Generative Adversarial Networks (GANs) on Magic: The Gathering Card Images

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Project Overview:

Goals:

- Use GANs to generate images of Magic: The Gathering cards

Methods:

- Download images of Magic: The Gathering cards from MTGJSON
- Use a Generative Adversarial Network (GAN) to generate images of Magic: The Gathering cards
- Make some improvements and use a DCGAN

Notes:

- MTG cards have many different types and many variants
- To train a high performing GAN, I will use a single card type (creature cards) to train the GAN

Literature Review:

Magic: The Gathering has been around for quite some time now and in recent years had a resurgence in popularity due to a new format called EDH or now known as Commander. With the increasing demand of cards came with player finding new ways to play. This may be from proxying their favorite characters onto their favorite cards or making totally new games out of existing cards. With this in mind some have even tried to create cards on their own. From color pencils on paper to adobe photoshop, but none could produce at a larger scale.

Reviewing what the community has done, I've found one attempt by a reddit user who finetuned a GPT-2 model to produce magic cards in text format but it did not generate images. Other attempts I've seen shared on online did not stratify by card type to get better results. I will attempt to try something different by using only creature types who have the most diverity but also prevent discriminator overfitting or mode collapse.

The only paper I've seen come close to what I wanted to do is a paper titled "Looks Like Magic: Transfer Learning in GANs to Generate New Card Illustrations" by Venturelli and Wehrmann 2022. They used a STYLEGAN model to generate illustrations and put them on cards. The mode was able to get really good results. Their model had access to metadata of the magic cards and took 480 GPU hours to just train.

I can't really replicate what they did in this paper for various reasons. My laptop isn't that great and also I would have to do several instances of requesting images with metadata from the Scryfall API. I was able to write a script to pull just images from the MTGJSON repository thing. I will try to do something similar with a regular GAN and a DCGAN, to see if I could generate some close images.

Link to paper:
https://www.researchgate.net/publication/360960919_Looks_Like_Magic_Transfer_Learning_in_GANs_to_Generate_New_Card_Illustrations

Mining the Images

I wrote a script that pulled images from MTGJSON until it basically timed me out or until it gave me an error. Out of approximately 11,0000 creature card images available, I was able to pull about 8,500 which is a small to moderate size for a GAN I've heard.

In [ ]:
```
import json
import os
import requests
import time
import re

# Load the AllPrintings JSON file
with open("AllPrintings.json", "r", encoding="utf-8") as file:
    all_cards_data = json.load(file)

# Define the target folder and card type
target_card_type = "Creature"
image_folder = "mtg_images/creature_cards"
os.makedirs(image_folder, exist_ok=True)

# Track the number of images downloaded
images_downloaded = 0
```

```python
# Loop through each set and card
for set_code, set_data in all_cards_data["data"].items():
    for card in set_data["cards"]:
        # Filter by card type
        if target_card_type in card.get("type", ""):
            # Sanitize card name for URL
            card_name = re.sub(r'[<>:"/\\|?*]', '', card["name"]).replace(" ", "_")
            file_path = f"{image_folder}/{card_name}_{set_code}.jpg"

            # Skip if file already exists
            if os.path.exists(file_path):
                continue

            # Construct the API URL for the exact card and set
            card_name_for_url = requests.utils.quote(card["name"])
            api_url = f"https://api.scryfall.com/cards/named?exact={card_name_for_url}&set={set_code}"

            # Request card data from Scryfall
            response = requests.get(api_url)
            if response.status_code == 200:
                card_data = response.json()
                if "image_uris" in card_data and "normal" in card_data["image_uris"]:
                    image_url = card_data["image_uris"]["normal"]

                    # Download the image
                    image_response = requests.get(image_url)
                    if image_response.status_code == 200:
                        with open(file_path, "wb") as img_file:
                            img_file.write(image_response.content)
                        print(f"Downloaded image for {card['name']} from {set_code}")
                        images_downloaded += 1
                    else:
                        print(f"Failed to download image for {card['name']} - Image status: {image_response.sta
                else:
                    print(f"No image URL available for {card['name']} in set {set_code}")
            else:
                print(f"Failed to retrieve data for {card['name']} from {set_code} - API status: {response.statu

            # Respect Scryfall's rate limit
            time.sleep(0.1)

print(f"Total images downloaded: {images_downloaded}")
```

In [6]:

```python
#Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt


#PyTorch Libraries
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms.v2 as transforms

from torch.utils.data import Dataset, DataLoader
from torchvision.datasets import ImageFolder
from torchvision import datasets
from torch.utils.data import Dataset, DataLoader
from PIL import Image
import os
from torchvision import transforms
```

Preprocessing/Data Loading

In [7]:

```python
transform = transforms.Compose([
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(degrees=15),
    transforms.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1),
    transforms.Resize((64, 64)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
])
```

```
c:\Users\cgrob\anaconda3\Lib\site-packages\torchvision\transforms\v2\_deprecated.py:42: UserWarning: The transfo
rm `ToTensor()` is deprecated and will be removed in a future release. Instead, please use `v2.Compose([v2.ToIma
ge(), v2.ToDtype(torch.float32, scale=True)])`.Output is equivalent up to float precision.
  warnings.warn(
```

In [ ]:

```python
class CreatureCardDataset(Dataset):
```

```
    def __init__(self, image_folder, transform=None):
        self.image_folder = image_folder
        self.transform = transform
        self.image_paths = [os.path.join(image_folder, f) for f in os.listdir(image_folder) if f.endswith('.jpg

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

    def __getitem__(self, idx):
        img_path = self.image_paths[idx]
        img = Image.open(img_path).convert("RGB")

        if self.transform:
            img = self.transform(img)

        return img

# Initialize the dataset and dataloader
dataset = CreatureCardDataset(image_folder="creature_cards", transform=transform)
dataloader = DataLoader(dataset, batch_size=64, shuffle=True)

# Example of iterating through the dataloader
for i, images in enumerate(dataloader):
    print(images.shape)
    if i == 1:
        break
```

```
torch.Size([64, 3, 64, 64])
torch.Size([64, 3, 64, 64])
```

