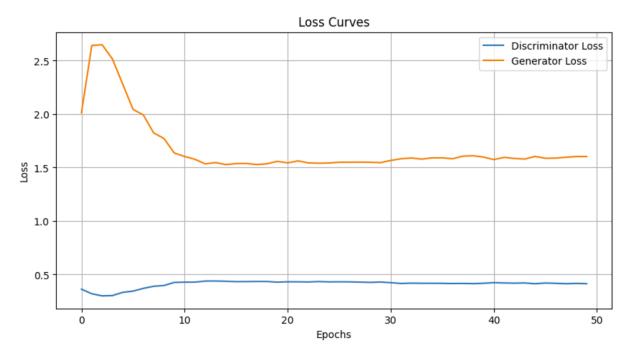
Assignment 6

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Exercise 1: Implementing a Basic GAN

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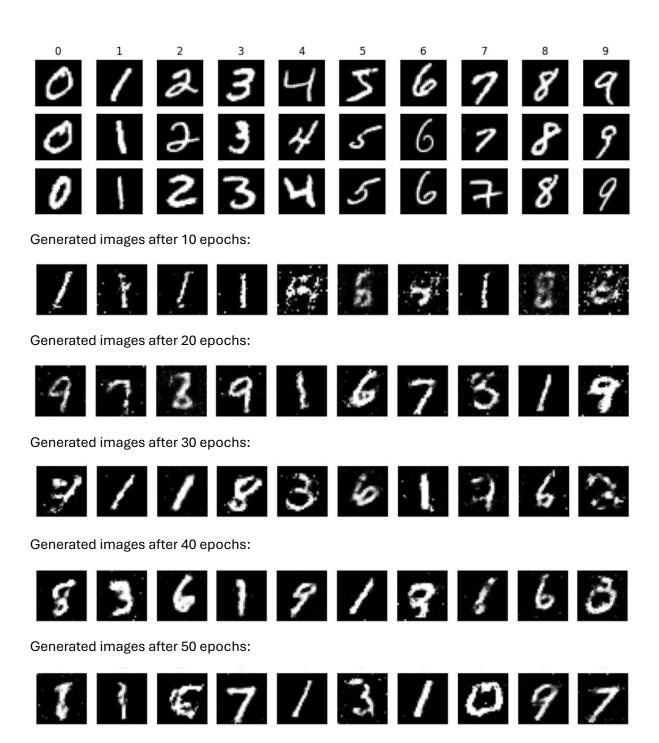


Discriminator/Generator Loss Plot

<u>Discriminator Loss:</u> As we can see from the plot, the discriminator loss fluctuates around 0.4 throughout the epochs.

<u>Generator Loss:</u> As we can see from the plot, the generator loss starts at around 2.0 and then increases reaching its highest value of around 2.7 at the 4th epoch, and then decreases reaching its lowest value of 1.6 at around the 12th. The generator loss fluctuates around that value for the remaining epochs.

Real Image Sample from MNIST dataset:



We can compare the generated images with real images samples from the MNIST dataset provided above. We can see that the generated images get closer and closer to the real images of the dataset as the epochs go by.

Quality Evolution

1. **Epochs 10 to 20**:

- Epoch 10: The generated images show vague, distorted representations of digits, with significant noise and unclear shapes. While the structure of digits starts to emerge, most images are far from realistic.
- Epoch 20: The digits become more recognizable, and their structure improves.
 Noise decreases significantly, and specific digits like "7", "3", and "9" are distinguishable. However, some images still lack clarity, and features like edges remain blurry.

2. **Epochs 30 to 40**:

- Epoch 30: The digits show noticeable improvements in clarity and structure.
 Most images resemble human-recognizable digits, although some digits still appear stretched or poorly shaped. Fine details (e.g., curves or straight edges) are inconsistent.
- Epoch 40: There is significant progress in realism. The images are sharper, with less noise. Digits like "3", "6", and "9" appear more well-formed. Although the quality has increased, occasional inconsistencies in style or small distortions are present.

3. **Epoch 50**:

 By this point, the images are the most realistic. Most digits have sharp outlines and recognizable shapes. The network has achieved a balance between generator and discriminator performance. The variety among digits is better, with distinct representations of all numbers.

Observed Patterns

- **Image Realism**: The realism of the generated digits improves steadily. Early epochs focus on coarse features, while later epochs refine details.
- **Diversity**: As training progresses, the variety of digits increases. By epoch 50, the model successfully generates a diverse range of digits without significant repetition or collapse into a single mode.
- Noise Reduction: The background noise reduces gradually, particularly from epoch 20 onward.

Challenges Encountered During Training

1. Convergence:

 Early epochs (10-20) show difficulty in convergence, as the generator struggles to produce structured outputs while the discriminator effectively rejects noisy samples. Loss curves indicate gradual stabilization, but the discriminator remains slightly stronger during the early stages.

2. Mode Collapse:

 No evidence of mode collapse (where the generator outputs repetitive images) is visible in the final results. The model successfully generates diverse digits by later epochs.

3. Instability in Loss Curves:

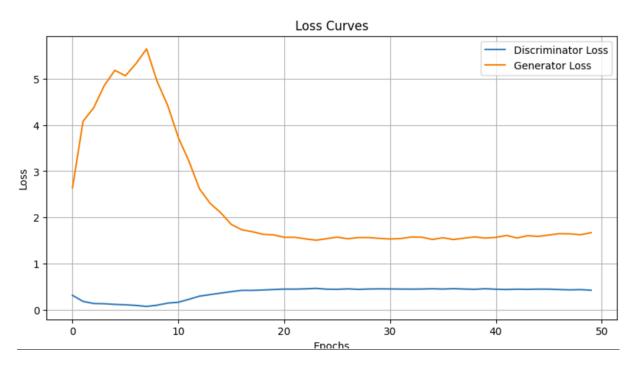
- The generator loss (G Loss) starts high (~2.7) and decreases, showing the generator's improving ability to produce realistic outputs.
- Discriminator loss (D Loss) remains relatively stable (~0.3-0.4), indicating effective learning without overpowering the generator.

