HW8

March 29, 2025

Please complete the `NotImplemented` parts of the code cells and write your answers in the markdown cells designated for your response to any questions asked. The tag `# AUTOGRADED` (all caps, with a space after `#`) should be at the beginning of each autograded code cell, so make sure that you do not change that. You are also not allowed to import any new package other than the ones already imported. Doing so will prevent the autograder from grading your code.

For the code submission, run the last cell in the notebook to create the submission zip file. If you are working in Colab, make sure to download and then upload a copy of the completed notebook itself to its working directory to be included in the zip file. Finally, submit the zip file to Gradescope.

After you finish the assignment and fill in your code and response where needed (all cells should have been run), save the notebook as a PDF using the `jupyter nbconvert --to pdf HW8.ipynb` command (via a notebook code cell or the command line directly) and submit the PDF to Gradescope under the PDF submission item. If you cannot get this to work locally, you can upload the notebook to Google Colab and create the PDF there. You can find the notebook containing the instruction for this on Canvas.

If you are running the notebook locally, make sure you have created a virtual environment (using `conda` for example) and have the proper packages installed. We are working with `python=3.10` and `torch>=2`.

Files to be included in submission:

- `HW8.ipynb`
- `generator_config.yaml`
- `discriminator_config.yaml`
- `train_config.yaml`

[20]:
```
"""
DO NOT MODIFY THIS CELL OR ADD ANY ADDITIONAL IMPORTS ANYWHERE ELSE IN THIS␣
↪NOTEBOOK!
"""
from typing import Sequence, Union
from tqdm import tqdm
import numpy as np

import matplotlib.pyplot as plt
# plt.rcParams.update({'figure.autolayout': True})
from IPython.display import display, clear_output
```

```python
import torch
from torch import nn, optim
from torch.optim import lr_scheduler
from torch.nn import functional as F
from torch.utils.data import Dataset, DataLoader

from HW8_utils import AirfoilDataset

if torch.cuda.is_available():
    Device = 'cuda'
elif torch.backends.mps.is_available():
    Device = 'mps'
else:
    Device = 'cpu'
print(f'Device is {Device}')
```

```
Device is cpu
```

1 Fundamentals of Generative Adversarial Networks (30)

First, you have to answer some questions to validate your knowledge about the fundamentals of GANs. Explain your reasoning for each question, and keep your response concise.

You can also verify your answers by what you observe in the programming section of the assignment.

1.1 QUESTION 1 (10)

For a GAN with a well-balanced generator and discriminator, what should the output of the discriminator be for real data $D(x)$ and fake data $D(G(z))$ in the early iterations of training? How should $D(x)$ and $D(G(z))$ change as the training progresses? (For each case, should it be closer to 0 or 0.5 or 1?)

What would indicate getting close to a successfully trained GAN?

RESPONSE:

Early Training: For real data the output is closer to 1 while the fake data is closer to 0 because real samples are easier to determine while the generator produces *bad* samples

Mid-ish Training: The generated samples should be getting better, and the discriminator should be less accurate at determining fakes so both the real and fake data should begin getting closer to 0.5 than 0

Toward End Training: The generated samples should be tough to discriminate between real and fake so the discriminator's output should be close to 0.5

1.2 QUESTION 2 (10)

Assume you have started training a GAN, and you observe in the early iterations that the generator and discriminator losses are similar. The output of the discriminator for real and fake data are also similar.

Do you think that the training will be successful and lead to a good GAN capable of generating realistic samples? If not, what is the problem and how could you mitigate it?

RESPONSE: If this is happening, it is likely that the discriminator is underfitting and doesn't provide a proper gradient to improve the gererator so we'll produce a poor GAN. Either a larger architecture capable of capturing more unique connections/patterns should be created or the hyperparameters need tuning.

1.3 QUESTION 3 (10)

Assume you have started training a GAN, and you observe that the discriminator loss quickly converges to zero, while the generator loss seems unstable or very large even after training for some time. What do you think the discriminator score is for real and fake data?

Do you think that the training will be successful and lead to a good GAN capable of generating realistic samples? If not, what is the problem and how could you mitigate it?