Let's Sample Three Images from the Dataset

In [ ]:

```
import os
import random
from PIL import Image
from IPython.display import display

# Define the directory where images are saved
output_dir = "creature_cards"

# Get a list of image files in the directory
image_files = os.listdir(output_dir)

# Choose a few random images to display
sample_images = random.sample(image_files, 3)

# Display each selected image
for img_file in sample_images:
    img_path = os.path.join(output_dir, img_file)
    img = Image.open(img_path)
    display(img)
    print(f"Displaying image: {img_file}")
```

Displaying image: Hearth_Kami_CHK.jpg

Displaying image: Angel_of_Serenity_C15.jpg


```
Displaying image: Flayer_of_Loyalties_CMM.jpg
```

Set up the GAN architecture

In [10]:

```python
import torch
import torch.nn as nn
import torch.optim as optim

# Generator
class Generator(nn.Module):
    def __init__(self, latent_dim):
        super(Generator, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(latent_dim, 256),
            nn.ReLU(),
            nn.Linear(256, 512),
            nn.ReLU(),
            nn.Linear(512, 1024),
            nn.ReLU(),
            nn.Linear(1024, 3 * 64 * 64),
            nn.Tanh()
        )

    def forward(self, z):
        out = self.model(z)
        return out.view(-1, 3, 64, 64)


# Discriminator
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.model = nn.Sequential(
            nn.Flatten(),
            nn.Linear(3 * 64 * 64, 1024),
            nn.LeakyReLU(0.2),
            nn.Linear(1024, 512),
            nn.LeakyReLU(0.2),
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, 1),
            nn.Sigmoid()  # Output probability
```

```python
        )

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


# Initialize models
latent_dim = 100
generator = Generator(latent_dim)
discriminator = Discriminator()

# Loss and optimizers
criterion = nn.BCELoss()
optimizer_g = optim.Adam(generator.parameters(), lr=0.0002, betas=(0.5, 0.999))
optimizer_d = optim.Adam(discriminator.parameters(), lr=0.0002, betas=(0.5, 0.999))
```

Train the GAN

In [11]:

```python
# Training loop
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
generator.to(device)
discriminator.to(device)

num_epochs = 50
batch_size = 64
real_label = 1.0
fake_label = 0.0

for epoch in range(num_epochs):
    for i, real_images in enumerate(dataloader):
        real_images = real_images.to(device)

        # Train Discriminator
        optimizer_d.zero_grad()

        # Real images
        real_labels = torch.full((real_images.size(0),), real_label, device=device)
        output_real = discriminator(real_images)
        loss_real = criterion(output_real.squeeze(), real_labels)

        # Fake images
        z = torch.randn(real_images.size(0), latent_dim, device=device)
        fake_images = generator(z)
        fake_labels = torch.full((real_images.size(0),), fake_label, device=device)
        output_fake = discriminator(fake_images.detach())
        loss_fake = criterion(output_fake.squeeze(), fake_labels)

        # Total discriminator loss
        loss_d = loss_real + loss_fake
        loss_d.backward()
        optimizer_d.step()

        # Train Generator
        optimizer_g.zero_grad()
        output_fake = discriminator(fake_images)
        loss_g = criterion(output_fake.squeeze(), real_labels)
        loss_g.backward()
        optimizer_g.step()

        if i % 100 == 0:
            print(f"Epoch [{epoch+1}/{num_epochs}], Step [{i}/{len(dataloader)}], "
                  f"D Loss: {loss_d.item():.4f}, G Loss: {loss_g.item():.4f}")

    # Save model checkpoints periodically
    if (epoch + 1) % 10 == 0:
        torch.save(generator.state_dict(), f"generator_epoch_{epoch+1}.pth")
        torch.save(discriminator.state_dict(), f"discriminator_epoch_{epoch+1}.pth")
```

```
Epoch [1/50], Step [0/138], D Loss: 1.3835, G Loss: 0.6782
Epoch [1/50], Step [100/138], D Loss: 0.4917, G Loss: 1.0661
Epoch [2/50], Step [0/138], D Loss: 2.0313, G Loss: 0.5106
Epoch [2/50], Step [100/138], D Loss: 0.4196, G Loss: 1.2969
Epoch [3/50], Step [0/138], D Loss: 0.2960, G Loss: 1.6333
Epoch [3/50], Step [100/138], D Loss: 0.3677, G Loss: 2.2020
Epoch [4/50], Step [0/138], D Loss: 1.4654, G Loss: 1.4853
Epoch [4/50], Step [100/138], D Loss: 0.4901, G Loss: 1.6833
Epoch [5/50], Step [0/138], D Loss: 0.6185, G Loss: 2.0385
Epoch [5/50], Step [100/138], D Loss: 0.4288, G Loss: 1.7610
Epoch [6/50], Step [0/138], D Loss: 1.9289, G Loss: 0.7520
Epoch [6/50], Step [100/138], D Loss: 0.5670, G Loss: 2.4460
Epoch [7/50], Step [0/138], D Loss: 1.1782, G Loss: 1.5231
Epoch [7/50], Step [100/138], D Loss: 0.7816, G Loss: 0.7133
```

