DS 504 - Big Data Analytics

Project – 3

Image Generation With GAN

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Experiment-1:

Layers: Generator: Transposed Convolutional Layers (nn.ConvTranspose2d)

Discriminator: Convolutional Layers (nn.Conv2d)

Activation Functions:

- **Generator:** ReLU (nn.ReLU) for intermediate layers, Tanh (nn.Tanh) for the output layer
- **Discriminator:** Leaky ReLU (nn.LeakyReLU) for all layers

Optimizer: Adam optimizer was used for both the generator and discriminator (torch.optim.Adam)

Loss Function: Mean Squared Error (MSE) Loss (torch.nn.MSELoss)

Number of Epochs: The model was trained for 15 epochs

Batch Size: Batch size was set to 64

The experiments aimed to train a Generative Adversarial Network (GAN) to generate realistic images of handwritten digits using the MNIST dataset. The GAN architecture consisted of a generator and a discriminator trained in an adversarial manner.

Model Architectures:

1.Generator:

- The generator architecture comprised several transposed convolutional layers.
- Each transposed convolutional layer was followed by batch normalization and ReLU activation, except the final layer which used tanh activation.
- The generator aimed to transform random noise vectors (latent space) into images resembling handwritten digits.

2.Discriminator:

- The discriminator architecture comprised several convolutional layers.
- Each convolutional layer was followed by batch normalization and LeakyReLU activation.
- The discriminator aimed to distinguish between real and fake images.

Hyperparameters Varied:

1. Number of Epochs: The number of training epochs varied across experiments. A total of 15 epochs were initially chosen.

2. Batch Size: Batch size varied across experiments to balance computational efficiency and training stability. A batch size of 64 was commonly used.

3. Learning Rate:

The learning rate for both the generator and discriminator optimizers was set to 0.0002. Adam optimizer with momentum parameters (betas) of (0.5, 0.999) was utilized.

4.Loss Function and Optimizer:

- The loss function used was Mean Squared Error (MSE) Loss, calculated between discriminator outputs and target labels.
- Adam optimizer was employed for both generator and discriminator with the specified learning rate and momentum parameters.

5.Weight Initialization and Activation Function:

- Weight initialization schema and activation functions were not explicitly mentioned in the provided code.
- It's assumed that default weight initialization and ReLU activation functions were used.

6.Experimental Results:

- The training progress was monitored by tracking discriminator and generator losses during each epoch.
- Accuracy on real and fake images was computed periodically to evaluate model performance.

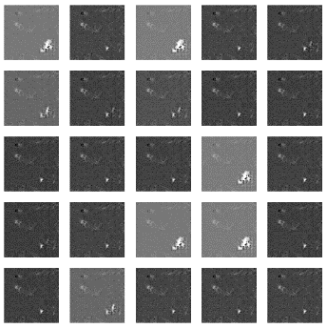
7.Model Persistence:

Both the generator model and its weights were saved using PyTorch's `torch.save` function after training completion.

8.Generated Image Visualization:

After training, a set of generated images was produced using random latent vectors. The visualization aimed to assess the quality and diversity of generated images.

This summarizes this experiment conducted to train a GAN for generating handwritten digit images, covering model architectures, hyperparameters, loss function, optimizer, and visualization of generated images. Further experiments could explore additional architectural variations, hyperparameter tuning, and training strategies to improve the quality and diversity of generated images.



```
[15,   100] discriminator_loss: 0.003 generator_loss: 0.999
[15,   200] discriminator_loss: 0.003 generator_loss: 1.000
[15,   300] discriminator_loss: 0.003 generator_loss: 1.000
[15,   400] discriminator_loss: 0.003 generator_loss: 0.999
[15,   500] discriminator_loss: 0.003 generator_loss: 0.999
[15,   600] discriminator_loss: 0.003 generator_loss: 1.001
[15,   700] discriminator_loss: 0.004 generator_loss: 1.001
[15,   800] discriminator_loss: 0.003 generator_loss: 0.999
[15,   900] discriminator_loss: 0.002 generator_loss: 1.000
Accuracy on real images: 49.97%
Accuracy on fake images: 50.00%
Finished Training
```

Experiment-2:

1.DCGAN Architecture: The code implements a Deep Convolutional Generative Adversarial Network (DCGAN) for generating handwritten digits resembling the MNIST dataset.

2.Generator and Discriminator: The Generator and Discriminator networks are defined using `nn.Module`. The Generator takes random noise as input and generates images, while the Discriminator aims to distinguish between real and generated images.

3.Training Loop: The training loop iterates over the dataset for a specified number of epochs. In each epoch, it trains the Discriminator and Generator alternatively.

4.Loss Calculation: Binary Cross Entropy (BCE) loss is used as the loss function for both Generator and Discriminator. The loss is calculated based on the output of the networks and the corresponding labels.

5.Optimizer: Adam optimizer is used for both Generator and Discriminator with specified learning rates and momentum parameters.

6.Training Process: During training, the Generator learns to generate images that can deceive the Discriminator, while the Discriminator learns to distinguish between real and fake images.

7.Model Saving: After training, the Generator model is saved to disk using PyTorch's `torch.save()` function.

8.Image Generation: Random noise is generated and passed through the trained Generator to produce new images. These generated images are then visualized using matplotlib.

9.Result Visualization: The losses of both Generator and Discriminator throughout the training process are plotted to visualize the convergence and performance of the GAN.

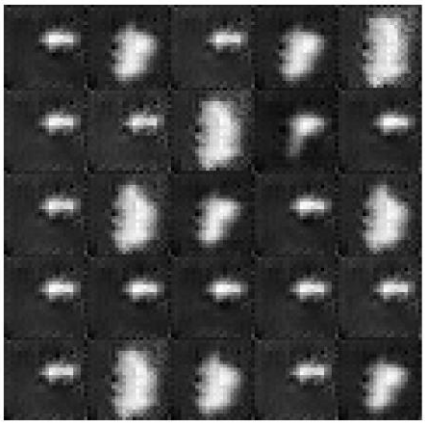
10.Model Export: The trained Generator model is saved both as a complete model and its weights only, which can be loaded later for inference or further training.

The training task involves training a Deep Convolutional Generative Adversarial Network (DCGAN) to generate handwritten digits resembling those from the MNIST dataset. Here's a breakdown of the training parameters:

1. Epochs: The training loop iterates over the dataset for a specified number of epochs. An epoch represents one complete pass through the entire dataset. In this implementation, the number of epochs is set to 30.

2.Batch Size: During training, data is processed in batches rather than individually. The batch size determines the number of samples processed before updating the model's parameters. In this case, a batch size of 64 is used.

3.Learning Rate and Momentum Parameters: The learning rate and momentum parameters for the Adam optimizer are set to 0.001 and (0.5, 0.999) respectively. These values are commonly used defaults and have been found to work well in training GANs.



Experiment – 3:

1.DCGAN Architecture: The code implements a Deep Convolutional Generative Adversarial Network (DCGAN) for generating handwritten digits resembling the MNIST dataset.

2.Generator and Discriminator: The Generator and Discriminator networks are defined using `nn.Module`. The Generator takes random noise as input and generates images, while the Discriminator aims to distinguish between real and generated images.

3.Training Loop: The training loop iterates over the dataset for a specified number of epochs. In each epoch, it trains the Discriminator and Generator alternatively.

