Assignment-5 Report

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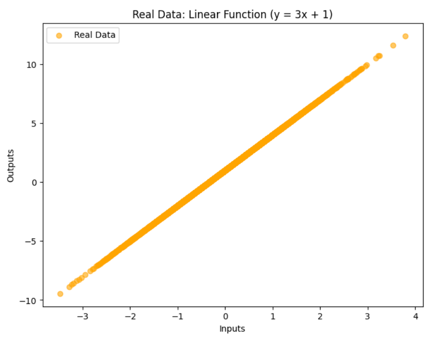
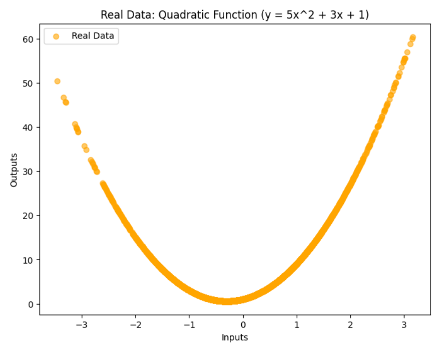
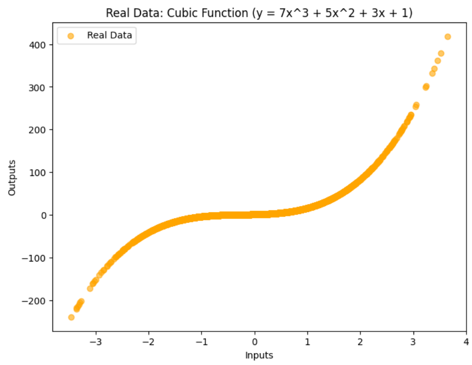
1. Generate the real data for each equation and plot it. For this question my real data plots are:







2. Create a GAN model with a Generator and Discriminator. For the classes gan is like this:

```
class Generator(nn.Module):
    def __init__(self, latent_dim, input_dim, output_dim):
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(latent_dim + input_dim, 64),
            nn.ReLU(),
            nn.Linear(64, 64),
            nn.ReLU(),
            nn.Linear(64, output_dim)
        )

    def forward(self, z, x):
        combined = torch.cat((z, x), dim=1)
        return self.model(combined)

# Define the discriminator
class Discriminator(nn.Module):
    def __init__(self, input_dim):
        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_dim, 64),
            nn.LeakyReLU(0.2),
            nn.Linear(64, 64),
            nn.LeakyReLU(0.2),
            nn.Linear(64, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.model(x)
```

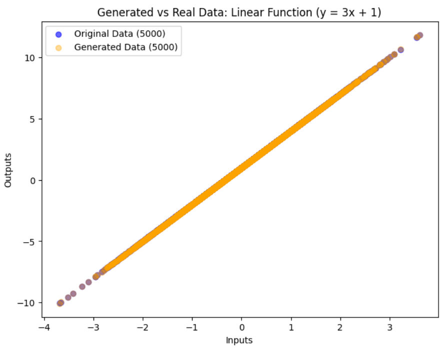
3. Train your generator and discriminator to produce their expected behavior. For this question my logs looks like this:

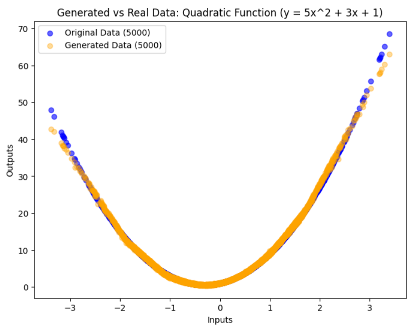
Linear:
Epoch 0/10000, D Loss: 1.4147, G Loss: 0.7268
Epoch 1000/10000, D Loss: 1.3713, G Loss: 0.6964
Epoch 2000/10000, D Loss: 1.3761, G Loss: 0.6987
Epoch 3000/10000, D Loss: 1.3808, G Loss: 0.6969
Epoch 4000/10000, D Loss: 1.3835, G Loss: 0.6921
Epoch 5000/10000, D Loss: 1.3843, G Loss: 0.6994
Epoch 6000/10000, D Loss: 1.3828, G Loss: 0.6952
Epoch 7000/10000, D Loss: 1.3832, G Loss: 0.6925
Epoch 8000/10000, D Loss: 1.3821, G Loss: 0.6952
Epoch 9000/10000, D Loss: 1.3825, G Loss: 0.6901

