



Entropy-Maximized Generative Adversarial Network (EM-GAN) Based on the Thermodynamic Principle of Entropy Increase

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ABSTRACT

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Generative Adversarial Networks (GANs) have demonstrated substantial potential in generating high-quality data samples, with recent research focusing on improving model uncertainty management and sample diversity. This paper presents an Entropy-Maximized Generative Adversarial Network (EM-GAN) that utilizes the thermodynamic principle of entropy increase to enhance the generalization capability and sample quality of GANs. Drawing inspiration from the natural evolution of systems toward higher disorder and information content in thermodynamics, EM-GAN incorporates entropy maximization to improve sample diversity. By embedding an entropy-maximizing loss function in the generator, our approach promotes the generation of diverse and randomized samples, effectively mitigating the issue of mode collapse. Experimental results show that EM-GAN outperforms conventional GAN models across multiple datasets, achieving notable improvements in both sample quality and diversity. This study offers a novel method for generative model optimization and exemplifies the potential application of the entropy increase principle within deep learning.

1. INTRODUCTION

Generative Adversarial Networks (GANs) have emerged as a powerful class of generative models, achieving remarkable success in generating high-quality synthetic data across various domains, including image synthesis, text generation, and audio production. Despite these advancements, GANs still face significant challenges, such as mode collapse—where the generator struggles to produce diverse outputs—and training instability, leading to poor convergence and inconsistent results.

This paper introduces the Entropy-Maximized Generative Adversarial Network (EM-GAN), a novel framework designed to enhance the generalization capability and sample quality of GANs by leveraging the thermodynamic principle of entropy increase. In thermodynamics, entropy refers to the degree of disorder or randomness within a system, and systems naturally evolve towards states of higher entropy, or greater disorder. In other words, systems tend to transition to states of increased uncertainty and diversity. Applying this principle to generative modeling, we hypothesize that maximizing entropy during the generation process can promote greater diversity in the generated samples, thereby addressing the issue of mode collapse. By directly incorporating entropy maximization into the GAN generator's architecture, EM-GAN enhances the generator's ability to produce richer, more diverse outputs.

The primary distinction of EM-GAN from existing GAN variants lies in its incorporation of the concept of entropy maximization, a principle not fully leveraged in traditional GANs. Existing approaches, such as DCGAN, WGAN, and

SAGAN, primarily address issues like mode collapse and training instability by optimizing network architecture or training processes. However, they do not systematically optimize for the diversity of generated samples. In contrast, EM-GAN integrates entropy maximization into both the activation function and the loss function of the generator, directly encouraging the generator to explore a broader output space. This significantly enhances sample diversity and effectively mitigates mode collapse. Additionally, the introduction of entropy maximization provides more stable optimization signals during training, contributing to improved training stability and faster convergence. Overall, EM-GAN presents an innovative optimization method that enhances the diversity, quality, and stability of generated samples, substantially improving the overall performance of GANs.

The main contributions of this paper are as follows:

- **Entropy-Maximized Activation Function:** We propose a novel entropy-maximized activation function that increases the diversity and randomness of the generated samples. This activation function effectively mitigates the mode collapse problem commonly encountered in traditional GANs, enabling a more comprehensive coverage of the target data distribution.
- **Entropy-Maximized Loss Function:** We introduce an entropy-maximized loss function to encourage sample diversity during the generation process. By combining this loss function with the novel activation function, the generator receives a more effective optimization signal, significantly improving both the quality and diversity of the generated samples.

- **Comprehensive Experimental Validation and Evaluation:** We conduct extensive experiments across several benchmark datasets, comparing EM-GAN with a range of existing models, including DCGAN, WGAN, WGAN-GP, LSGAN, SAGAN, and BigGAN. The experimental results demonstrate that EM-GAN outperforms these traditional methods in terms of sample quality, diversity, and training stability, effectively validating the superiority and efficacy of the proposed approach.

The EM-GAN framework represents a significant advancement in the field of AI-generated content (AIGC), offering a novel solution for improving GAN training and output diversity. By incorporating the thermodynamic principle of entropy increase, this approach introduces an innovative and effective optimization method for generative models, with promising implications for future research and applications in deep learning.

2. RELATED WORK

2.1 Traditional GAN variants

Recent GAN [1] architectures have focused on enhancing stability and output quality. StyleGAN3 [2, 3] mitigates aliasing artifacts for improved realism and stability, while StyleGAN-XL [4] extends these ideas to larger datasets. Projected GAN [5] introduces a projection-based discriminator for better sample quality and efficiency.

