FUNCTION GENERATION USING GAN

UML501-MACHINE LEARNING

Submitted By-

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BE Third Year, COE

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1. Introduction

1.1 Problem Statement

In the ever-evolving landscape of artificial intelligence and machine learning, the demand for large, labeled datasets for training models has become a significant bottleneck. The project at hand addresses this challenge by harnessing the power of Generative Adversarial Networks (GANs) to synthesize realistic data points. The specific focus is on generating synthetic data in both 2D and 3D spaces, paving the way for innovative solutions to data scarcity issues.

1.2 Scope of the Project

The project extends beyond the conventional implementation of GANs. It delves into the nuanced exploration of the generated data's characteristics, ensuring not only statistical fidelity but also diverse and faithful representation of the target distribution. Dynamic adjustments to learning rates, mode collapse detection mechanisms, and the introduction of comprehensive convergence metrics elevate this project from a simple implementation to an in-depth analysis of the underlying processes governing GAN training dynamics.

2. Proposed Work

2.1 Proposed Model

Generative Adversarial Networks (GANs) represent a powerful class of machine learning models consisting of a generator and a discriminator. The generator aims to create data indistinguishable from real data, while the discriminator attempts to differentiate between real and generated samples. This adversarial training process results in a generator capable of producing high-quality synthetic data.

Model Architecture:

In the 2D case, the discriminator comprises a neural network with one input layer (2 nodes for X and Y coordinates), a hidden layer with 25 nodes using ReLU activation, and an output layer with a sigmoid activation for binary classification. The 2D generator includes one hidden layer with 15 nodes using ReLU activation and an output layer with 2 nodes for X and Y coordinates. **For the 3D case**, the architecture is extended to accommodate three-dimensional data, with adjustments made to both discriminator and generator structures.

Experimental Setup:

Synthetic data is generated based on predefined functions for real samples. The 2D function involves a relationship between X and Y coordinates, while the 3D function incorporates a sinusoidal component in addition to X and Y. Data preprocessing involves normalization and splitting into training and evaluation sets. The Adam optimizer with binary cross-entropy loss is employed during training.

Training Procedure:

The training process spans a defined number of epochs with dynamic adjustments to the learning rate. Discriminator and generator losses are monitored throughout the training phase.

2.2 Results and Comparison

A multi-faceted evaluation approach is employed to gauge the success of the proposed models. Discriminator and generator losses, accuracy rates, and visualizations of generated samples provide a quantitative and qualitative understanding of the models' performance. Going beyond the basics, various metrics, including diversity, mode collapse detection, learning rate adjustments, and convergence metrics, are incorporated to offer a more comprehensive view of the models' behavior.

The visualization of generated samples not only serves as a qualitative measure but also offers an intuitive grasp of the models' ability to capture the intricate nuances of the underlying data distribution. By comparing the results of the 2D and 3D models, a deeper understanding of the challenges and successes associated with different data dimensionalities is obtained.