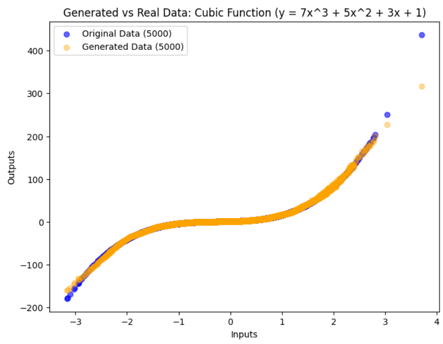
Quadratic:
Epoch 0/10000, D Loss: 1.3816, G Loss: 0.7617
Epoch 1000/10000, D Loss: 1.0653, G Loss: 0.9943
Epoch 2000/10000, D Loss: 1.2859, G Loss: 0.7429
Epoch 3000/10000, D Loss: 1.3206, G Loss: 0.7688
Epoch 4000/10000, D Loss: 1.3385, G Loss: 0.7271
Epoch 5000/10000, D Loss: 1.3428, G Loss: 0.7442
Epoch 6000/10000, D Loss: 1.3573, G Loss: 0.7145
Epoch 7000/10000, D Loss: 1.3653, G Loss: 0.6997
Epoch 8000/10000, D Loss: 1.3703, G Loss: 0.7045
Epoch 9000/10000, D Loss: 1.3739, G Loss: 0.6902

Cubic:
Epoch 0/25000, D Loss: 1.2246, G Loss: 0.6973
Epoch 1000/25000, D Loss: 1.1501, G Loss: 0.9648
Epoch 2000/25000, D Loss: 1.0695, G Loss: 1.0313
Epoch 3000/25000, D Loss: 1.1503, G Loss: 0.9626
Epoch 4000/25000, D Loss: 1.2478, G Loss: 0.8411
Epoch 5000/25000, D Loss: 1.2948, G Loss: 0.7552
Epoch 6000/25000, D Loss: 1.3008, G Loss: 0.7544
Epoch 7000/25000, D Loss: 1.3224, G Loss: 0.7581
Epoch 8000/25000, D Loss: 1.3461, G Loss: 0.7153
Epoch 9000/25000, D Loss: 1.3376, G Loss: 0.7587
Epoch 10000/25000, D Loss: 1.3555, G Loss: 0.7155
Epoch 11000/25000, D Loss: 1.3473, G Loss: 0.7435
Epoch 12000/25000, D Loss: 1.3547, G Loss: 0.7187
Epoch 13000/25000, D Loss: 1.3588, G Loss: 0.7010
Epoch 14000/25000, D Loss: 1.3643, G Loss: 0.7130
Epoch 15000/25000, D Loss: 1.3605, G Loss: 0.7064
Epoch 16000/25000, D Loss: 1.3744, G Loss: 0.7102
Epoch 17000/25000, D Loss: 1.3759, G Loss: 0.6908
Epoch 18000/25000, D Loss: 1.3726, G Loss: 0.6930
Epoch 19000/25000, D Loss: 1.3763, G Loss: 0.7073
Epoch 20000/25000, D Loss: 1.3700, G Loss: 0.7029
Epoch 21000/25000, D Loss: 1.3698, G Loss: 0.6838
Epoch 22000/25000, D Loss: 1.3838, G Loss: 0.6620
Epoch 23000/25000, D Loss: 1.3714, G Loss: 0.7012
Epoch 24000/25000, D Loss: 1.3769, G Loss: 0.6924

4. After training the GAN use the trained generator to generate fake samples. Once you have fake samples, plot real (total 5000) and fake samples (total 5000). For this question my plots for all the functions are:







5. Summary:

The linear function performed the best because its simplicity made it easy for the model to learn . The quadratic function also fit well, but there were small differences at the edges due to its increased complexity. The cubic function had the most difficulty, with larger gaps between the real

and generated data, especially for extreme inputs so I tried it with more epochs and it made it better compared to other models in terms of epochs.
These results show that simpler models like the linear function are easier to train, while quadratic and cubic functions require more effort to capture their complexity. Overall, the performance matches the expected behavior of each function.

```python
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

#import necesseray libraries
```

Define the functions here

```python
# Define functions as per the instructions
def linear_function(x):
    return 3 * x + 1

def quadratic_function(x):
    return 5 * x**2 + 3 * x + 1

def cubic_function(x):
    return 7 * x**3 + 5 * x**2 + 3 * x + 1

# Data generation function
def data_generation(function, batch_s=256, x_range=(-50, 50)):
    data = []
    x = np.random.randn(batch_s)  # Uniformly distributed inputs
    for i in range(batch_s):
        y = function(x[i])
        data.append([x[i], y])
    return torch.FloatTensor(data)

# Normalize and denormalize functions
def normalize(data, min_val, max_val):
    return (data - min_val) / (max_val - min_val) * 2 - 1

def denormalize(data, min_val, max_val):
    return (data + 1) / 2 * (max_val - min_val) + min_val

# Plot real data
def plot_real_data(function, title, x_range=(-50, 50)):
    data = data_generation(function, batch_s=5000, x_range=x_range)
    x = data[:, 0].numpy()
    y = data[:, 1].numpy()
    plt.figure(figsize=(8, 6))
    plt.scatter(x, y, label="Real Data", color="orange", alpha=0.6)
    plt.title(title)
    plt.xlabel("Inputs")
    plt.ylabel("Outputs")
    plt.legend()
    plt.show()
```