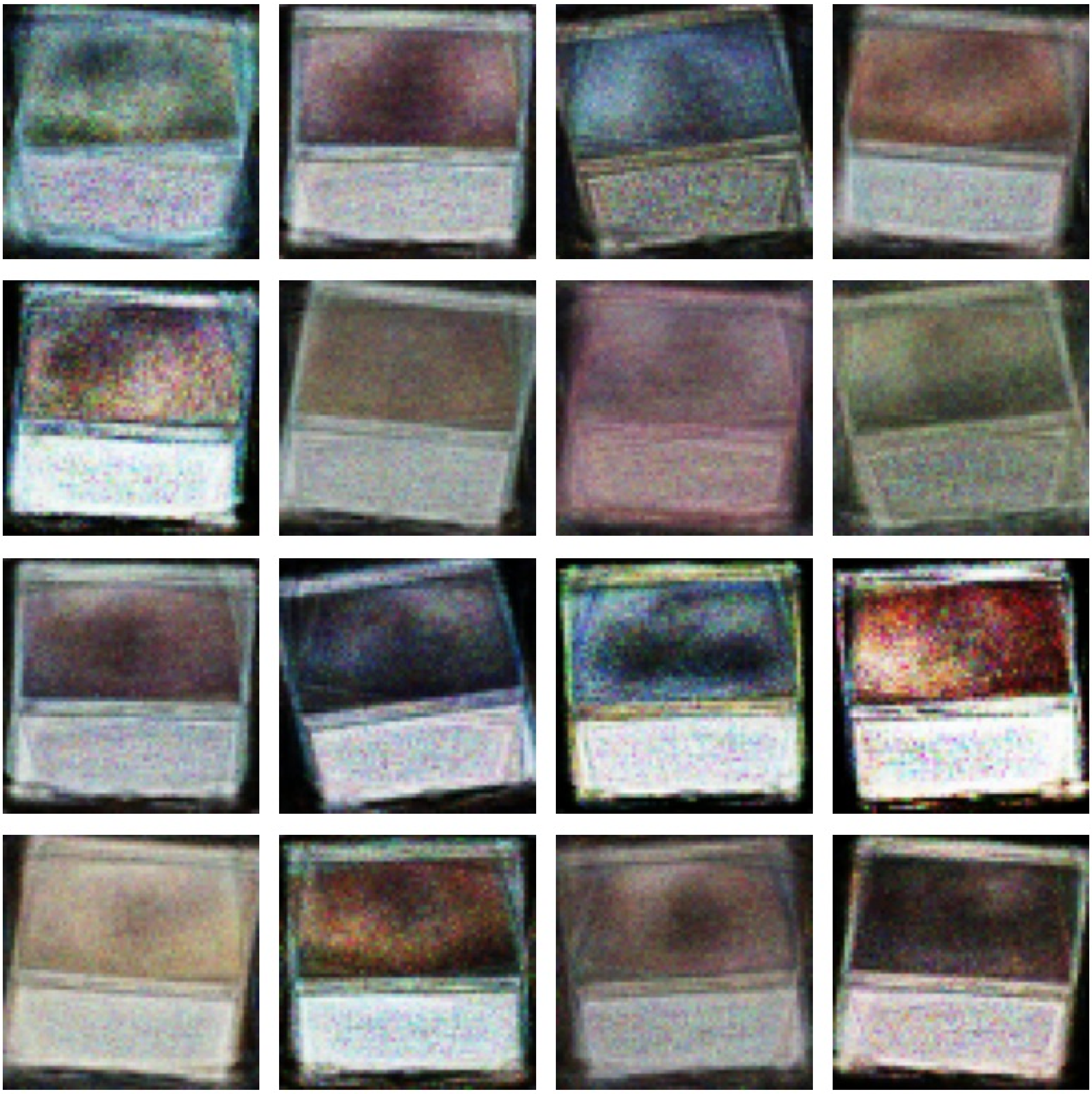
```
Epoch [8/50], Step [0/138], D Loss: 0.8677, G Loss: 1.3509
Epoch [8/50], Step [100/138], D Loss: 0.9620, G Loss: 2.7095
Epoch [9/50], Step [0/138], D Loss: 0.8012, G Loss: 1.1404
Epoch [9/50], Step [100/138], D Loss: 0.6691, G Loss: 1.5751
Epoch [10/50], Step [0/138], D Loss: 1.1113, G Loss: 1.3672
Epoch [10/50], Step [100/138], D Loss: 0.7160, G Loss: 1.8703
Epoch [11/50], Step [0/138], D Loss: 0.8065, G Loss: 1.9011
Epoch [11/50], Step [100/138], D Loss: 0.8750, G Loss: 1.4853
Epoch [12/50], Step [0/138], D Loss: 0.7776, G Loss: 2.2177
Epoch [12/50], Step [100/138], D Loss: 0.8876, G Loss: 1.3864
Epoch [13/50], Step [0/138], D Loss: 0.6885, G Loss: 2.6185
Epoch [13/50], Step [100/138], D Loss: 0.9003, G Loss: 1.3835
Epoch [14/50], Step [0/138], D Loss: 1.0255, G Loss: 2.2397
Epoch [14/50], Step [100/138], D Loss: 0.9060, G Loss: 1.7765
Epoch [15/50], Step [0/138], D Loss: 1.0942, G Loss: 1.5426
Epoch [15/50], Step [100/138], D Loss: 0.8232, G Loss: 1.4491
Epoch [16/50], Step [0/138], D Loss: 1.0141, G Loss: 1.5440
Epoch [16/50], Step [100/138], D Loss: 0.6445, G Loss: 1.7085
Epoch [17/50], Step [0/138], D Loss: 1.5111, G Loss: 2.5821
Epoch [17/50], Step [100/138], D Loss: 0.8199, G Loss: 1.6322
Epoch [18/50], Step [0/138], D Loss: 0.8967, G Loss: 2.4846
Epoch [18/50], Step [100/138], D Loss: 1.2687, G Loss: 1.4332
Epoch [19/50], Step [0/138], D Loss: 1.2118, G Loss: 1.6412
Epoch [19/50], Step [100/138], D Loss: 0.7729, G Loss: 2.4413
Epoch [20/50], Step [0/138], D Loss: 1.3108, G Loss: 1.9063
Epoch [20/50], Step [100/138], D Loss: 1.0361, G Loss: 1.4641
Epoch [21/50], Step [0/138], D Loss: 0.6513, G Loss: 1.9309
Epoch [21/50], Step [100/138], D Loss: 0.8919, G Loss: 1.5544
Epoch [22/50], Step [0/138], D Loss: 0.9511, G Loss: 1.7080
Epoch [22/50], Step [100/138], D Loss: 0.8951, G Loss: 2.0303
Epoch [23/50], Step [0/138], D Loss: 0.8047, G Loss: 2.1123
Epoch [23/50], Step [100/138], D Loss: 0.8888, G Loss: 2.8073
Epoch [24/50], Step [0/138], D Loss: 0.9463, G Loss: 3.1645
Epoch [24/50], Step [100/138], D Loss: 0.6866, G Loss: 2.0600
Epoch [25/50], Step [0/138], D Loss: 0.6937, G Loss: 1.8918
Epoch [25/50], Step [100/138], D Loss: 0.8049, G Loss: 1.3650
Epoch [26/50], Step [0/138], D Loss: 1.5735, G Loss: 1.2318
Epoch [26/50], Step [100/138], D Loss: 1.2260, G Loss: 1.4692
Epoch [27/50], Step [0/138], D Loss: 0.9447, G Loss: 3.0418
Epoch [27/50], Step [100/138], D Loss: 0.9379, G Loss: 2.8862
Epoch [28/50], Step [0/138], D Loss: 1.1520, G Loss: 2.6586
Epoch [28/50], Step [100/138], D Loss: 0.8136, G Loss: 2.1132
Epoch [29/50], Step [0/138], D Loss: 1.3540, G Loss: 3.0049