RESPONSE: The discriminator is actually too strong here, and the generator doesn't receive a large enough gradient to learn from. Here we do the opposite of above and create a simpler architecture in the discriminator or again, adjusting hyperparameters like lowering the learning rate should improve the GAN.

2 Implement and train a GAN to generate airfoils (70)

You are provided with the UIUC airfoil dataset consisting of 1547 airfoil profiles. The Dataset class to load the data is provided in `HW8_utils.py`. Let's take a look at the dataset. Each sample consists of the y-coordinates of points at pre-defined locations on the x-axis, as well as the name of the airfoil. You will not need the names.

[2]:
```python
airfoil_dataset = AirfoilDataset()
print(f'dataset has {len(airfoil_dataset)} samples')
```

```
dataset has 1547 samples
```

[3]:
```python
sample_idx = 431
y, name = airfoil_dataset[sample_idx]
print(f'y is {type(y)} and has shape {y.shape} and dtype {y.dtype}')
```

```
y is <class 'numpy.ndarray'> and has shape (200,) and dtype float32
```

2.1 Implement a Generator and a Discriminator (20)

You do not need a complicated architecture for the generator and discriminator in this assignment. You can use the example from the recitation to implement the general architecture, but do not copy the exact models, since there might be details specific to the datasets. Try to implement the models by yourself to get comfortable with defining soft-coded atchutectures.

[81]:
```python
# AUTOGRADED

class Generator(nn.Module):
```

```python
    def __init__(
            self,
            latent_size: int,
            output_size: int,
            hidden_dims: list = [128, 256],
            batchnorm: bool = True,
            activation_name: str = 'ReLU',
            ):
        super().__init__()

        activation = getattr(nn, activation_name)
        self.latent_size = latent_size

        layers = []
        in_features = latent_size

        for i, hdim in enumerate(hidden_dims):
            layers.append(nn.Linear(in_features, hdim))

            # BatchNorm1d is often helpful for hidden layers
            if batchnorm:
                layers.append(nn.BatchNorm1d(hdim))

            layers.append(activation())
            in_features = hdim

        # Final layer outputs a 1D vector of size 200
        layers.append(nn.Linear(in_features, output_size))
        # Sigmoid to keep values in [0, 1], if that's desired for your␣
↪particular data
        layers.append(nn.Tanh())

        self.net = nn.Sequential(*layers)

    def forward(
            self,
            z: torch.FloatTensor, # (batch_size, latent_size)
            ) -> torch.FloatTensor: # (batch_size, *output_shape)
        """
        Input z is the latent vector, typically sampled from N(0, I)
        Outputs generated samples
        """
        return self.net(z)

    def generate(
            self,
```

```
            n_samples: int,
            device: str = Device,
            no_grad: bool = False,
            ) -> torch.FloatTensor: # (n_samples, output_size)
        """
        move self to the device
        sample n_samples latent vectors from N(0, I)
        generate n_samples samples
        """
        self.to(device)
        z = torch.randn(n_samples, self.latent_size, device=device)
        samples = self.forward(z)
        return samples


class Discriminator(nn.Module):

    def __init__(
            self,
            input_size: int,
            hidden_dims: list = [512, 256],
            activation_name: str = 'ReLU',
            ):
        super().__init__()

        activation = getattr(nn, activation_name)

        layers = []
        in_features = input_size

        for i, hdim in enumerate(hidden_dims):
            layers.append(nn.Linear(in_features, hdim))
            layers.append(activation())
            in_features = hdim

        # Final layer: single output (REAL vs FAKE)
        layers.append(nn.Linear(in_features, 1))
        layers.append(nn.Sigmoid())  # Probability that the sample is real

        self.net = nn.Sequential(*layers)

    def forward(
            self,
            x: torch.FloatTensor, # (batch_size, input_size)
            ) -> torch.FloatTensor: # (batch_size, 1)

        return self.net(x)
```

