Index

Problem Statement:

The task is to develop a Generative Adversarial Network (GAN) capable of generating abstract art. Abstract art is characterized by its departure from representational accuracy, often focusing on shapes, colors, and forms to convey emotions or concepts rather than depicting specific objects or scenes. The challenge lies in training a GAN architecture to learn the intricate patterns, textures, and compositions that define abstract art, while also ensuring the generated images possess aesthetic appeal, creativity, and diversity. The model should be capable of producing novel, visually engaging abstract artworks that evoke emotions, spark imagination, and resonate with viewers. These generated Images can be used anywhere from wall paintings, phone cases, aesthetic paintings, pillow covers and in many decorations.

Code :

```
import os
import torch
import torchvision
import torch.nn as nn
from tqdm.notebook import tqdm
import torch.nn.functional as F
import matplotlib.pyplot as plt
from IPython.display import Image
import torchvision.transforms as T
from torch.utils.data import DataLoader
from torchvision.utils import make_grid
from torchvision.utils import save_image
!unzip -u "/content/drive/MyDrive/DeepLearning/data/art.zip" -d
"/content/drive/MyDrive/DeepLearning/data/art"
DATA_DIR = "/content/drive/MyDrive/DeepLearning/data/art"
stats = (.5, .5, .5), (.5, .5, .5)
transform_ds = T.Compose([
    T.Resize((128, 128)),
    T.CenterCrop(128),
    T.RandomHorizontalFlip(),
    T.RandomVerticalFlip(),
    T.ToTensor(),
    T.Normalize(*stats)
])
ds = torchvision.datasets.ImageFolder(root=DATA_DIR,
transform=transform_ds)
def denorm(img_tensor):
```

```
    return img_tensor * stats[1][0] + stats[0][0]
batch_size=128
train_dl = DataLoader(ds, batch_size, shuffle=True, num_workers=3,
pin_memory=True)
def  show_image(train_dl):
    for images,_ in train_dl:
        fig, ax = plt.subplots(figsize=(8,8))
        ax.set_xticks([]); ax.set_yticks([])
        ax.imshow(make_grid(denorm(images.detach()[:32]),
nrow=8).permute(1,2,0))
        break

show_image(train_dl)
def get_device():
    if torch.cuda.is_available():
        return torch.device("cuda")
    else:
        return torch.device("cpu")

def to_device(data, device):
    if isinstance(data, (list,tuple)):
        return [to_device(x, device) for x in data]
    return data.to(device, non_blocking=True)

class DeviceDataLoader():
    def __init_(self, dl, device):
        self.dl = dl
        self.device = device

    def __iter__(self):
        for x in self.dl:
            yield to_device(x, self.device)

    def __len__(self):
        return len(self.dl)

device = get_device()
