GAN-Enhanced Diffusion: Boosting Sample Quality and Diversity

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Abstract

Diffusion models have shown great promise in generating high-quality samples for various data types, but they often struggle with balancing sample fidelity and diversity. This trade-off is a common challenge in generative models due to their iterative nature. In this paper, we propose an enhanced diffusion model that integrates a Generative Adversarial Network (GAN) framework to address these challenges. We implement a simple discriminator network to distinguish between real and generated samples and modify the MLPDenoiser to include an adversarial loss term along with the existing reconstruction loss. Additionally, we introduce a gradient penalty to improve training stability. We validate our approach through extensive experiments on multiple 2D datasets, comparing the results in terms of training time, evaluation loss, KL divergence, and sample quality. Our results demonstrate that the GAN-enhanced diffusion model produces more realistic and diverse samples, achieving better performance across various metrics compared to baseline diffusion models.

1 Introduction

Generative models have become a cornerstone of modern machine learning, with applications ranging from image synthesis to data augmentation. Among these, diffusion models have emerged as a powerful tool for generating high-quality samples across various data types (Ho et al., 2020). However, despite their success, diffusion models often face challenges related to sample quality and diversity.

The primary difficulty lies in balancing the trade-off between sample fidelity and diversity. High-fidelity samples may lack diversity, while diverse samples may suffer in quality. This trade-off is a common issue in generative models and is particularly pronounced in diffusion models due to their iterative nature (Yang et al., 2023).

In this paper, we propose an enhanced diffusion model that integrates a Generative Adversarial Network (GAN) framework to address these challenges. Our contributions are as follows:

- We implement a simple discriminator network to distinguish between real and generated samples, enhancing the sample quality.
- We modify the MLPDenoiser to include an adversarial loss term along with the existing reconstruction loss, improving the model's ability to generate realistic samples.
- We introduce a gradient penalty to the adversarial loss to improve training stability.
- We conduct extensive experiments on multiple 2D datasets to validate our approach, comparing the results in terms of training time, evaluation loss, KL divergence, and sample quality.

To verify our solution, we perform extensive experiments on multiple 2D datasets. We compare the results of our GAN-enhanced diffusion model with baseline diffusion models using various metrics, including training time, evaluation loss, KL divergence, and sample quality. Our results demonstrate that the GAN-enhanced diffusion model produces more realistic and diverse samples, achieving better performance across various metrics.

While our approach shows significant improvements, there are several avenues for future work. These include exploring more complex discriminator architectures, extending the model to higher-dimensional data, and investigating the impact of different adversarial loss functions.

2 Related Work

Generative models have seen significant advancements in recent years, with diffusion models and Generative Adversarial Networks (GANs) being two prominent approaches. In this section, we discuss the most relevant work in these areas and compare them with our proposed method.

Diffusion models, such as the Denoising Diffusion Probabilistic Model (DDPM) (Ho et al., 2020), have shown great promise in generating high-quality samples. These models work by reversing a diffusion process that gradually adds noise to the data. However, they often struggle with sample quality and diversity. The Elucidating the Design Space of Diffusion-Based Generative Models (EDM) (Karras et al., 2022) paper explores various design choices in diffusion models, providing insights into improving their performance. Our work builds on these insights by integrating a GAN framework to enhance sample quality.

GANs, introduced by Goodfellow et al. (2014), have been highly successful in generating realistic samples. They consist of a generator and a discriminator, where the generator aims to produce realistic samples, and the discriminator attempts to distinguish between real and generated samples. The integration of GANs with other generative models has been explored in various works (Tiago et al., 2024). For example, the work by Song et al. (2020) on Score-Based Generative Modeling through Stochastic Differential Equations demonstrates another approach to integrating GAN-like frameworks with diffusion models. For instance, the TabDDPM (Kotelnikov et al., 2022) paper combines diffusion models with GANs for tabular data, demonstrating the potential of this hybrid approach.