Epoch [29/50], Step [100/138], D Loss: 0.8659, G Loss: 2.4866
Epoch [30/50], Step [0/138], D Loss: 0.9441, G Loss: 1.5898
Epoch [30/50], Step [100/138], D Loss: 0.8457, G Loss: 1.8519
Epoch [31/50], Step [0/138], D Loss: 1.3775, G Loss: 1.0678
Epoch [31/50], Step [100/138], D Loss: 0.7858, G Loss: 2.1127
Epoch [32/50], Step [0/138], D Loss: 1.0047, G Loss: 1.6178
Epoch [32/50], Step [100/138], D Loss: 0.8376, G Loss: 1.4435
Epoch [33/50], Step [0/138], D Loss: 1.0241, G Loss: 2.5300
Epoch [33/50], Step [100/138], D Loss: 1.0118, G Loss: 1.9209
Epoch [34/50], Step [0/138], D Loss: 0.9997, G Loss: 2.5062
Epoch [34/50], Step [100/138], D Loss: 0.9478, G Loss: 2.0640
Epoch [35/50], Step [0/138], D Loss: 1.0151, G Loss: 2.5956
Epoch [35/50], Step [100/138], D Loss: 0.8834, G Loss: 1.7799
Epoch [36/50], Step [0/138], D Loss: 0.9726, G Loss: 2.6253
Epoch [36/50], Step [100/138], D Loss: 1.0028, G Loss: 1.7469
Epoch [37/50], Step [0/138], D Loss: 0.9905, G Loss: 1.6244
Epoch [37/50], Step [100/138], D Loss: 0.8242, G Loss: 2.3100
Epoch [38/50], Step [0/138], D Loss: 0.7556, G Loss: 2.2257
Epoch [38/50], Step [100/138], D Loss: 0.8348, G Loss: 1.9953
Epoch [39/50], Step [0/138], D Loss: 0.7659, G Loss: 1.8935
Epoch [39/50], Step [100/138], D Loss: 1.0578, G Loss: 1.3309
Epoch [40/50], Step [0/138], D Loss: 0.9089, G Loss: 1.9173
Epoch [40/50], Step [100/138], D Loss: 0.9894, G Loss: 2.5441
Epoch [41/50], Step [0/138], D Loss: 0.9957, G Loss: 2.5646
Epoch [41/50], Step [100/138], D Loss: 0.7075, G Loss: 2.0510
Epoch [42/50], Step [0/138], D Loss: 0.8409, G Loss: 2.1437
Epoch [42/50], Step [100/138], D Loss: 0.7991, G Loss: 2.0255
Epoch [43/50], Step [0/138], D Loss: 0.9464, G Loss: 2.0087
Epoch [43/50], Step [100/138], D Loss: 1.1117, G Loss: 1.5753
Epoch [44/50], Step [0/138], D Loss: 0.9382, G Loss: 2.3808
Epoch [44/50], Step [100/138], D Loss: 0.7567, G Loss: 1.7876
Epoch [45/50], Step [0/138], D Loss: 0.9826, G Loss: 1.4231
Epoch [45/50], Step [100/138], D Loss: 1.0627, G Loss: 1.8884
Epoch [46/50], Step [0/138], D Loss: 0.9918, G Loss: 1.5851
Epoch [46/50], Step [100/138], D Loss: 0.8700, G Loss: 2.2605
Epoch [47/50], Step [0/138], D Loss: 0.9276, G Loss: 1.8780
Epoch [47/50], Step [100/138], D Loss: 0.8714, G Loss: 1.2929
Epoch [48/50], Step [0/138], D Loss: 0.9562, G Loss: 2.4179
Epoch [48/50], Step [100/138], D Loss: 0.9668, G Loss: 1.8926
Epoch [49/50], Step [0/138], D Loss: 0.9329, G Loss: 1.8808
```

```
Epoch [49/50], Step [100/138], D Loss: 0.9051, G Loss: 2.0459
Epoch [50/50], Step [0/138], D Loss: 1.2645, G Loss: 2.0436
Epoch [50/50], Step [100/138], D Loss: 0.8823, G Loss: 1.6673
```