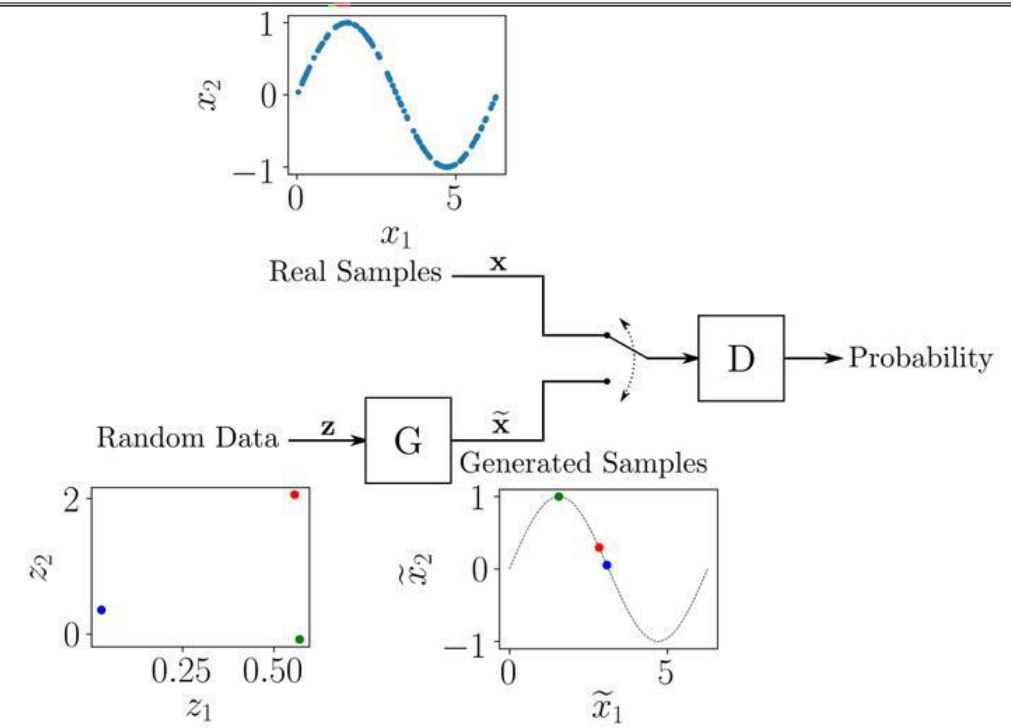

Fig 2.2 GAN Workflow

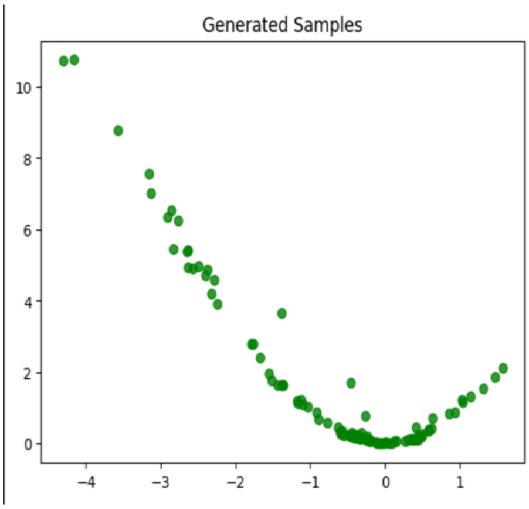

Fig 2.2.(i) Generated Sample 2D

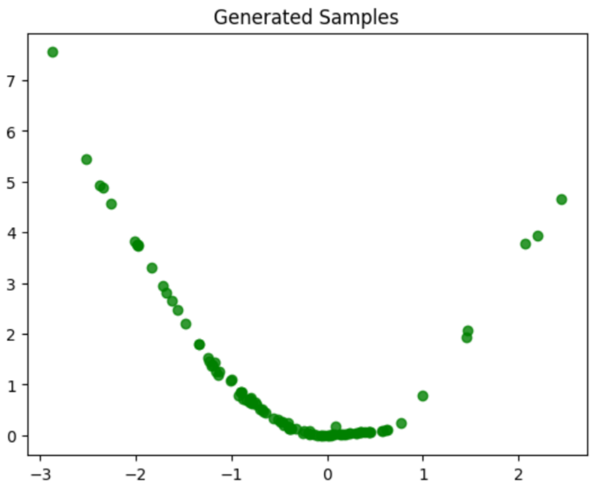

Fig 2.2.(ii) Generated Sample 2D

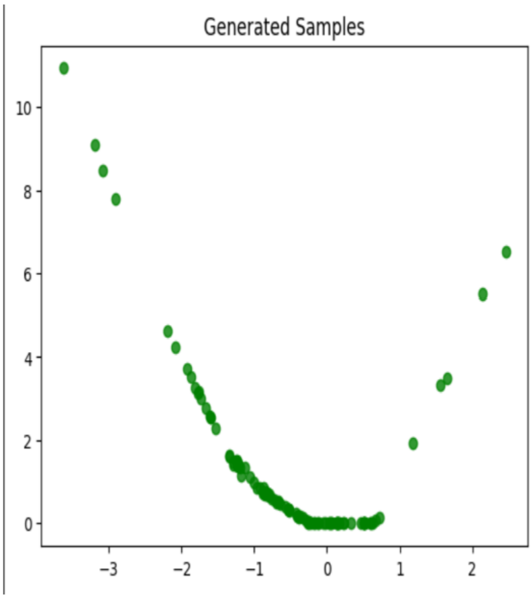

Fig 2.2.(iii) Generated Sample 2D

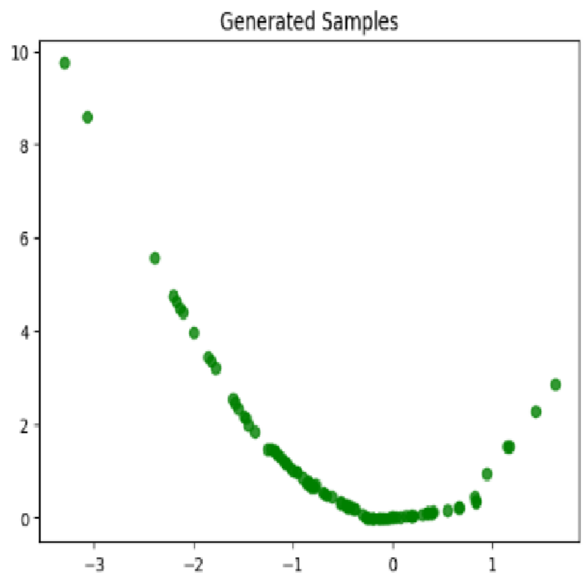

Fig 2.2.(iv) Generated Sample 2D