Defining generator and discriminator class

```
class Generator(nn.Module):
    def __init__(self, latent_dim, input_dim, output_dim):
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(latent_dim + input_dim, 64),
            nn.ReLU(),
            nn.Linear(64, 64),
            nn.ReLU(),
            nn.Linear(64, output_dim)
        )

    def forward(self, z, x):
        combined = torch.cat((z, x), dim=1)
        return self.model(combined)

# Define the discriminator
class Discriminator(nn.Module):
    def __init__(self, input_dim):
        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_dim, 64),
            nn.LeakyReLU(0.2),
            nn.Linear(64, 64),
            nn.LeakyReLU(0.2),
            nn.Linear(64, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.model(x)
```

train the GAN

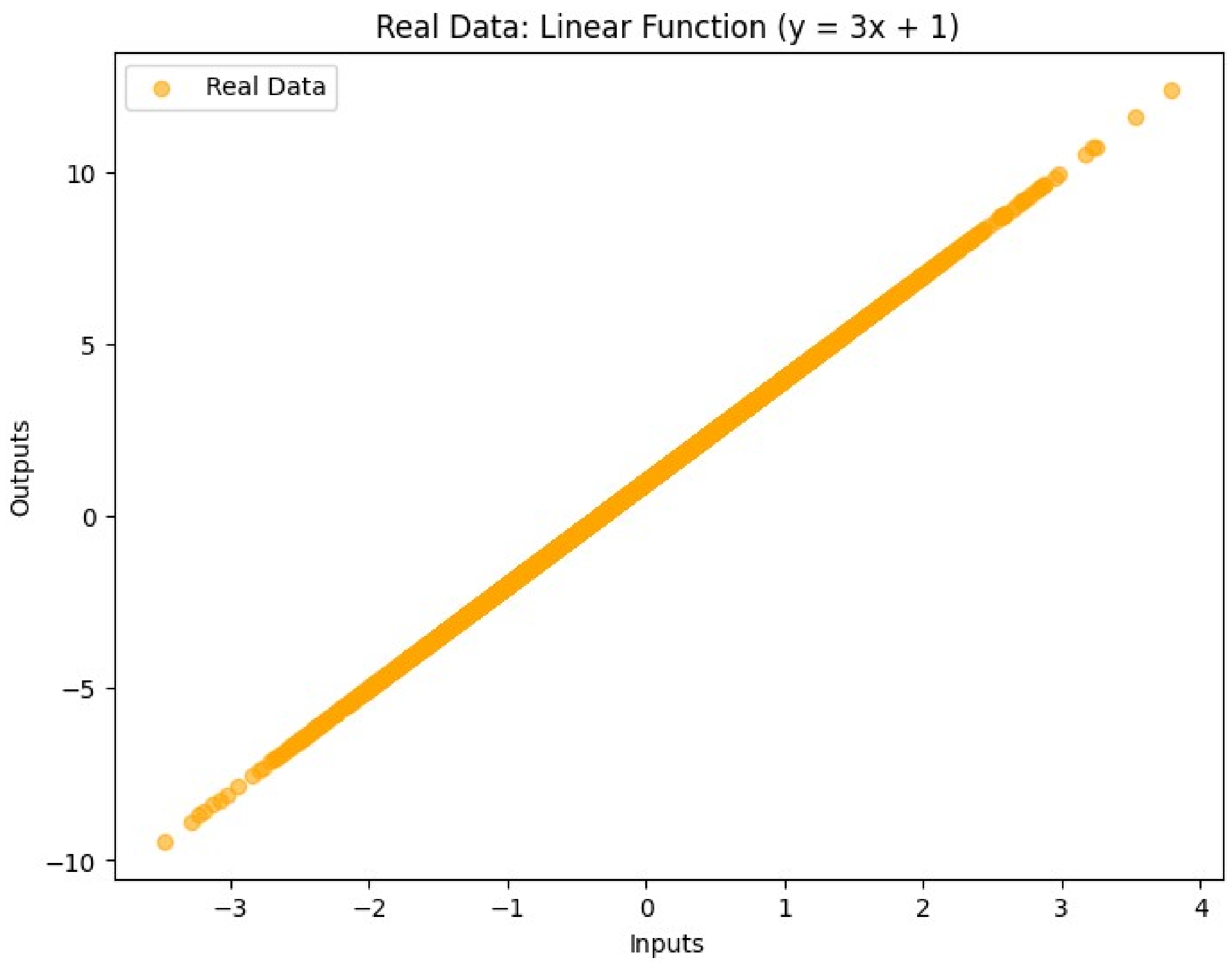
```
def train_gan(generator, discriminator, function, epochs=10000,
batch_size=256, x_range=(-50, 50), lr=0.0002):
    g_optimizer = optim.Adam(generator.parameters(), lr=lr)
    d_optimizer = optim.Adam(discriminator.parameters(), lr=lr)
    criterion = nn.BCELoss()

    for epoch in range(epochs):
        # Generate real data
        real_data = data_generation(function, batch_s=batch_size,
x_range=x_range)
        x_real = real_data[:, 0].unsqueeze(1)  # Inputs
        y_real = real_data[:, 1].unsqueeze(1)  # Outputs

        # Generate fake data
        z_fake = torch.randn(batch_size, 5)  # Latent space
```