2.2 Tracking and Visualization

[82]:
```python
class GAN_Tracker:
    """
    Logs and plots different loss terms of a GAN during training.
    """
    def __init__(
            self,
            n_iters: int,
            plot_freq: Union[int, None] = None, # plot every plot_freq␣
↪iterations
            ):

        self.real_scores = []
        self.fake_scores = []
        self.D_losses = []
        self.G_losses = []

        self.plot = plot_freq is not None
        self.iter = 0
        self.n_iters = n_iters

        if self.plot:
            self.plot_freq = plot_freq
            self.plot_results()


    def plot_results(self):
        self.fig, (self.ax1, self.ax2) = plt.subplots(1, 2, figsize=(13, 3),␣
↪sharex=True)

        # Score plot:
        self.real_score_curve, = self.ax1.plot(
            range(1, self.iter+1),
            self.real_scores,
                        label = r'$D(x)$',
            )
        self.fake_score_curve, = self.ax1.plot(
            range(1, self.iter+1),
            self.fake_scores,
            label = r'$D(G(z))$',
            )

        self.ax1.set_xlim(0, self.n_iters+1)
        self.ax1.set_ylim(0, 1)
        self.ax1.set_xlabel('Iteration')
        self.ax1.set_ylabel('Discriminator Score')
```

```
        self.ax1.set_title('Discriminator Score')
        self.ax1.grid(linestyle='--')
        self.ax1.legend()

        # Loss plot:
        self.D_loss_curve, = self.ax2.plot(
            range(1, self.iter+1),
            self.D_losses,
                        label = 'D',
            )
        self.G_loss_curve, = self.ax2.plot(
            range(1, self.iter+1),
            self.G_losses,
            label = 'G',
            )
        self.ax2.set_xlim(0, self.n_iters+1)
        self.ax2.set_xlabel('Iteration')
        self.ax2.set_ylabel('Loss')
        self.ax2.set_title('Learning Curve')
        self.ax2.grid(linestyle='--')
        self.ax2.legend()

        self.samples_fig, self.samples_axes = plt.subplots(4, 6, figsize=(12,␣
↪8), sharex=True, sharey=True)
        self.sample_axes = self.samples_axes.flat
        self.samples = []
        for ax in self.sample_axes:
            self.samples.append(ax.plot(airfoil_dataset.get_x(), np.
↪zeros_like(airfoil_dataset.get_x()))[0])
            ax.set_xlim(-0.1, 1.1)
            ax.set_ylim(-0.6, 0.6)
            ax.set_aspect('equal')
            ax.grid(linestyle='--')


    def update(
            self,
            real_score: float,
            fake_score: float,
            D_loss: float,
            G_loss: float,
            ):
        self.real_scores.append(real_score)
        self.fake_scores.append(fake_score)
        self.D_losses.append(D_loss)
        self.G_losses.append(G_loss)
        self.iter += 1
```

```
        if self.plot and self.iter % self.plot_freq == 0:

            # score plot:
            self.real_score_curve.set_data(range(1, self.iter+1), self.
↪real_scores)
            self.fake_score_curve.set_data(range(1, self.iter+1), self.
↪fake_scores)
            self.ax1.relim()
            self.ax1.autoscale_view()

            # loss plot:
            self.D_loss_curve.set_data(range(1, self.iter+1), self.D_losses)
            self.G_loss_curve.set_data(range(1, self.iter+1), self.G_losses)
            self.ax2.relim()
            self.ax2.autoscale_view()

            self.samples_fig.suptitle(f'Generated Samples at Iteration {self.
↪iter}')

            self.fig.canvas.draw()
            clear_output(wait=True)
            display(self.fig)
            display(self.samples_fig)


    def get_samples(
            self,
            samples: torch.FloatTensor, # (n_samples, *output_shape)
            ):
        for sample, sample_img in zip(samples, self.samples):
            sample_img.set_ydata(sample.detach().cpu().numpy())
```

2.3 Losses (15)

Hint: use `F.binary_cross_entropy` with the right input and target.

