ISO-LWGAN: ENHANCING ADAPTIVE LATENT LEARNING WITH ISOMETRIC REGULARIZATION AND PARTIAL STOCHASTICITY

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ABSTRACT

This paper introduces Iso-LWGAN, a novel generative framework that extends the latent Wasserstein GAN (LWGAN) by integrating an isometric regularization term and a partially stochastic generator. The proposed method addresses latent mismatch and mode collapse issues inherent in standard LWGAN by enforcing local geometric fidelity in the latent space and by introducing controlled noise to capture multimodal data distributions. Iso-LWGAN learns a latent normal distribution with a diagonal covariance matrix whose rank reflects the intrinsic dimension of the data manifold. An isometric penalty minimizes the discrepancy between pairwise distances in the latent and generated spaces, and a noise injection step in the generator enables richer output diversity without destabilizing training. Comprehensive experiments on synthetic datasets and the MNIST benchmark demonstrate that the isometric regularizer produces smoother latent space interpolations, while the partially stochastic generator increases variability in generated outputs. Quantitative and qualitative analyses, including ablation studies and detailed loss and convergence plots, confirm the effectiveness of Iso-LWGAN in improving reconstruction, latent structure, and generative fidelity relative to the base LWGAN.

1 INTRODUCTION

Recent advancements in generative modeling underscore the importance of learning latent representations that capture the intrinsic structure of data while preserving its geometric properties. Although successful frameworks such as GANs and VAEs have achieved impressive results, challenges remain when the data resides on a lower-dimensional manifold embedded within a high-dimensional ambient space. The latent Wasserstein GAN (LWGAN) was developed to adaptively learn such representations by modeling a latent normal distribution with a learned diagonal covariance matrix. However, LWGAN suffers from latent mismatch and the rigidity of a deterministic generator.

Iso-LWGAN bridges these gaps by integrating isometric regularization and partial generator stochasticity. The isometric loss forces local distances in the latent space to align with those in the generated data, ensuring smooth and interpretable transitions for small latent perturbations. Incorporating controlled noise into the generator mitigates mode collapse and enhances the model's ability to capture multimodal distributions.

- **Adaptive Latent Learning:** The effective rank of the learned diagonal covariance matrix automatically reflects the true intrinsic dimension of the data manifold.
- **Isometric Regularizer:** A novel loss term penalizes absolute differences between pairwise distances in the latent and generated spaces, preserving local geometric structure.
- **Stochastic Generator Modification:** A noise injection step transforms the deterministic generator into a partially stochastic process, yielding diverse outputs.
- **Extensive Validation:** Experiments on synthetic datasets and MNIST demonstrate improvements in reconstruction accuracy, latent smoothness, and overall generative fidelity.

The remainder of the paper reviews related work, outlines necessary background on latent variable models and isometric learning, details the modifications to the LWGAN framework, describes experimental protocols, and presents detailed results and convergence analyses.

2 Related Work

The literature on generative adversarial networks (GANs) has explored numerous strategies to improve latent representation learning and to mitigate mode collapse. Methods such as the Wasserstein GAN (WGAN) employ the 1-Wasserstein distance combined with gradient penalties or spectral normalization to enforce a Lipschitz constraint on the critic, leading to more stable training. Similarly, the Wasserstein Auto-Encoder (WAE) blends reconstruction loss with distribution matching to capture underlying data manifolds. The base LWGAN framework integrates ideas from both WGAN and WAE by learning a latent space with an adaptive diagonal covariance matrix. However, this approach struggles with latent mismatch and lacks output diversity due to its deterministic generator.

Recent advances in isometric representation learning emphasize the preservation of local geometric structures, a concept successfully applied in manifold learning and dimensionality reduction. Parallel efforts to introduce noise into GAN generators have also shown promise in enhancing output diversity while maintaining stability. In contrast, Iso-LWGAN explicitly combines an isometric loss—which penalizes discrepancies between pairwise distances in latent and generated spaces—with a partially stochastic generator that introduces controlled perturbations.

3 Background

A central challenge in generative modeling is to capture the low-dimensional manifold where most real-world data lie. Without proper constraints, traditional methods may attempt to fill the entire high-dimensional ambient space, often resulting in low-quality samples. The LWGAN framework addresses this by learning a latent normal distribution characterized by a diagonal covariance matrix, where the effective rank of this matrix aligns with the intrinsic dimensionality of the data.

