Learning and Implementing Generative Adversarial Networks (GANs)

Comparative Study of Basic and Improved GAN Using PyTorch

Purpose: Gaining Hands-on Experience and Understanding of GANs through Coding Implementation with the MNIST Dataset

Basic GAN Overview

- **Objective**: To generate data that's similar to some real data.
- Architecture:

Utilizes Multi-Layer Perceptron (MLP) with fully connected layers.

- **Generator** (creates images):
 - o Linear Layers: [100, 256], [256, 512], [512, 784]
 - o Activation: LeakyReLU, Tanh
- **Discriminator** (evaluates them):
 - o Linear Layers: [784, 512], [512, 256], [256, 1]
 - o Activation: LeakyReLU, Sigmoid

• Training:

o Learning Rate: 0.0002

o Batch Size: 100

o Number of Epochs: 100

o Optimizer: Adam

Loss: Binary Cross Entropy Loss

Steps for Coding Implementation:

- 1: Import Necessary Libraries
- 2: Set Hyperparameters
- 3: Load the MNIST dataset
- 4: Construct the architecture of the Generator
- 5: Develop the architecture of the Discriminator
- 6: Initialize Models and Optimizers
- 7: Implement the training loop
- 8: Assess the model's performance using FID and IS
- 9: Inspect the quality of images generated

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• Training:

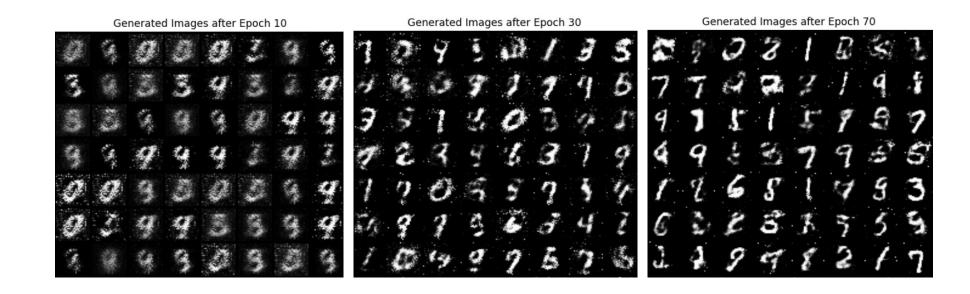
o Learning Rate: 0.0002

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Convolutional GAN

• **Objective**: Enhance Basic GAN for refined image generation and increased model complexity via CNN incorporation, aiming for clearer and more detailed outputs.

Improvements:

- o Employ **Convolutional Layers** in both Generator and Discriminator.
- o Incorporate **Batch Normalization** in Generator.
- o Apply **Dropout** & **Label Smoothing** in Discriminator.

Architecture:

Convolutional Generator :

- o ConvTranspose2D layers
- o ReLU Activations
- o Batch Normalization
- Output: Tanh Activation

Convolutional Discriminator:

- o Conv2D layers with Dropout: 0.3
- o LeakyReLU Activations
- o Output: Sigmoid Activation

• Training:

o Learning Rate: 0.0002

o Batch Size: 100

o Number of Epochs: 100

Optimizer: Adam (β1 = 0.5, β2 = 0.999)

o Loss: Binary Cross Entropy Loss

o Real Labels: 0.9 (for Label Smoothing)

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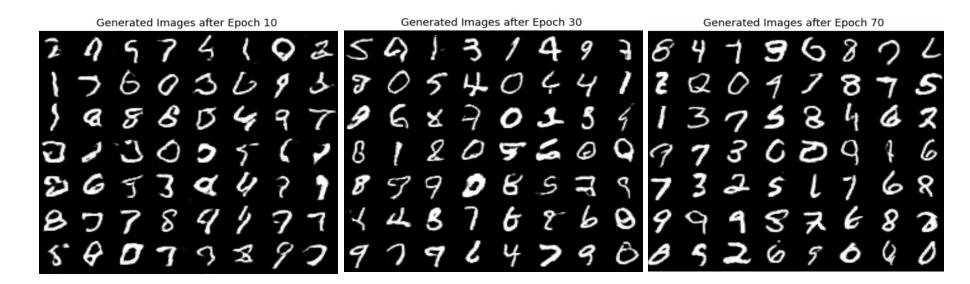
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o Number of Epochs: 100

Optimizer: Adam (β1 = 0.5, β2 = 0.999)

o Loss: Binary Cross Entropy Loss

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Comparative Analysis

Resolution Comparison:

- The generated images after 100 epochs show a marked difference in clarity between the Basic and Convolutional GANs.
- It is evident that the Convolutional GAN produces images with sharper and clearer details compared to its Basic counterpart.