Save and Generate Images

In [12]:
```python
import matplotlib.pyplot as plt

# Function to generate and save images
def generate_images(generator, latent_dim, num_images=16, save_path="generated_images.png"):
    generator.eval()
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

    # Generate latent vectors
    z = torch.randn(num_images, latent_dim, device=device)

    # Generate images
    with torch.no_grad():
        generated_images = generator(z).cpu()

    # Denormalize images from [-1, 1] back to [0, 1]
    generated_images = (generated_images + 1) / 2

    # Plot images in a grid
    grid_size = int(num_images ** 0.5)
    fig, axs = plt.subplots(grid_size, grid_size, figsize=(8, 8))
    for i, ax in enumerate(axs.flatten()):
        ax.imshow(generated_images[i].permute(1, 2, 0))
        ax.axis("off")

    # Save the grid of images
    plt.tight_layout()
    plt.savefig(save_path)
    print(f"Generated images saved to {save_path}")
    plt.show()


# Example usage
generator.load_state_dict(torch.load("generator_epoch_50.pth", map_location=device))
generate_images(generator, latent_dim=100, num_images=16)
```

```
C:\Users\cgrob\AppData\Local\Temp\ipykernel_14048\2021752620.py:33: FutureWarning: You are using `torch.load` wi
th `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is poss
ible to construct malicious pickle data which will execute arbitrary code during unpickling (See https://github.
com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default v
alue for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpic
kling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowli
sted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True`
for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any is
sues related to this experimental feature.
  generator.load_state_dict(torch.load("generator_epoch_50.pth", map_location=device))
Generated images saved to generated_images.png
```



Intermediate Conclusions:

The GAN did ok but could do better. I could try using other card types, but I will stick to creature cards for now since they are the most diverse. I'm surprised honestly. A simple GAN did pretty well and I'm surprised at the extent at which the model was able to recognize certain patterns like edges of the card, the colors, and even the power and toughness. But I do think I am not training enough. I would like to increase the number of epochs but it would take a lot of time. The training loop took 6 hours.

Then I will try to do a DC GAN.

Finally, I will try to do some evaluations.

In [13]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import datasets, transforms
from torchvision.utils import save_image
import os
import torchvision.utils as vutils
```

DC GAN Generator

In [14]:
```
# DC GAN Generator architecture
class DCGANGenerator(nn.Module):
    def __init__(self, latent_dim, num_channels=3):
        super(DCGANGenerator, self).__init__()
        self.main = nn.Sequential(
            nn.ConvTranspose2d(latent_dim, 512, 4, 1, 0, bias=False),
            nn.BatchNorm2d(512),
            nn.ReLU(True),
            nn.ConvTranspose2d(512, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256),
            nn.ReLU(True),
            nn.ConvTranspose2d(256, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128),
            nn.ReLU(True),
            nn.ConvTranspose2d(128, 64, 4, 2, 1, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU(True),
            nn.ConvTranspose2d(64, num_channels, 4, 2, 1, bias=False),
            nn.Tanh()
        )

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

DC GAN Discriminator

In [15]:
```
# DC GAN Discriminator architecture
class DCGANDiscriminator(nn.Module):
    def __init__(self, num_channels=3):
        super(DCGANDiscriminator, self).__init__()
        self.main = nn.Sequential(
            nn.Conv2d(num_channels, 64, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(64, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(128, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(256, 512, 4, 2, 1, bias=False),
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Conv2d(512, 1, 4, 1, 0, bias=False),
            nn.Sigmoid()
        )

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

Training Loop Initializations

In [16]:
```
# Hyperparameters
latent_dim = 100
num_epochs = 50
lr = 0.0002
beta1 = 0.5
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Initialize models
```

```python
netG = DCGANGenerator(latent_dim).to(device)
netD = DCGANDiscriminator().to(device)

# Loss function and optimizers
criterion = nn.BCELoss()
optimizerD = torch.optim.Adam(netD.parameters(), lr=lr, betas=(beta1, 0.999))
optimizerG = torch.optim.Adam(netG.parameters(), lr=lr, betas=(beta1, 0.999))
```

Training Loop

In [ ]:
```python
# Training loop
for epoch in range(num_epochs):
    for i, real_images in enumerate(dataloader):
        batch_size = real_images.size(0)
        real_images = real_images.to(device)

        # Train Discriminator
        netD.zero_grad()

        label_real = torch.ones(batch_size, device=device)
        output_real = netD(real_images)
        loss_real = criterion(output_real, label_real)

        noise = torch.randn(batch_size, latent_dim, 1, 1, device=device)
        fake_images = netG(noise)
        label_fake = torch.zeros(batch_size, device=device)
        output_fake = netD(fake_images.detach())
        loss_fake = criterion(output_fake, label_fake)

        loss_D = loss_real + loss_fake
        loss_D.backward()
        optimizerD.step()

        # Train Generator
        netG.zero_grad()
        label_real = torch.ones(batch_size, device=device)
        output = netD(fake_images)
        loss_G = criterion(output, label_real)
        loss_G.backward()
        optimizerG.step()

        if i % 50 == 0:
            print(f"Epoch [{epoch}/{num_epochs}] Batch [{i}/{len(dataloader)}] "
                  f"Loss D: {loss_D.item():.4f}, Loss G: {loss_G.item():.4f}")