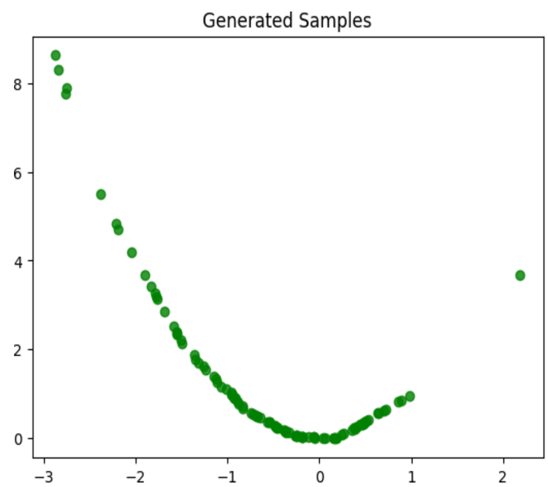

Fig2.2.(v) Generated Sample 2D

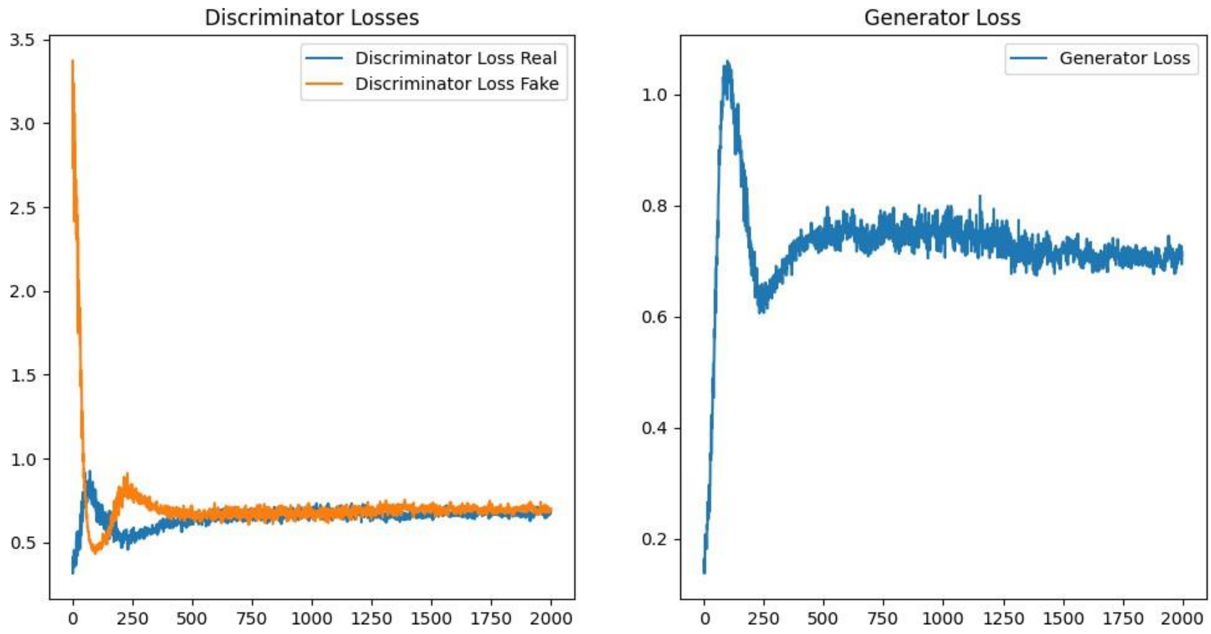

Fig 2.2.(vi) Discriminator Loses and Generator Loss respectively

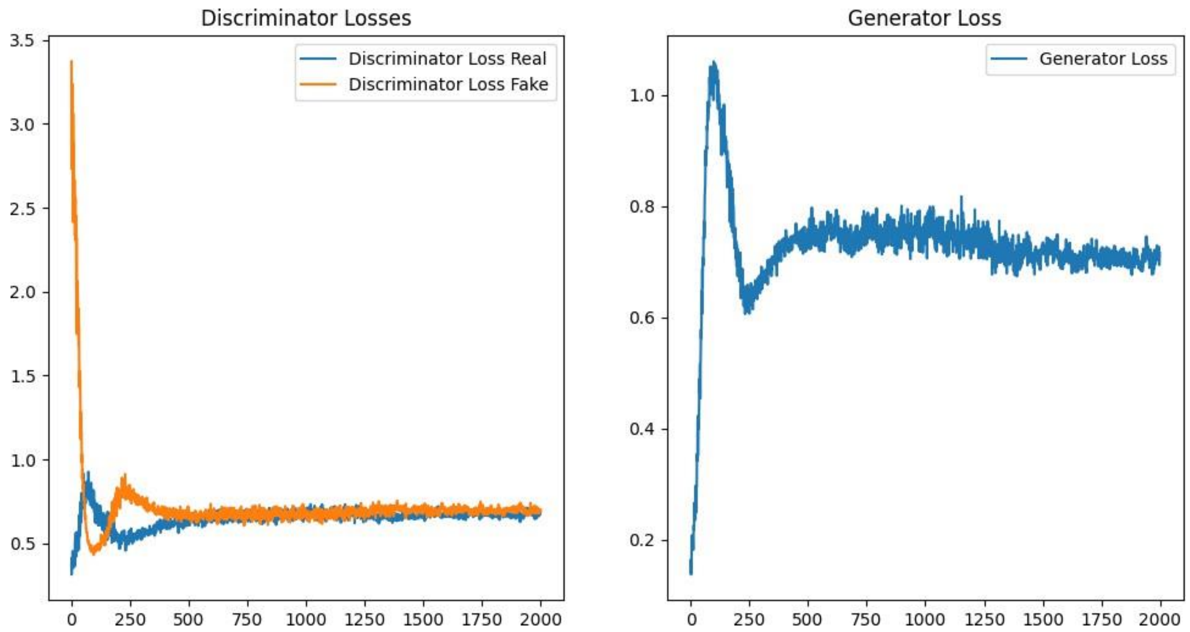

Fig 2.2.(vii) Discriminator Loses and Generator Loss respectively

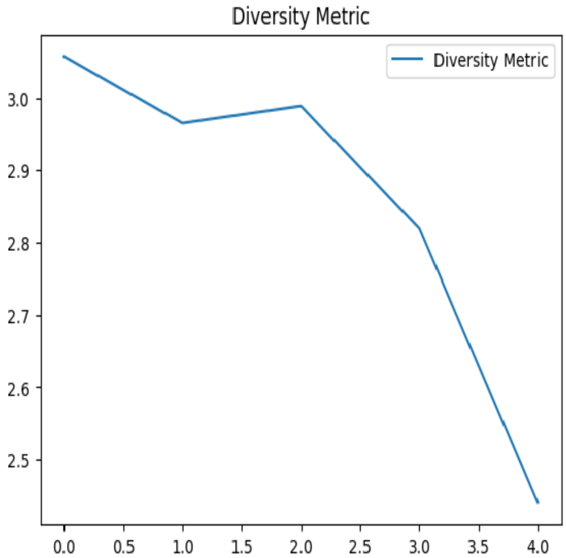

Fig2.2.(viii) Diversity Metric

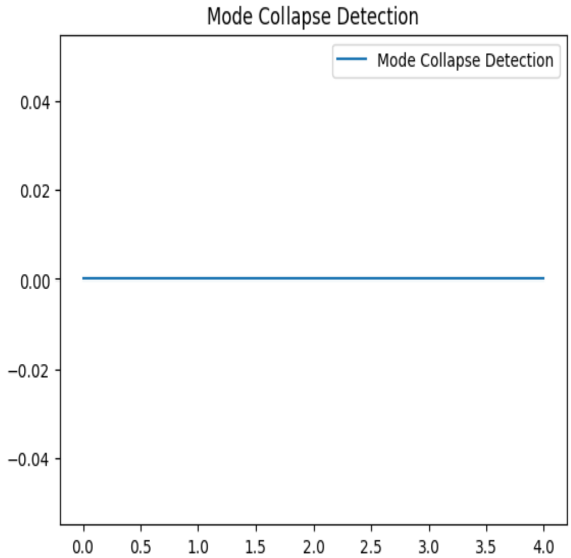