4. Training Balance:

Maintaining the balance between the generator and discriminator was critical.
 Early generator losses (~1.9-2.2) show some challenges, as the discriminator dominated early phases. The balance stabilizes in later epochs.

Exercise 2: Implementing a Conditional GAN (cGAN)

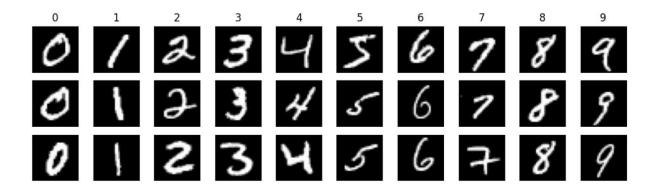
3.



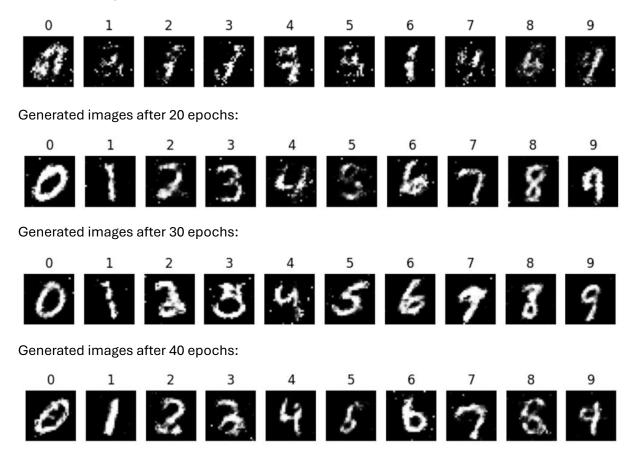
Discriminator/Generator Loss Plot

<u>Discriminator Loss:</u> As we can see from the plot, the discriminator loss fluctuates around 0.4 throughout the epochs.

<u>Generator Loss:</u> As we can see from the plot, the generator loss starts at around 2.7 and then increases reaching its highest value of around 5.5 at the 7th epoch, and then decreases reaching its lowest value of 2.5 at around the 20th. The generator loss fluctuates around that value for the remaining epochs.



Generated images after 10 epochs:



Generated images after 50 epochs:



We can compare the generated images with real images samples from the MNIST dataset provided above. We can see that the generated images get closer and closer to the real images of the dataset as the epochs go by.

<u>4.</u>

Analysis of the Quality of Generated Images Over Time

The cGAN-generated images improve significantly in realism and detail across the 50 epochs. Below is a detailed breakdown of observations and patterns in the evolution of image quality:

Quality Improvements by Epoch

1. Epochs 10-20:

- Epoch 10: The images are dominated by noise, and only hints of digit structures are visible. There is little distinction between numbers, and the results suggest the generator is in the early stages of learning.
- Epoch 20: The images show reduced noise, and the digits are more distinguishable. However, the strokes of some digits are broken, and the clarity is inconsistent across the generated samples. Background noise is still present.

2. Epochs 30-40:

- Epoch 30: The digits become significantly more legible, with improved structure and sharper strokes. Most numbers are distinguishable, though occasional distortions or imperfections remain.
- Epoch 40: The generated digits show further refinement, with smoother curves and reduced background noise. While some digits (e.g., "4" or "7") are particularly clear, others (e.g., "6") still exhibit slight irregularities.

3. **Epoch 50**:

At this point, the cGAN achieves its best performance. The digits are sharp, well-structured, and highly realistic. Variations among digits are well represented, showing a diverse and reliable generation process. Background noise is minimal, and the overall quality suggests the cGAN has learned the target distribution effectively.

Observed Patterns in Training

• **Realism**: The transition from noise-filled, barely legible images in epoch 10 to sharp and distinct digits in epoch 50 highlights the cGAN's progressive learning. The generator improves at creating realistic outputs while the discriminator fine-tunes its feedback.

- **Diversity**: Initially, the generated digits lack variation, but by epoch 50, the model outputs a diverse set of numbers, indicating that it successfully avoids mode collapse.
- Noise Reduction: Across epochs, background noise steadily decreases, particularly from epochs 20–40. This reflects the generator's improving ability to focus on relevant digit features.

Challenges Encountered

1. Convergence Issues:

- Early epochs (e.g., 1–10) show significant challenges in convergence. The generator produces almost random noise, and the loss curves indicate an imbalance between the generator and discriminator.
- As training progresses, the losses stabilize, suggesting improved convergence between the two networks.

2. Loss Instability:

- The generator loss (G Loss) fluctuates considerably in the early epochs but gradually declines, reflecting its improved ability to generate realistic samples.
- The discriminator loss (D Loss) starts low (around 0.3) but rises slightly, suggesting the discriminator continues to learn alongside the generator without becoming overly dominant.

3. Mode Collapse:

 No mode collapse (i.e., where the generator outputs identical samples) is observed. The generator consistently improves in producing diverse digits, indicating that the cGAN training is well-tuned.

4. Saturation in Mid-Epochs:

 In epochs 15–30, the improvements in image quality slow down, as evidenced by smaller reductions in noise and minor refinements in digit clarity. This suggests a plateau in learning during this phase before further refinement resumes in later epochs