    # Save generated images
    with torch.no_grad():
        test_noise = torch.randn(64, latent_dim, 1, 1, device=device)
        generated_images = netG(test_noise).cpu()
        save_image(generated_images, f"generated_images_epoch_{epoch}.png", normalize=True)
```

```
Epoch [0/50] Batch [0/138] Loss D: 1.4781, Loss G: 2.9192
Epoch [0/50] Batch [50/138] Loss D: 0.8525, Loss G: 8.9265
Epoch [0/50] Batch [100/138] Loss D: 0.4699, Loss G: 3.3907
Epoch [1/50] Batch [0/138] Loss D: 0.4411, Loss G: 2.7885
Epoch [1/50] Batch [50/138] Loss D: 0.3797, Loss G: 3.6439
Epoch [1/50] Batch [100/138] Loss D: 0.5256, Loss G: 2.5723
Epoch [2/50] Batch [0/138] Loss D: 0.4170, Loss G: 3.8163
Epoch [2/50] Batch [50/138] Loss D: 0.4688, Loss G: 3.5405
Epoch [2/50] Batch [100/138] Loss D: 0.7647, Loss G: 2.9714
Epoch [3/50] Batch [0/138] Loss D: 0.6564, Loss G: 4.4593
Epoch [3/50] Batch [50/138] Loss D: 0.5611, Loss G: 2.9094
Epoch [3/50] Batch [100/138] Loss D: 0.6179, Loss G: 2.0920
Epoch [4/50] Batch [0/138] Loss D: 0.8013, Loss G: 2.7769
Epoch [4/50] Batch [50/138] Loss D: 0.3395, Loss G: 2.5280
Epoch [4/50] Batch [100/138] Loss D: 0.2716, Loss G: 4.1197
Epoch [5/50] Batch [0/138] Loss D: 0.8528, Loss G: 7.2363
Epoch [5/50] Batch [50/138] Loss D: 0.2298, Loss G: 3.2035
Epoch [5/50] Batch [100/138] Loss D: 0.4718, Loss G: 3.7805
Epoch [6/50] Batch [0/138] Loss D: 0.7028, Loss G: 5.5107
Epoch [6/50] Batch [50/138] Loss D: 2.3029, Loss G: 6.4537
Epoch [6/50] Batch [100/138] Loss D: 0.5683, Loss G: 3.2939
Epoch [7/50] Batch [0/138] Loss D: 0.6077, Loss G: 2.1040
Epoch [7/50] Batch [50/138] Loss D: 0.7440, Loss G: 6.4802
Epoch [7/50] Batch [100/138] Loss D: 0.5091, Loss G: 3.0830
Epoch [8/50] Batch [0/138] Loss D: 0.4055, Loss G: 4.5989
Epoch [8/50] Batch [50/138] Loss D: 0.6013, Loss G: 5.8070
Epoch [8/50] Batch [100/138] Loss D: 0.7571, Loss G: 4.1565
Epoch [9/50] Batch [0/138] Loss D: 0.5460, Loss G: 3.6910
Epoch [9/50] Batch [50/138] Loss D: 0.7772, Loss G: 3.0679
Epoch [9/50] Batch [100/138] Loss D: 0.6794, Loss G: 2.8101
Epoch [10/50] Batch [0/138] Loss D: 0.4636, Loss G: 5.5579
```

