```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

change to whatever your path is to homework4 folder

```
%cd "drive/MyDrive/cs7643-deep-learning-homeworks/hw4/hw4_code_student_version/part1-GANs"
```

```
/content/drive/MyDrive/cs7643-deep-learning-homeworks/hw4/hw4_code_student_version/part1
```

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

```
# 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")

from gan_pytorch import preprocess_img, deprocess_img, rel_error, count_params, ChunkSampler

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

%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 change it to (32, 32, 3
        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/

[ ] ↳ 2 cells hidden

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:

Note: If you get error about tensors not being on same device, make sure that all your tensors are on the same device using `.type(dtype)`

```
from gan_pytorch import sample_noise
from 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. It is also recommended to include batch normalization as well.

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.

```
from 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:  142913
```

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). It is recommended to include batch normalization as well. Remember 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]`.

```
from 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:  3439747
```

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.

Hint: Use Pytorch's `nn.functional.binary_cross_entropy_with_logits()` when implementing `bce_loss()`

Note: `binary_cross_entropy_with_logits()` already contains a Sigmoid layer so issues may arise later if you already have it in your discriminator architecture

```
from gan_pytorch import bce_loss, discriminator_loss, generator_loss

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)).cpu()
    assert torch.allclose(torch.Tensor(d_loss_true), torch.Tensor(d_loss), rtol=1e-05, atol=
    print("Maximum error in d_loss: %g"%rel_error(d_loss_true, d_loss.numpy()))

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().numpy()
    assert torch.allclose(torch.Tensor([0.581159]), torch.Tensor(g_loss), rtol=1e-05, atol=1
```

```
    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()
    assert torch.allclose(torch.Tensor([0.7637264728546143]), torch.Tensor([bc_loss]), rtol=
    print("Maximum error in d_loss: %g"%rel_error(0.7637264728546143, bc_loss))

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
```

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.

Note: Make sure to detach the tensors that track gradients using `.detach()` if you get in-place modification errors

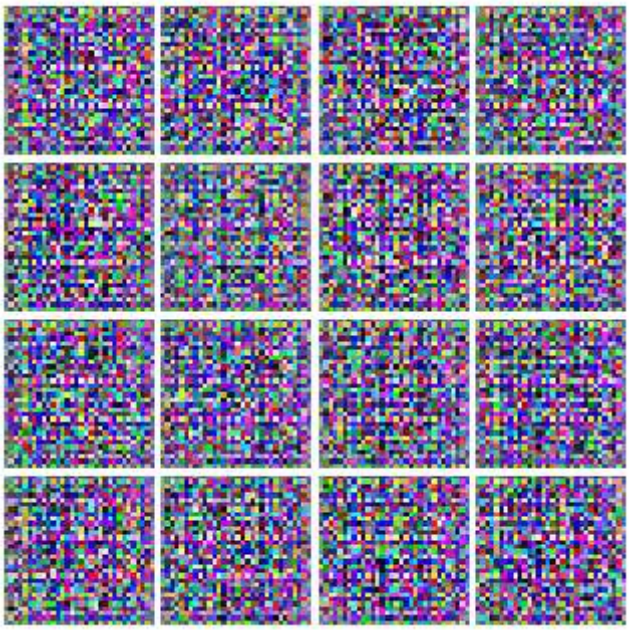
```
from gan_pytorch import get_optimizer, train_gan

# 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 Discriminator and the Generat
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=30
    )
```

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

```
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: 4000

Iter: 8000

Iter: 12000

Iter: 16000

Iter: 20000

Iter: 24000

Iter: 28000

Iter: 32000

[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. Common problems with GANs are listed below in the following resources and can help you get a better understanding as to why you GAN maybe producing an unreasonable output.