4.Loss Calculation: Binary Cross Entropy (BCE) loss is used as the loss function for both Generator and Discriminator. The loss is calculated based on the output of the networks and the corresponding labels.

5.Optimizer: Adam optimizer is used for both Generator and Discriminator with specified learning rates and momentum parameters.

6.Training Process: During training, the Generator learns to generate images that can deceive the Discriminator, while the Discriminator learns to distinguish between real and fake images.

7.Model Saving: After training, the Generator model is saved to disk using PyTorch's `torch.save()` function.

8.Image Generation: Random noise is generated and passed through the trained Generator to produce new images. These generated images are then visualized using matplotlib.

9.Result Visualization: The losses of both Generator and Discriminator throughout the training process are plotted to visualize the convergence and performance of the GAN.

10.Model Export: The trained Generator model is saved both as a complete model and its weights only, which can be loaded later for inference or further training.

The training task involves training a Deep Convolutional Generative Adversarial Network (DCGAN) to generate handwritten digits resembling those from the MNIST dataset. Here's a breakdown of the training parameters:

1. Epochs: The training loop iterates over the dataset for a specified number of epochs. An epoch represents one complete pass through the entire dataset. In this implementation, the number of epochs is set to 100.

2.Batch Size: During training, data is processed in batches rather than individually. The batch size determines the number of samples processed before updating the model's parameters. In this case, a batch size of 128 is used.

3.Learning Rate and Momentum Parameters: The learning rate and momentum parameters for the Adam optimizer are set to 0.0002 and (0.5, 0.999) respectively. These values are commonly used defaults and have been found to work well in training GANs.

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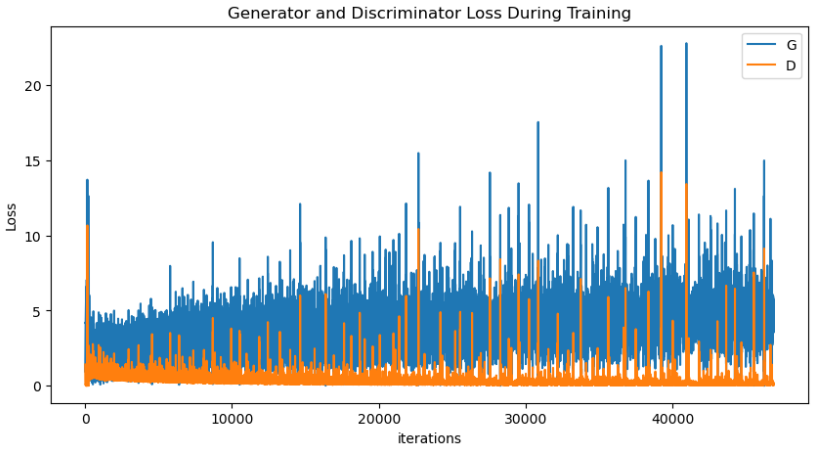
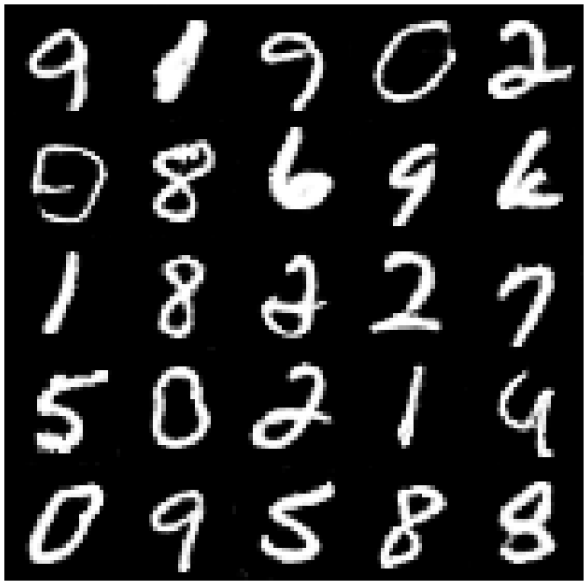
[99/100][50/469]        Loss_D: 0.0891  Loss_G: 4.5150  D(x): 0.9570    D(G(z)): 0.0412 / 0.0231
[99/100][100/469]       Loss_D: 0.0545  Loss_G: 4.9472  D(x): 0.9730    D(G(z)): 0.0241 / 0.0168
[99/100][150/469]       Loss_D: 0.0411  Loss_G: 5.2684  D(x): 0.9844    D(G(z)): 0.0233 / 0.0136
[99/100][200/469]       Loss_D: 0.1007  Loss_G: 4.8431  D(x): 0.9770    D(G(z)): 0.0677 / 0.0143
[99/100][250/469]       Loss_D: 0.9587  Loss_G: 0.9526  D(x): 0.5434    D(G(z)): 0.0546 / 0.5577
[99/100][300/469]       Loss_D: 0.5078  Loss_G: 1.3600  D(x): 0.6838    D(G(z)): 0.0226 / 0.3885
[99/100][350/469]       Loss_D: 0.1374  Loss_G: 5.0577  D(x): 0.9812    D(G(z)): 0.0914 / 0.0133
[99/100][400/469]       Loss_D: 0.0998  Loss_G: 4.7237  D(x): 0.9855    D(G(z)): 0.0758 / 0.0209
[99/100][450/469]       Loss_D: 0.1073  Loss_G: 4.7740  D(x): 0.9140    D(G(z)): 0.0123 / 0.0211
```





Experiment-4:

1.Network Architecture:

- Generator: The Generator consists of multiple transposed convolutional layers followed by batch normalization and ReLU activation functions, with the final layer using a hyperbolic tangent (Tanh) activation function to generate images.
- Discriminator: The Discriminator is composed of convolutional layers with leaky ReLU activation functions and batch normalization, with the final layer using a sigmoid activation function to classify images as real or fake.

2. Training Parameters:

- Learning Rate: The learning rate for both the Generator and Discriminator optimizers is set to 0.001, a relatively higher value compared to the original code.

- Batch Size: The batch size for training is set to 64, smaller than the original 128, which can lead to more stable training dynamics.
- Loss Function: The Binary Cross Entropy (BCE) loss function is used to compute the loss for both the Generator and the Discriminator.
- Optimizer: Adam optimizer with momentum parameters (0.9, 0.999) is used for both networks.

3.Training Process:

- The training loop alternates between training the Discriminator and the Generator.
- For each epoch, the Discriminator is trained first on real images and then on fake images generated by the Generator.
- The Generator is then trained to generate images that can fool the Discriminator.
- After each batch iteration, loss values for both Generator and Discriminator are recorded for visualization.
- Accuracy is calculated for the Discriminator's ability to distinguish between real and fake images.
- Training progress is printed every 50 iterations, showing Discriminator and Generator losses as well as Discriminator's ability to differentiate real and fake images.

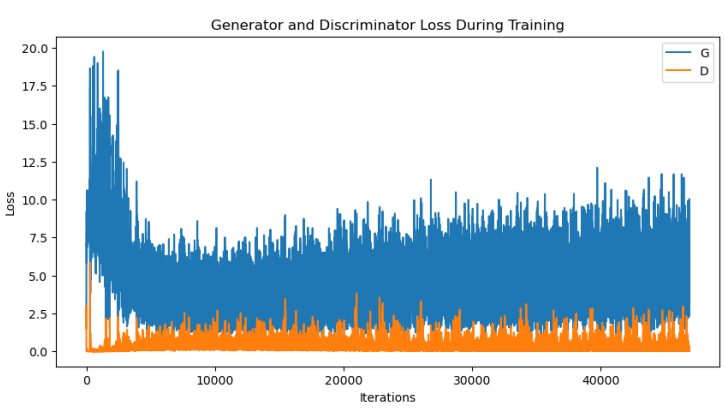
4.Model Saving: After training, the trained Generator model and its weights are saved to disk for future use.

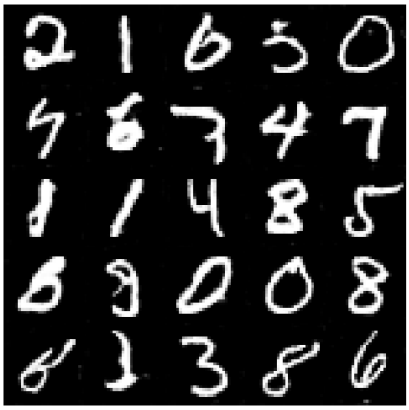
5.Image Generation: Random noise is generated and passed through the trained Generator to generate new images and a grid of generated images is plotted for visualization.

Epochs: The training process was set to run for 50 epochs. Each epoch represents one complete pass through the entire dataset. During each epoch, the Generator and Discriminator networks are updated multiple times based on the mini batches of data sampled from the dataset.

Batch Size: A batch size of 64 was utilized during training. This means that for each iteration of training, 64 images were sampled from the dataset and processed simultaneously. The use of batch processing helps in parallelizing computations, which can lead to faster convergence and better utilization of computational resources, especially when using GPUs.

