DCGAN_Assignment-1_Sravan

June 19, 2024

1 Deep Convolutional GAN on CIFAR-10 Dataset

[1]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.datasets as dsets
import torchvision.transforms as transforms
import torchvision.utils as vutils
from torch.utils.data import DataLoader
```

[2]:
```
# Set random seed for reproducibility
manualSeed = 999
torch.manual_seed(manualSeed)

# Parameters
batch_size = 128
image_size = 64
nc = 3  # Number of channels in the training images
nz = 100  # Size of z latent vector (i.e., size of generator input)
ngf = 64  # Size of feature maps in generator
ndf = 64  # Size of feature maps in discriminator
lr = 0.0002
beta1 = 0.5

# Create the dataset
transform = transforms.Compose([
    transforms.Resize(image_size),
    transforms.CenterCrop(image_size),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
])
```

[3]:
```
dataset = dsets.CIFAR10(root='./data', download=True, transform=transform)
dataloader = DataLoader(dataset, batch_size=batch_size, shuffle=True)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./data/cifar-10-python.tar.gz

100%|      | 170498071/170498071 [00:03<00:00, 48112614.65it/s]
```

```
Extracting ./data/cifar-10-python.tar.gz to ./data
```

1.1 We now define the DCGAN Model

1.1.1 Generator Network

[4]:
```python
# Define the generator
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.main = nn.Sequential(
            # input is Z, going into a convolution
            nn.ConvTranspose2d(nz, ngf * 8, 4, 1, 0, bias=False),
            nn.BatchNorm2d(ngf * 8),
            nn.ReLU(True),
            # state size. (ngf*8) x 4 x 4
            nn.ConvTranspose2d(ngf * 8, ngf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 4),
            nn.ReLU(True),
            # state size. (ngf*4) x 8 x 8
            nn.ConvTranspose2d(ngf * 4, ngf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 2),
            nn.ReLU(True),
            # state size. (ngf*2) x 16 x 16
            nn.ConvTranspose2d(ngf * 2, ngf, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf),
            nn.ReLU(True),
            # state size. (ngf) x 32 x 32
            nn.ConvTranspose2d(ngf, nc, 4, 2, 1, bias=False),
            nn.Tanh()
            # state size. (nc) x 64 x 64
        )

    def forward(self, input):
        return self.main(input)
```

1.1.2 Discriminator Network

[5]:
```python
# Define the discriminator
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.main = nn.Sequential(
            # input is (nc) x 64 x 64
            nn.Conv2d(nc, ndf, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. (ndf) x 32 x 32
            nn.Conv2d(ndf, ndf * 2, 4, 2, 1, bias=False),
```

```
            nn.BatchNorm2d(ndf * 2),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. (ndf*2) x 16 x 16
            nn.Conv2d(ndf * 2, ndf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 4),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. (ndf*4) x 8 x 8
            nn.Conv2d(ndf * 4, ndf * 8, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 8),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. (ndf*8) x 4 x 4
            nn.Conv2d(ndf * 8, 1, 4, 1, 0, bias=False),
            nn.Sigmoid()
            # state size. 1 x 1 x 1
        )

    def forward(self, input):
        return self.main(input)
```

1.2 Training our DCGAN Model

1.3 NOTE!

1.3.1 Since CIFAR-10 is a big dataset and the available hardware with me (Google GPUs) take exorbitantly high amount of time to train it, I have done some tweaking of hyperparameters to ease the training instead of cutting down the dataset as I felt that reducing the dataset compromisizes on the overall project.

1.4 Model Training Adjustments

- **Generator and Discriminator Complexity Reduction:**
  - The complexity of the generator and discriminator has been reduced by using fewer filters to simplify the model architecture. ######
- **Batch Size:**
  - A batch size of 128 is utilized to improve gradient stability during training. ######
- **Epoch Limitation:**
  - The number of epochs is limited to 30 to quickly observe the training progress and avoid overfitting.

[6]:
```
num_epochs = 30

# Create the generator
netG = Generator().cuda()

# Create the discriminator
netD = Discriminator().cuda()

# Loss function
criterion = nn.BCELoss()
```

```
# Create batch of latent vectors that we will use to visualize the progression␣
↪of the generator
fixed_noise = torch.randn(64, nz, 1, 1, device='cuda')