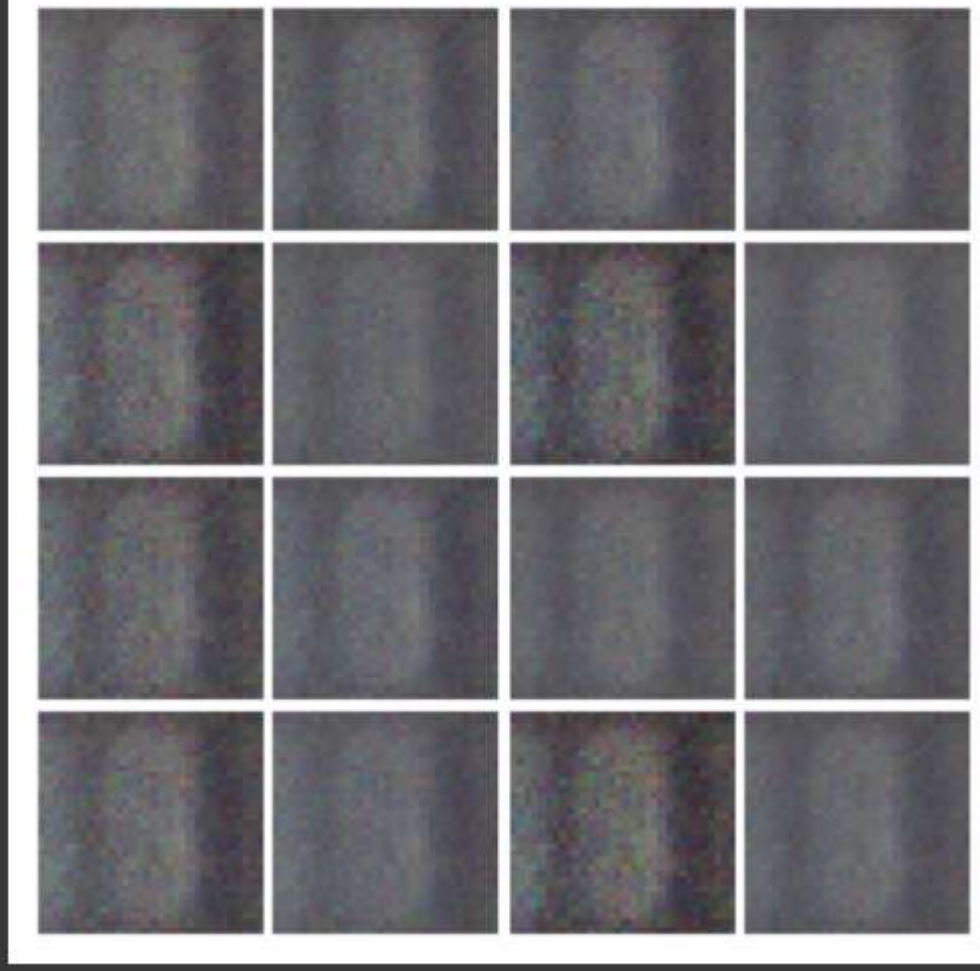
Website: https://developers.google.com/machine-learning/gan/problems

Website: https://medium.com/@miraytopal/what-is-mode-collapse-in-gans-d3428a7bd9b8

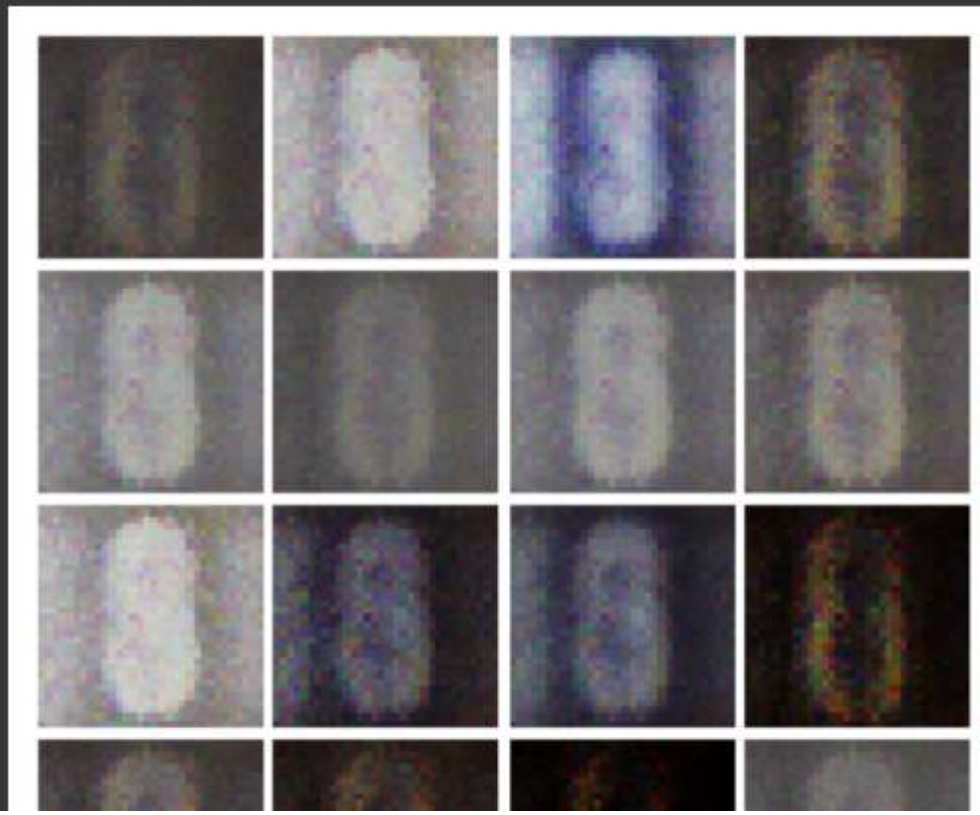
Acceptable Output:

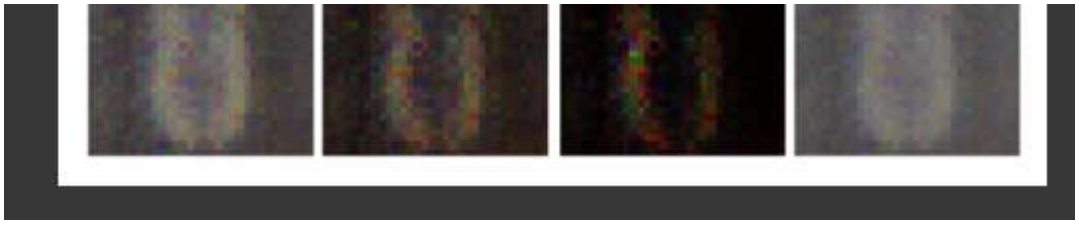
Unreasonable Output:

Iter: 500



Iter: 750





```
# 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].min())
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?

Answer:

There is slow initial progress -> The first iterations (Iter: 0) show completely random noise with no structure. The generator struggles to produce anything resembling digits in the first set of hundred iterations (up to iteration 750).

I witnessed instability while training -> The losses fluctuate significantly throughout training, showing the well-known instable nature GAN training where two networks constantly adapt to each

other.

The classic problem of GANs known as mode collapse -> In several iterations, the generator produces similar patterns across multiple images rather than capturing the full diversity of the SVHN dataset.

A big challenge was tuning hyperparameters of each neural network so as to ensure that I balance network strength -> When the discriminator becomes too strong (like at Iter: 250 with D loss at 0.004687), the generator struggles to learn (G loss at 9.144). So, if either of the neural network architectures is improperly set up, the GAN won't perform as well because either the generator or the discriminator will dominate the other.

Quality of Generated Outputs

The quality improves progressively:

Iter 0-250: Mostly random noise

Iter 500-750: Vertical striping patterns begin to emerge

Iter 1000-1500: Basic digit-like shapes start to form, though blurry

Iter 2000-2500: More recognizable digits with better definition

Iter 3500+: Clearer digit shapes, though still not as sharp as real SVHN images

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

Answer:

Mode collapse occurs when the generator produces only a limited variety of outputs instead of capturing the full diversity of the training data distribution. The generator collapses to producing only a few modes of outputs, while the discriminator potentially gets stuck in local minimum. This is a classic GAN problem where the generator finds a few outputs that successfully fool the discriminator and gets stuck generating variations of just those patterns.

Examples in the training:

Around Iter 500, many generated images show the same vertical striping pattern.

Similar background colors or patterns appear repeatedly in some iterations, for example at iteration 1000 the same pattern occurs in multiple fields.

In several batches, the diversity of digits appears limited - for example for iterations 4500 to 5000 there are quite a lot of 2s and 3s and/or combination of these numbers.

The generator sometimes just generates certain digit styles or shapes, for example similar styles in iterations 6000 and 6250.

[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.

Answer:

Initial high losses (Iter 0: D: 1.508, G: 2.589): Both networks are untrained and performing poorly. Images are essentially pure noise.

Discriminator dominance over generator (Iter 250: D: 0.004687, G: 9.144): Extremely low D loss indicates the discriminator easily identifies fake images Very high G loss shows the generator is failing to fool the discriminator Images still look like random patterns

Competitive phase (Iter 500-1750): D loss increases (0.227 → ~1.2) as the generator improves G loss decreases (4.095 → ~1.1) as it learns to create more convincing images. Images begin resembling actual digits during this phase

Approaching equilibrium (Iter 2000-2500): More stable losses. D loss fluctuating between 1.3-1.6. Generated images become more recognizable as digits. This indicates a healthier adversarial balance between generator and discriminator.

Generator's loss starts off high and trends downward overtime, which makes sense as images