Generated Images after Epoch 100



Basic GANs

Generated Images after Epoch 100



Convolutional GANs

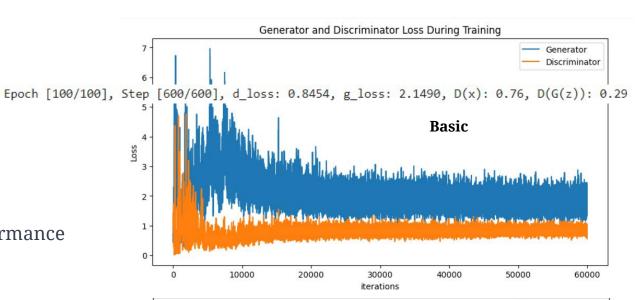
Analyzing Training Dynamics GANs

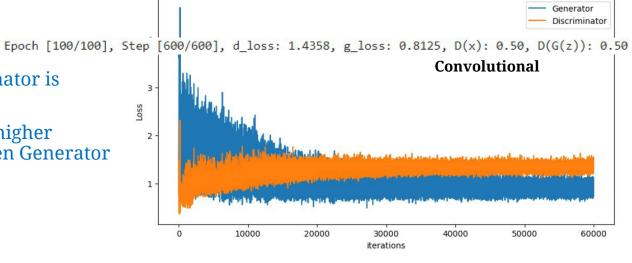
• Key Metrics:

- D(x): Discriminator's prediction on real images
 Closer to 1 is ideal.
- D(G(z)): Discriminator's prediction on generated images
 Closer to 1 indicates better Generator.
- g_loss & d_loss
 Lower values are better, indicating improved model performance
 Balancing is crucial to avoid model collapse.

Observations:

- o **Basic GANs** seem to have a disparity where the discriminator is dominating the generator.
- Convolutional GANs exhibit more balanced values, but higher Discriminator loss, indicating a better competition between Generator and Discriminator.





Comparative Analysis

Generator Performance:

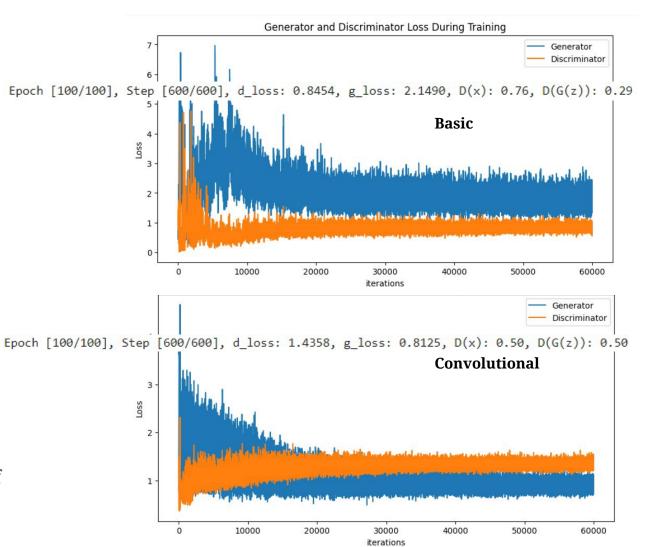
- In Basic GANs, the generator struggles more, reflected by higher g_loss, implying less convincing generation of images.
- Convolutional GANs have lower g_loss, suggesting the generator can create more believable images.

Discriminator Performance:

- The Basic GAN's discriminator is more proficient at differentiating between real and fake, evidenced by its lower d_loss and higher D(x).
- the discriminator in Convolutional GANs struggles more, with a higher d_loss and D(G(z)) values nearing 0.5, suggesting a more balanced competition between the Generator and the Discriminator.

Model Balance:

 Convolutional GANs illustrate a more balanced competition, which is crucial for the sustained learning of both the generator and the discriminator.



Evaluating GAN models:

• Frechet Inception Distance (FID):

- Measures the similarity between generated and real images, taking into account the feature distribution in the image representation space.
- Lower FID indicates better model performance and more realistic generated images.

Inception Score (IS):

- Evaluates the quality and diversity of generated images by computing the KL divergence between the conditional label distribution and the marginal label distribution of generated samples.
- Higher IS implies better image quality and diversity.

• Basic GAN:

o FID: 281.92

o Inception Score: 1.46 (±0.13)

Convolutional GANs:

o FID: 162.17

o Inception Score: 2.11 (±0.26)

Comparative Insight:

- The Convolutional GAN outperforms the Basic GAN, evident by a lower FID and a higher Inception Score, indicating that the images generated by the Convolutional GAN are of higher quality and more realism.
- The higher standard deviation in IS for the Convolutional GAN also suggests more diversity in the generated images.

Thank you

feedback, suggestions, continuous learning