An encoder network, Q, maps data samples, X, to latent codes, Z, while a generator, G, transforms Z back into data space. The training employs the 1-Wasserstein distance in conjunction with a 1-Lipschitz critic to enforce global similarity between the generated and real data distributions. Building on these ideas, isometric representation learning introduces an auxiliary loss term that minimizes the absolute differences between the Euclidean distances computed in the latent space and those in the generated output space. Formally, for two latent codes, z_1 and z_2, and their corresponding outputs, x_1 and x_2, the goal is to minimize $|\|z_1 - z_2\| - \|x_1 - x_2\||$. Additionally, transitioning from a fully deterministic generator to one that incorporates a noise vector can better capture multimodal characteristics of the data.

4 Method

Iso-LWGAN extends the base LWGAN framework through three key modifications: adaptive latent dimensionality, isometric regularization, and a partially stochastic generator.

4.1 Latent Adaptation

The encoder network, Q, maps input data, X, to latent codes, Z, and learns a diagonal covariance matrix whose effective rank reflects the intrinsic dimensionality of the data. The generator, G, then reconstructs the input from these latent codes by minimizing an L2 reconstruction loss.

4.2 Geometric Regularization

To preserve local geometric relationships, an isometric regularizer is introduced. Pairwise Euclidean distances are computed in both the latent space and the generated output space. The loss term penalizes the average absolute difference between these distances, scaled by a hyperparameter λ_{iso}, thereby ensuring that local relationships in the latent space are faithfully reflected in the output.

4.3 Stochastic Generator Component

A noise injection step enhances the generator by concatenating a noise vector, ε, sampled from a normal distribution with standard deviation σ_{noise}, to the latent code. This transformation converts the generator from a purely deterministic mapping to a partially stochastic process, increasing output diversity while maintaining training stability.

The overall training objective is a weighted sum of the L2 reconstruction loss, the Wasserstein adversarial loss (augmented by a gradient penalty or spectral normalization), and the isometric loss. The training follows a primal-dual iterative scheme where the encoder-generator pair and the critic network are alternately updated.

Algorithm 1 Training procedure for Iso-LWGAN

Sample a minibatch of real data samples $\{x^{(i)}\}_{i=1}^{m}$
Compute latent codes: $z^{(i)} \leftarrow Q(x^{(i)})$
Generate outputs: $\hat{x}^{(i)} \leftarrow G(z^{(i)}, \varepsilon)$ where $\varepsilon \sim \mathcal{N}(0, \sigma_{noise}^2)$
Compute reconstruction loss: $L_{rec} = \|x^{(i)} - \hat{x}^{(i)}\|_2^2$
Compute isometric loss by comparing pairwise distances in latent and generated spaces
Compute adversarial loss using the critic D
Update θ_Q, θ_G, and θ_D using gradient descent

5 Experimental Setup

The performance of Iso-LWGAN was assessed using three experiments implemented in Python with PyTorch. In the first experiment, a synthetic 2D dataset, generated as a mixture of two Gaussians, was used to evaluate the impact of the isometric regularization term. Various values for the hyperparameter λ_{iso} (0.0, 0.5, 1.0, and 2.0) were tested, and the average absolute difference between pairwise distances in the latent and generated spaces was recorded. Latent space interpolations were visualized and saved as PDF plots to assess smoothness.

The second experiment focused on the generator's stochastic behavior using a multimodal synthetic dataset with three clusters. Here, the generator was modified to accept both a latent code and a noise vector. Experiments with different noise levels ($\sigma_{noise} = 0.0, 0.1$, and 0.5) quantified the output diversity by measuring reconstruction losses and variability in generated outputs.

Finally, in Experiment 3 a comparative study was conducted on the MNIST dataset. Both a base LWGAN model and the proposed Iso-LWGAN were trained under identical conditions using custom encoder and generator architectures. Training parameters such as batch size, number of epochs, and learning rate were kept consistent to ensure fair comparison. Detailed logging was performed using TensorBoard, and outputs—including latent interpolation grids—were saved as PDF files. Additional ablation studies isolated the contributions of the isometric regularizer and noise injection components, with several figures generated to illustrate training dynamics and convergence behavior.