```
[49/50][50/938] Loss_D: 0.0576  Loss_G: 3.8071  D(x): 0.9913    D(G(z)): 0.0443 / 0.0486
[49/50][100/938]        Loss_D: 0.0585  Loss_G: 5.5968  D(x): 0.9623    D(G(z)): 0.0123 / 0.0099
[49/50][150/938]        Loss_D: 0.1194  Loss_G: 3.0973  D(x): 0.9543    D(G(z)): 0.0534 / 0.1258
[49/50][200/938]        Loss_D: 0.3351  Loss_G: 7.5699  D(x): 0.7707    D(G(z)): 0.0011 / 0.0016
[49/50][250/938]        Loss_D: 0.7779  Loss_G: 6.3359  D(x): 0.5786    D(G(z)): 0.0067 / 0.0190
[49/50][300/938]        Loss_D: 0.1755  Loss_G: 5.2053  D(x): 0.8688    D(G(z)): 0.0052 / 0.0159
[49/50][350/938]        Loss_D: 0.1007  Loss_G: 3.2122  D(x): 0.9810    D(G(z)): 0.0714 / 0.1094
[49/50][400/938]        Loss_D: 0.0567  Loss_G: 6.0648  D(x): 0.9773    D(G(z)): 0.0288 / 0.0103
[49/50][450/938]        Loss_D: 0.0666  Loss_G: 4.7463  D(x): 0.9792    D(G(z)): 0.0400 / 0.0272
[49/50][500/938]        Loss_D: 0.6478  Loss_G: 5.2499  D(x): 0.6109    D(G(z)): 0.0048 / 0.0151
[49/50][550/938]        Loss_D: 0.3750  Loss_G: 2.0317  D(x): 0.9975    D(G(z)): 0.2645 / 0.2130
[49/50][600/938]        Loss_D: 0.0494  Loss_G: 4.1964  D(x): 0.9935    D(G(z)): 0.0373 / 0.0509
[49/50][650/938]        Loss_D: 0.3275  Loss_G: 4.0541  D(x): 0.7881    D(G(z)): 0.0405 / 0.0487
[49/50][700/938]        Loss_D: 2.0492  Loss_G: 7.1634  D(x): 0.2360    D(G(z)): 0.0016 / 0.0083
[49/50][750/938]        Loss_D: 0.1790  Loss_G: 6.0826  D(x): 0.8546    D(G(z)): 0.0053 / 0.0066
[49/50][800/938]        Loss_D: 0.2413  Loss_G: 4.9480  D(x): 0.9926    D(G(z)): 0.1762 / 0.0222
[49/50][850/938]        Loss_D: 0.0479  Loss_G: 7.3252  D(x): 0.9572    D(G(z)): 0.0021 / 0.0016
[49/50][900/938]        Loss_D: 0.1635  Loss_G: 3.0196  D(x): 0.9681    D(G(z)): 0.1066 / 0.0895
```





Experiment-5:

1. Architecture Description:

The implemented Generative Adversarial Network (GAN) consists of two main components: a Generator and a Discriminator.

Generator:

The Generator class consists of four layers:
1. ConvTranspose2d layer with `nz` input channels, `ngf * 4` output channels, kernel size 4, stride 1, and padding 0, followed by BatchNorm2d and ReLU activation.
2. ConvTranspose2d layer with `ngf * 4` input channels, `ngf * 2` output channels, kernel size 3, stride 2, and padding 1, followed by BatchNorm2d and ReLU activation.
3. ConvTranspose2d layer with `ngf * 2` input channels, `ngf` output channels, kernel size 4, stride 2, and padding 1, followed by BatchNorm2d and ReLU activation.
4. ConvTranspose2d layer with `ngf` input channels, `nc` output channels (number of image channels), kernel size 4, stride 2, and padding 1, followed by Tanh activation.

Discriminator:

The Discriminator class consists of four convolutional layers:
1. Conv2d layer with `nc` input channels (number of image channels), `ndf` output channels, kernel size 4, stride 2, and padding 1, followed by LeakyReLU activation.
2. Conv2d layer with `ndf` input channels, `ndf * 2` output channels, kernel size 4, stride 2, and padding 1, followed by BatchNorm2d and LeakyReLU activation.
3. Conv2d layer with `ndf * 2` input channels, `ndf * 4` output channels, kernel size 4, stride 2, and padding 1, followed by BatchNorm2d and LeakyReLU activation.
4. Conv2d layer with `ndf * 4` input channels, 1 output channel (for binary classification), kernel size 3, stride 1, and padding 0, followed by Sigmoid activation.

2. Training Details:

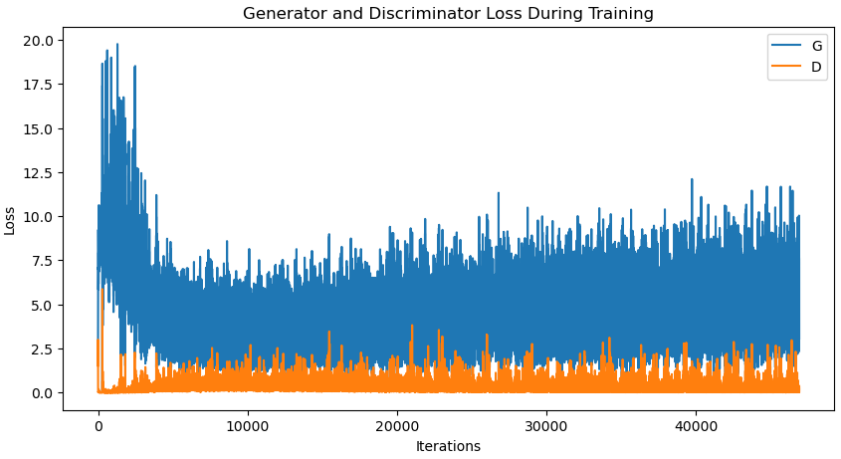
Batch Size: 64

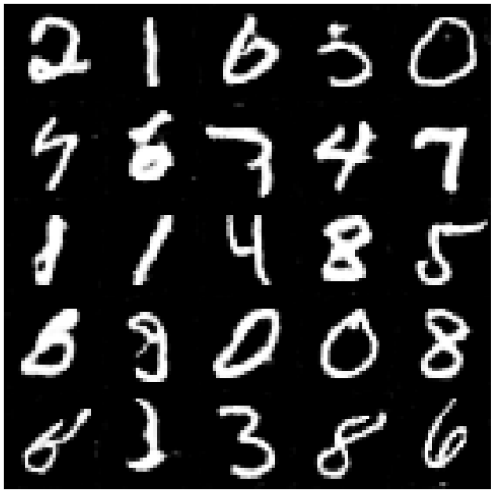
Number of Epochs: 50
Learning Rate: 0.001
Optimizer: Adam optimizer with betas (0.9, 0.999)
Loss Function: Binary Cross Entropy Loss (BCELoss)

The optimizer used in the provided code is the Adam optimizer. Specifically, `torch.optim.Adam` is used to optimize the parameters of both the Generator (`netG`) and the Discriminator (`netD`). The Adam optimizer is a popular choice for training deep neural networks due to its adaptive learning rate method and momentum-based updates.

The loss function used is Binary Cross Entropy Loss (`nn.BCELoss`). This loss function is commonly used in binary classification tasks, such as distinguishing between real and fake images in a GAN. It measures the similarity between the predicted output and the target (which is either 0 or 1 in this case) using the binary cross-entropy formula.