[46]:
```
def D_real_loss_fn(
        D_real: torch.FloatTensor, # (batch_size, 1)
        ) -> torch.FloatTensor: # ()
    """
    D_real is D(x), the discriminator's output when fed with real images
    We want this to be close to 1, because the discriminator should recognize␣
↪real images
    """
    target = torch.ones_like(D_real)
```

```
    return F.binary_cross_entropy(D_real, target)


def D_fake_loss_fn(
        D_fake: torch.FloatTensor, # (batch_size, 1)
        ) -> torch.FloatTensor: # ()
    """
    D_fake is D(G(z)), the discriminator's output when fed with generated images
    We want this to be close to 0, because the discriminator should not be␣
 ↪fooled
    """
    target = torch.zeros_like(D_fake)
    return F.binary_cross_entropy(D_fake, target)


def G_loss_fn(
        D_fake: torch.FloatTensor, # (batch_size, 1)
        ) -> torch.FloatTensor: # ()
    """
    D_fake is D(G(z)), the discriminator's output when fed with generated images
    We want this to be close to 1, because the generator wants to fool the␣
 ↪discriminator
    """
    target = torch.ones_like(D_fake)
    return F.binary_cross_entropy(D_fake, target)
```

2.4 Training (15)

We suggest you avoid copy-pasting from the recitation and try to remember the steps in training a GAN to learn it well. After you implement your solution, compare with the recitation and correct your code accordingly.

[47]:
```
def train_GAN(
        generator: Generator,
        discriminator: Discriminator,
        train_dataset: Dataset,
        device: str = Device,
        plot_freq: int = 100,

        # Generator
        optimizer_name_G: str = 'Adam',
        optimizer_config_G: dict = dict(lr=1e-3),
        lr_scheduler_name_G: Union[str, None] = None,
        lr_scheduler_config_G: dict = dict(),

        # Discriminator
        optimizer_name_D: str = 'Adam',
```

```
        optimizer_config_D: dict = dict(lr=1e-3),
        lr_scheduler_name_D: Union[str, None] = None,
        lr_scheduler_config_D: dict = dict(),

        n_iters: int = 100,
        batch_size: int = 64,
        ):

    generator = generator.to(device)
    discriminator = discriminator.to(device)

    optimizer_G: optim.Optimizer = optim.
↪__getattribute__(optimizer_name_G)(generator.parameters(),␣
↪**optimizer_config_G)
    if lr_scheduler_name_G is not None:
        lr_scheduler_G: lr_scheduler._LRScheduler = lr_scheduler.
↪__getattribute__(lr_scheduler_name_G)(optimizer_G, **lr_scheduler_config_G)

    optimizer_D: optim.Optimizer = optim.
↪__getattribute__(optimizer_name_D)(discriminator.parameters(),␣
↪**optimizer_config_D)
    if lr_scheduler_name_D is not None:
        lr_scheduler_D: lr_scheduler._LRScheduler = lr_scheduler.
↪__getattribute__(lr_scheduler_name_D)(optimizer_D, **lr_scheduler_config_D)

    train_loader = DataLoader(train_dataset, batch_size=batch_size,␣
↪shuffle=True, drop_last=True)

    tracker = GAN_Tracker(n_iters=n_iters, plot_freq=plot_freq)

    iter_pbar = tqdm(range(n_iters), desc='Training', unit='iter')
    iter = 0

    while iter < n_iters:

        for x_real, _ in train_loader:

            x_real = x_real.to(device)
            n_samples = len(x_real)

            # ============ Train Discriminator ============
            generator.train(False).requires_grad_(False)
            discriminator.train(True).requires_grad_(True)

            # Real data
            D_real = discriminator(x_real)
            D_real_loss = D_real_loss_fn(D_real)
```

```
            # Fake data
            x_fake_detached = generator.generate(n_samples, device=device).
↪detach()
            # x_fake already should have required_grad=False, but let's make␣
↪sure with detach()

            assert not x_fake_detached.requires_grad

            D_fake = discriminator(x_fake_detached)
            D_fake_loss = D_fake_loss_fn(D_fake)

            D_loss = (D_real_loss + D_fake_loss) / 2
            D_loss.backward()
            optimizer_D.step()
            if lr_scheduler_name_D is not None:
                lr_scheduler_D.step()
            optimizer_D.zero_grad()

            D_real_avg: float = D_real.mean().item() # average output of␣
↪discriminator on real data, for logging
            D_fake_avg: float = D_fake.mean().item() # average output of␣
↪discriminator on fake data, for logging
            D_loss_item: float = D_loss.item() # For logging

            # ============ Train Generator ============

            generator.train(True).requires_grad_(True)
            discriminator.train(False).requires_grad_(False)

            x_fake_for_g = generator.generate(n_samples, device=device)
            D_fake_for_g = discriminator(x_fake_for_g)
            G_loss = G_loss_fn(D_fake_for_g)

            G_loss.backward()
            optimizer_G.step()
            if lr_scheduler_name_G is not None:
                lr_scheduler_G.step()
            optimizer_G.zero_grad()

            G_loss_item: float = G_loss.item() # For logging

            # ============ Logging =================
            iter += 1
            iter_pbar.update(1)
            if iter % plot_freq == 0:
                with torch.inference_mode():
```

```
                    tracker.get_samples(generator.generate(n_samples=24,␣
↪device=device))
            tracker.update(D_real_avg, D_fake_avg, D_loss_item, G_loss_item)

            if iter >= n_iters:
                break
```