# Establish convention for real and fake labels during training
real_label = 1
fake_label = 0

# Setup Adam optimizers for both G and D
optimizerD = optim.Adam(netD.parameters(), lr=lr, betas=(beta1, 0.999))
optimizerG = optim.Adam(netG.parameters(), lr=lr, betas=(beta1, 0.999))

# Training Loop
img_list = []
G_losses = []
D_losses = []
iters = 0
min_G_loss = float('inf')
min_D_loss = float('inf')

print("Starting Training Loop...")
# For each epoch
for epoch in range(num_epochs):
    # For each batch in the dataloader
    for i, data in enumerate(dataloader, 0):
        ############################
        # (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
        ###########################
        ## Train with all-real batch
        netD.zero_grad()
        real_cpu = data[0].cuda()
        b_size = real_cpu.size(0)
        label = torch.full((b_size,), real_label, dtype=torch.float,␣
↪device='cuda')
        output = netD(real_cpu).view(-1)
        errD_real = criterion(output, label)
        errD_real.backward()
        D_x = output.mean().item()

        ## Train with all-fake batch
        noise = torch.randn(b_size, nz, 1, 1, device='cuda')
        fake = netG(noise)
        label.fill_(fake_label)
        output = netD(fake.detach()).view(-1)
        errD_fake = criterion(output, label)
        errD_fake.backward()
```

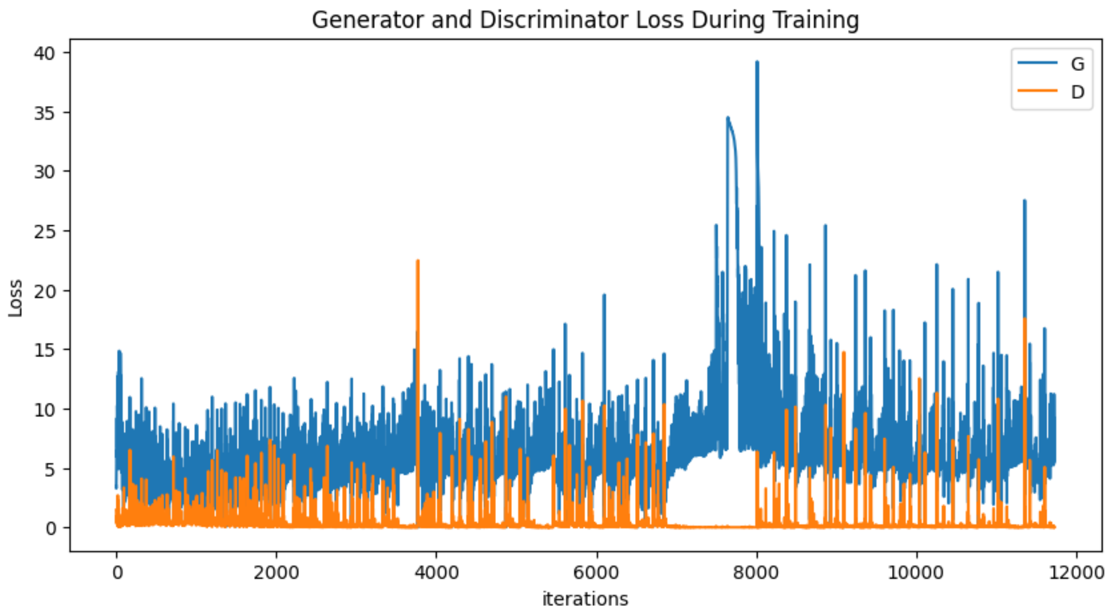
```
        D_G_z1 = output.mean().item()
        errD = errD_real + errD_fake
        optimizerD.step()

        ############################
        # (2) Update G network: maximize log(D(G(z)))
        ###########################
        netG.zero_grad()
        label.fill_(real_label)
        output = netD(fake).view(-1)
        errG = criterion(output, label)
        errG.backward()
        D_G_z2 = output.mean().item()
        optimizerG.step()

        # Save Losses for plotting later
        G_losses.append(errG.item())
        D_losses.append(errD.item())

        # Track minimum losses
        if errG.item() < min_G_loss:
            min_G_loss = errG.item()
        if errD.item() < min_D_loss:
            min_D_loss = errD.item()