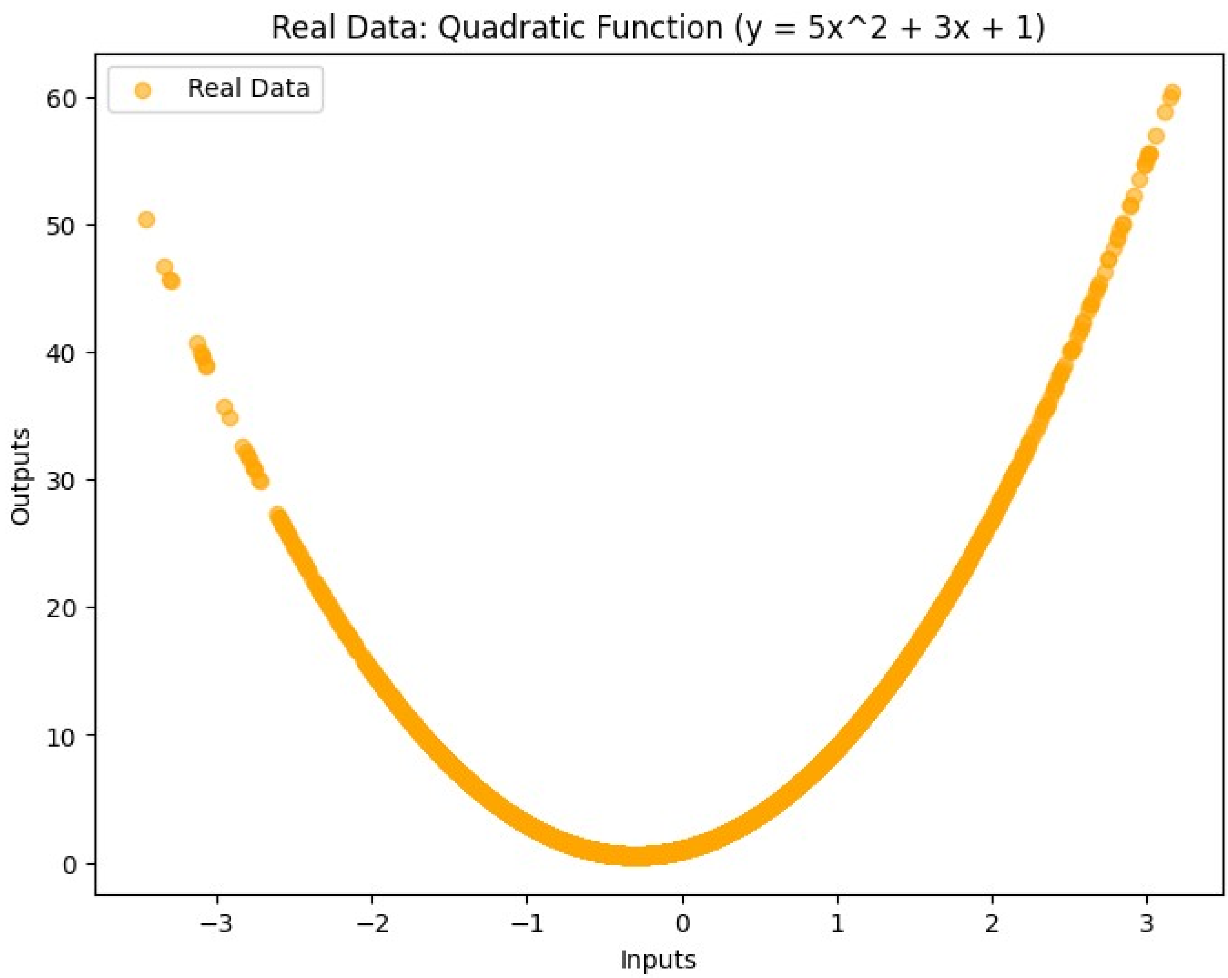
```
        y_fake = generator(z_fake, x_real)
        fake_data = torch.cat((x_real, y_fake), dim=1)

        # Train discriminator
        real_labels = torch.ones(batch_size, 1)
        fake_labels = torch.zeros(batch_size, 1)

        d_loss_real = criterion(discriminator(real_data), real_labels)
        d_loss_fake = criterion(discriminator(fake_data.detach()),
fake_labels)
        d_loss = d_loss_real + d_loss_fake

        d_optimizer.zero_grad()
        d_loss.backward()
        d_optimizer.step()

        # Train generator
        g_loss = criterion(discriminator(fake_data), real_labels)
        g_optimizer.zero_grad()
        g_loss.backward()
        g_optimizer.step()

        if epoch % 1000 == 0:
            print(f"Epoch {epoch}/{epochs}, D Loss:
{d_loss.item():.4f}, G Loss: {g_loss.item():.4f}")
```