```
Epoch [10/50] Batch [50/138] Loss D: 0.3695, Loss G: 5.3273
Epoch [10/50] Batch [100/138] Loss D: 1.2337, Loss G: 6.9841
Epoch [11/50] Batch [0/138] Loss D: 0.4004, Loss G: 4.3284
Epoch [11/50] Batch [50/138] Loss D: 0.2621, Loss G: 3.7473
Epoch [11/50] Batch [100/138] Loss D: 0.2117, Loss G: 3.9988
Epoch [12/50] Batch [0/138] Loss D: 0.4438, Loss G: 3.1658
Epoch [12/50] Batch [50/138] Loss D: 0.3276, Loss G: 3.3106
Epoch [12/50] Batch [100/138] Loss D: 0.3417, Loss G: 4.2838
Epoch [13/50] Batch [0/138] Loss D: 1.0704, Loss G: 8.1199
Epoch [13/50] Batch [50/138] Loss D: 0.4375, Loss G: 4.7425
Epoch [13/50] Batch [100/138] Loss D: 0.1978, Loss G: 4.5126
Epoch [14/50] Batch [0/138] Loss D: 0.3694, Loss G: 4.1452
Epoch [14/50] Batch [50/138] Loss D: 0.7424, Loss G: 7.9774
Epoch [14/50] Batch [100/138] Loss D: 0.4022, Loss G: 3.6094
Epoch [15/50] Batch [0/138] Loss D: 0.2495, Loss G: 3.4585
Epoch [15/50] Batch [50/138] Loss D: 0.2165, Loss G: 3.5679
Epoch [15/50] Batch [100/138] Loss D: 0.2507, Loss G: 5.0347
Epoch [16/50] Batch [0/138] Loss D: 0.6454, Loss G: 5.3839
Epoch [16/50] Batch [50/138] Loss D: 1.3794, Loss G: 9.2648
Epoch [16/50] Batch [100/138] Loss D: 0.2037, Loss G: 4.5032
Epoch [17/50] Batch [0/138] Loss D: 0.5983, Loss G: 2.6341
Epoch [17/50] Batch [50/138] Loss D: 0.2848, Loss G: 2.4268
Epoch [17/50] Batch [100/138] Loss D: 0.3511, Loss G: 2.0985
Epoch [18/50] Batch [0/138] Loss D: 0.2831, Loss G: 4.6146
Epoch [18/50] Batch [50/138] Loss D: 0.2346, Loss G: 3.5618
Epoch [18/50] Batch [100/138] Loss D: 0.2763, Loss G: 3.5269
Epoch [19/50] Batch [0/138] Loss D: 0.9260, Loss G: 2.8221
Epoch [19/50] Batch [50/138] Loss D: 0.1950, Loss G: 4.2894
Epoch [19/50] Batch [100/138] Loss D: 0.2098, Loss G: 3.1521
Epoch [20/50] Batch [0/138] Loss D: 0.3727, Loss G: 2.3788
Epoch [20/50] Batch [50/138] Loss D: 0.4227, Loss G: 7.0671
Epoch [20/50] Batch [100/138] Loss D: 0.3038, Loss G: 5.4744
Epoch [21/50] Batch [0/138] Loss D: 0.3447, Loss G: 6.9437
Epoch [21/50] Batch [50/138] Loss D: 0.4036, Loss G: 3.0678
Epoch [21/50] Batch [100/138] Loss D: 0.2577, Loss G: 3.9874
Epoch [22/50] Batch [0/138] Loss D: 0.8252, Loss G: 2.1704
Epoch [22/50] Batch [50/138] Loss D: 0.2865, Loss G: 4.6545
Epoch [22/50] Batch [100/138] Loss D: 0.2895, Loss G: 4.2462
Epoch [23/50] Batch [0/138] Loss D: 0.1574, Loss G: 3.7663
Epoch [23/50] Batch [50/138] Loss D: 0.3018, Loss G: 3.3835
Epoch [23/50] Batch [100/138] Loss D: 0.2883, Loss G: 3.9307
Epoch [24/50] Batch [0/138] Loss D: 0.3909, Loss G: 2.5919
Epoch [24/50] Batch [50/138] Loss D: 0.2616, Loss G: 3.4848
Epoch [24/50] Batch [100/138] Loss D: 0.2523, Loss G: 5.7268
Epoch [25/50] Batch [0/138] Loss D: 0.3071, Loss G: 4.2889
Epoch [25/50] Batch [50/138] Loss D: 0.1466, Loss G: 4.9912
Epoch [25/50] Batch [100/138] Loss D: 0.3750, Loss G: 4.3141
Epoch [26/50] Batch [0/138] Loss D: 0.3874, Loss G: 6.6149
Epoch [26/50] Batch [50/138] Loss D: 0.3432, Loss G: 5.2264
Epoch [26/50] Batch [100/138] Loss D: 0.3564, Loss G: 2.8348
Epoch [27/50] Batch [0/138] Loss D: 0.2271, Loss G: 5.7125
Epoch [27/50] Batch [50/138] Loss D: 0.2718, Loss G: 4.1010
Epoch [27/50] Batch [100/138] Loss D: 0.1419, Loss G: 5.4569
Epoch [28/50] Batch [0/138] Loss D: 0.2178, Loss G: 4.5458
Epoch [28/50] Batch [50/138] Loss D: 0.2518, Loss G: 4.4711
Epoch [28/50] Batch [100/138] Loss D: 0.1631, Loss G: 3.5703
Epoch [29/50] Batch [0/138] Loss D: 0.7206, Loss G: 6.2764
Epoch [29/50] Batch [50/138] Loss D: 0.2370, Loss G: 4.3349
Epoch [29/50] Batch [100/138] Loss D: 0.1858, Loss G: 3.6819
Epoch [30/50] Batch [0/138] Loss D: 0.3242, Loss G: 4.0121
Epoch [30/50] Batch [50/138] Loss D: 0.1189, Loss G: 5.8922
Epoch [30/50] Batch [100/138] Loss D: 0.1708, Loss G: 5.5979
Epoch [31/50] Batch [0/138] Loss D: 0.2429, Loss G: 5.2659
Epoch [31/50] Batch [50/138] Loss D: 0.1451, Loss G: 4.5592
Epoch [31/50] Batch [100/138] Loss D: 0.6141, Loss G: 6.1214
Epoch [32/50] Batch [0/138] Loss D: 0.2151, Loss G: 4.9803
Epoch [32/50] Batch [50/138] Loss D: 0.1761, Loss G: 4.2842
Epoch [32/50] Batch [100/138] Loss D: 0.2850, Loss G: 5.6681
Epoch [33/50] Batch [0/138] Loss D: 0.1455, Loss G: 3.7297
Epoch [33/50] Batch [50/138] Loss D: 0.1452, Loss G: 3.9228
Epoch [33/50] Batch [100/138] Loss D: 0.2372, Loss G: 4.3710
Epoch [34/50] Batch [0/138] Loss D: 0.4653, Loss G: 6.6497
Epoch [34/50] Batch [50/138] Loss D: 0.2087, Loss G: 5.2689
Epoch [34/50] Batch [100/138] Loss D: 0.2380, Loss G: 4.8110
Epoch [35/50] Batch [0/138] Loss D: 0.1686, Loss G: 3.6077
Epoch [35/50] Batch [50/138] Loss D: 0.2706, Loss G: 5.7084
Epoch [35/50] Batch [100/138] Loss D: 0.2653, Loss G: 5.0810
Epoch [36/50] Batch [0/138] Loss D: 0.5032, Loss G: 8.9842
Epoch [36/50] Batch [50/138] Loss D: 0.5477, Loss G: 1.8176
Epoch [36/50] Batch [100/138] Loss D: 0.1801, Loss G: 4.4069
Epoch [37/50] Batch [0/138] Loss D: 0.2434, Loss G: 4.9862
Epoch [37/50] Batch [50/138] Loss D: 0.1940, Loss G: 5.0737
Epoch [37/50] Batch [100/138] Loss D: 0.1402, Loss G: 4.5863
```