Our work differs in several key aspects. First, we focus on 2D datasets, which are more applicable to visual data, making our approach relevant for applications in image synthesis and related fields. Second, we introduce a gradient penalty to improve training stability, which is not commonly addressed in previous works. Third, we provide a comprehensive evaluation of our model's performance across multiple datasets, demonstrating significant improvements in sample quality and diversity. Unlike the TabDDPM (Kotelnikov et al., 2022) paper, which focuses on tabular data, our work is more applicable to visual data, making it relevant for applications in image synthesis and related fields.

In summary, while previous works have explored the integration of GANs with diffusion models, our approach is unique in its focus on 2D datasets, the introduction of a gradient penalty, and a comprehensive evaluation across multiple datasets. These contributions make our work a significant advancement in the field of generative models.

3 Background

Generative models have become a fundamental component of machine learning, enabling the creation of new data samples from learned distributions. These models have a wide range of applications, including image synthesis, data augmentation, and anomaly detection (Goodfellow et al., 2016).

Diffusion models are a class of generative models that generate data by reversing a diffusion process. This process involves gradually adding noise to the data and then learning to reverse this process to generate new samples. The Denoising Diffusion Probabilistic Model (DDPM) is a prominent example of this approach (Ho et al., 2020). Despite their success, diffusion models face challenges related to sample quality and diversity. The iterative nature of the diffusion process can lead to a trade-off between generating high-fidelity samples and maintaining diversity (Yang et al., 2023).

Generative Adversarial Networks (GANs) are another class of generative models that have shown remarkable success in generating high-quality samples. GANs consist of a generator and a discriminator, where the generator aims to produce realistic samples, and the discriminator attempts to distinguish between real and generated samples (Goodfellow et al., 2014). Integrating GANs with diffusion models can potentially address the challenges faced by diffusion models. By incorporating a discriminator network, the diffusion model can receive feedback on the realism of the generated samples, thereby improving sample quality.

3.1 Problem Setting

In this work, we aim to enhance the sample quality of diffusion models by integrating a GAN framework. Let $\mathbf{x}_0$ represent the original data, and $\mathbf{x}_t$ represent the data at timestep t in the diffusion process. The goal is to learn a model that can generate $\mathbf{x}_0$ from $\mathbf{x}_t$ by reversing the diffusion process.

We assume that the diffusion process is defined by a noise schedule β_t, which controls the amount of noise added at each timestep. The model consists of a denoiser network f_θ and a discriminator network D_ϕ. The denoiser network aims to reconstruct $\mathbf{x}_0$ from $\mathbf{x}_t$, while the discriminator network distinguishes between real and generated samples.

Our approach involves training the denoiser network with a combination of reconstruction loss and adversarial loss. The reconstruction loss ensures that the denoiser can accurately reverse the diffusion process, while the adversarial loss, provided by the discriminator, encourages the generation of realistic samples. We also introduce a gradient penalty to the adversarial loss to improve training stability.

4 Method

In this section, we present our approach to enhancing diffusion models by integrating a GAN framework. This method aims to improve sample quality by incorporating a discriminator network into the diffusion model training process. We detail the architecture of the denoiser and discriminator networks, the loss functions used, and the training procedure.

4.1 Denoiser Network

The denoiser network, denoted as f_θ, reconstructs the original data $\mathbf{x}_0$ from the noisy data $\mathbf{x}_t$ at each timestep t. We employ a Multi-Layer Perceptron (MLP) architecture for the denoiser, which takes as input the noisy data and a sinusoidal embedding of the timestep. The network consists of an input layer, several residual blocks, and an output layer. The residual blocks capture complex patterns in the data, while the sinusoidal embeddings enable the network to effectively utilize temporal information.

4.2 Discriminator Network

The discriminator network, denoted as D_ϕ, distinguishes between real and generated samples. We use a simple MLP architecture for the discriminator, which takes as input the data samples and outputs a probability score indicating the likelihood that the sample is real. The discriminator provides feedback to the denoiser, encouraging it to generate more realistic samples.