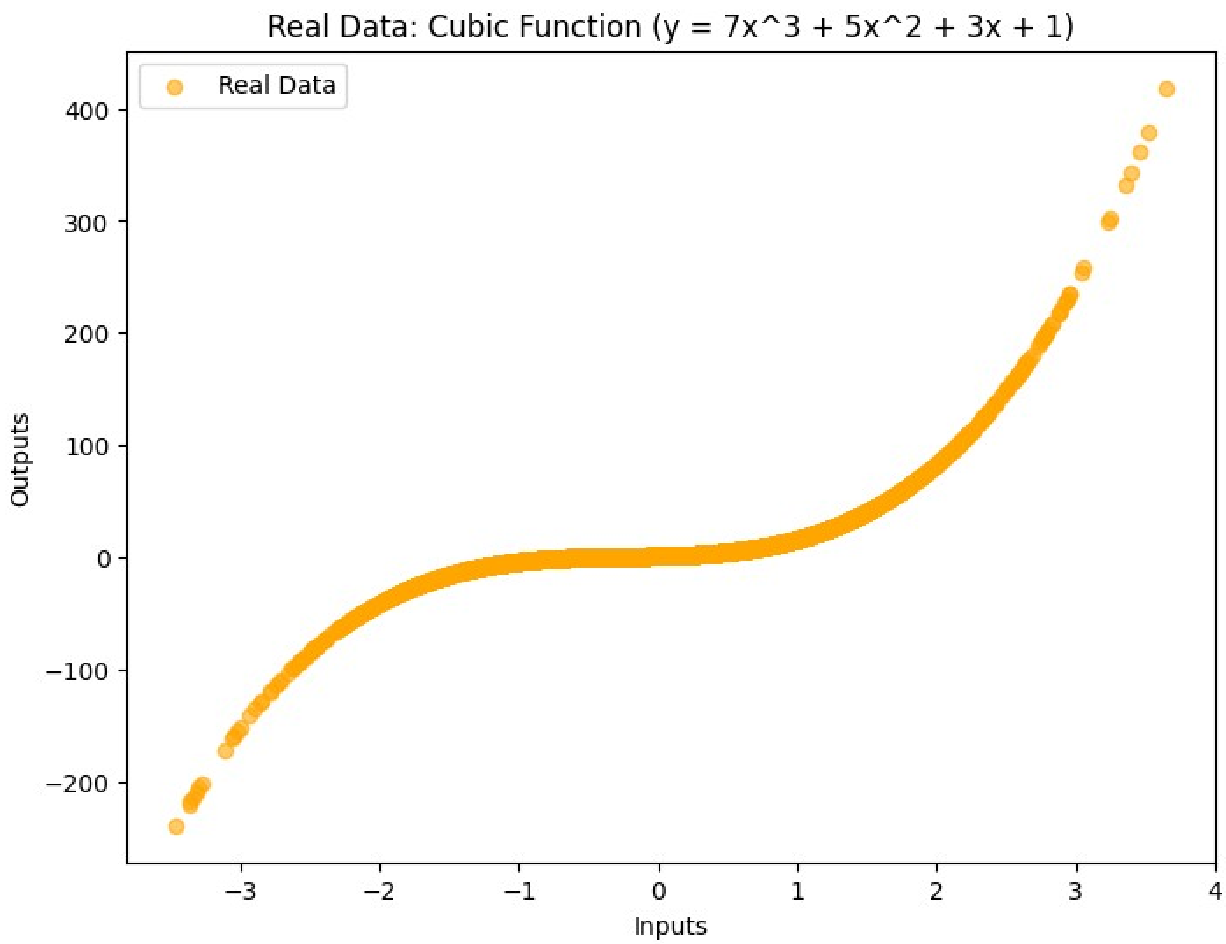
Plot the results for linear quadratic and cubic functions

```
def plot_gan_results(generator, function, title, x_range=(-50, 50)):
    real_data = data_generation(function, batch_s=5000,
x_range=x_range)
    x_real = real_data[:, 0].unsqueeze(1)
    z_fake = torch.randn(5000, 5)
    y_real = real_data[:, 1].numpy()
    y_fake = generator(z_fake, x_real).detach().numpy()

    plt.figure(figsize=(8, 6))
    plt.scatter(real_data[:, 0].numpy(), y_real, label="Original Data
(5000)", color="blue", alpha=0.6)
    plt.scatter(real_data[:, 0].numpy(), y_fake, label="Generated Data
(5000)", color="orange", alpha=0.4)
    plt.title(title)
    plt.xlabel("Inputs")
    plt.ylabel("Outputs")
    plt.legend()
    plt.show()

# Step 1: Plot real data for all functions
plot_real_data(linear_function, "Real Data: Linear Function (y = 3x +
1)")
```