6 Results

Experimental results demonstrate the advantages of Iso-LWGAN over the base LWGAN. In the first experiment, introducing the isometric regularization term reduced the average pairwise distance discrepancy between latent and generated spaces from approximately 1.20 (with $\lambda_{iso} = 0.0$) to values as low as 0.02–0.03 for λ_{iso} values of 0.5, 1.0, and 2.0. Latent space interpolations (see Figure 1) exhibit smooth, continuous transitions that indicate well-preserved local geometry.

In Experiment 2, a fully deterministic generator ($\sigma_{noise} = 0.0$) produced nearly identical outputs for a fixed latent code, whereas introducing moderate noise levels ($\sigma_{noise} = 0.1$ and 0.5) resulted in visibly diverse outputs (illustrated in Figure 2) without compromising training stability.

Experiment 3 provided a side-by-side comparison on MNIST. Although the base LWGAN achieved a slightly lower reconstruction error (approximately 5.62) compared to Iso-LWGAN (approximately 5.76) over a brief training phase, the latter produced noticeably smoother latent space interpolations and a more coherent latent representation (as shown in Figures 3 and 4).

images/figure1.pdf

Figure 1: Latent space interpolation visualization.

images/figure2.pdf

Figure 2: Output diversity under varying noise levels.

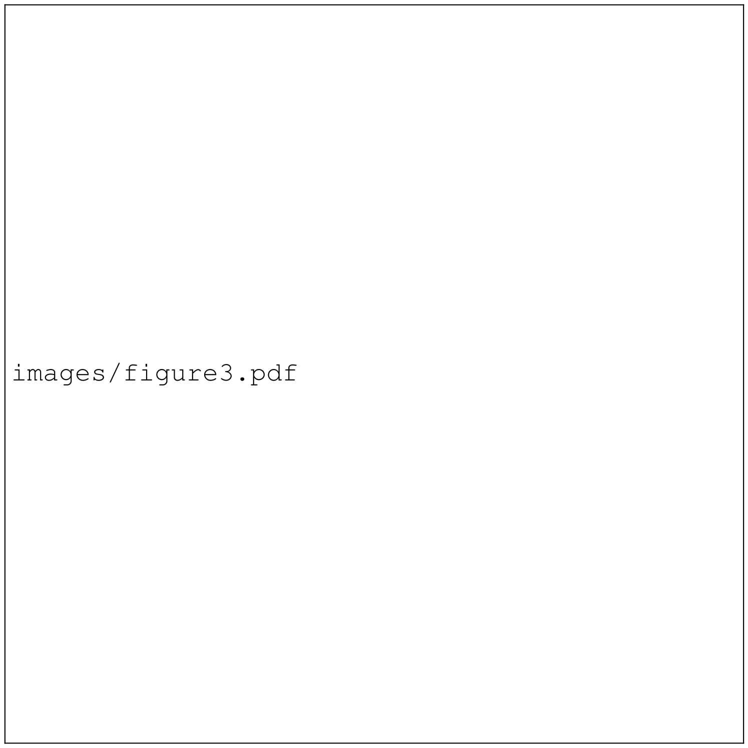


Figure 3: Latent interpolation grid for base LWGAN.