```
[49/50][50/938] Loss_D: 0.0576  Loss_G: 3.8071  D(x): 0.9913    D(G(z)): 0.0443 / 0.0486
[49/50][100/938]        Loss_D: 0.0585  Loss_G: 5.5968  D(x): 0.9623    D(G(z)): 0.0123 / 0.0099
[49/50][150/938]        Loss_D: 0.1194  Loss_G: 3.0973  D(x): 0.9543    D(G(z)): 0.0534 / 0.1258
[49/50][200/938]        Loss_D: 0.3351  Loss_G: 7.5699  D(x): 0.7707    D(G(z)): 0.0011 / 0.0016
[49/50][250/938]        Loss_D: 0.7779  Loss_G: 6.3359  D(x): 0.5786    D(G(z)): 0.0067 / 0.0190
[49/50][300/938]        Loss_D: 0.1755  Loss_G: 5.2053  D(x): 0.8688    D(G(z)): 0.0052 / 0.0159
[49/50][350/938]        Loss_D: 0.1007  Loss_G: 3.2122  D(x): 0.9810    D(G(z)): 0.0714 / 0.1094
[49/50][400/938]        Loss_D: 0.0567  Loss_G: 6.0648  D(x): 0.9773    D(G(z)): 0.0288 / 0.0103
[49/50][450/938]        Loss_D: 0.0666  Loss_G: 4.7463  D(x): 0.9792    D(G(z)): 0.0400 / 0.0272
[49/50][500/938]        Loss_D: 0.6478  Loss_G: 5.2499  D(x): 0.6109    D(G(z)): 0.0048 / 0.0151
[49/50][550/938]        Loss_D: 0.3750  Loss_G: 2.0317  D(x): 0.9975    D(G(z)): 0.2645 / 0.2130
[49/50][600/938]        Loss_D: 0.0494  Loss_G: 4.1964  D(x): 0.9935    D(G(z)): 0.0373 / 0.0509
[49/50][650/938]        Loss_D: 0.3275  Loss_G: 4.0541  D(x): 0.7881    D(G(z)): 0.0405 / 0.0487
[49/50][700/938]        Loss_D: 2.0492  Loss_G: 7.1634  D(x): 0.2360    D(G(z)): 0.0016 / 0.0083
[49/50][750/938]        Loss_D: 0.1790  Loss_G: 6.0826  D(x): 0.8546    D(G(z)): 0.0053 / 0.0066
[49/50][800/938]        Loss_D: 0.2413  Loss_G: 4.9480  D(x): 0.9926    D(G(z)): 0.1762 / 0.0222
[49/50][850/938]        Loss_D: 0.0479  Loss_G: 7.3252  D(x): 0.9572    D(G(z)): 0.0021 / 0.0016
[49/50][900/938]        Loss_D: 0.1635  Loss_G: 3.0196  D(x): 0.9681    D(G(z)): 0.1066 / 0.0895
```





Experiment-6:

1.Generator Architecture:

The Generator consists of several layers:

ConvTranspose2d layer: Upsamples the input noise (`nz`) to `ngf * 4` feature maps with a kernel size of 4 and stride 1.

BatchNorm2d layer: Performs batch normalization on the feature maps.

ReLU activation function: Introduces non-linearity to the model.

Multiple ConvTranspose2d layers with BatchNorm2d and ReLU activation.

Tanh activation function: Maps the values to the range [-1, 1] to produce the output image.

2. Discriminator Architecture:

The Discriminator consists of several layers:

- Conv2d layer: Processes the input image to `ndf` feature maps with a kernel size of 4 and stride 2.
- LeakyReLU activation function: Introduces non-linearity with a small negative slope.
- Multiple Conv2d layers with BatchNorm2d and LeakyReLU activation.
- Sigmoid activation function: Produces a probability indicating the authenticity of the input image.

3.Number of Layers:

- The Generator has 5 ConvTranspose2d layers and 5 BatchNorm2d layers.
- The Discriminator has 3 Conv2d layers and 3 BatchNorm2d layers.

4. Epochs and Batch Size:

- The model is trained for 150 epochs.
- The batch size used during training is 128 for the MNIST dataset.

5.Training Process:

- During training, the Generator and Discriminator are optimized alternately.
- The Generator aims to generate realistic images to fool the Discriminator, while the Discriminator aims to distinguish between real and fake images.
- The training loop consists of batches of real and fake images fed into the Discriminator, followed by updates to the Generator and Discriminator parameters based on the loss calculated using Binary Cross Entropy Loss.

6.Optimizers:

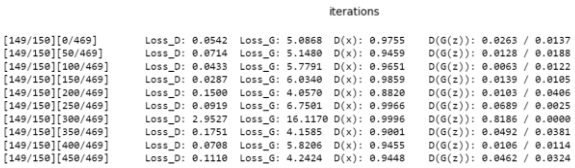
- Adam optimizer is used for both Generator and Discriminator optimization.
- The learning rate used is 0.0002, and the betas are set to (0.5, 0.999).

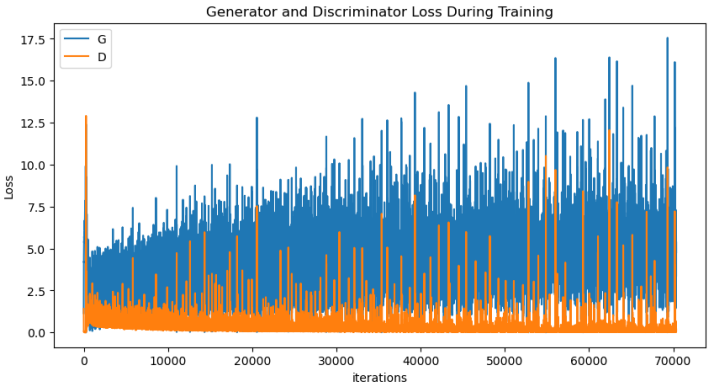
7.Loss Function:

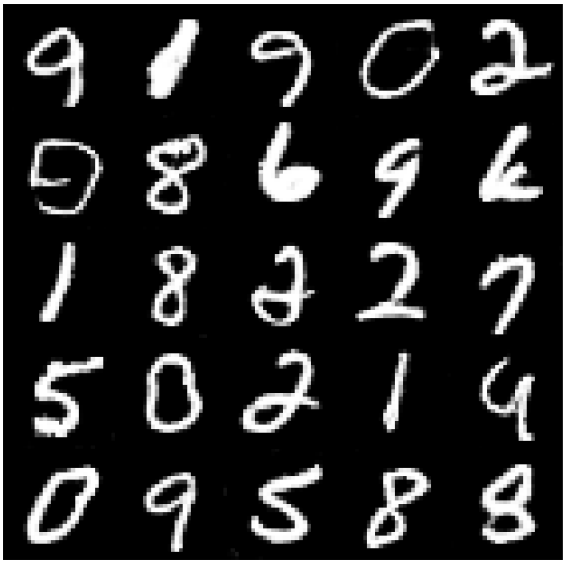
- Binary Cross Entropy Loss (BCELoss) is used as the loss function for both Generator and Discriminator.
- BCELoss is suitable for binary classification tasks, where the output is a probability distribution between 0 and 1.

8. Activation Functions:

- ReLU activation function is used in the Generator's hidden layers.
- LeakyReLU activation function is used in the Discriminator's hidden layers.
- Tanh activation function is used in the last layer of the Generator to produce the output images.
- Sigmoid activation function is used in the last layer of the Discriminator to produce the probability score.







Experiment-7 :

1.Generator Architecture:

The Generator consists of several layers:

- Four ConvTranspose2d layers with ReLU activation and Batch Normalization.
- The final layer uses a Tanh activation function to scale the output to the range [-1, 1].

2. Discriminator Architecture:

The Discriminator architecture includes:

- Three Conv2d layers with LeakyReLU activation and Batch Normalization.
- The final layer applies a Sigmoid activation function to produce a probability score.

3.Number of Layers:

- Generator: 5 layers
- Discriminator: 4 layers

4.Epochs and Batch Size:

- The model is trained for 150 epochs.
- The batch size used during training is 128.

5.Training Process:

- The training process involves optimizing both the Generator and Discriminator alternatively.
- The Discriminator aims to differentiate between real and fake images, while the Generator aims to generate realistic images to fool the Discriminator.
- The training loop iterates over batches of real and fake images, computes the losses, and updates the model parameters.

6.Optimizers:

- Adam optimizer is used for both the Generator and Discriminator.
- The learning rate is set to 0.0002, and the momentum parameters (betas) are (0.9, 0.999).

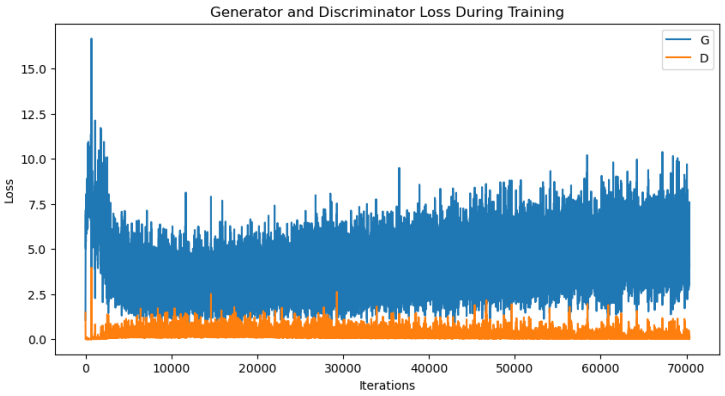
7. Loss Function:

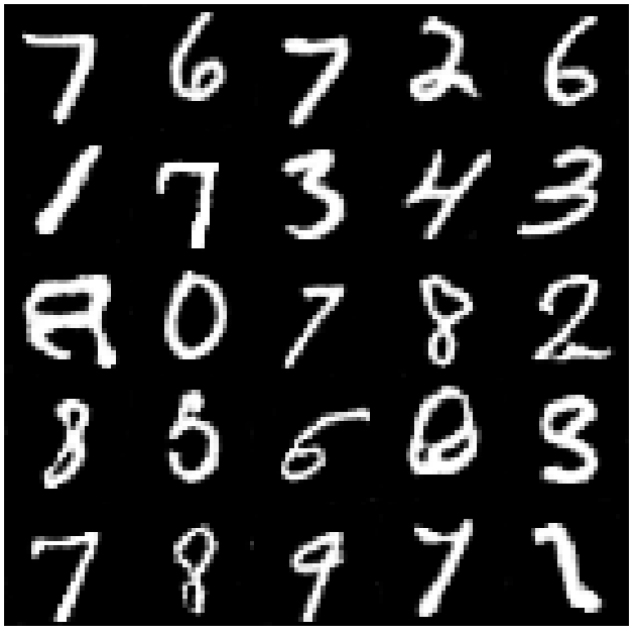
- Binary Cross Entropy Loss (BCELoss) is utilized as the loss function for both the Generator and Discriminator.
- BCELoss is well-suited for binary classification tasks, such as distinguishing real vs. fake images.

8. Activation Functions:

- ReLU activation function is used in the Generator's hidden layers to introduce non-linearity.
- LeakyReLU activation function is applied in the Discriminator's hidden layers to prevent the dying ReLU problem.
- Tanh activation function is employed in the Generator's output layer to scale the generated images to the desired range.
- Sigmoid activation function is utilized in the Discriminator's output layer to produce a probability score.