device
train_dl = DeviceDataLoader(train_dl, device)
discriminator = nn.Sequential(
    #in: 128 x 3 x 128 x 128

    nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(64),
    nn.LeakyReLU(0.2, inplace=True),
```

```
    #128 x 64 x 64 x 64

    nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(128),
    nn.LeakyReLU(0.2, inplace=True),
    #128 x 128 x 32 x 32

    nn.Conv2d(128, 256, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(256),
    nn.LeakyReLU(0.2, inplace=True),
    #128 x 256 x 16 x 16

    nn.Conv2d(256, 512, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(512),
    nn.LeakyReLU(0.2, inplace=True),
    #128 x 512 x 8 x 8

    nn.Conv2d(512, 1024, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(1024),
    nn.LeakyReLU(0.2, inplace=True),
    #128 x 1024 x 4 x 4

    nn.Conv2d(1024, 1, kernel_size=4, stride=1, padding=0, bias=False),
    #128 x 1 x 1 x 1

    nn.Flatten(),
    nn.Sigmoid()

)
discriminator = to_device(discriminator, device)
latent_size=128
generator = nn.Sequential(
    #in: 128 x 1 x 1

    nn.ConvTranspose2d(latent_size, 1024, kernel_size=4, stride=1,
padding=0, bias=False),
    nn.BatchNorm2d(1024),
    nn.ReLU(True),
    #128 x 1024 x 4 x 4

    nn.ConvTranspose2d(1024, 512, kernel_size=4, stride=2, padding=1,
bias=False),
    nn.BatchNorm2d(512),
    nn.ReLU(True),
    #128 x 512 x 8 x 8
```

```
    nn.ConvTranspose2d(512, 256, kernel_size=4, stride=2, padding=1,
bias=False),
    nn.BatchNorm2d(256),
    nn.ReLU(True),
    #128 x 256 x 16 x 16

    nn.ConvTranspose2d(256, 128, kernel_size=4, stride=2, padding=1,
bias=False),
    nn.BatchNorm2d(128),
    nn.ReLU(True),
    #128 x 128 x 32 x 32

    nn.ConvTranspose2d(128, 64, kernel_size=4, stride=2, padding=1,
bias=False),
    nn.BatchNorm2d(64),
    nn.ReLU(True),
    #128 x 64 x 64 x 64

    nn.ConvTranspose2d(64, 3, kernel_size=4, stride=2, padding=1,
bias=False),
    #128 x 3 x 128 x 128
    nn.Tanh()


)
generator = to_device(generator, device)
def train_discriminator(real_images, opt_d):
    opt_d.zero_grad()

    real_preds= discriminator(real_images)
    real_targets = torch.ones(real_images.size(0), 1, device=device)
    real_loss = F.binary_cross_entropy(real_preds, real_targets)
    real_score = torch.mean(real_preds).item()

    latent = torch.randn(latent_size, latent_size, 1, 1, device=device)
    fake_images = generator(latent)

    fake_preds= discriminator(fake_images)
    fake_targets = torch.zeros(fake_images.size(0), 1, device=device)
    fake_loss = F.binary_cross_entropy(fake_preds, fake_targets)
    fake_score = torch.mean(fake_preds).item()

    loss = real_loss + fake_loss
    loss.backward(),
```