2.5 Find and train a good model (20)

As usual, find a good set of hyperparameters and train your model. However, you have to evaluate your model qualitatively by looking at some generated samples. A nice airfoil would be an airfoil with a smooth surface. For this dataset, making a GAN work is more tricky than what you experienced with a VAE, so the generated samples may not be as smooth. In the figure below, all samples are considered nice enough except one.

Your grade also depends on the diversity of the generated samples. If all your samples look the same, your GAN is suffering from *mode collapse*, and you will get at most 5 points depending on the quality of the sample. If your samples are diverse but not nice, you will get 0 (garbage), 5 (too bad, but looks like airfoils), 10 (not bad), or 15 (almost there) points depending on how nice they are. The grading will be generously done.

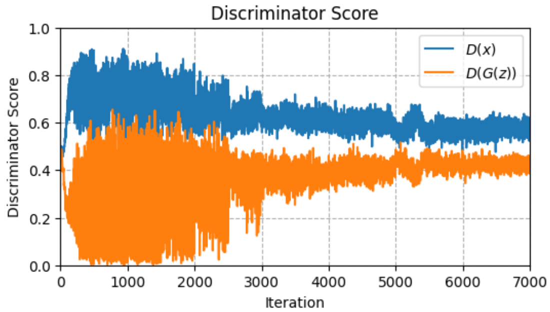
HINT: Think about how to balance the generator and discriminator and stabilize the training as it progresses. You may find using learning rate schedulers useful.

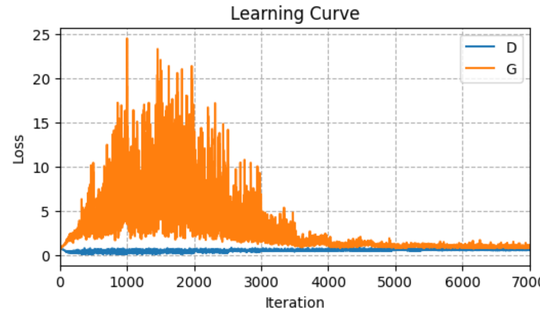
DO NOT CHANGE `input_size` and `latent_size`.

[111]:
```
"""
Choose model and training configuration
"""
input_size = 200 # DO NOT CHANGE
latent_size = 16 # DO NOT CHANGE

generator_config = dict(
    latent_size = latent_size,
    output_size = input_size,
    hidden_dims = [256, 512, 1024],
    batchnorm = True,
    )

discriminator_config = dict(
    input_size = input_size,
    hidden_dims = [1024, 256, 128],
    )

train_config = dict(
    # Generator
```

