the losses don't just go down as they usually do for common classification tasks, but instead they bounce around some number (in my case between 0.7 and 1.6).

Saving Models

In [ ]:
```
# You must save these models to run the next cells
torch.save(D.state_dict(), "d_smart.pth")
torch.save(G.state_dict(), "g_smart.pth")
```

Evaluating GANS

Evaluating via FID Score

It is hard to evaluate GANs effectiveness quantiatively. One way we can do this is by calculating FID (Frechet-Inception-Distance).

Website: https://wandb.ai/ayush-thakur/gan-evaluation/reports/How-to-Evaluate-GANs-using-Frechet-Inception-Distance-FID---Vmlldzo0MTAxOTI

But for this assignment, we will visually evaluate the GAN outputs.

TODO: Evaluating Discriminator

Not graded but for fun see how well your discriminator does against a sample generator.

In [ ]:
```
from part1_GANs.gan_pytorch import get_optimizer, eval_gan, eval_discrimi
from part1_GANs.gan_pytorch import generator, discriminator, discriminato

D = discriminator().type(dtype)
D.load_state_dict(torch.load("d_smart.pth"))
D.eval()

# oracle_g = torch.jit.load("../test_resources/g_smart_o.pt")
oracle_g = torch.jit.load("test_resources/g_smart_o.pt")
oracle_g.eval()

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

accuracy, p, r = eval_discriminator(D, oracle_g, loader_val, device)

# Test accuracy is greater than 0.55
assert accuracy > 0.55
```

```
Accuracy: 0.7161510555926917
Precision: 0.8934291885141465
Recall: 0.47673332899051074
```

Preparing for Submission

Run the following cell to collect `hw4_submission_part1.zip`. You will submit this to HW4: Part 2 - GANs on gradescope. Make sure to also export a PDF of this jupyter notebook and attach that to the end of your theory section. This PDF must show your answers to all the questions in the document, please include the final photos that you generate as well. Do not include all of your training images! You will not be given credit for anything that is not visible to us in this PDF.

In [ ]:
```
!sh collect_submission_part1.sh
```

```
sh: 0: cannot open collect_submission_part1.sh: No such file
```

Contributers

- Manav Agrawal (Lead)
- Matthew Bronars
- Mihir Bafna