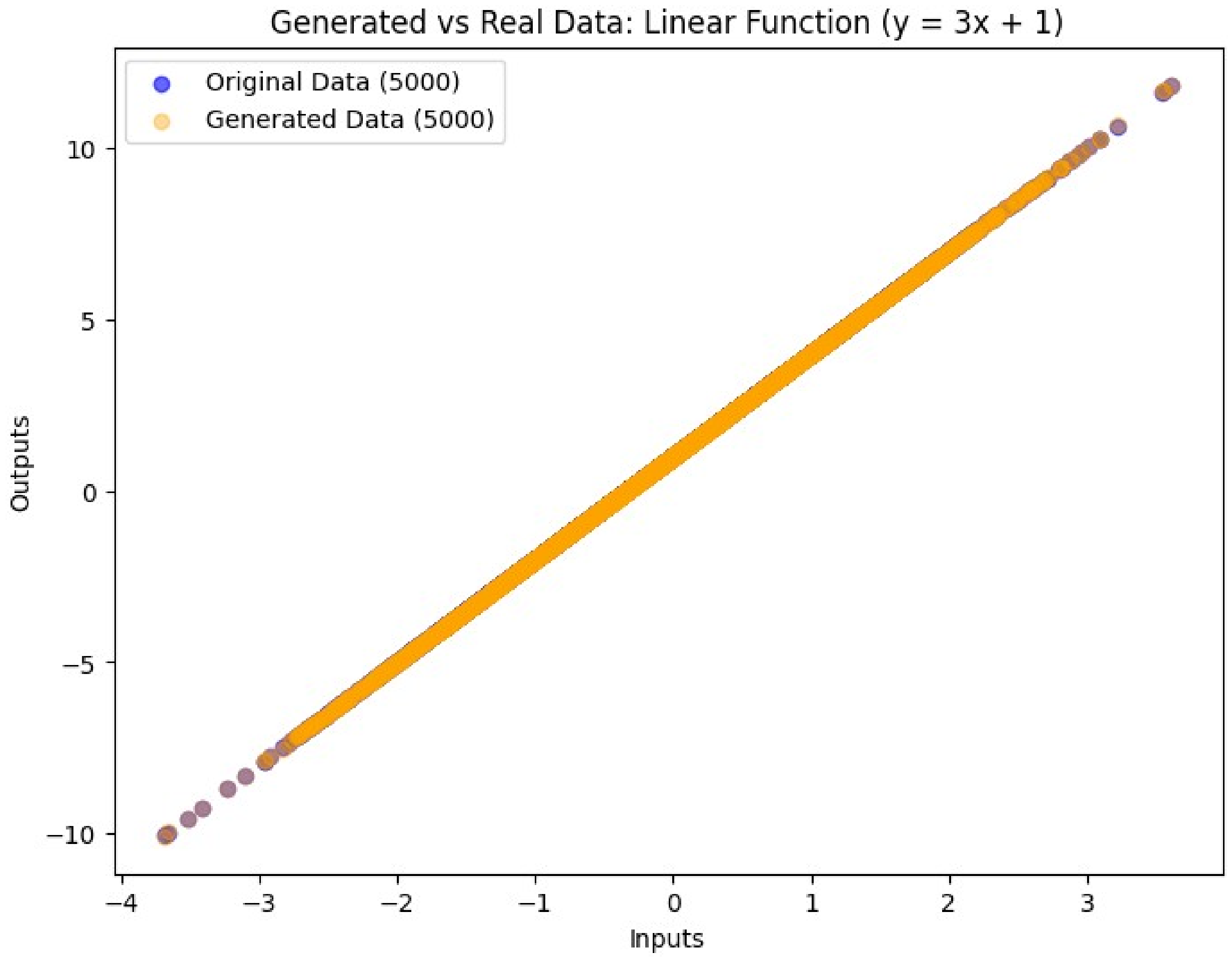
```
plot_real_data(quadratic_function, "Real Data: Quadratic Function (y =
5x^2 + 3x + 1)")
plot_real_data(cubic_function, "Real Data: Cubic Function (y = 7x^3 +
5x^2 + 3x + 1)")

# Step 2: Train GAN and plot results
latent_dim = 5

# Linear
linear_gen = Generator(latent_dim, 1, 1)
linear_disc = Discriminator(2)
train_gan(linear_gen, linear_disc, linear_function, epochs=10000)
plot_gan_results(linear_gen, linear_function, "Generated vs Real Data:
Linear Function (y = 3x + 1)")

# Quadratic
quadratic_gen = Generator(latent_dim, 1, 1)
quadratic_disc = Discriminator(2)
train_gan(quadratic_gen, quadratic_disc, quadratic_function,
epochs=10000)
plot_gan_results(quadratic_gen, quadratic_function, "Generated vs Real
Data: Quadratic Function (y = 5x^2 + 3x + 1)")

# Cubic
cubic_gen = Generator(latent_dim, 1, 1)
cubic_disc = Discriminator(2)
train_gan(cubic_gen, cubic_disc, cubic_function, epochs=25000)
plot_gan_results(cubic_gen, cubic_function, "Generated vs Real Data:
Cubic Function (y = 7x^3 + 5x^2 + 3x + 1)")
```