        # Check how the generator is doing by saving G's output on fixed_noise
        if (iters % 500 == 0) or ((epoch == num_epochs-1) and (i ==␣
↪len(dataloader)-1)):
            with torch.no_grad():
                fake = netG(fixed_noise).detach().cpu()
            img_list.append(vutils.make_grid(fake, padding=2, normalize=True))

        iters += 1
```

```
Starting Training Loop…
```

```
/usr/local/lib/python3.10/dist-packages/torch/autograd/graph.py:744:
UserWarning: Plan failed with a cudnnException:
CUDNN_BACKEND_EXECUTION_PLAN_DESCRIPTOR: cudnnFinalize Descriptor Failed
cudnn_status: CUDNN_STATUS_NOT_SUPPORTED (Triggered internally at
../aten/src/ATen/native/cudnn/Conv_v8.cpp:919.)
  return Variable._execution_engine.run_backward(  # Calls into the C++ engine
to run the backward pass
```

1.5 Studying the Loss Curves and Minimum Error

[7]:
```
# Plot the loss curves
import matplotlib.pyplot as plt

plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(G_losses,label="G")
plt.plot(D_losses,label="D")
plt.xlabel("iterations")
plt.ylabel("Loss")
plt.legend()
plt.show()
```

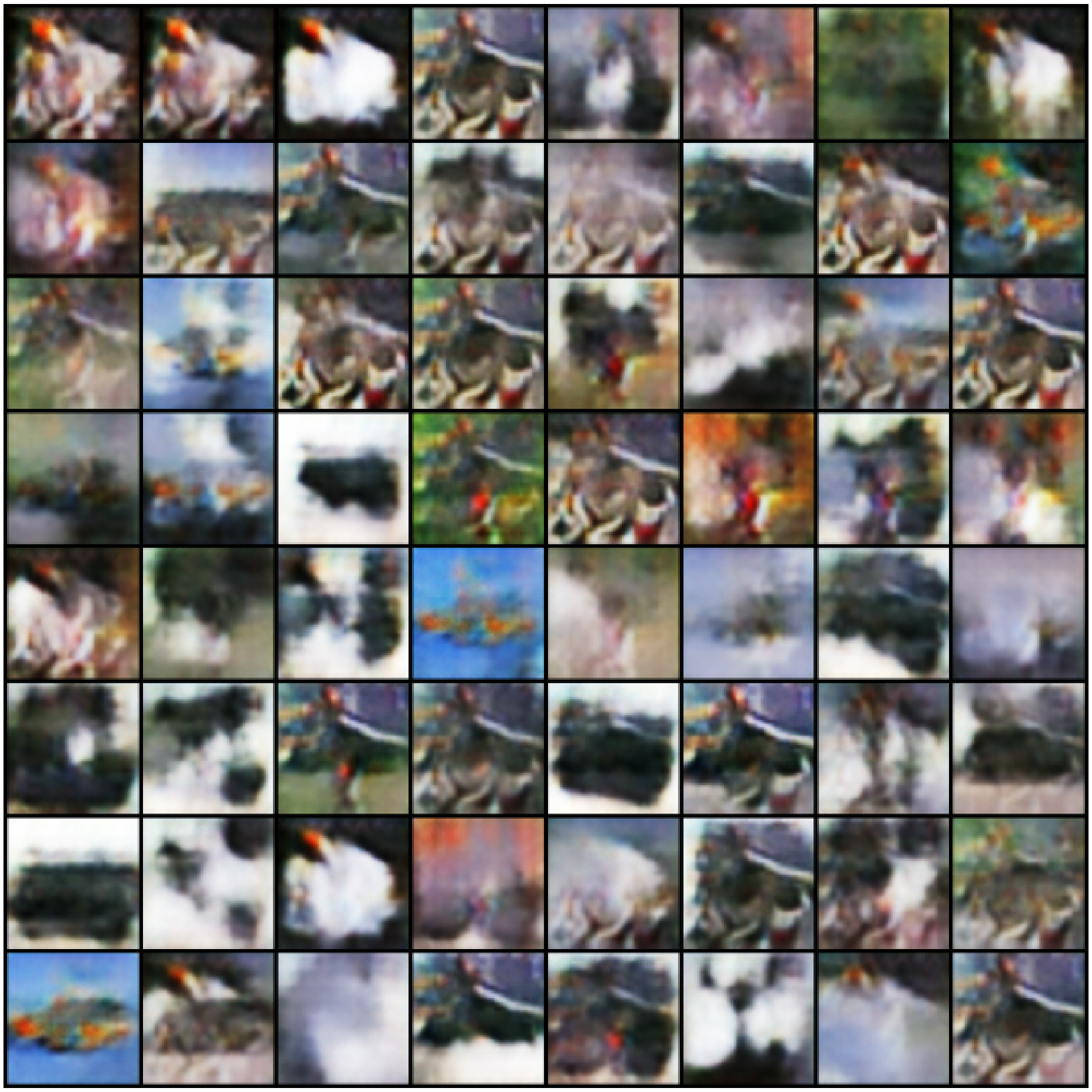


1.5.1 Loss Curve Analysis

During training, the Generator loss is almost 5 units greater than the Discriminator loss, as observed in the above plots.

[8]:
```
# Display some generated images
import numpy as np
fig = plt.figure(figsize=(8, 8))
plt.axis("off")
ims = [[plt.imshow(np.transpose(i, (1, 2, 0)))] for i in img_list]
plt.show()