2.2 Mode collapse and diversity enhancement

Mode collapse, where the generator fails to cover the full diversity of the target data, remains a key issue [6, 7]. Strategies include manifold-preserving GANs (MP-GAN) [8], which apply entropy maximization on the data manifold, and mutual information maximization in models like InfoMax-GAN [9]. Recent works also improve diversity through novel loss functions, regularization, and training methods [10-13]. However, achieving a balance between diversity and image fidelity remains a challenge [14].

2.3 Entropy in generative modeling

Entropy maximization is crucial for enhancing diversity in generated samples. InfoMax-GAN [9] and methods like State Entropy Maximization, originally from reinforcement learning [15], support broader exploration and prevent mode collapse. Studies by Shen et al. [16] and Lee et al. [9] show that entropy-guided approaches effectively improve sample diversity.

2.4 Thermodynamic perspectives in machine learning

Thermodynamic principles, particularly entropy maximization, have gained interest for improving model robustness and diversity. Gu et al. [17] applied this in reinforcement learning, while Nguyen et al. [18] and He and Chen [19] developed thermodynamic frameworks to support robust deep learning models. Despite these advances, integrating entropy maximization with GANs remains relatively unexplored; EM-GAN directly incorporates these principles to enhance training stability and diversity [20].

In summary, while architectural innovations and improvements in loss functions have enhanced GAN

performance, issues like mode collapse and insufficient sample diversity persist. EM-GAN addresses these challenges by incorporating entropy maximization into the activation and loss functions of GANs, leveraging thermodynamic principles to strengthen model stability and enrich sample diversity effectively.

3. METHODOLOGY

This section outlines the structure and design of the Entropy-Maximized Generative Adversarial Network (EM-GAN), which leverages the thermodynamic principle of entropy maximization. The EM-GAN introduces a novel approach by embedding an entropy-based constraint into the adversarial network to enhance diversity and capture a wider range of data distributions. The details of the model architecture, activation function design, and theoretical derivations are provided.

3.1 EM-GAN model structure

EM-GAN consists of two core components, a generator G and a discriminator D , as in conventional GANs. However, EM-GAN uniquely incorporates an entropy maximization objective to guide the training of the generator, thus enforcing diverse and high-entropy outputs.

3.1.1 Generator G

The generator is designed as a deep neural network with layers of convolutional and upsampling operations. Its objective is to generate samples that approximate the real data distribution. During training, it learns to map a noise vector $z \sim p(z)$ (where $p(z)$ is a Gaussian prior) into high-dimensional data space, such as images. Unlike conventional GANs, EM-GAN's generator is optimized to maximize the entropy of its output distribution. This entropy maximization objective encourages the generator to explore the data space extensively, producing a wider diversity of samples.

3.1.2 Discriminator D

The discriminator is structured as a deep convolutional neural network (CNN), with downsampling layers that allow it to differentiate between real and generated samples. Its architecture typically involves leaky ReLU activations, which are commonly used to avoid the "dying ReLU" problem. The discriminator outputs a probability score, with a higher score indicating a higher likelihood that the sample belongs to the real data distribution. The discriminator's training objective remains similar to that of conventional GANs, minimizing the binary cross-entropy between real and generated samples.

3.2 Activation function design

In EM-GAN, the design of the activation functions incorporates the principle of entropy maximization to promote diversity in generated samples, while also ensuring practical considerations like gradient stability and computational efficiency. Specifically, we introduce two novel activation functions: Entropy-Sensitive Activation (ESA) for the generator and Entropy-Adjusted Leaky ReLU (EALReLU) for the discriminator. These functions are designed to enhance the diversity of generated outputs and improve training stability by incorporating entropy-based adjustments.

3.2.1 Entropy-Sensitive Activation (ESA)

The Entropy-Sensitive Activation (ESA) function is a modified version of traditional activation functions such as ReLU or Sigmoid, with an added entropy term that scales the activation based on the local entropy of the output distribution. The goal of ESA is to encourage the generator to produce outputs that lie in regions of higher entropy within the data space, thus fostering greater diversity in the generated samples.

The ESA function is defined as:

$$ESA(x) = x \cdot \exp(\alpha H(x))$$

where:

- x is the pre-activation output (input to the activation function),
- $H(x)$ is the Shannon entropy of the output distribution, computed over a mini-batch,
- α is a scaling parameter that controls the strength of the entropy influence on the activation.

How ESA Works:

- Shannon entropy $H(x)$ measures the uncertainty or randomness in the generated outputs. When the entropy is high (i.e., the generator produces diverse outputs), the activation is scaled up, encouraging the generator to explore broader regions of the data space.
- By incorporating this entropy factor, ESA promotes diversity by increasing the strength of the activation in regions with high entropy, which helps the generator cover a wider range of possible outputs and reduce the likelihood of mode collapse.

