HyperNeRFGAN: Hypernetwork approach to 3D NeRF GAN

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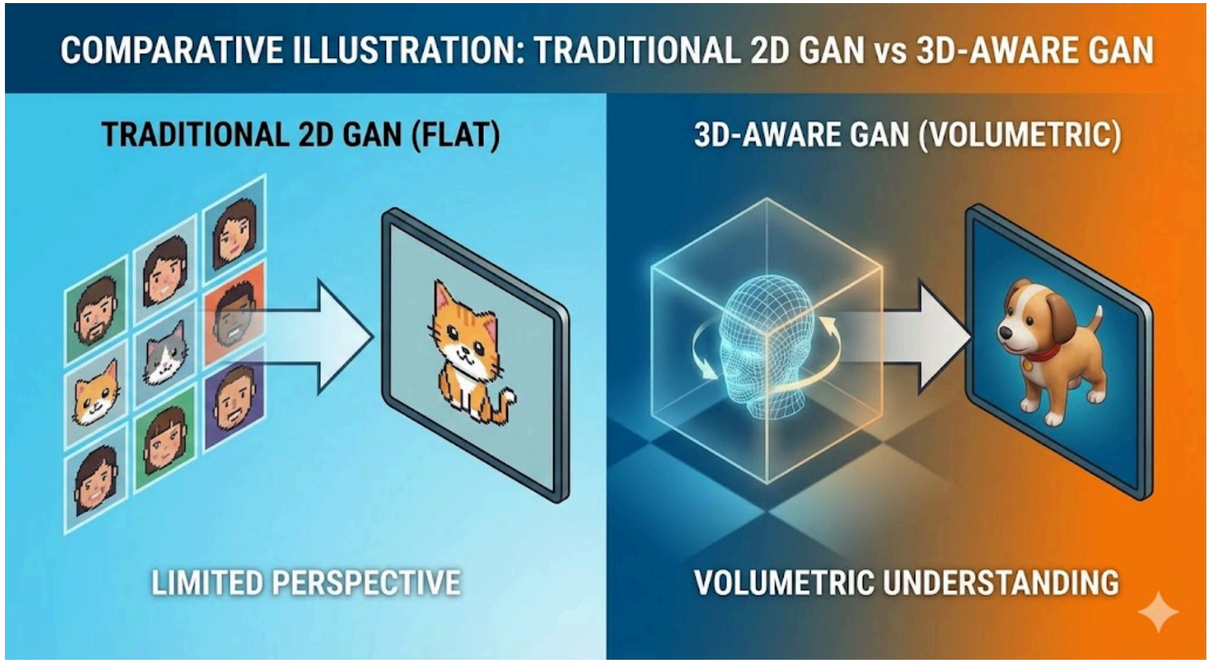
Ho Chi Minh City, December 28, 2025

1. INTRODUCTION

1.1 Background & Motivation

- **Context:** 3D-aware Image Synthesis combines GANs (Generative) + NeRF (3D Consistency).
- **The Problem:**
  - **Computational Cost:** Rendering requires millions of queries. Typically needs NVIDIA V100/A100.
  - **Pose Dependency:** Standard NeRF needs camera labels. Real-world data is often unposed.
- **Our Goal:** Reproduce and optimize HyperNeRFGAN on a Single Tesla T4 (16GB).



1. INTRODUCTION

1.2 Problem Formulation (Mathematical)

Input: Unstructured 2D image collection $\mathcal{D} = \{I_1, \ldots, I_N\}$. Unknown poses.

Objective: Learn a generator G and volume representation V such that:

$$\hat{I} = \pi(V(z, \theta), \xi)$$

- z~N(0,I): Latent code.
- ξ: Random camera pose.
- π: Differentiable Volumetric Rendering operator.

Adversarial Game:

$$\min_G \max_D \mathbb{E}_x[\log D(x)] + \mathbb{E}_z[\log(1 - D(\hat{I}))]$$

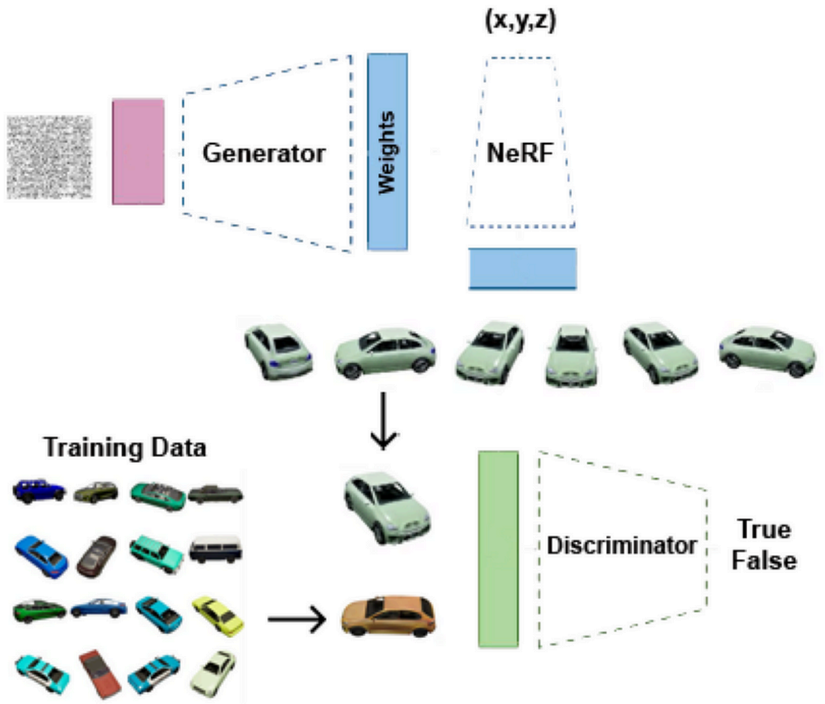
2. METHODOLOGY

2.1 Architecture Overview

1. **Hypernetwork (G):** StyleGAN2 backbone. Maps $z \rightarrow \text{Weights } \theta$.