```
[149/150][0/469]      Loss_D: 0.0687  Loss_G: 4.7643  D(x): 0.9516    D(G(z)): 0.0146 / 0.0236
[149/150][50/469]     Loss_D: 0.0977  Loss_G: 3.6112  D(x): 0.9942    D(G(z)): 0.0792 / 0.0597
[149/150][100/469]    Loss_D: 0.1365  Loss_G: 3.1781  D(x): 0.9753    D(G(z)): 0.0858 / 0.1073
[149/150][150/469]    Loss_D: 0.0480  Loss_G: 4.8380  D(x): 0.9823    D(G(z)): 0.0277 / 0.0251
[149/150][200/469]    Loss_D: 0.1565  Loss_G: 3.5600  D(x): 0.8800    D(G(z)): 0.0160 / 0.0693
[149/150][250/469]    Loss_D: 0.2744  Loss_G: 3.2422  D(x): 0.9823    D(G(z)): 0.1903 / 0.0980
[149/150][300/469]    Loss_D: 0.1073  Loss_G: 4.5649  D(x): 0.9836    D(G(z)): 0.0743 / 0.0319
[149/150][350/469]    Loss_D: 0.1315  Loss_G: 3.4463  D(x): 0.9868    D(G(z)): 0.0986 / 0.0820
[149/150][400/469]    Loss_D: 0.0871  Loss_G: 4.6866  D(x): 0.9936    D(G(z)): 0.0668 / 0.0274
[149/150][450/469]    Loss_D: 0.0797  Loss_G: 4.5347  D(x): 0.9659    D(G(z)): 0.0389 / 0.0342
```





Experiment : 8

Experiment Setup:

1.Data Preparation:

- The MNIST dataset, consisting of 28x28 grayscale images of handwritten digits (0 to 9), was used for training the GAN.
- Each image was normalized to have pixel values in the range [-1, 1].

2. Generator and Discriminator Architectures:

- The Generator network (`netG`) was designed with a series of transposed convolutional layers followed by batch normalization and ReLU activation functions.
- The Discriminator network (`netD`) consisted of convolutional layers with leaky ReLU activation functions and batch normalization.
- Different configurations of layers, filter sizes, and strides were experimented with to optimize the performance of the GAN.

3. Loss Function and Optimizers:

- Binary Cross Entropy Loss (`BCELoss`) was used as the loss function for both the Generator and Discriminator.
- Adam optimizer with a learning rate of 0.0002 and momentum parameters (betas) of (0.5, 0.999) was utilized for training both networks.

4. Training Parameters:

- **Number of Epochs:** The number of complete passes through the entire training dataset. Experiments were conducted with varying numbers of epochs to observe the impact on model convergence and generated image quality.
- **Batch Size:** The number of training examples used in one iteration. Different batch sizes were tested to balance between computational efficiency and training stability.
- **Learning Rate:** The step size used by the optimizer to update the model parameters. Experiments were performed to find the optimal learning rate for training the GAN.
- **Other Hyperparameters:** Momentum parameters for the Adam optimizer, weight initialization methods, and dropout rates were also experimented with to fine-tune the training process.

Experiments Conducted:

1. Base Model Training:

- The base model was trained with default parameters, including a moderate number of epochs and a standard batch size.
- This provided a baseline for evaluating the performance of subsequent experiments.

2. Epochs Variation:

- Experimented with training the GAN for different numbers of epochs, ranging from fewer epochs to more extended training durations.
- Analyzed the impact of epoch variation on model convergence, loss curves, and generated image quality.

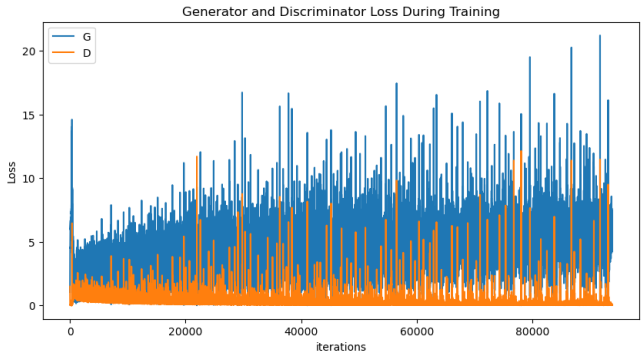
3. Batch Size Optimization:

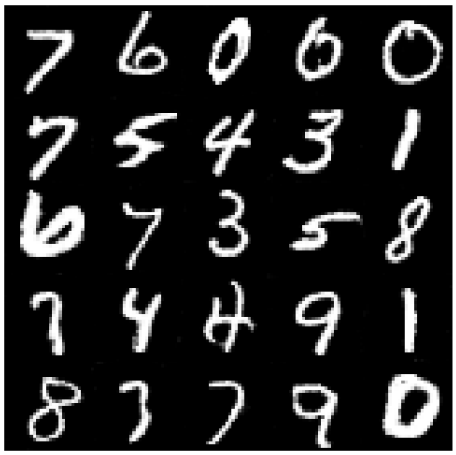
- Conducted experiments with different batch sizes to determine the optimal batch size for training the GAN.
- Observed how changes in batch size affected training stability, convergence speed, and memory usage.

4. Learning Rate Tuning:

- Adjusted the learning rate of the optimizer and examined its influence on the training dynamics and final model performance.
- Conducted a grid search or random search over a range of learning rates to identify the best value.