Fig2.2.(ix) Mode Collapse Detection

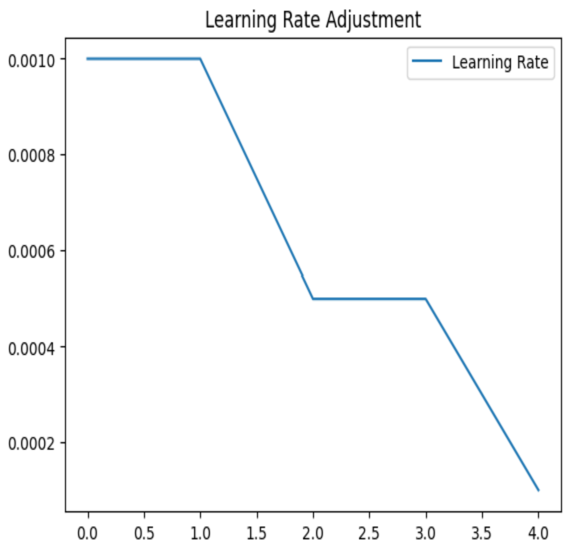

Fig2.2.(x) Learning Rate Adjustment

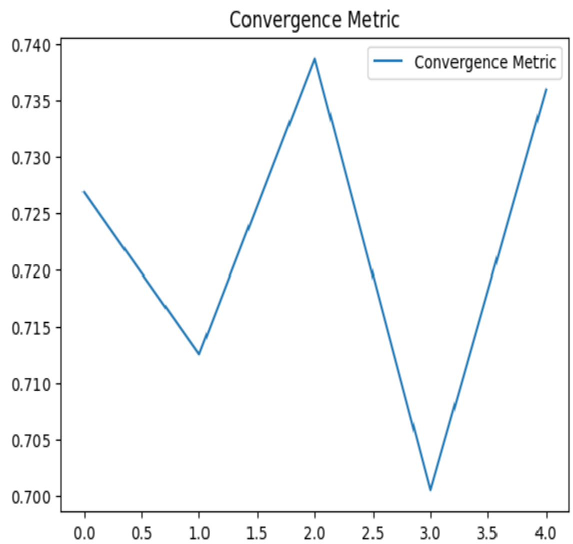

Fig2.2.(xi) Convergence Matrix

Epoch	D Loss Rea	D Loss Fak	G Loss	D Accurac	D Accurac	G Accurac	Diversity	Mode Coll	Learning R	Converger	Function Data
2000	0.710549	0.684602	0.709949	0.251	0.794	0.167	2.440036	FALSE	0.0001	0.735897	19990
4000	0.710549	0.684602	0.709949	0.251	0.794	0.167	2.440036	FALSE	0.0001	0.735897	39990
6000	0.710549	0.684602	0.709949	0.251	0.794	0.167	2.440036	FALSE	0.0001	0.735897	59990
8000	0.710549	0.684602	0.709949	0.251	0.794	0.167	2.440036	FALSE	0.0001	0.735897	79990
10000	0.710549	0.684602	0.709949	0.251	0.794	0.167	2.440036	FALSE	0.0001	0.735897	99990