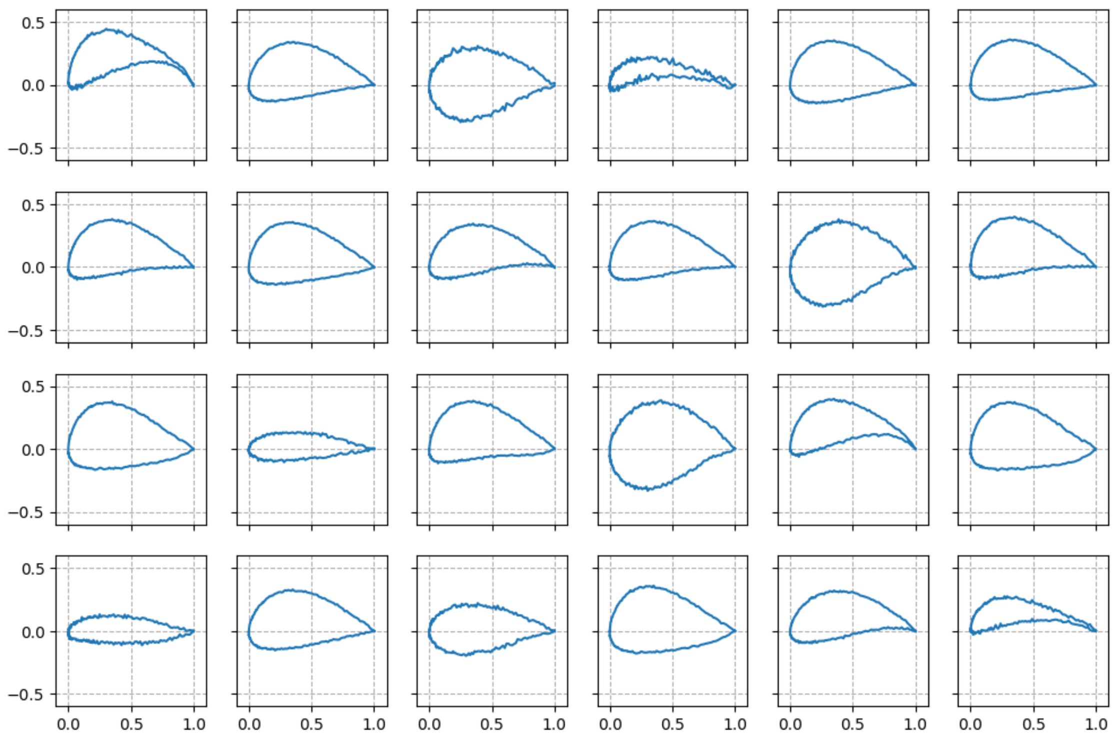
```
    optimizer_name_G = 'Adam',
    optimizer_config_G = dict(
        lr=2e-4,
        betas=(0.5, 0.999),
    ),
    lr_scheduler_name_G = 'StepLR',  # or 'StepLR', 'ExponentialLR', etc.
    lr_scheduler_config_G = dict(
        step_size=500,
        gamma=0.7
    ),

    # Discriminator
    optimizer_name_D = 'Adam',
    optimizer_config_D = dict(
        lr=1e-4,
        betas=(0.5, 0.999),
    ),
    lr_scheduler_name_D = 'StepLR',  # or 'StepLR', 'ExponentialLR', etc.
    lr_scheduler_config_D = dict(
        step_size=500,
        gamma=0.7
    ),

    n_iters = 7000,
    batch_size = 32,
    )
```

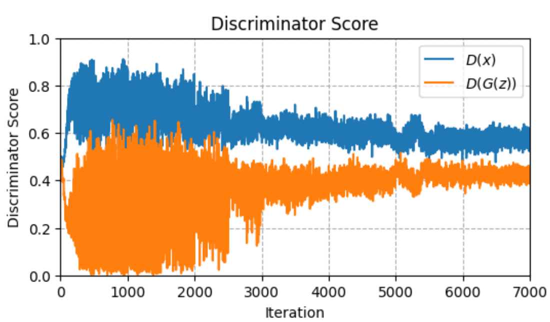
[112]:
```
if __name__ == '__main__':
    generator = Generator(**generator_config)
    discriminator = Discriminator(**discriminator_config)
    train_GAN(
        generator = generator,
        discriminator = discriminator,
        train_dataset = airfoil_dataset,
        device = Device,
        plot_freq = 500,
        **train_config,
        )
```