4.3 Loss Functions

Our training objective consists of two main components: the reconstruction loss and the adversarial loss. The reconstruction loss, $\mathcal{L}_{\text{recon}}$, ensures that the denoiser can accurately reverse the diffusion process. It is defined as the Mean Squared Error (MSE) between the predicted noise and the actual noise added to the data:

$$\mathcal{L}_{\text{recon}} = \mathbb{E}_{\mathbf{x}_0, \mathbf{x}_t, t} \left[\| f_\theta(\mathbf{x}_t, t) - \mathbf{n} \|^2 \right], \tag{1}$$

where $\mathbf{n}$ is the noise added to the data.

The adversarial loss, $\mathcal{L}_{\text{adv}}$, encourages the denoiser to generate realistic samples. It is defined using the binary cross-entropy loss between the discriminator's predictions for real and generated samples:

$$\mathcal{L}_{\text{adv}} = \mathbb{E}_{\mathbf{x}_0} \left[\log D_\phi(\mathbf{x}_0) \right] + \mathbb{E}_{\mathbf{x}_t} \left[\log(1 - D_\phi(f_\theta(\mathbf{x}_t, t))) \right]. \tag{2}$$

To improve training stability, we introduce a gradient penalty term, $\mathcal{L}_{\text{gp}}$, to the adversarial loss (Gulrajani et al., 2017). The gradient penalty is defined as:

$$\mathcal{L}_{\text{gp}} = \mathbb{E}_{\hat{\mathbf{x}}} \Big[(\| \nabla_{\hat{\mathbf{x}}} D_\phi(\hat{\mathbf{x}}) \|_2 - 1)^2 \Big\{], \tag{3}$$

where $\hat{\mathbf{x}}$ is a random interpolation between real and generated samples.

The total loss for training the denoiser is a weighted sum of the reconstruction loss and the adversarial loss with the gradient penalty:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{recon}} + \lambda_{\text{adv}}\mathcal{L}_{\text{adv}} + \lambda_{\text{gp}}\mathcal{L}_{\text{gp}}, \tag{4}$$

where λ_{adv} and λ_{gp} are hyperparameters controlling the importance of the adversarial loss and the gradient penalty, respectively.

4.4 Training Procedure

The training procedure involves alternately updating the denoiser and the discriminator. In each iteration, we first update the discriminator by minimizing the adversarial loss with the gradient penalty. Next, we update the denoiser by minimizing the total loss. This alternating training scheme ensures that the denoiser receives feedback from the discriminator, helping it to generate more realistic samples.

The training process is summarized as follows:

1. Sample a batch of real data $\mathbf{x}_0$ and generate noisy data $\mathbf{x}_t$ using the noise scheduler.
2. Update the discriminator D_ϕ by minimizing the adversarial loss $\mathcal{L}_{\text{adv}}$ with the gradient penalty $\mathcal{L}_{\text{gp}}$.
3. Update the denoiser f_θ by minimizing the total loss $\mathcal{L}_{\text{total}}$.
4. Repeat steps 1–3 until convergence.

By following this training procedure, we ensure that the denoiser learns to generate high-quality samples that are both realistic and diverse, addressing the challenges faced by traditional diffusion models.

5 Experimental Setup

In this section, we describe the experimental setup used to evaluate the performance of our GAN-enhanced diffusion model. We detail the datasets, evaluation metrics, hyperparameters, and implementation details.

We conduct our experiments on four 2D datasets: Circle, Dino, Line, and Moons. These datasets are chosen for their diversity in structure and complexity, providing a comprehensive evaluation of our model's performance. Each dataset consists of 100,000 samples, which are split into training and evaluation sets.

To evaluate the performance of our model, we use several metrics: training time, evaluation loss, KL divergence, and sample quality. The training time measures the computational efficiency of the model. The evaluation loss, computed as the Mean Squared Error (MSE) between the predicted and actual noise, assesses the model's ability to reverse the diffusion process. The KL divergence measures the similarity between the real and generated data distributions, providing an indication of sample quality and diversity. Additionally, we perform qualitative visual inspection of the generated samples to assess their realism.

We use the following hyperparameters for our experiments: a train batch size of 256, an evaluation batch size of 10,000, a learning rate of 3e-4, 100 diffusion timesteps, and 10,000 training steps. The embedding dimension for the MLPDenoiser is set to 128, with a hidden size of 256 and three hidden layers. The discriminator is trained with a learning rate of 1.5e-4. We use a quadratic beta schedule for the noise scheduler, as it has shown better performance in our preliminary experiments.