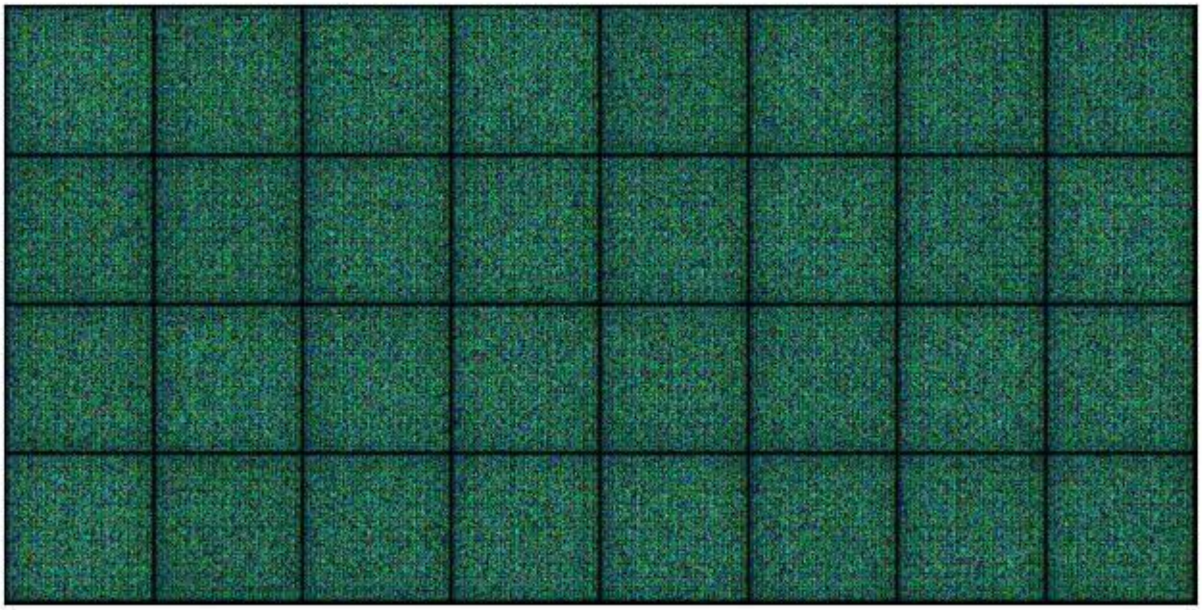
```
    opt_d.step()

    return loss.item(), real_score, fake_score
def train_generator(opt_g):
    opt_g.zero_grad()

    latent = torch.randn(latent_size, latent_size, 1, 1, device=device)
    fake_images = generator(latent)

    preds = discriminator(fake_images)
    targets = torch.ones(fake_images.size(0), 1, device=device)
    loss = F.binary_cross_entropy(preds, targets)

    loss.backward(),
    opt_g.step()

    return loss.item()
sample_dir = "generated"
os.makedirs(sample_dir, exist_ok=True)
def save_sample(index, fixed_latent, show=True):
    fake_images = generator(fixed_latent)
    fake_fname = "generated-images-{0:0=4d}.png".format(index)
    save_image(denorm(fake_images), os.path.join(sample_dir, fake_fname),
nrow=8)
    if show:
        fig, ax = plt.subplots(figsize=(8,8))
        ax.set_xticks([]); ax.set_yticks([])
        ax.imshow(make_grid(fake_images.cpu().detach()[:32],
nrow=8).permute(1,2,0))
fixed_latent = torch.randn(128, latent_size, 1, 1, device=device)
save_sample(0, fixed_latent, show=True)
def fit(epochs, lr_d, lr_g, start_idx=1):
    torch.cuda.empty_cache()

    losses_d = []
    losses_g = []
    real_scores = []
    fake_scores = []

    opt_d = torch.optim.Adam(discriminator.parameters(), lr=lr_d,
betas=(0.5, 0.999))
    opt_g = torch.optim.Adam(generator.parameters(), lr=lr_g, betas=(0.5,
0.999))

    for epoch in range(epochs):
```

```
        for real_images,_ in tqdm(train_dl):
            loss_d, real_score, fake_score =
train_discriminator(real_images, opt_d)
            loss_g = train_generator(opt_g)

        losses_d.append(loss_d)
        losses_g.append(loss_g)
        real_scores.append(real_score)
        fake_scores.append(fake_score)

        print("Epoch: [{}/{}], loss_d: {:.4f}, loss_g: {:.4f}, real_score:
{:.4f}, fake_score: {:.4f}".format(
        epoch+1, epochs, loss_d, loss_g, real_score, fake_score))

        save_sample(epoch+start_idx, fixed_latent, show=False)

    return losses_d, losses_g, real_scores, fake_scores
epochs = 200
lr_d = 10e-5
lr_g = 10e-4
history = [fit(epochs, lr_d, lr_g, start_idx=1)]
Image("/content/generated/generated-images-0200.png")
```