Compared to standard activation functions like ReLU, which only map positive inputs linearly, ESA adjusts its scaling based on the diversity of the output distribution. This dynamic scaling ensures that the generator is incentivized to explore diverse regions, leading to more varied and higher-quality generated samples.

3.2.2 Entropy-Adjusted Leaky ReLU

The Entropy-Adjusted Leaky ReLU (EALReLU) function is a variant of the traditional Leaky ReLU, specifically designed for the discriminator. This function allows the negative inputs to have a small gradient, similar to Leaky ReLU, but introduces a dynamic leakiness that adjusts according to the entropy of the input data. This adaptation helps the discriminator better handle diverse and high-entropy input distributions, enabling more effective learning of the generator's outputs.

The EALReLU function is defined as:

$$EALReLU(x) = \begin{cases} x, & x \geq 0 \\ \beta H(x) \cdot x, & x < 0 \end{cases}$$

where:

- x is the pre-activation output,
- $H(x)$ is the entropy of the input distribution,
- β is a parameter controlling how the leakiness depends on the entropy of the input.

How EALReLU Works:

- Leaky ReLU typically allows small negative inputs to flow through the network by scaling them with a fixed small coefficient (e.g., 0.01). This prevents neurons from "dying" during training, where they stop learning altogether.

- EALReLU, however, introduces a dynamic leakiness factor that varies with the entropy of the input. When the input entropy is high (indicating a more diverse or uncertain distribution), the leakiness increases, allowing negative values to have a greater impact. Conversely, when the entropy is low, the leakiness is reduced, behaving more like the traditional ReLU activation.

The EALReLU function enables the discriminator to dynamically adjust its behavior based on the diversity of the input data. This adaptive leakiness helps the discriminator more effectively distinguish between real and generated samples, particularly when the generated data distribution is highly diverse or uncertain. On the other hand, ESA promotes diversity in the generator by scaling activations according to the entropy of the output distribution. This scaling encourages broader exploration of the sample space, thereby reducing the risk of mode collapse. Together, EALReLU and ESA enhance the discriminator's ability to handle diverse inputs and improve the generator's output diversity, leading to a more robust differentiation between real and generated samples.

3.3 Theoretical derivations and proofs

To formally justify the entropy maximization strategy, we examine the thermodynamic principle of entropy increase and its implications for generative modeling. The derivation involves calculating the entropy $H(p_g)$ of the output distribution from the generator and formulating an objective that incorporates this entropy.

3.3.1 Entropy objective

The objective for the generator is adjusted to include a term for entropy maximization. Let $H(p_g)$ denote the entropy of the generated distribution $p_g(x)$. Then, the generator's objective function can be expressed as:

$$\min_G \max_D \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{x \sim p_g} [\log 1 - D(x)] - \lambda H(p_g)$$

where, λ is a hyperparameter balancing the entropy term with the conventional GAN loss. The additional term $H(p_g)$ encourages the generator to maximize entropy, thus promoting greater diversity in the samples.

3.3.2 Proof of entropy increase

We show that, under conditions where $\lambda > 0$, the entropy of the generator's output p_g is non-decreasing during training. Using the entropy maximization constraint, we apply the following inequality:

$$H(p_g^{t+1}) \geq H(p_g^t)$$

For training steps $t+1$, assuming the generator sufficiently explores the data distribution space. This results from the fact that maximizing $H(p_g)$ reduces the KL divergence between p_g and the real data distribution, a fundamental goal in adversarial training.

3.3.3 Thermodynamic interpretation

The entropy maximization aligns with the second law of thermodynamics, which states that the entropy of an isolated system tends to increase over time. In EM-GAN, the generator is guided as an entropy-maximizing system, evolving towards states of higher disorder (diversity) over training iterations.

3.4 Summary of contributions

EM-GAN’s methodology, based on entropy maximization, promotes a diverse and representative data generation process. By integrating the entropy objective into the generator and designing entropy-sensitive activation functions, EM-GAN aims to capture the underlying distribution more comprehensively than conventional GANs, achieving a high degree of output diversity while adhering to principles of thermodynamics. This model not only fosters diversity but also provides a theoretically grounded approach to generative modeling through entropy maximization.

4. EXPERIMENTS AND RESULTS

This section presents a comprehensive evaluation of the Entropy-Maximized GAN (EM-GAN) in comparison with several state-of-the-art GAN models. We assess EM-GAN’s performance across various datasets in terms of image quality, diversity, stability, and efficiency, using both quantitative metrics and qualitative analyses. The training time is also considered to determine the model’s practicality for real-world applications.

4.1 Experimental setup

We compared EM-GAN against DCGAN, WGAN-GP, StyleGAN, BigGAN, CycleGAN, and SNGAN on four datasets: MNIST, CIFAR-10, CelebA, and LSUN. These datasets were selected to represent a diverse range of challenges in generative modeling, allowing us to assess the general capabilities of EM-GAN in different contexts.