Real Data: Linear Function (y = 3x + 1)
Real Data
Outputs
Inputs
10
5
0
−5
−10
−3
−2
−1
0
1
2
3
4


Real Data: Quadratic Function (y = 5x^2 + 3x + 1)
Real Data
Outputs
Inputs
60
50
40
30
20
10
0
−3
−2
−1
0
1
2
3




```
Epoch 0/10000, D Loss: 1.4147, G Loss: 0.7268
Epoch 1000/10000, D Loss: 1.3713, G Loss: 0.6964
Epoch 2000/10000, D Loss: 1.3761, G Loss: 0.6987
Epoch 3000/10000, D Loss: 1.3808, G Loss: 0.6969
Epoch 4000/10000, D Loss: 1.3835, G Loss: 0.6921
Epoch 5000/10000, D Loss: 1.3843, G Loss: 0.6994
Epoch 6000/10000, D Loss: 1.3828, G Loss: 0.6952
Epoch 7000/10000, D Loss: 1.3832, G Loss: 0.6925
Epoch 8000/10000, D Loss: 1.3821, G Loss: 0.6952
Epoch 9000/10000, D Loss: 1.3825, G Loss: 0.6901
```




```
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Epoch 4000/10000, D Loss: 1.3385, G Loss: 0.7271
Epoch 5000/10000, D Loss: 1.3428, G Loss: 0.7442
Epoch 6000/10000, D Loss: 1.3573, G Loss: 0.7145
Epoch 7000/10000, D Loss: 1.3653, G Loss: 0.6997
Epoch 8000/10000, D Loss: 1.3703, G Loss: 0.7045
Epoch 9000/10000, D Loss: 1.3739, G Loss: 0.6902
```