Fig2.2.(xii) Synthetic dataset generated from 2D trained GAN Model

3D sample –

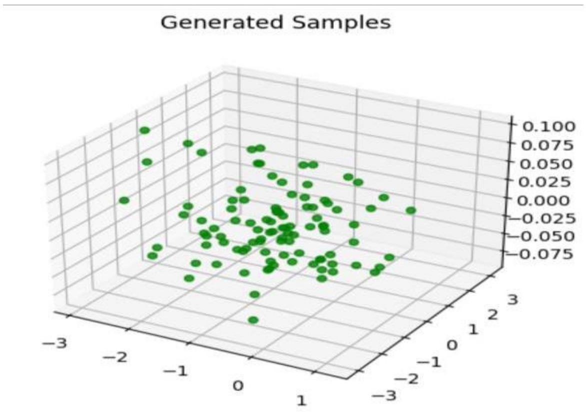

Fig 2.2.(xiii) Generated Sample 3D

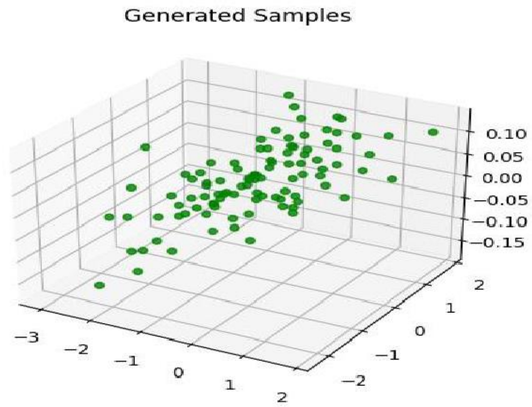

Fig 2.2.(xiv) Generated Sample 3D

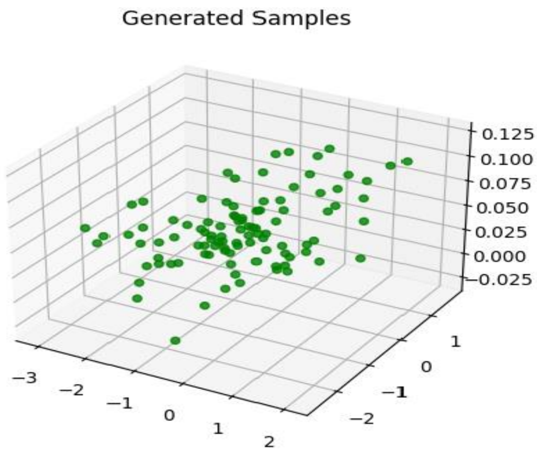

Fig 2.2.(xvi) Generated Sample 3D

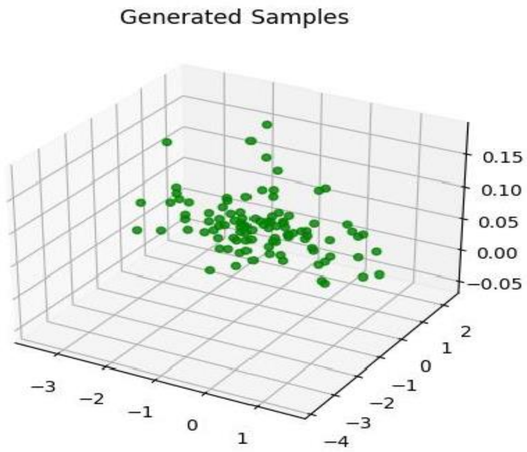

Fig 2.2.(xvi) Generated Sample 3D

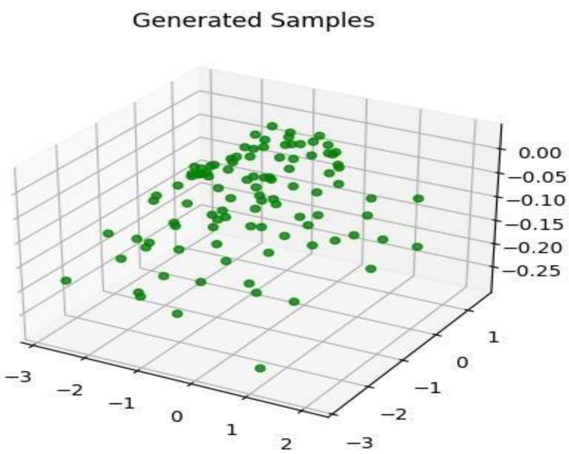

Fig2.2.(xvii) Generated Sample3D

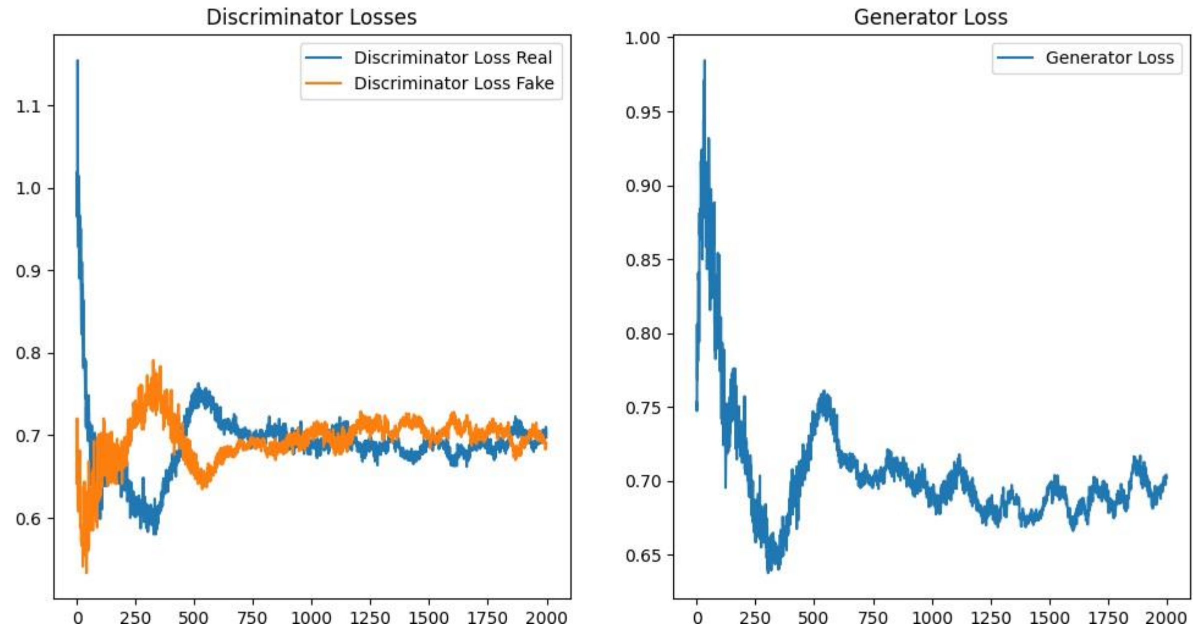

Fig2.2.(xviii) Discriminator Loses and Generator Loss respectively

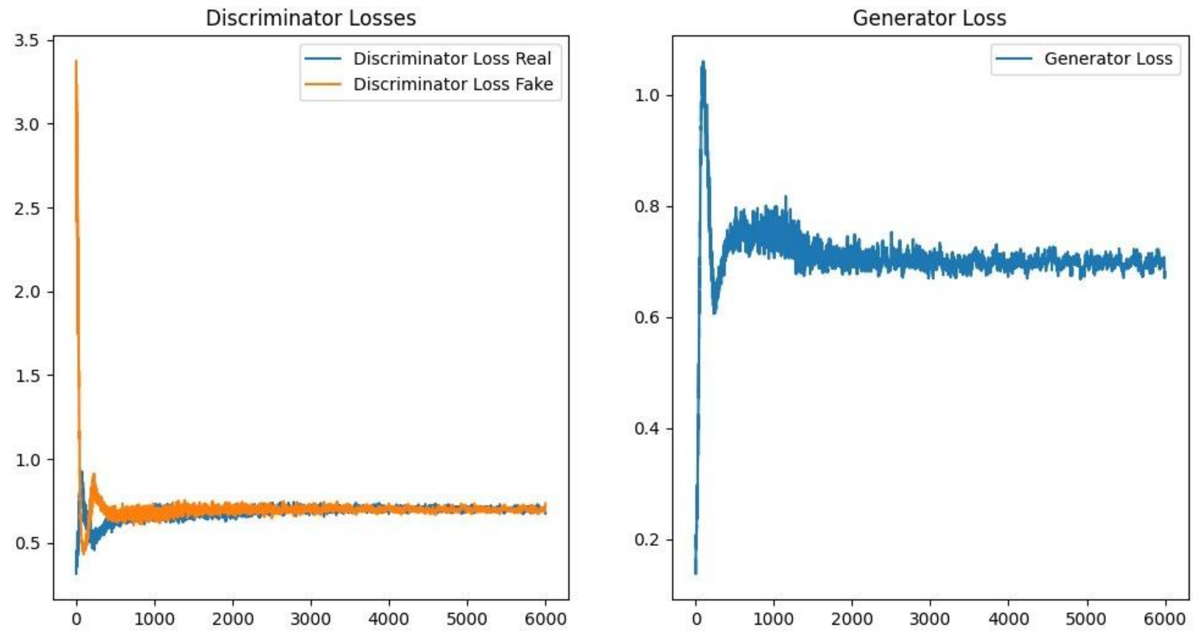

Fig2.2.(xix) Discriminator Loses and Generator Loss respectively

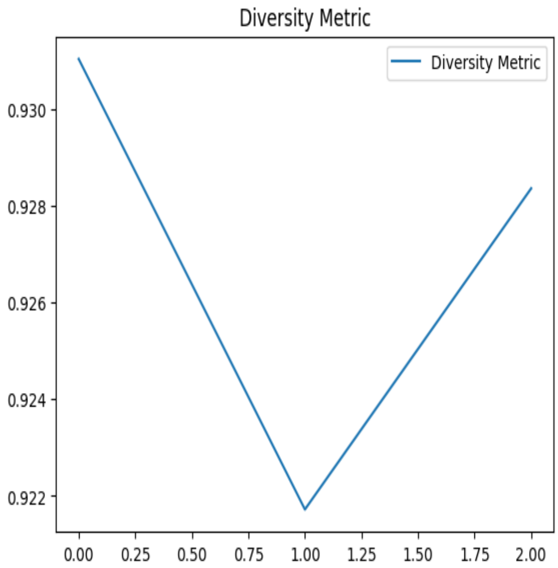

Fig2.2.(xx) Diversity Metric

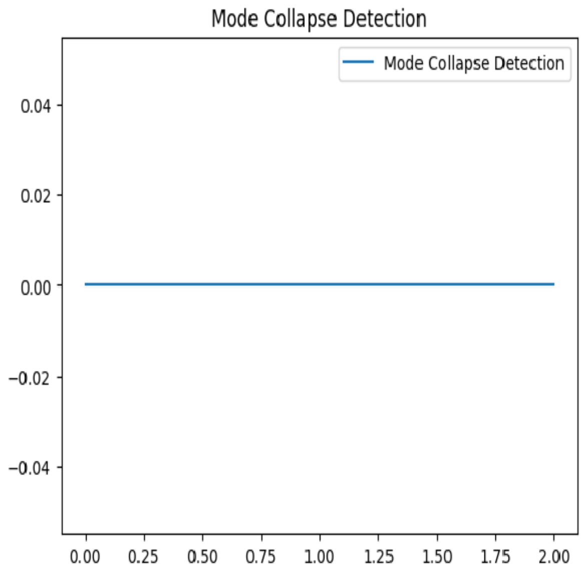

Fig2.2.(xxi) Mode Collapse Detection

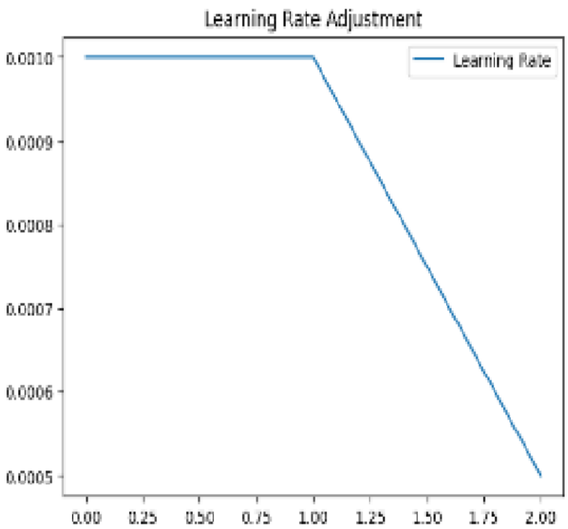

Fig 2.2.(xxii) Learning Rate Adjustment

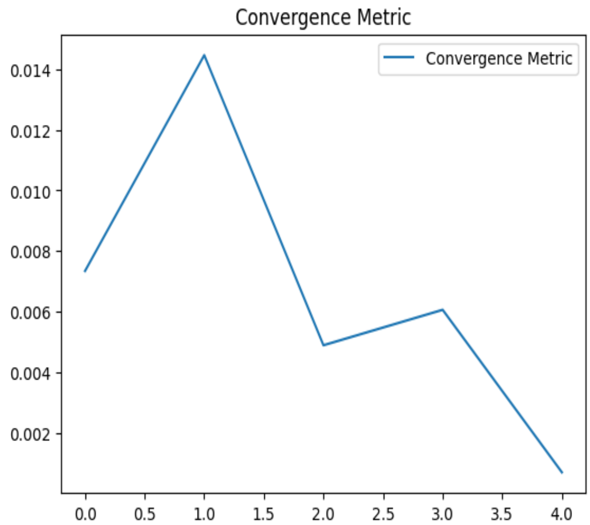

Fig 2.2.(xxiii) Convergence Metric

Epoch	D Loss Rea	D Loss Fak	G Loss	D Accurac	D Accurac	G Accurac	Diversity	Mode Coll	Learning R	Convergence
100	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
200	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
300	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
400	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
500	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
600	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
700	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
800	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