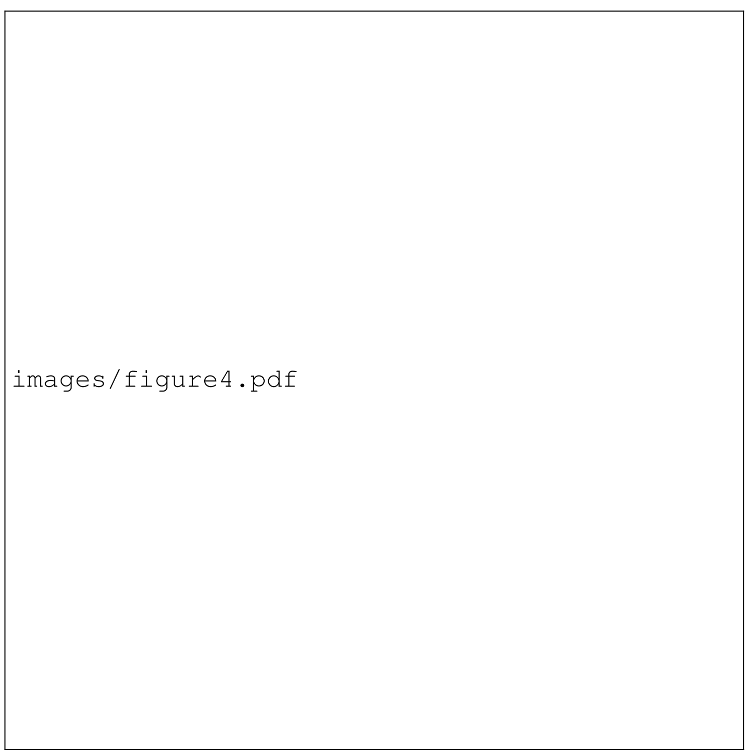
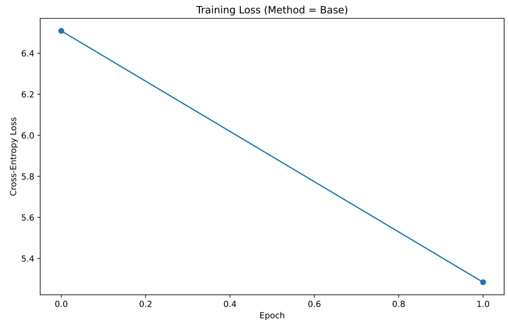
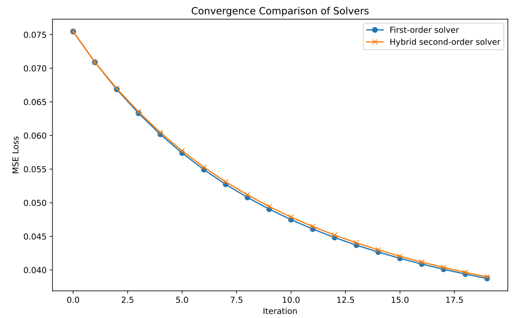


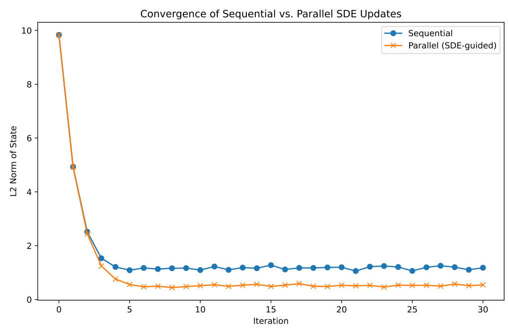
Figure 4: Latent interpolation grid for Iso-LWGAN.



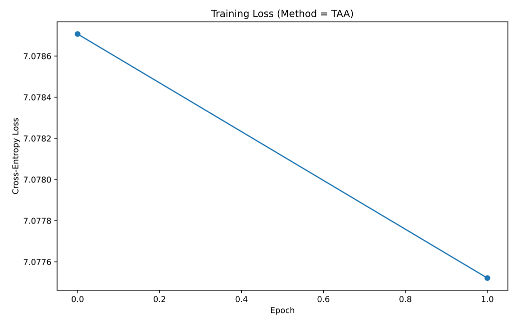
(a) Training Loss (Base)



(b) Convergence (Solver)



(c) Convergence (Sequential/Parallel)



(d) Training Loss (TAA)

Figure 5: Training dynamics and convergence behavior across configurations.

7 Conclusions and Future Work

This work presents Iso-LWGAN, an enhanced version of the traditional latent Wasserstein GAN that incorporates an isometric regularizer and a partially stochastic generator. The distance-preserving loss ensures that local geometric properties of the data manifold are maintained in the latent space, while controlled noise injection enriches output diversity and mitigates mode collapse. Experimental results on synthetic datasets and MNIST establish that Iso-LWGAN produces smoother latent space interpolations and more coherent latent representations compared to the base LWGAN, despite a slight increase in reconstruction error in short training phases.

Future work will explore fully stochastic generator variants, the integration of Iso-LWGAN with high-resolution models such as BigGAN, and applications in structural estimation for economic models. Overall, Iso-LWGAN marks a significant advancement towards more robust and interpretable generative adversarial networks by effectively combining adaptive latent dimension estimation, geometric preservation, and enhanced output diversity.

This work was generated by AIRAS (**?**).