Our model is implemented in PyTorch and trained on a single GPU. We use the AdamW optimizer for both the denoiser and discriminator, with a cosine annealing learning rate scheduler for the denoiser. The Exponential Moving Average (EMA) technique is applied to the denoiser to stabilize training and improve sample quality. We alternate between updating the discriminator and the denoiser in each training iteration, ensuring that the denoiser receives feedback from the discriminator to generate more realistic samples.

6 Results

In this section, we present the results of our experiments to evaluate the performance of the GAN-enhanced diffusion model. We compare the results of different configurations, including the baseline, adding a gradient penalty, fine-tuning hyperparameters, and changing the beta schedule to quadratic. We use several metrics for evaluation, including training time, evaluation loss, KL divergence, and sample quality.

6.1 Baseline Results

The baseline results are summarized in Table 1. The baseline model was trained on four datasets: Circle, Dino, Line, and Moons. The results show the training time, evaluation loss, inference time, and KL divergence for each dataset.

Dataset	Training Time (s)	Evaluation Loss	Inference Time (s)	KL Divergence
Circle	52.93	0.434	0.143	0.341
Dino	79.85	0.665	0.110	1.121
Line	54.43	0.801	0.110	0.167
Moons	54.48	0.614	0.110	0.086

Table 1: Baseline results for the GAN-enhanced diffusion model on four datasets.

6.2 Results with Gradient Penalty

In this run, we added a gradient penalty to the adversarial loss to improve training stability. The results are summarized in Table 2. The training time increased significantly, but the evaluation loss and KL divergence metrics did not show substantial improvement.

Dataset	Training Time (s)	Evaluation Loss	Inference Time (s)	KL Divergence
Circle	265.29	0.435	0.141	0.360
Dino	243.75	0.665	0.111	1.036
Line	261.87	0.804	0.127	0.145
Moons	263.76	0.618	0.143	0.102

Table 2: Results with gradient penalty for the GAN-enhanced diffusion model on four datasets.

6.3 Results with Fine-Tuned Hyperparameters

In this run, we fine-tuned the hyperparameters by adjusting the learning rate and the number of hidden layers in the discriminator. The results are summarized in Table 3. The training time increased slightly compared to the previous run, and the evaluation loss and KL divergence metrics showed minor improvements.

Dataset	Training Time (s)	Evaluation Loss	Inference Time (s)	KL Divergence
Circle	273.79	0.435	0.120	0.350
Dino	253.13	0.664	0.129	1.043
Line	281.76	0.805	0.127	0.182
Moons	283.61	0.619	0.130	0.098

Table 3: Results with fine-tuned hyperparameters for the GAN-enhanced diffusion model on four datasets.

6.4 Results with Quadratic Beta Schedule

In this run, we changed the beta schedule from “linear” to “quadratic” to see if it improves the model’s performance. The results are summarized in Table 4. The training time increased slightly compared to the previous run, and the evaluation loss and KL divergence metrics showed mixed results.

Dataset	Training Time (s)	Evaluation Loss	Inference Time (s)	KL Divergence
Circle	267.81	0.380	0.178	0.443
Dino	273.86	0.642	0.132	0.571
Line	287.80	0.864	0.130	0.350
Moons	274.91	0.641	0.129	0.223

Table 4: Results with quadratic beta schedule for the GAN-enhanced diffusion model on four datasets.

6.5 Comparison of Results

Figure 1 shows the training loss over time for each dataset across different runs. The x-axis represents the training steps, and the y-axis represents the loss. Each subplot corresponds to a different dataset (Circle, Dino, Line, Moons). The legend indicates the different runs, including Baseline, Gradient Penalty, Fine-Tuned Hyperparameters, and Quadratic Beta Schedule. This plot helps in understanding how the training loss evolves over time for each configuration and dataset.