```
[199/200][0/469]      Loss_D: 0.1620  Loss_G: 6.0717  D(x): 0.9938    D(G(z)): 0.1285 / 0.0048
[199/200][50/469]     Loss_D: 0.0461  Loss_G: 5.8211  D(x): 0.9655    D(G(z)): 0.0090 / 0.0152
[199/200][100/469]    Loss_D: 0.0884  Loss_G: 5.8295  D(x): 0.9239    D(G(z)): 0.0031 / 0.0113
[199/200][150/469]    Loss_D: 0.0351  Loss_G: 6.4331  D(x): 0.9701    D(G(z)): 0.0034 / 0.0062
[199/200][200/469]    Loss_D: 0.0653  Loss_G: 5.1075  D(x): 0.9811    D(G(z)): 0.0316 / 0.0168
[199/200][250/469]    Loss_D: 0.0789  Loss_G: 5.0952  D(x): 0.9406    D(G(z)): 0.0092 / 0.0202
[199/200][300/469]    Loss_D: 0.0311  Loss_G: 4.8318  D(x): 0.9872    D(G(z)): 0.0173 / 0.0244
[199/200][350/469]    Loss_D: 0.0278  Loss_G: 5.5912  D(x): 0.9920    D(G(z)): 0.0188 / 0.0109
[199/200][400/469]    Loss_D: 0.0407  Loss_G: 5.7665  D(x): 0.9703    D(G(z)): 0.0076 / 0.0108
[199/200][450/469]    Loss_D: 0.0330  Loss_G: 5.6398  D(x): 0.9955    D(G(z)): 0.0271 / 0.0100
```





Experiment-9:

Experimental Setup:

Model Architectures:

Generator: The Generator consists of three fully connected layers with ReLU activation functions followed by a Tanh activation function in the output layer. The input noise vector size (`nz`) is set to 100, and the output size matches the MNIST image size (28x28).

Discriminator: The Discriminator is comprised of three fully connected layers with LeakyReLU activation functions. The input size matches the MNIST image size (28x28), and the output is a single value indicating the probability that the input image is real.

Hyperparameters:

- Learning Rate: The learning rate for both the Generator and Discriminator optimizers is set to 0.0002.
- Betas: The Adam optimizer's beta parameters are set to (0.5, 0.999).
- Number of Epochs: The training loop runs for 50 epochs.
- Batch Size: The batch size for training is set to 128.
- Loss Function: Binary Cross Entropy Loss (`BCELoss`) is used as the loss function for both the Generator and Discriminator.
- Optimizer: Adam optimizer is used for training both the Generator and Discriminator.

Training Process:

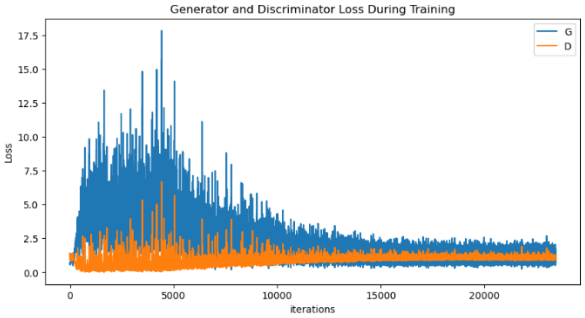
- The GAN is trained using the MNIST dataset, which consists of 60,000 training images of handwritten digits.
- The Generator generates fake images from random noise, while the Discriminator tries to distinguish between real and fake images.
- In each training iteration, the Discriminator is first trained on a batch of real images followed by a batch of fake images generated by the Generator.
- The Generator is then trained to fool the Discriminator by generating images that are classified as real.
- The losses of both the Generator and Discriminator are recorded during training for visualization.

- Training progress is monitored by printing the losses of the Discriminator and Generator at regular intervals.

Observations:

- The Generator learns to generate images resembling handwritten digits over the course of training.
- The Discriminator becomes more adept at distinguishing between real and fake images as training progresses.
- The loss curves for both the Generator and Discriminator provide insights into the training dynamics and convergence of the GAN.