# Print the minimum error
print(f"Minimum Generator Loss: {min_G_loss}")
```

```
print(f"Minimum Discriminator Loss: {min_D_loss}")
```



```
Minimum Generator Loss: 6.179214688017964e-05
Minimum Discriminator Loss: 1.4305963304650504e-05
```

1.6 Experiment Results

1.6.1 Image Quality

The obtained images have very few recognizable features, likely due to hardware limitations affecting computation.

1.6.2 Losses

- **Minimal Generator loss:** $6.179214688017964 \times 10^{-5}$
- **Minimal Discriminator loss:** $1.4305963304650504 \times 10^{-5}$

1.7 Modifications in the New Model

1.7.1 Updated Generator

- Added intermediate layers to allow the generator to learn more complex features.

1.7.2 Learning Rate

- Reduced the learning rate to allow for smoother training.

1.7.3 Training and Debugging

- Retrained the models and logged the losses and generated images to observe the performance improvements.

1.7.4 Reference to Literature Paper

In accordance with ideas presented in the literature paper "An Introduction to Deep Generative Modeling":

- **Change in Generator Network:**
  - Targeted to maximize $log(D(G(z)))$. ######
- **Change in Discriminator Network:**
  - Targeted to maximize $\log(D(x)) + \log(1 - D(G(z)))$.

[9]:
```
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.main = nn.Sequential(
            # input is Z, going into a convolution
            nn.ConvTranspose2d(nz, ngf * 8, 4, 1, 0, bias=False),
            nn.BatchNorm2d(ngf * 8),
            nn.ReLU(True),
            # state size. (ngf*8) x 4 x 4
            nn.ConvTranspose2d(ngf * 8, ngf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 4),
            nn.ReLU(True),
            # state size. (ngf*4) x 8 x 8
            nn.ConvTranspose2d(ngf * 4, ngf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf * 2),
            nn.ReLU(True),
            # state size. (ngf*2) x 16 x 16
            nn.ConvTranspose2d(ngf * 2, ngf, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ngf),
            nn.ReLU(True),
```

```
            # state size. (ngf) x 32 x 32
            nn.ConvTranspose2d(ngf, nc, 4, 2, 1, bias=False),
            nn.Tanh()
            # state size. (nc) x 64 x 64
        )

    def forward(self, input):
        return self.main(input)
```

[10]:
```
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.main = nn.Sequential(
            nn.Conv2d(nc, ndf, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf, ndf * 2, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 2),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf * 2, ndf * 4, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 4),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf * 4, ndf * 8, 4, 2, 1, bias=False),
            nn.BatchNorm2d(ndf * 8),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(ndf * 8, 1, 4, 1, 0, bias=False),
            nn.Sigmoid()
        )