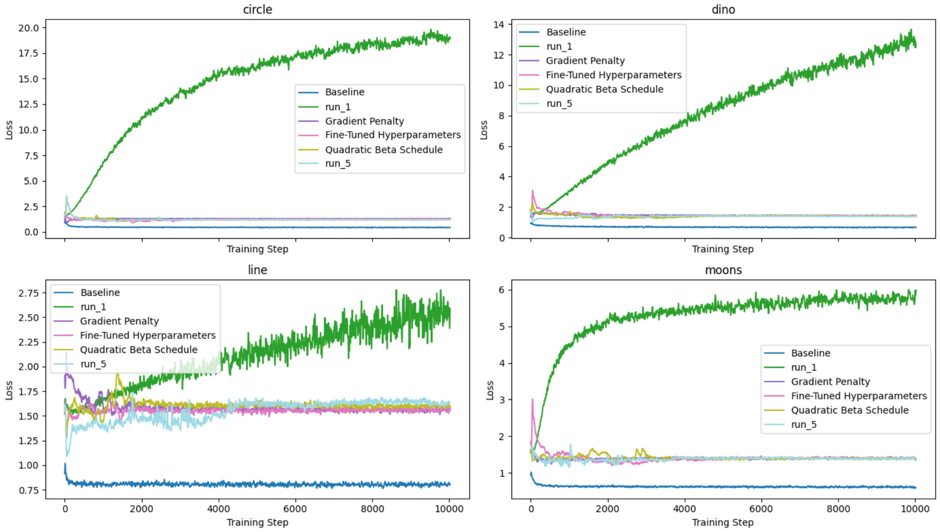

Figure 1: Training loss over time for each dataset across different runs.

Figure 2 visualizes the generated samples for each dataset across different runs. Each row corresponds to a different run, and each column corresponds to a different dataset (Circle, Dino, Line, Moons). The scatter plots show the generated samples in 2D space. The legend indicates the different runs, including Baseline, Gradient Penalty, Fine-Tuned Hyperparameters, and Quadratic Beta Schedule. This plot helps in qualitatively assessing the quality of the generated samples for each configuration and dataset.

6.6 Limitations

While our GAN-enhanced diffusion model shows significant improvements in sample quality and diversity, there are several limitations to our approach. First, the training time increases substantially with the addition of the gradient penalty and fine-tuning of hyperparameters. Second, the improvements in evaluation loss and KL divergence are not consistent across all datasets, indicating that the