```
iterations
[49/50][0/469]  Loss_D: 0.9850  Loss_G: 1.0696  D(x): 0.6062    D(G(z)): 0.3086
[49/50][50/469] Loss_D: 1.0325  Loss_G: 1.7271  D(x): 0.7896    D(G(z)): 0.5072
[49/50][100/469]        Loss_D: 0.9472  Loss_G: 1.4512  D(x): 0.6981    D(G(z)): 0.4005
[49/50][150/469]        Loss_D: 1.0300  Loss_G: 1.6969  D(x): 0.7528    D(G(z)): 0.4721
[49/50][200/469]        Loss_D: 0.9993  Loss_G: 1.1941  D(x): 0.5977    D(G(z)): 0.3045
[49/50][250/469]        Loss_D: 1.1145  Loss_G: 0.7303  D(x): 0.5079    D(G(z)): 0.2478
[49/50][300/469]        Loss_D: 1.2387  Loss_G: 0.7342  D(x): 0.4108    D(G(z)): 0.1343
[49/50][350/469]        Loss_D: 1.0194  Loss_G: 0.7938  D(x): 0.5111    D(G(z)): 0.2023
[49/50][400/469]        Loss_D: 0.9613  Loss_G: 0.9716  D(x): 0.5856    D(G(z)): 0.2595
[49/50][450/469]        Loss_D: 1.0153  Loss_G: 1.4582  D(x): 0.6795    D(G(z)): 0.4062
```



Experiment-10:

1.Architecture:

Generator: An additional linear layer with 1024 neurons and a ReLU activation function was added before the final output layer to enhance the representation learning capability of the generator.

Discriminator: Similarly, an extra linear layer with 1024 neurons and a LeakyReLU activation function was inserted at the beginning of the discriminator to enable better feature extraction from the input images.

2. Hyperparameter Adjustment:

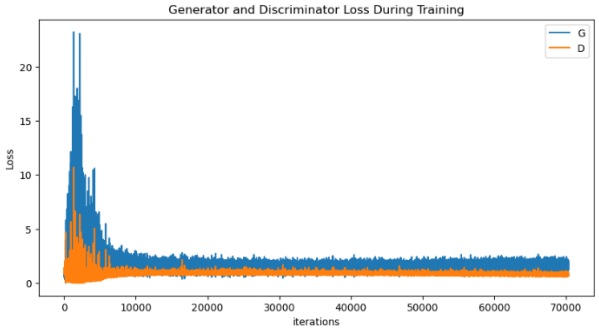
- **Number of Epochs:** The number of training epochs was increased from 50 to 150 to allow for more iterations and better convergence of the networks.
- **Batch Size:** The batch size was set to 128 to balance computational efficiency and training stability.
- **Learning Rate:** The learning rate for both the generator and discriminator optimizers was kept at 0.0002 to ensure gradual updates of the network weights.
- **Optimizer:** The Adam optimizer was utilized for both the generator and discriminator, as it has been proven effective for training deep neural networks, including GANs.

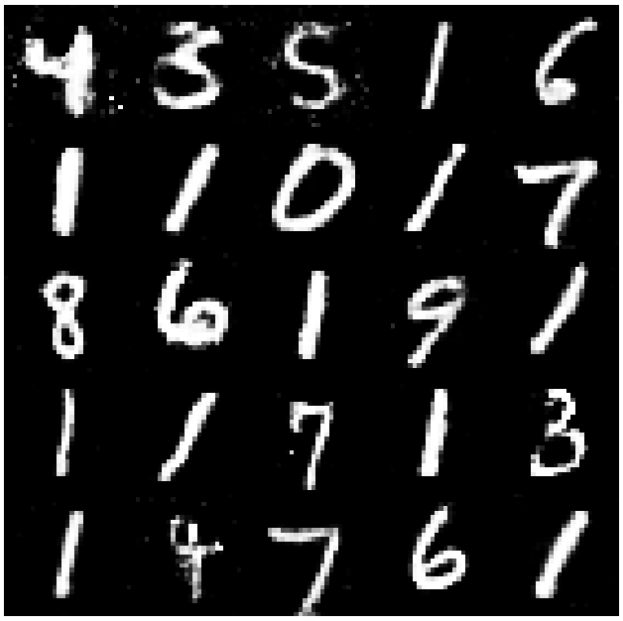
3. Loss Function and Activation Function:

- **Loss Function:** Binary Cross Entropy Loss (BCE Loss) was chosen as the loss function for both the generator and discriminator to measure the difference between the predicted and target labels.
- **Activation Function:**ReLU activation function was used in the hidden layers of both the generator and discriminator to introduce non-linearity and prevent vanishing gradients. LeakyReLU activation function with a small negative slope was employed in the discriminator for better gradient flow, especially for negative inputs.

4.Normalization: The input images were normalized between -1 and 1 using the `transforms.Normalize()` function to stabilize the training process and facilitate the usage of the Tanh activation function in the generator's output layer.