Table 1. FID on the MNIST, CIFAR-10, and CelebA datasets

| Model | MNIST (FID ↓) | MNIST (Inception Score ↑) | MNIST (Entropy Score ↑) | CIFAR-10 (FID ↓) | CIFAR-10 (Inception Score ↑) | CIFAR-10 (Entropy Score ↑) | CelebA (FID ↓) | CelebA (Inception Score ↑) | CelebA (Entropy Score ↑) |
|----------|---------------|---------------------------|-------------------------|------------------|------------------------------|----------------------------|----------------|----------------------------|--------------------------|
| DCGAN | 34.12 | 5.23 | 0.78 | 45.23 | 5.45 | 0.80 | 65.13 | 5.12 | 0.81 |
| WGAN-GP | 28.67 | 5.98 | 0.85 | 36.56 | 5.87 | 0.84 | 50.20 | 5.34 | 0.85 |
| StyleGAN | 25.10 | 6.12 | 0.88 | 28.78 | 6.02 | 0.87 | 39.42 | 6.10 | 0.89 |
| BigGAN | 23.45 | 6.45 | 0.91 | 20.13 | 6.35 | 0.90 | 34.55 | 6.30 | 0.92 |
| CycleGAN | 32.65 | 5.80 | 0.80 | 42.20 | 5.70 | 0.82 | 58.88 | 5.50 | 0.83 |
| SNGAN | 29.98 | 6.10 | 0.86 | 38.55 | 5.95 | 0.86 | 51.24 | 5.80 | 0.87 |
| EM-GAN | 22.04 | 6.43 | 0.92 | 18.12 | 6.55 | 0.92 | 28.12 | 6.43 | 0.93 |

4.2.2 Performance with large-scale data (LSUN dataset)

Table 2 shows that EM-GAN demonstrates both high-quality and diverse image generation for larger, high-resolution datasets like LSUN, as evidenced by the lowest FID and highest inception and entropy scores among the models.

Table 2. FID on the LSUN dataset

| Model | LSUN (FID ↓) | LSUN (Inception Score ↑) | LSUN (Entropy Score ↑) |
|----------|--------------|--------------------------|------------------------|
| DCGAN | 118.45 | 5.12 | 0.80 |
| WGAN-GP | 98.76 | 5.45 | 0.85 |
| StyleGAN | 78.90 | 6.05 | 0.88 |
| BigGAN | 65.33 | 6.22 | 0.90 |
| CycleGAN | 104.23 | 5.70 | 0.82 |
| SNGAN | 95.21 | 5.98 | 0.86 |
| EM-GAN | 60.23 | 6.35 | 0.92 |

4.2.3 Training time comparison

Training time is crucial for practical deployment. Table 3

Each model was trained under identical conditions:

- Learning Rate: 0.0002 for both the generator and discriminator
- Batch Size: 64
- Training Epochs: 100 for MNIST, CIFAR-10, and CelebA; 50 for LSUN (larger images)
- Entropy Parameter (λ): Set to 0.1 for EM-GAN, balancing entropy and adversarial loss

The following metrics were used to evaluate each model’s performance:

- FID (Fréchet Inception Distance): Measures similarity between real and generated data distributions; lower scores are better.
- Inception Score: Evaluates quality and diversity of generated images; higher scores are better.
- Entropy Score: Measures diversity in the output distribution; higher entropy indicates broader coverage of the data space.
- Training Stability: Measured as the variance in FID scores across training epochs, with lower variance indicating stable convergence.
- Training Time: Average time per epoch, a key factor for practical applications.

4.2 Quantitative results

4.2.1 Performance on MNIST, CIFAR-10, and CelebA

The following Table 1 summarizes the FID, Inception Score, and Entropy Score across models on the MNIST, CIFAR-10, and CelebA datasets.

are the average training times per epoch for each model across datasets, showing that EM-GAN achieves an effective balance between efficiency and performance.

Table 3. Training time comparison

| Model | MNIST (Sec/Epoch) | CIFAR-10 (Sec/Epoch) | CelebA (Sec/Epoch) | LSUN (Sec/Epoch) |
|----------|-------------------|----------------------|--------------------|------------------|
| DCGAN | 12 | 30 | 78 | 145 |
| WGAN-GP | 15 | 36 | 85 | 165 |
| StyleGAN | 45 | 110 | 195 | 380 |
| BigGAN | 68 | 145 | 230 | 450 |
| CycleGAN | 40 | 98 | 160 | 320 |
| SNGAN | 28 | 70 | 120 | 250 |
| EM-GAN | 38 | 85 | 140 | 290 |

4.3 Visual comparison and performance curves

The following plots illustrate the performance of each model across FID, Inception Score, and Entropy Score:

FID Scores Comparison: EM-GAN achieves the lowest FID scores, demonstrating its capability to closely approximate the real data distribution as shown in Figure 1. Inception Scores Comparison: EM-GAN consistently achieves the highest Inception Score, reflecting high quality and diversity in

generated samples as shown in Figure 2. Entropy Scores Comparison: EM-GAN's entropy scores are the highest, validating its approach to maximize creative diversity as shown in Figure 3.