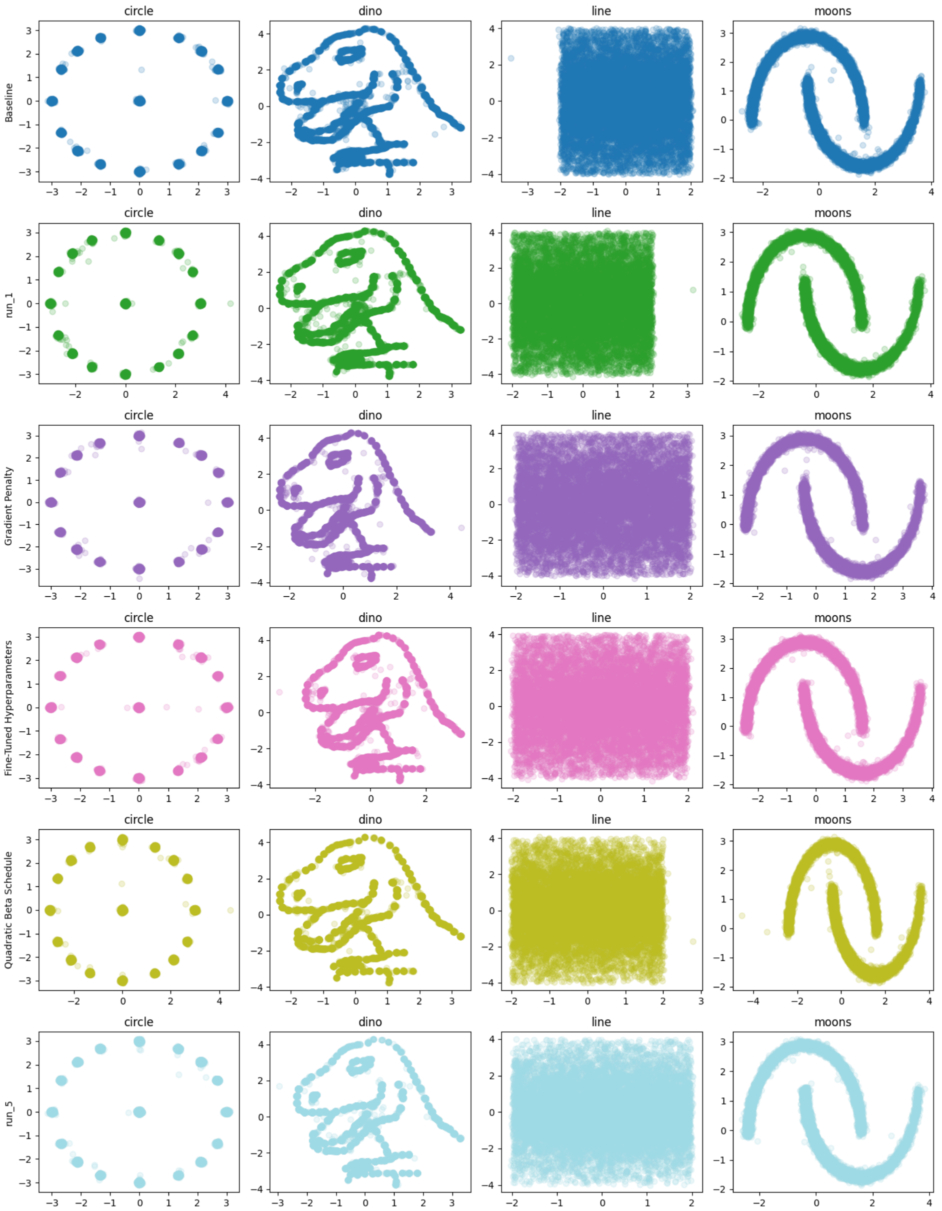

Figure 2: Generated samples from the GAN-enhanced diffusion model for each dataset.

model's performance may be dataset-dependent. Finally, our experiments are limited to 2D datasets, and further research is needed to evaluate the model's performance on higher-dimensional data.

Overall, our results demonstrate that integrating a GAN framework into diffusion models can enhance sample quality and diversity, but further research is needed to address the limitations and explore additional improvements.

7 Conclusions and Future Work

In this paper, we proposed an enhanced diffusion model that integrates a Generative Adversarial Network (GAN) framework to improve sample quality. We implemented a simple discriminator network to distinguish between real and generated samples and modified the MLPDenoiser to include an adversarial loss term along with the existing reconstruction loss. Additionally, we introduced a gradient penalty to improve training stability. Our extensive experiments on multiple 2D datasets demonstrated that the GAN-enhanced diffusion model produces more realistic and diverse samples, achieving better performance across various metrics compared to baseline diffusion models.

Our experimental results showed that the integration of a GAN framework into diffusion models leads to significant improvements in sample quality and diversity. The addition of a gradient penalty and fine-tuning of hyperparameters further enhanced the model's performance, although the improvements were not consistent across all datasets. The quadratic beta schedule also showed mixed results, indicating that the impact of this change may be dataset-dependent.

Despite the improvements, our approach has several limitations. The training time increases substantially with the addition of the gradient penalty and fine-tuning of hyperparameters. Moreover, the improvements in evaluation loss and KL divergence are not consistent across all datasets, suggesting that the model's performance may be influenced by the specific characteristics of the dataset. Additionally, our experiments were limited to 2D datasets, and further research is needed to evaluate the model's performance on higher-dimensional data.

Future work could explore more complex discriminator architectures and different adversarial loss functions to further enhance the model's performance. Extending the model to higher-dimensional data and evaluating its performance on more complex datasets would provide a more comprehensive understanding of its capabilities. Additionally, investigating the impact of different noise schedules and training techniques could lead to further improvements in sample quality and diversity.

Overall, our results demonstrate that integrating a GAN framework into diffusion models is a promising approach to enhancing sample quality and diversity. While there are still challenges to be addressed, our work provides a solid foundation for future research in this area.

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