Results:

Train Data

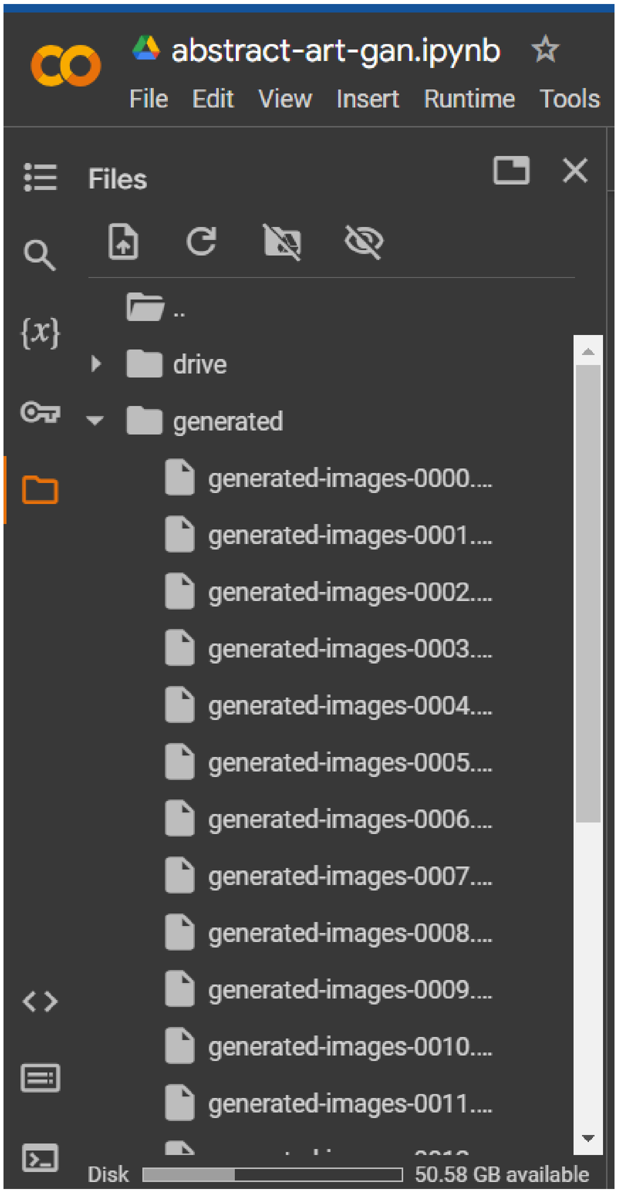
Noise Image before any training



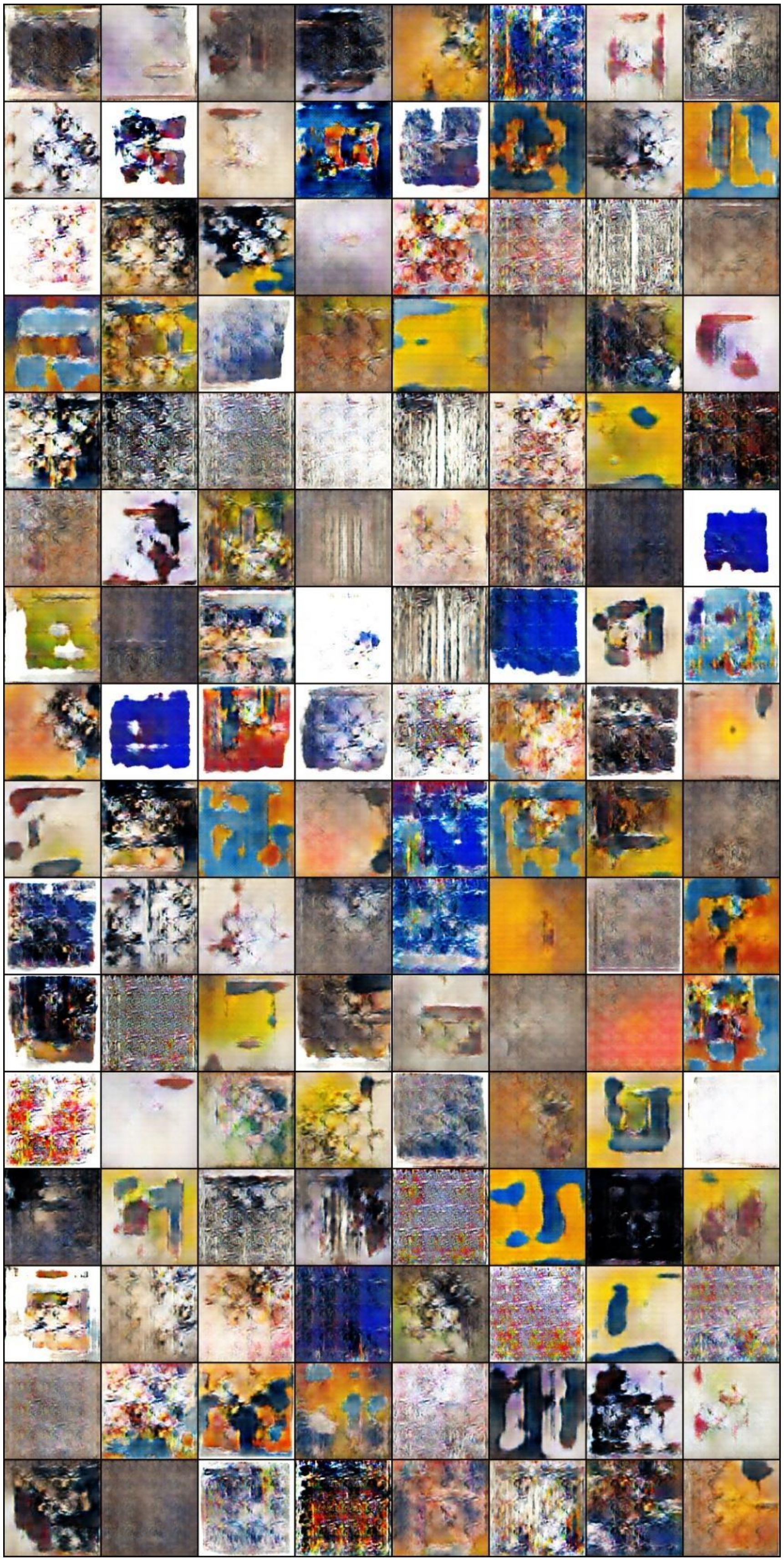
Model fit:

```
history = [fit(epochs, lr_d, lr_g, start_idx=1)]

100% 23/23 [01:10<00:00,  2.61s/it]
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:558: UserWarning: This DataLoader will create 3 worker processes in total. Our suggested max number of worker
  warnings.warn(_create_warning_msg(
/usr/lib/python3.10/multiprocessing/popen_fork.py:66: RuntimeWarning: os.fork() was called. os.fork() is incompatible with multithreaded code, and JAX is multithreaded, so this wil
  self.pid = os.fork()
/usr/lib/python3.10/multiprocessing/popen_fork.py:66: RuntimeWarning: os.fork() was called. os.fork() is incompatible with multithreaded code, and JAX is multithreaded, so this wil
  self.pid = os.fork()
Epoch: [1/20], loss_d: 1.6200, loss_g: 4.4563, real_score: 0.5199, fake_score: 0.5413
100% 23/23 [01:08<00:00,  2.25s/it]
Epoch: [2/20], loss_d: 1.6059, loss_g: 2.3090, real_score: 0.4564, fake_score: 0.5140
100% 23/23 [01:07<00:00,  1.40s/it]
Epoch: [3/20], loss_d: 1.0013, loss_g: 2.6111, real_score: 0.6211, fake_score: 0.3846
100% 23/23 [01:07<00:00,  1.55s/it]
Epoch: [4/20], loss_d: 0.8627, loss_g: 2.0301, real_score: 0.5599, fake_score: 0.2127
100% 23/23 [01:06<00:00,  2.06s/it]
Epoch: [5/20], loss_d: 0.2018, loss_g: 3.7260, real_score: 0.8903, fake_score: 0.0788
100% 23/23 [01:08<00:00,  2.29s/it]
Epoch: [6/20], loss_d: 0.4929, loss_g: 5.3909, real_score: 0.6582, fake_score: 0.0430
100% 23/23 [01:04<00:00,  1.50s/it]
Epoch: [7/20], loss_d: 0.2936, loss_g: 5.1727, real_score: 0.9544, fake_score: 0.2149
100% 23/23 [01:04<00:00,  1.89s/it]
```

Location where images are stored in collab



Generated GAN Images:



Conclusion:

In summary, the development of a Generative Adversarial Network (GAN) for abstract art generation has been a journey of merging technology and creativity. Through meticulous design and training, the essence of abstract art is captured, producing visually compelling artworks that evoke emotions. The deployed interface allows users to interactively explore and generate artworks, fostering deeper engagement with the creative process. While significant progress has been made, further research and ethical considerations remain essential as we continue to push the boundaries of AI-driven artistic expression. This art work can be further improved if Capable GPU and RAM are available for use as the more epochs the model runs the better the quality of those GAN generated Images.