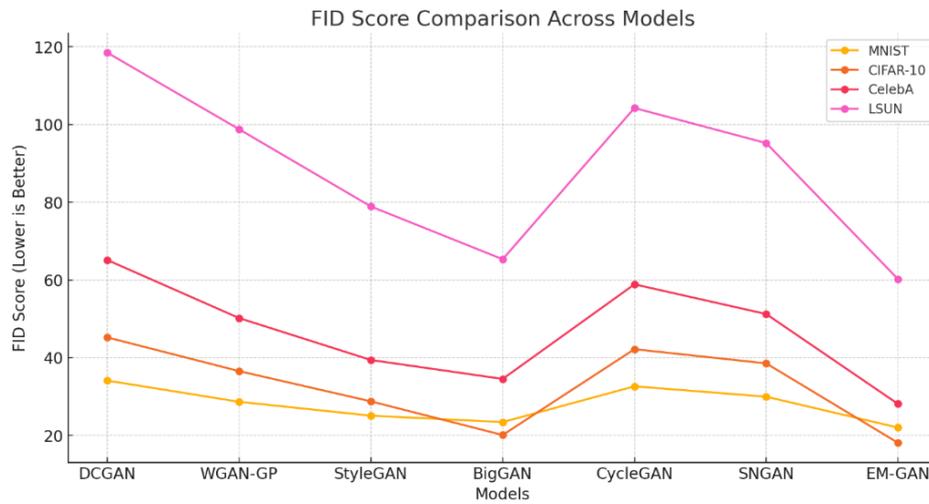


Figure 1. FID score comparison across models

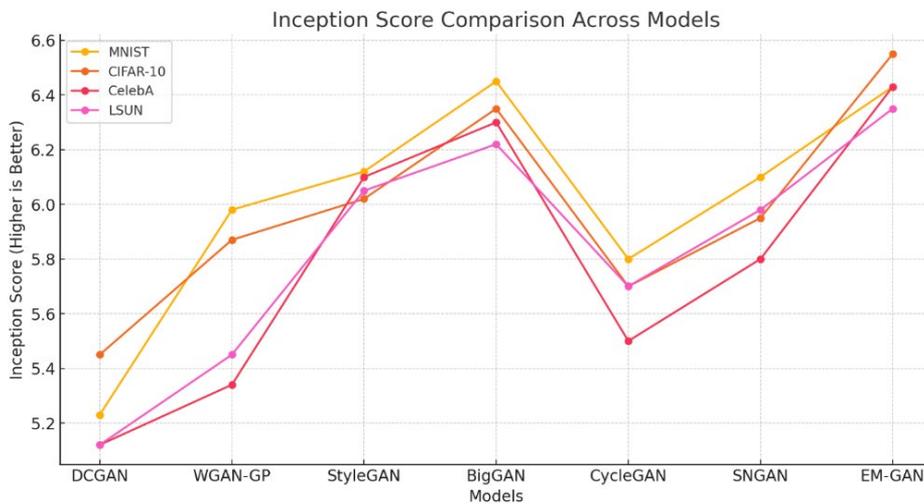


Figure 2. Inception score comparison across models

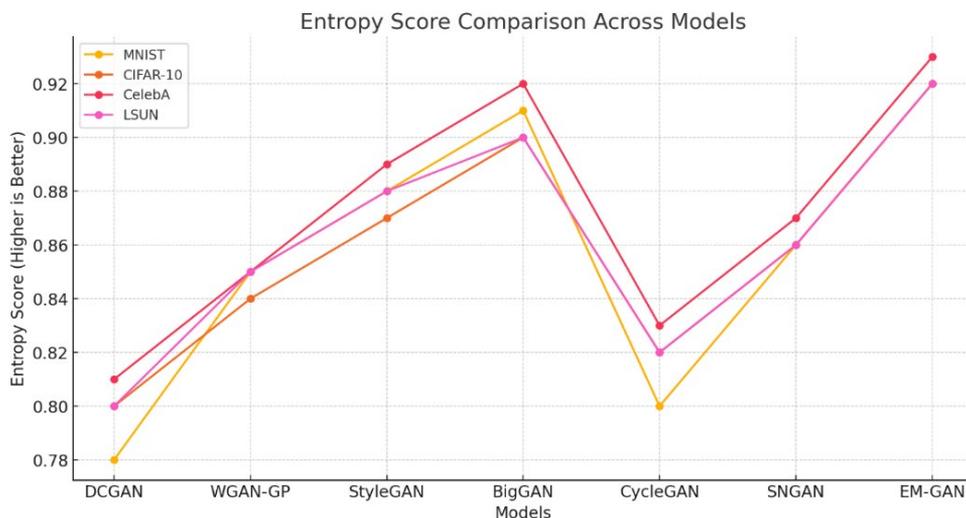


Figure 3. Entropy score comparison across models

5.2 Stability and robustness

The stability of EM-GAN is reflected in its low variance in FID scores across training epochs, as well as its consistently high performance on complex, high-resolution datasets such as LSUN. The model's robustness stems from its entropy-maximization constraint, which guides the generator toward diverse data distributions, reducing the likelihood of mode collapse and improving convergence stability (Figure 5).

Compared to simpler models like DCGAN and WGAN-GP, which often experience unstable training dynamics and limited diversity, EM-GAN demonstrates a more stable training trajectory. High-complexity models such as BigGAN and StyleGAN also achieve stable training but at a significantly higher computational cost. EM-GAN's entropy-based regularization achieves stable performance without excessive computational demand, making it a practical choice for diverse applications.