```
Epoch [38/50] Batch [0/138] Loss D: 0.3223, Loss G: 3.4946
Epoch [38/50] Batch [50/138] Loss D: 0.2244, Loss G: 3.8458
Epoch [38/50] Batch [100/138] Loss D: 0.0955, Loss G: 4.1213
Epoch [39/50] Batch [0/138] Loss D: 1.0540, Loss G: 13.4565
Epoch [39/50] Batch [50/138] Loss D: 0.1669, Loss G: 3.9781
Epoch [39/50] Batch [100/138] Loss D: 0.0968, Loss G: 4.5603
Epoch [40/50] Batch [0/138] Loss D: 0.2191, Loss G: 3.6302
Epoch [40/50] Batch [50/138] Loss D: 0.1064, Loss G: 5.2473
Epoch [40/50] Batch [100/138] Loss D: 0.3380, Loss G: 5.6737
Epoch [41/50] Batch [0/138] Loss D: 2.5498, Loss G: 16.6825
Epoch [41/50] Batch [50/138] Loss D: 0.2138, Loss G: 3.6680
Epoch [41/50] Batch [100/138] Loss D: 0.2950, Loss G: 7.6284
Epoch [42/50] Batch [0/138] Loss D: 0.1365, Loss G: 4.8790
Epoch [42/50] Batch [50/138] Loss D: 0.0676, Loss G: 5.5430
Epoch [42/50] Batch [100/138] Loss D: 0.2350, Loss G: 3.9674
Epoch [43/50] Batch [0/138] Loss D: 0.2938, Loss G: 7.1118
Epoch [43/50] Batch [50/138] Loss D: 0.2011, Loss G: 5.4582
Epoch [43/50] Batch [100/138] Loss D: 0.2115, Loss G: 3.1565
Epoch [44/50] Batch [0/138] Loss D: 0.0517, Loss G: 4.8781
Epoch [44/50] Batch [50/138] Loss D: 0.1835, Loss G: 5.5260
Epoch [44/50] Batch [100/138] Loss D: 0.0683, Loss G: 4.6929
Epoch [45/50] Batch [0/138] Loss D: 0.1113, Loss G: 5.0510
Epoch [45/50] Batch [50/138] Loss D: 0.1181, Loss G: 6.0731
Epoch [45/50] Batch [100/138] Loss D: 0.0565, Loss G: 5.3317
Epoch [46/50] Batch [0/138] Loss D: 3.3066, Loss G: 17.8469
Epoch [46/50] Batch [50/138] Loss D: 0.2560, Loss G: 3.4549
Epoch [46/50] Batch [100/138] Loss D: 0.1549, Loss G: 5.2076
Epoch [47/50] Batch [0/138] Loss D: 0.4447, Loss G: 6.9492
Epoch [47/50] Batch [50/138] Loss D: 0.1421, Loss G: 4.5711
Epoch [47/50] Batch [100/138] Loss D: 0.2146, Loss G: 6.1436
Epoch [48/50] Batch [0/138] Loss D: 0.2277, Loss G: 6.6517
Epoch [48/50] Batch [50/138] Loss D: 0.1280, Loss G: 4.4548
Epoch [48/50] Batch [100/138] Loss D: 0.0636, Loss G: 6.1703
Epoch [49/50] Batch [0/138] Loss D: 0.4686, Loss G: 10.6119
Epoch [49/50] Batch [50/138] Loss D: 0.0844, Loss G: 5.1877
Epoch [49/50] Batch [100/138] Loss D: 0.0914, Loss G: 4.1529
```

Generating Images

In [18]:

```
def generate_and_show_samples(generator, z_dim, device, num_samples=9):

    # Create a batch of random noise
    noise = torch.randn(num_samples, z_dim, 1, 1).to(device)

    # Generate images from the noise
    with torch.no_grad():
        fake_images = generator(noise)

    # Generate a grid of images (9 images in a 3x3 grid)
    grid = vutils.make_grid(fake_images, nrow=3, padding=2, normalize=True)

    plt.figure(figsize=(8, 8))
    plt.imshow(grid.permute(1, 2, 0).cpu().numpy())
    plt.axis('off')
    plt.show()

generate_and_show_samples(netG, z_dim=100, device=device, num_samples=9)
```

Conclusions

After 423 minutes to train the GAN and 535 minutes to train the DCGAN, I finally arrived to some generated images and conclusions. The generated images from the GAN were not bad. I was very impressed how a simple GAN could understand at least the structure of the card. There were still hazy ones which I believe is because of short training, but I was impressed (mostly at what I had accomplished). The DCGAN was even more surprising. Aftering squinting, they look like real cards. There is some variance in color/art and some cards even look foiled. After a lengthy training, the DCGAN was still not able to pick up on the power and toughness of creatures. It appears it has picked up on set symbols (top left, middle, bottom right) but not so much on the power and toughness.

Limitations:

I wasn't able to use a decently balanced dataset. Data mining took a while to get right but data cleaning may have taken even longer if I had took the time to do it. The script that mined the data just went through the database and requested card images alphabetically and indiscriminately. If I had coded better, or if I could access some of the metadata as well, I have been able to stratify and sample only the newer cards or ones that don't fit the creature type structure, or have the same number of cards for each color combination.

Next time:

I want to learn more about STYLE GANs and how to use my GPU during training. Taking nearly 16 hours to train is not quite ideal. I wouldn't call this a failure but I was still impressed.