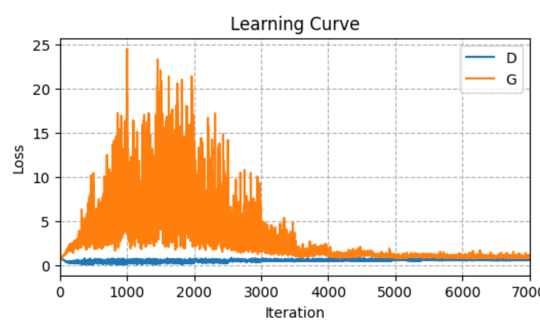


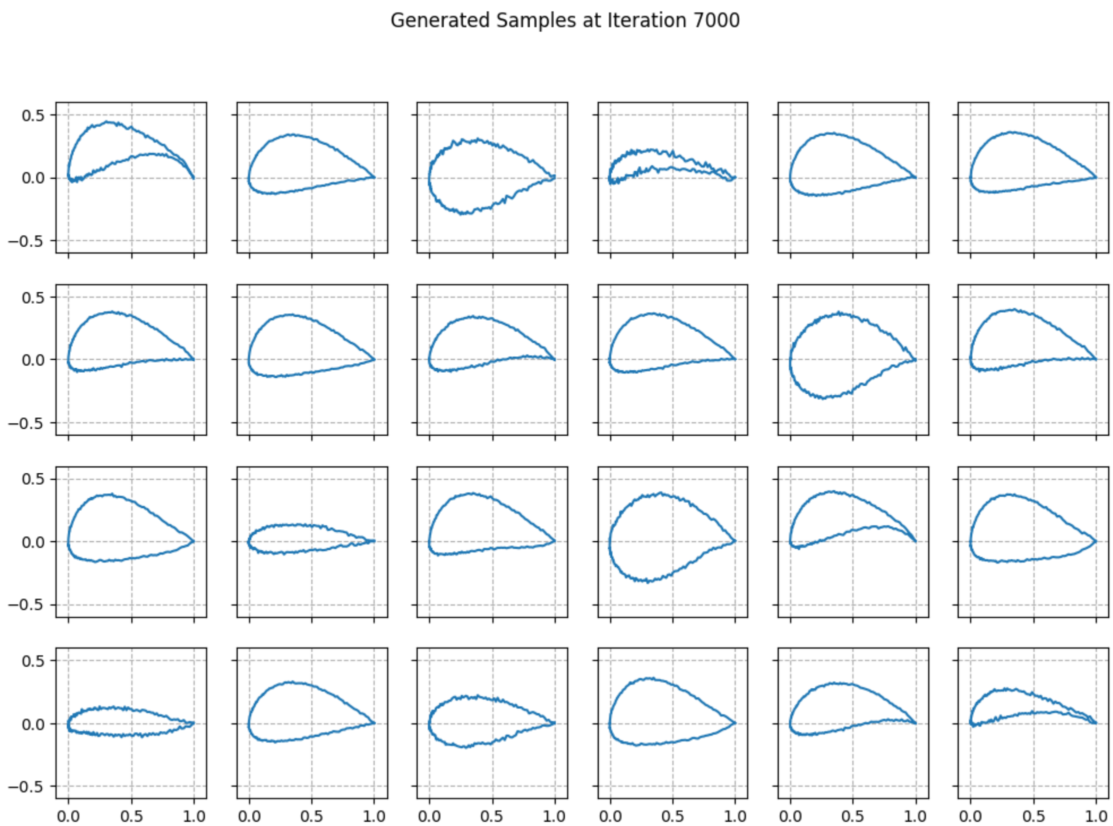


Generated Samples at Iteration 7000









3 Zip files for submission

[ ]:
```
from HW8_utils import save_yaml, zip_files

save_yaml(generator_config, 'generator_config.yaml')
save_yaml(discriminator_config, 'discriminator_config.yaml')
save_yaml(train_config, 'train_config.yaml')

submission_files = ['HW8.ipynb', 'generator_config.yaml', 'discriminator_config.
  ↪yaml', 'train_config.yaml']
zip_files('HW8_submission.zip', submission_files)
```