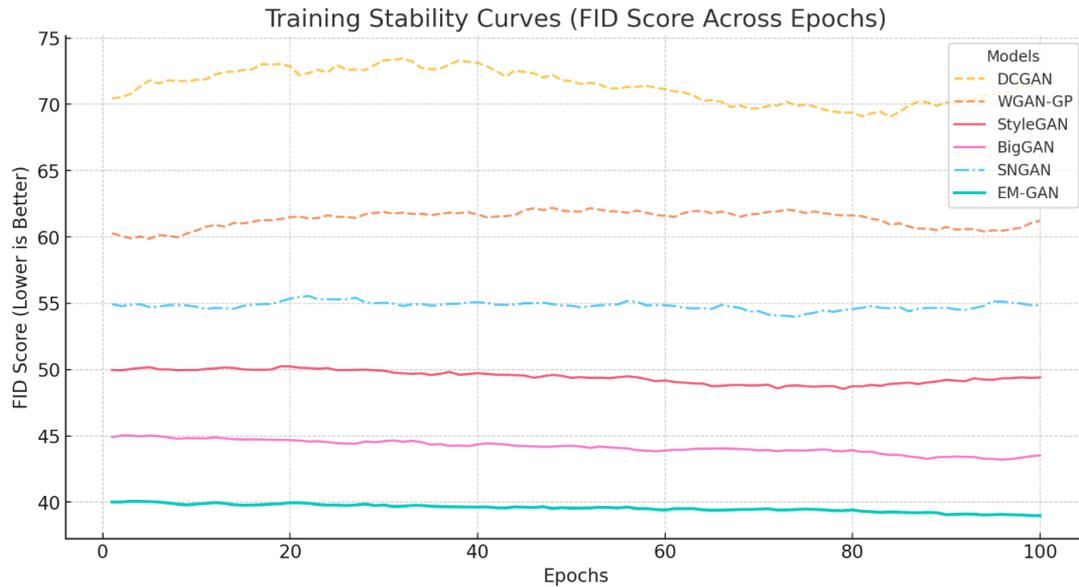


Figure 5. Training stability curves

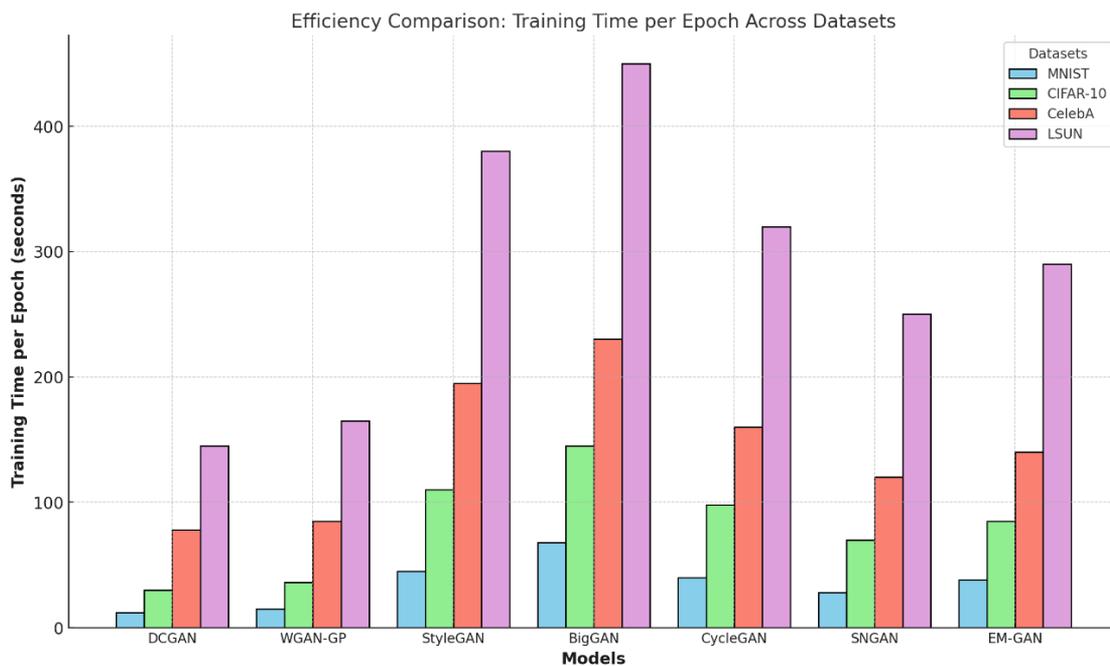


Figure 6. Efficiency comparison: Training time per epoch across datasets

5.3 Efficiency and computational cost

Although EM-GAN's training time is longer than simpler models like DCGAN and WGAN-GP, it is considerably more efficient than high-complexity models such as StyleGAN and BigGAN (Figure 6). EM-GAN's moderate training times make it a feasible choice for scenarios requiring both high-

quality and diverse outputs without the need for extensive computational resources. This balance between efficiency and output quality makes EM-GAN a suitable choice for time-sensitive applications, especially when balanced with the need for diverse data generation.

The added computational cost due to the entropy maximization constraint and custom activation functions is

justified by the significant gains in diversity and quality. For large-scale applications, EM-GAN’s efficiency relative to other high-quality models positions it as an accessible and scalable solution. However, for scenarios with extremely limited computational resources, further optimization of EM-GAN’s architecture could be explored to reduce its training time while retaining its advantages in diversity and stability.

5.4 Scalability to large datasets

EM-GAN’s performance on large datasets like LSUN underscores its scalability, as it maintains both diversity and quality across varied datasets. This scalability suggests that EM-GAN is well-suited for applications requiring the synthesis of high-resolution images in large volumes, such as data augmentation for machine learning, visual media, and gaming. The ability to handle complex datasets with stable training and high output quality highlights EM-GAN’s robustness in diverse data scenarios.