900	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1000	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1100	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1200	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1300	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1400	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1500	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1600	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1700	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694
1800	0.699371	0.698677	0.693154	0.412	0.484	0.499	0.919431	FALSE	0.0005	0.000694

Fig2.2.(xxiv)Synthetic dataset generated from 3D trained GAN Model

3. Conclusion and Future Work

3.1 Conclusion

The culmination of this project reveals that the implemented GAN models exhibit more than mere proficiency in generating synthetic data. They showcase a commendable capacity to mirror the nuanced characteristics of the real data distribution. Notable achievements include overcoming challenges such as mode collapse and dynamically adapting learning rates during training. The analysis of convergence metrics offers valuable insights into the intricate interplay between the generator and discriminator during the adversarial training process.

3.2 Future Work

While the current models stand as a testament to their efficacy, the journey does not end here. Opportunities for future work abound, beckoning for further optimization of hyperparameters, exploration of alternative GAN architectures such as Wasserstein GANs, and the integration of more sophisticated metrics for mode collapse detection and diversity assessment. The extension of the project to handle more complex data distributions and the exploration of transfer learning techniques could add layers of versatility to the synthetic data generation process.

1. **Complex Function Approximation:**
   Extend the scope to include more complex mathematical functions that mimic real-world data distributions. This can help evaluate the GAN's performance in scenarios where underlying patterns are intricate.

2. **Transfer Learning for Function Approximation:**
   Investigate the applicability of transfer learning techniques. Pre-training the GAN on simpler functions and fine-tuning on more complex ones could enhance the model's ability to approximate diverse mathematical structures.

3. **Real-world Application in Scientific Simulations:**
   Translate the learnings to real-world applications, particularly in scientific simulations. GAN-generated data could be used to simulate experimental outcomes in fields where the underlying processes can be mathematically modeled.

4. **Dynamic Learning Rate Strategies:**
   Experiment with more sophisticated strategies for dynamic learning rate adjustments. Adaptive learning rate algorithms could potentially enhance the efficiency and convergence speed of GAN training.

Real-world Applicability

The project's real-world applicability can be further explored by integrating it into practical scenarios, such as generating synthetic medical imaging data or augmenting datasets for computer vision tasks. This extension aligns with the broader goal of addressing real-world data scarcity issues.

5. References

[1] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. In Advances in neural information processing systems (pp. 2672-2680).

[2] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.