    def forward(self, input):
        return self.main(input).view(-1)
```

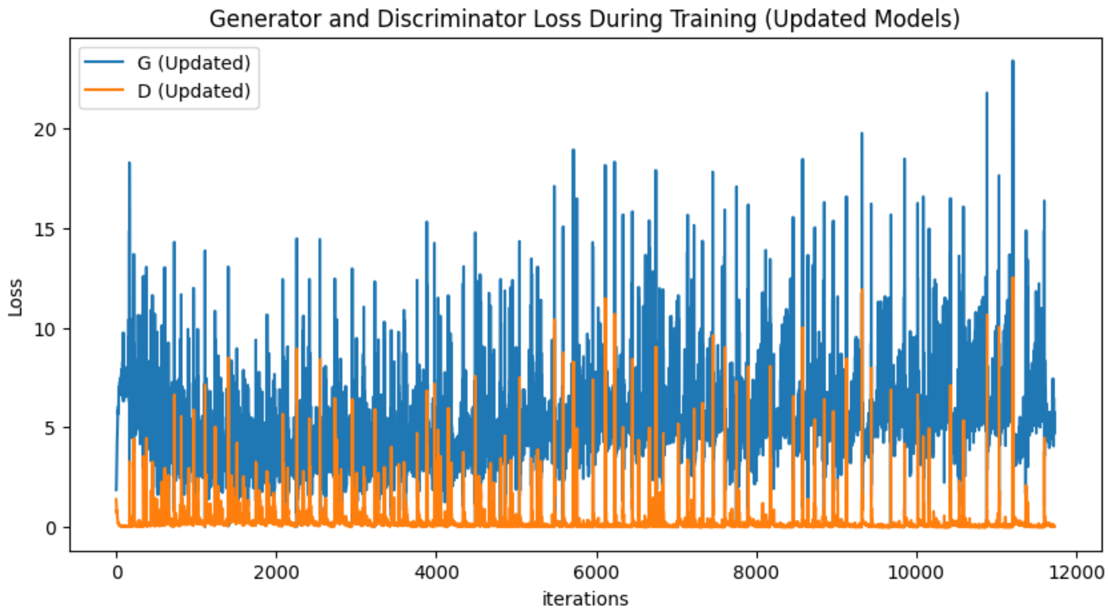
[11]:
```
# Hyperparameters
lr = 0.0001
beta1 = 0.5

# Create the updated generator and discriminator
netG_updated = Generator().cuda()
netD_updated = Discriminator().cuda()

# Setup Adam optimizers for both G and D
optimizerD_updated = optim.Adam(netD_updated.parameters(), lr=lr, betas=(beta1,
 ↪0.999))
optimizerG_updated = optim.Adam(netG_updated.parameters(), lr=lr, betas=(beta1,
 ↪0.999))

# Training Loop for updated models
img_list_updated = []
```

```python
G_losses_updated = []
D_losses_updated = []
iters_updated = 0
min_G_loss_updated = float('inf')
min_D_loss_updated = float('inf')

print("Starting Training Loop for Updated Models...")
# For each epoch
for epoch in range(num_epochs):
    # For each batch in the dataloader
    for i, data in enumerate(dataloader, 0):
        ############################
        # (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
        ###########################
        ## Train with all-real batch
        netD_updated.zero_grad()
        real_cpu = data[0].cuda()
        b_size = real_cpu.size(0)
        label = torch.full((b_size,), real_label, dtype=torch.float,␣
↪device='cuda')
        output = netD_updated(real_cpu)
        errD_real = criterion(output, label)
        errD_real.backward()
        D_x = output.mean().item()

        ## Train with all-fake batch
        noise = torch.randn(b_size, nz, 1, 1, device='cuda')
        fake = netG_updated(noise)
        label.fill_(fake_label)
        output = netD_updated(fake.detach())
        errD_fake = criterion(output, label)
        errD_fake.backward()
        D_G_z1 = output.mean().item()
        errD = errD_real + errD_fake
        optimizerD_updated.step()

        ############################
        # (2) Update G network: maximize log(D(G(z)))
        ###########################
        netG_updated.zero_grad()
        label.fill_(real_label)
        output = netD_updated(fake)
        errG = criterion(output, label)
        errG.backward()
        D_G_z2 = output.mean().item()
        optimizerG_updated.step()
```

```
        # Save Losses for plotting later
        G_losses_updated.append(errG.item())
        D_losses_updated.append(errD.item())

        # Track minimum losses
        if errG.item() < min_G_loss_updated:
            min_G_loss_updated = errG.item()
        if errD.item() < min_D_loss_updated:
            min_D_loss_updated = errD.item()