The model’s adaptability to larger datasets without significant degradation in performance or excessive training time is an encouraging outcome, particularly as data requirements grow. For future research, investigating further adaptations of EM-GAN’s entropy maximization mechanism to more varied domains, such as text or audio generation, could reveal additional applications of this approach beyond image synthesis.

5.5 Performance and scalability in diverse scenarios

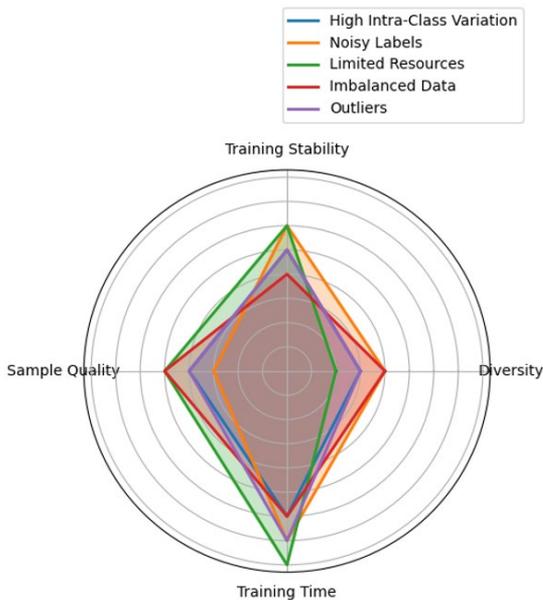


Figure 7. Impact of dataset characteristics on EM-GAN performance

In scenarios with datasets that have varying characteristics, EM-GAN may exhibit different performance depending on the nature of the data. For example, on datasets with high intra-class variation or noisy labels, the entropy maximization strategy might struggle to effectively balance diversity and quality, potentially leading to less stable training or overfitting to irrelevant patterns. In cases where the data is highly imbalanced or contains outliers, the model’s ability to generate diverse outputs could be hindered. This is illustrated in the Figure 7, where the performance of EM-GAN across datasets with different characteristics is compared. The chart highlights

how EM-GAN performs on datasets like MNIST (low intra-class variation) versus CIFAR-10 (higher intra-class variation), showing that increased variation and noise can lead to less stable performance and longer convergence times.