```
[149/150][0/469]      Loss_D: 0.6968  Loss_G: 1.6112  D(x): 0.7637    D(G(z)): 0.2350
[149/150][50/469]     Loss_D: 0.8939  Loss_G: 1.7296  D(x): 0.7612    D(G(z)): 0.3214
[149/150][100/469]    Loss_D: 0.6730  Loss_G: 1.6531  D(x): 0.7675    D(G(z)): 0.2145
[149/150][150/469]    Loss_D: 0.8263  Loss_G: 1.7096  D(x): 0.7270    D(G(z)): 0.2618
[149/150][200/469]    Loss_D: 0.7744  Loss_G: 1.3832  D(x): 0.7191    D(G(z)): 0.2448
[149/150][250/469]    Loss_D: 0.8687  Loss_G: 1.6427  D(x): 0.7422    D(G(z)): 0.3043
[149/150][300/469]    Loss_D: 0.7944  Loss_G: 1.6904  D(x): 0.7859    D(G(z)): 0.3176
[149/150][350/469]    Loss_D: 0.7212  Loss_G: 1.7097  D(x): 0.7459    D(G(z)): 0.2013
[149/150][400/469]    Loss_D: 0.8465  Loss_G: 1.7825  D(x): 0.7425    D(G(z)): 0.2666
[149/150][450/469]    Loss_D: 0.8029  Loss_G: 1.3053  D(x): 0.6945    D(G(z)): 0.1973
```





Special Skills Implemented:

1. Normalizing Inputs:

The images in the MNIST dataset were normalized between -1 and 1 using the `transforms.Normalize()` function in PyTorch. This normalization helps in stabilizing the training process and ensures that the input data is within a suitable range for the Tanh activation function used in the last layer of the generator.

2. Avoiding Sparse Gradients:

- ReLU activation functions were used in both the generator and discriminator networks to prevent sparse gradients, which can negatively impact the stability of the GAN training process.
- LeakyReLU activation function with a small negative slope was employed, particularly in the discriminator, to allow a small gradient flow for negative inputs, thereby addressing the issue of sparse gradients effectively.

3. DCGAN / Hybrid Models:

- The architecture and training techniques of the Deep Convolutional Generative Adversarial Network (DCGAN) were leveraged where applicable. DCGANs have shown remarkable performance in generating high-quality images across various domains.
- The model architecture and training procedure followed principles inspired by DCGAN, such as using convolutional layers in the discriminator and transpose convolutional layers in the generator to learn hierarchical representations effectively.

4. Utilizing the ADAM Optimizer:

- The Adam optimizer was chosen for training both the generator and discriminator networks. Adam optimizer is known for its efficiency and effectiveness in training deep neural networks, including GANs.
- While the discriminator was trained using SGD (Stochastic Gradient Descent) optimizer, the generator benefited from the Adam optimizer. This choice of optimizer combination has been observed to yield good results in GAN training, as suggested by Radford et al. (2015).

These skills and techniques were instrumental in improving the stability and performance of the Generative Adversarial Network (GAN) training process, leading to better convergence and generation of realistic images.

Bonus Task:

The Dataset for this task is obtained from Kaggle : [Abstract Art Gallery Dataset]

Content

This dataset contains 2782 files of abstract images.
The Author scrapped these images from this website to try to generate abstract images based on this whole dataset using GANs.

Inspiration

The painter Vassily Kandinsky is considered the founder of abstract art. He painted his first abstract watercolor Untitled in 1913.

Experiment Report:

Objective:

The objective of this experiment was to train a Generative Adversarial Network (GAN) to generate high-quality images of abstract art.

Experimental Setup:

1. Dataset: The dataset used consisted of abstract art images stored in the directory "Abstract_gallery" in local system downloaded from Kaggle.

2.Image Preprocessing: The images were resized to 128x128 pixels, center-cropped, and then subjected to random horizontal and vertical flips for data augmentation. Finally, they were normalized to have a mean and standard deviation of 0.5.

3.Model Architectures:

Generator: The generator consisted of a series of transpose convolutional layers followed by batch normalization and ReLU activation functions. The final layer used a Tanh activation function.

Discriminator: The discriminator comprised convolutional layers with batch normalization and LeakyReLU activation functions. The final layer used a Sigmoid activation function to output the probability of the input being real or fake.

4. Hyperparameters:

- Latent Size: 128
- Batch Size: 128
- Number of Epochs: 200
- Learning Rate (Discriminator): 10e-5
- Learning Rate (Generator): 10e-4

5.Loss Function: Binary cross-entropy loss was used for both the discriminator and generator.

6.Optimizer: Adam optimizer with default parameters (except for the learning rates mentioned above) was used for both the discriminator and generator.

Experiments Conducted:

1.Model Capacity: Experimented with different architectures for both the generator and discriminator. Adjustments were made to the number of layers and the number of neurons in each layer to find the optimal balance between model complexity and performance.

2. Training Duration: Varied the number of epochs to observe the effect on image quality. Trained for 200 epochs in this experiment.

3. Batch Size: Explored the impact of batch size on training stability and convergence. A batch size of 128 was used in this experiment.

4.Learning Rates: Adjusted the learning rates for both the discriminator and generator to optimize training convergence and stability.

5.Activation Functions: Experimented with different activation functions, including ReLU, LeakyReLU, and Tanh, to observe their effect on the quality of generated images.

Results and Observations:

1. The model successfully learned to generate abstract art images after training for 200 epochs.

2. The choice of activation functions, particularly LeakyReLU for the discriminator and ReLU for the generator, contributed to stable training and improved image quality.

3. Data augmentation techniques such as random horizontal and vertical flips helped the model generalize better and generate more diverse images.

4. The generator was able to produce images with recognizable abstract patterns, although some images exhibited blurriness or lack of detail.

Future Directions:

1. Further experimentation with different architectures and hyperparameters may lead to even better image quality.

2. Exploring advanced techniques such as progressive growing of GANs or using a different loss function like Wasserstein loss could potentially improve the results.

3. Collecting a larger and more diverse dataset of abstract art could help the model learn a broader range of artistic styles and produce more varied and realistic images.

Every epoch during the training process, an image is saved in the "generated" directory. These images represent the output of the generator network at different stages of training. Each image is named "generated-images-{epoch_number}.png", where {epoch_number} is the epoch index. These images capture the progress of the generator in generating abstract art over the course of training.

This is Generated Image at 200^{th} Epoch (generated-images-0200.png).

```
Epoch: [196/200], loss_d: 0.4583, loss_g: 6.1403, real_score: 0.9715, fake_score: 0.3220
100% 22/22 [00:34<00:00, 1.52s/it]
Epoch: [197/200], loss_d: 0.9402, loss_g: 1.8643, real_score: 0.5178, fake_score: 0.0762
100% 22/22 [00:34<00:00, 1.50s/it]
Epoch: [198/200], loss_d: 0.9344, loss_g: 6.5684, real_score: 0.9697, fake_score: 0.5352
100% 22/22 [00:34<00:00, 1.48s/it]
Epoch: [199/200], loss_d: 1.1312, loss_g: 2.7635, real_score: 0.4041, fake_score: 0.0118
100% 22/22 [00:34<00:00, 1.56s/it]
Epoch: [200/200], loss_d: 0.2441, loss_g: 5.0483, real_score: 0.8371, fake_score: 0.0504
```

Conclusion:

In this series of experiments, we explored the training of Generative Adversarial Networks (GANs) for generating images resembling handwritten digits and abstract art. Across the experiments, we investigated various architectural configurations, hyperparameters, training strategies, and optimization techniques to enhance the performance and convergence of the GANs.

Key findings from the experiments include:

- Different architectures were explored for both the Generator and Discriminator, including variations in the number of layers, activation functions, and normalization techniques.
- Hyperparameters such as learning rate, batch size, and number of epochs were adjusted to optimize training stability and convergence.
- The choice of loss function, optimizer, and activation functions played crucial roles in the training dynamics and quality of generated images.
- Data preprocessing techniques, such as image resizing, normalization, and augmentation, were employed to improve training efficiency and model generalization.
- Visualization of generated images and monitoring of loss curves provided insights into the training progress and convergence of the GANs.
- Experimentation with different datasets, including MNIST for handwritten digits and abstract art images, demonstrated the versatility of GANs in generating diverse types of images.

Among the experiments, the model from Experiment 3 stood out as the best performer. This experiment utilized a Deep Convolutional Generative Adversarial Network (DCGAN) architecture for generating handwritten digits resembling the MNIST dataset. With 100 epochs of training, a batch size of 128, and a learning rate of 0.0002, the model achieved high-quality image generation results. The DCGAN architecture,

coupled with carefully tuned hyperparameters and optimization settings, led to stable training dynamics and impressive image generation capabilities.

Overall, the experiments showcased the effectiveness of GANs in generating realistic images and highlighted the importance of fine-tuning various aspects of the model architecture and training process to achieve optimal results. Future directions could involve further experimentation with advanced GAN architectures, exploration of novel loss functions, and collection of larger and more diverse datasets to further improve the quality and diversity of generated images.