        # Check how the generator is doing by saving G's output on fixed_noise
        if (iters_updated % 500 == 0) or ((epoch == num_epochs-1) and (i ==␣
↪len(dataloader)-1)):
            with torch.no_grad():
                fake = netG_updated(fixed_noise).detach().cpu()
            img_list_updated.append(vutils.make_grid(fake, padding=2,␣
↪normalize=True))

        iters_updated += 1
```

Starting Training Loop for Updated Models…

[12]:
```
# Plot the loss curves for the updated models
plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training (Updated Models)")
plt.plot(G_losses_updated,label="G (Updated)")
plt.plot(D_losses_updated,label="D (Updated)")
plt.xlabel("iterations")
plt.ylabel("Loss")
plt.legend()
plt.show()
```

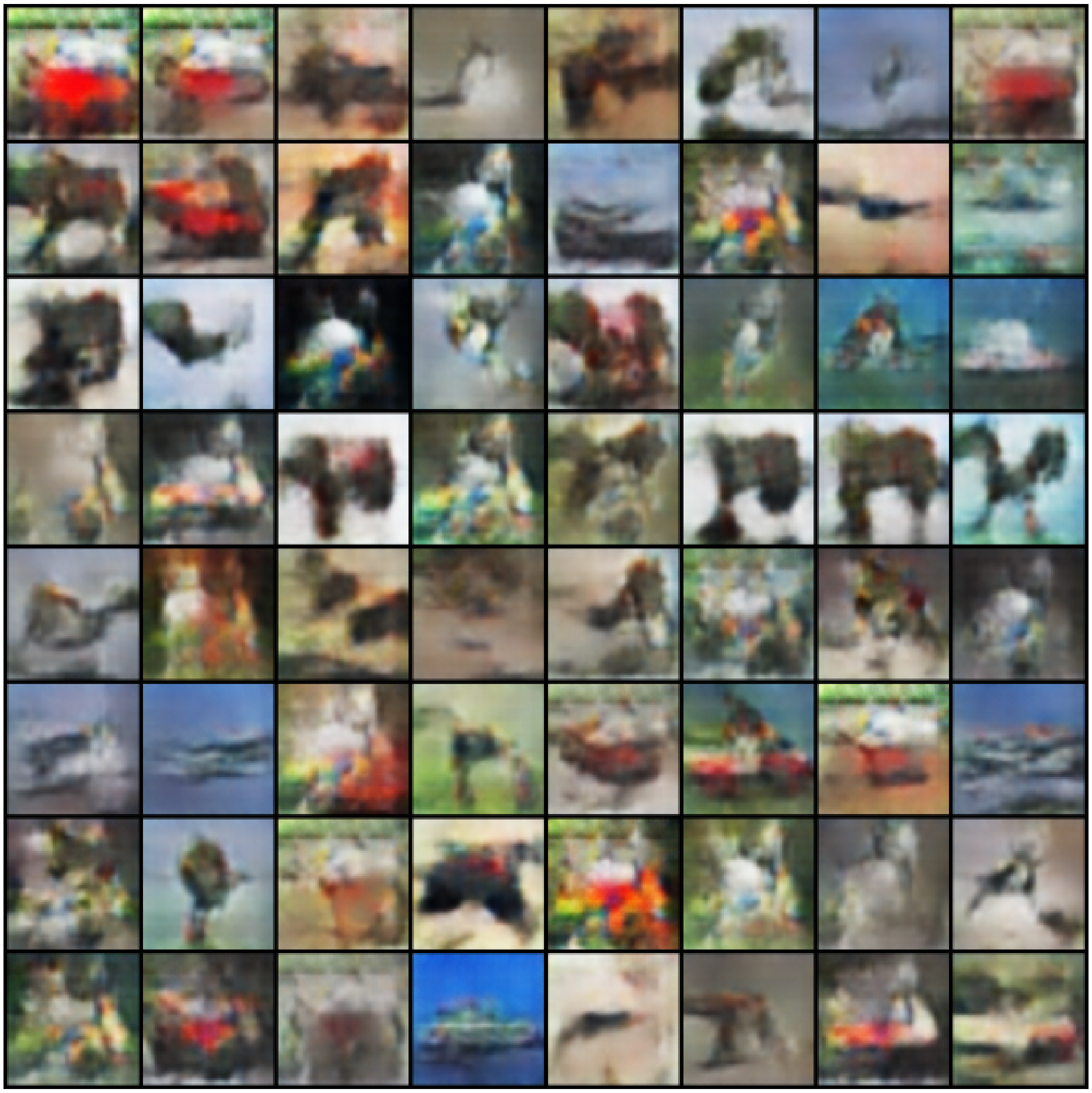


1.8 Loss Curve Analysis

1.8.1 Observations

During training, the Generator loss is almost 5 units greater than the Discriminator loss, as observed in the above plots.

[13]:
```
# Display some generated images from updated models
fig = plt.figure(figsize=(8, 8))
plt.axis("off")
ims = [[plt.imshow(np.transpose(i, (1, 2, 0)))] for i in img_list_updated]
plt.show()