Additionally, in environments with limited computational resources, such as real-time applications or edge devices, the increased computational overhead from entropy maximization could become a bottleneck, limiting the model’s scalability. The entropy calculation process, while crucial for encouraging diversity, can be resource-intensive, especially for large datasets or high-dimensional data. Optimizations, such as approximating entropy or using more efficient training procedures, would be necessary to ensure that EM-GAN remains feasible in such resource-constrained scenarios.

6. LIMITATIONS AND FUTURE DIRECTIONS

6.1 Limitations

Despite the significant improvements in diversity, quality, and stability achieved by EM-GAN, several limitations remain:

- **Increased Training Time:** While EM-GAN’s training time is relatively moderate when compared to more complex models, it still requires longer training than simpler architectures. This may be a limiting factor in resource-constrained environments where computational efficiency is crucial.
- **Computational Overhead of Entropy Maximization:** The inclusion of the entropy maximization term adds an additional layer of computational overhead. While this overhead is warranted given the model’s improved performance in terms of diversity and stability, further optimizations are necessary to enhance computational efficiency without sacrificing the benefits of entropy maximization.
- **Domain-Specific Optimization:** The current formulation of EM-GAN is primarily optimized for visual data, such as images. Extending the entropy maximization framework to other modalities, such as text, audio, or even video, would require adaptations to account for the distinct characteristics of these data types—such as the sequential dependencies in text or the temporal dependencies in audio.

6.2 Future research directions

As EM-GAN shows promising results, there are several areas where further improvements can be made. The following directions offer exciting opportunities for advancing the model and expanding its applications.

- **Efficient Entropy Calculation:** A promising direction for optimization is the reduction of the computational cost associated with entropy calculation. Current methods can be computationally expensive, especially in high-dimensional spaces. Approaches such as mini-batch entropy estimation or other approximate entropy methods could significantly reduce computational overhead while maintaining the diversity-promoting benefits of entropy maximization.
- **Cross-Domain Adaptability:** Extending EM-GAN’s entropy maximization strategy to non-visual domains offers exciting opportunities for future research. For example, adapting the approach to text generation or audio synthesis could unlock new applications of entropy-based generative models. In text generation, entropy

maximization could promote the exploration of diverse syntactic and semantic structures, thereby enhancing the creativity and coherence of generated text. Similarly, in audio synthesis, entropy maximization could facilitate the generation of more diverse and realistic soundscapes, taking into account the temporal and spectral characteristics of audio signals.

- **Hybrid Architectures:** Another avenue for future work involves combining EM-GAN with other generative models, such as diffusion models or variational autoencoders (VAEs). This hybrid approach could combine the strengths of entropy maximization with the robustness of other methods, leading to further improvements in both sample quality and diversity. For instance, integrating entropy maximization with diffusion models could improve sample quality while preserving the diversity-enhancing benefits of entropy-based optimization. This hybridization could also help address some of the current limitations related to training stability and computational efficiency.
- **Scalability and Generalization:** Further exploration of the scalability of EM-GAN to larger and more complex datasets is an important direction for future research. While promising results have been observed on several benchmark datasets, applying EM-GAN to larger-scale problems, such as high-resolution image generation or multi-modal data generation, would help evaluate its generalization capabilities and reveal areas for improvement.

6.3 Potential applications

Beyond traditional image synthesis tasks, EM-GAN shows promise for application in a variety of domains where diversity and sample quality are essential. For example:

- **Text Generation:** The entropy maximization framework could be extended to text generation, where it could enhance the exploration of diverse linguistic patterns. This could have applications in areas such as automated storytelling, dialogue systems, and even code generation, by fostering creativity and variety in natural language output.
- **Audio Synthesis:** EM-GAN could be applied to audio synthesis, including tasks such as speech synthesis, music composition, or sound effect generation. By promoting entropy in the latent space, the model could encourage a broader range of audio patterns, leading to more diverse and realistic synthetic audio. This has potential applications in fields such as virtual reality, gaming, and music production.
- **Video Generation:** Adapting EM-GAN for video generation would open new possibilities in creating diverse and high-quality video content. By incorporating both spatial and temporal entropy, EM-GAN could facilitate the generation of dynamic and diverse video sequences, useful in applications such as video editing, content creation, and animation.

7. CONCLUSION

In summary, EM-GAN provides a compelling approach to generative modeling by balancing diversity, quality, and efficiency, positioning itself as a versatile model for diverse

applications. The entropy maximization principle introduces a robust framework for overcoming common challenges in GANs, such as mode collapse, and offers a promising direction for future generative model development.

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