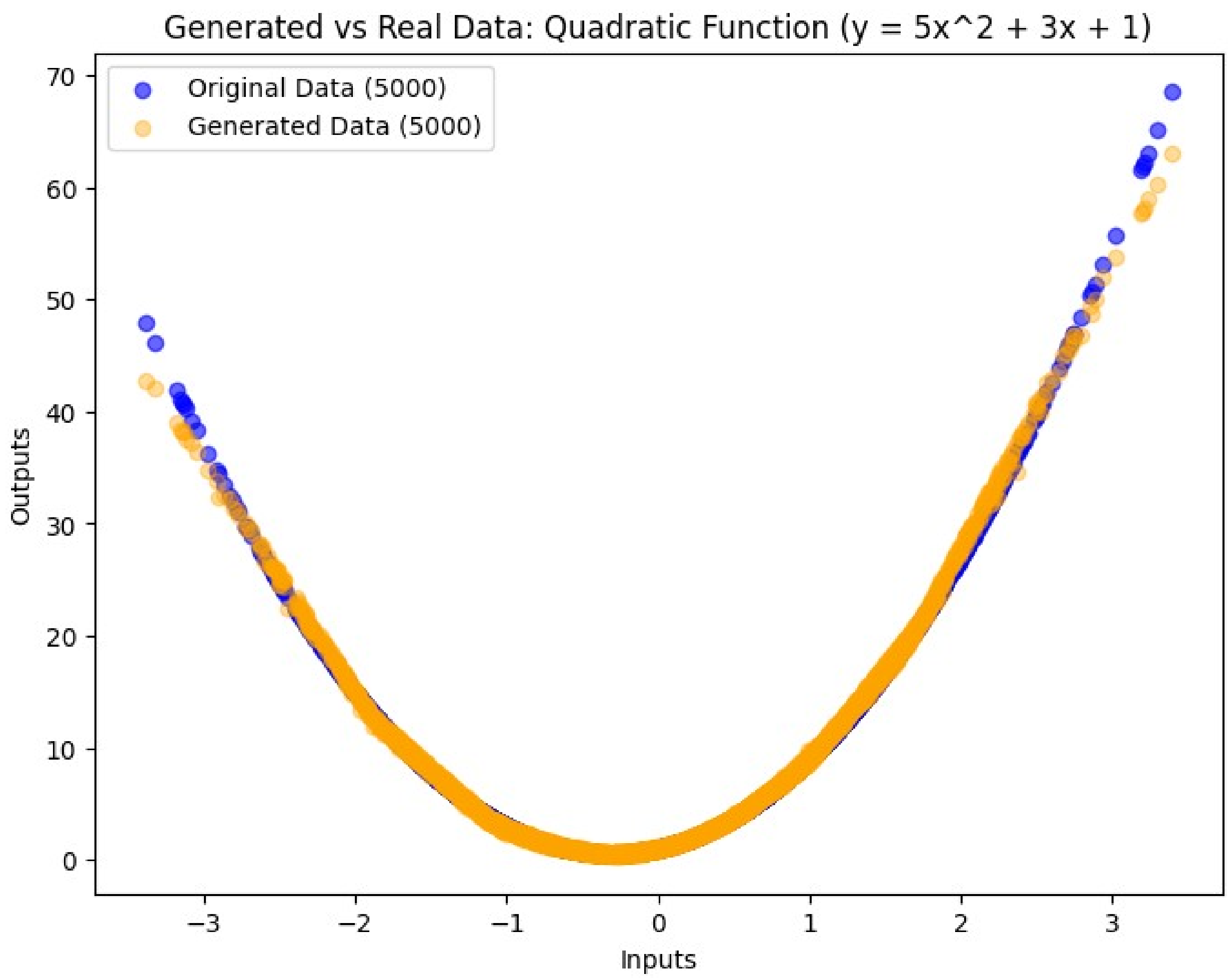


```
Epoch 0/25000, D Loss: 1.2246, G Loss: 0.6973
Epoch 1000/25000, D Loss: 1.1501, G Loss: 0.9648
Epoch 2000/25000, D Loss: 1.0695, G Loss: 1.0313
Epoch 3000/25000, D Loss: 1.1503, G Loss: 0.9626
Epoch 4000/25000, D Loss: 1.2478, G Loss: 0.8411
Epoch 5000/25000, D Loss: 1.2948, G Loss: 0.7552
Epoch 6000/25000, D Loss: 1.3008, G Loss: 0.7544
Epoch 7000/25000, D Loss: 1.3224, G Loss: 0.7581
Epoch 8000/25000, D Loss: 1.3461, G Loss: 0.7153
Epoch 9000/25000, D Loss: 1.3376, G Loss: 0.7587
Epoch 10000/25000, D Loss: 1.3555, G Loss: 0.7155
Epoch 11000/25000, D Loss: 1.3473, G Loss: 0.7435
Epoch 12000/25000, D Loss: 1.3547, G Loss: 0.7187
Epoch 13000/25000, D Loss: 1.3588, G Loss: 0.7010
Epoch 14000/25000, D Loss: 1.3643, G Loss: 0.7130
Epoch 15000/25000, D Loss: 1.3605, G Loss: 0.7064
Epoch 16000/25000, D Loss: 1.3744, G Loss: 0.7102
Epoch 17000/25000, D Loss: 1.3759, G Loss: 0.6908
Epoch 18000/25000, D Loss: 1.3726, G Loss: 0.6930
```

```
Epoch 19000/25000, D Loss: 1.3763, G Loss: 0.7073
Epoch 20000/25000, D Loss: 1.3700, G Loss: 0.7029
Epoch 21000/25000, D Loss: 1.3698, G Loss: 0.6838
Epoch 22000/25000, D Loss: 1.3838, G Loss: 0.6620
Epoch 23000/25000, D Loss: 1.3714, G Loss: 0.7012
Epoch 24000/25000, D Loss: 1.3769, G Loss: 0.6924
```