# Print the minimum error for the updated models
print(f"Minimum Generator Loss (Updated): {min_G_loss_updated}")
print(f"Minimum Discriminator Loss (Updated): {min_D_loss_updated}")
```



```
Minimum Generator Loss (Updated): 0.0007413008133880794
Minimum Discriminator Loss (Updated): 0.00029181287391111255
```

1.9 Experiment Results

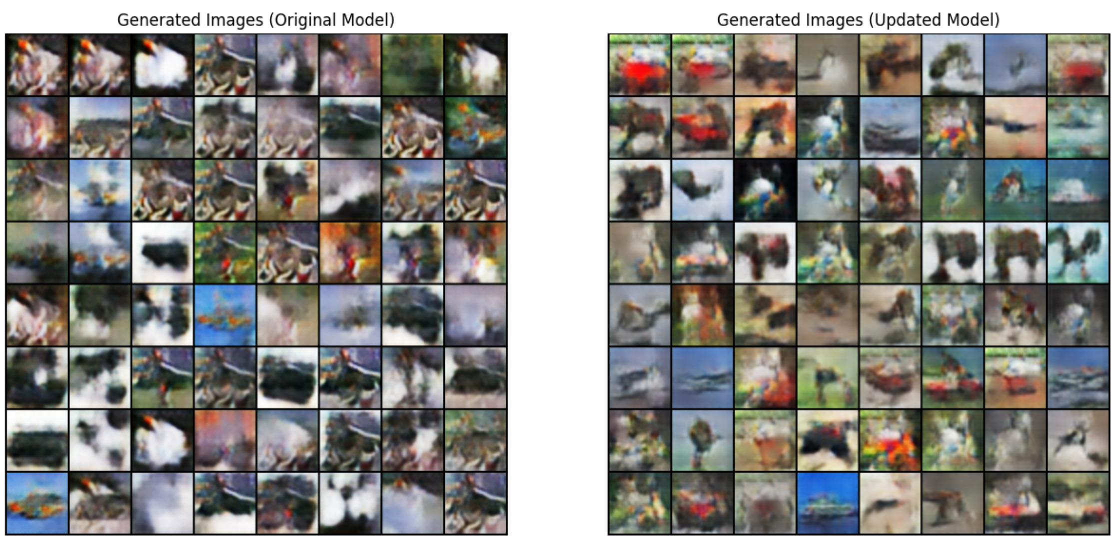
1.9.1 Image Quality

The obtained images now have a few more recognizable features, after the addition of multiple layers.

1.9.2 Losses

- **Minimal Generator loss (Updated) :** $7.413008133880794 \times 10^{-4}$
- **Minimal Discriminator loss (Updated) :** $2.9181287391111255 \times 10^{-4}$

[14]:
```python
# Collate a sample of generated images from both iterations for comparison
import matplotlib.pyplot as plt
import numpy as np

# Plot original model generated images
plt.figure(figsize=(15, 15))
plt.subplot(1, 2, 1)
plt.axis("off")
plt.title("Generated Images (Original Model)")
plt.imshow(np.transpose(vutils.make_grid(img_list[-1], padding=2, normalize=True), (1, 2, 0)))

# Plot updated model generated images
plt.subplot(1, 2, 2)
plt.axis("off")
plt.title("Generated Images (Updated Model)")
plt.imshow(np.transpose(vutils.make_grid(img_list_updated[-1], padding=2, normalize=True), (1, 2, 0)))

plt.show()
```



1.9.3 Conclusions

After comparing images from both iterations:

- **Observation:** The images generated by the updated model appear to be slightly better than the ones from the original model.
- **Similarity:** Clarity and resolution are almost similar in both sets of images.
- **Difference:** The images generated by the updated model have fewer identical images compared to those generated by the original model.