2. **Target Network (F_θ):** Simplified NeRF MLP. Uses weights from G.

3. **Discriminator (D):** 2D CNN. Critiques rendered images.



2. METHODOLOGY

2.2 Target Network & View-Independence

1. Mathematical Formulation:

- **Standard NeRF (View-Dependent):**

$$F : (\underbrace{\mathbf{x}}_{\in\mathbb{R}^3}, \underbrace{\mathbf{d}}_{\in\mathbb{S}^2}) \longrightarrow (\underbrace{\mathbf{c}}_{\in\mathbb{R}^3}, \underbrace{\sigma}_{\in\mathbb{R}_{\geq 0}})$$

  - *Inputs:* Spatial coordinate $\mathbf{x}$ and Viewing direction $\mathbf{d}$.
  - *Outputs:* Color vector $\mathbf{c}$ (RGB) and **Scalar** Volume Density σ.

- **HyperNeRFGAN Simplification:**

$$F_\theta : \mathbf{x} \in \mathbb{R}^3 \longrightarrow (\mathbf{c}, \sigma) \in \mathbb{R}^3 \times \mathbb{R}_{\geq 0}$$

  - *Note:* The input domain is reduced from 5D ($\mathbb{R}^3 \times \mathbb{S}^2$) to 3D ($\mathbb{R}^3$).

2. METHODOLOGY

2.2 Target Network & View-Independence

2. The Lambertian Surface Assumption:

- **Definition:** Surfaces reflect light uniformly in all directions (perfectly diffuse).
- **Implication:** Emitted color is **isotropic** (independent of viewing angle).

$$\mathbf{c}(\mathbf{x}, \mathbf{d}) \approx \mathbf{c}(\mathbf{x}) \implies \mathbf{d} \text{ is redundant.}$$

3. Why this Assumption Helps?

- **Removes Ambiguity:** Without camera pose labels (unposed data), the generator struggles to distinguish between *texture patterns* and *specular reflections*.
- **Stabilizes Training:** Reduces the mapping complexity for the Hypernetwork, allowing it to focus on learning accurate **Geometry (σ)** and **Texture ($\mathbf{c}$)**.

2. METHODOLOGY

2.3 Factorized Multiplicative Modulation (FMM)

- **Challenge:** Generating full weight matrix $W \in \mathbb{R}^{n_{out} \times n_{in}}$ is $O(n^2)$. Too heavy!
- **Solution (FMM):**

$$y = W \odot (A \times B) \cdot x_{in} + b$$

- **Derivation of Efficiency:**
  - Decompose into low-rank matrices $A(n \times k)$ and $B(k \times n)$.
  - Complexity: $\mathcal{O}(k \cdot (n_{out} + n_{in}))$.
  - With $k = 10, n = 128$: Reduction factor $\approx \mathbf{6.4}\times$.

2. METHODOLOGY

2.4 Volumetric Rendering & Discretization

- **The Integral:** $C(\mathbf{r}) = \int T(t)\sigma(\mathbf{r}(t))\mathbf{c}(\mathbf{r}(t))\,dt.$
- **Riemann Sum Approximation:**

$$\hat{C}(\mathbf{r}) \approx \sum_{i=1}^{N_s} T_i(1 - e^{-\sigma_i\delta_i})\mathbf{c}_i$$

- **Mathematical Insight for Failure ($N_s = 8$):**
  - Error $\propto \delta_i$ (distance between samples).
  - Low $N_s \implies$ High $\delta_i \implies$ Opacity term $(1 - e^{-\sigma_i\delta_i})$ fails to saturate.
  - Result: **"Cloudy" Artifacts**.

2. METHODOLOGY

2.5 Objective & R1 Regularization

- **R1 Gradient Penalty:**

$$R_1(\mathcal{D}) = \frac{\gamma}{2}\mathbb{E}_x[\|\nabla_x D(x)\|^2]$$

- **Why is it necessary?**
  - Enforces **Lipschitz Continuity** on D.
  - Bounds the gradient magnitude $\rightarrow$ Prevents exploding gradients.
  - Ensures a smooth optimization landscape for the Hypernetwork.

3. Resource-Aware Optimization (Tesla T4)

- **Constraint:** 16GB VRAM (Standard NeRF-GAN needs >32GB).
- **Our Solution (The "Low-Memory Baseline"):**
  1. **Patch Size:** $64^2 \rightarrow \mathbf{32^2}$ pixels (4x memory reduction).
  2. **Sampling:** $N_s = 64 \rightarrow \mathbf{32}$ steps.
  3. **Environment:** Micromamba + Pinned Versions (Torch 1.10).

Parameter	Standard Config	Our Config (T4)	Reduction
GPU VRAM	32GB+	**16GB**	**-50%**
Patch Size (P_s)	64×64	32×32	**4x**
Ray Samples (N_s)	64	**32**	**2x**
Volumetric Load	**262k pts**	**32k pts**	**8x Lighter**

Table 2: Comparison showing how we optimized the architecture to fit within the memory constraints of a Tesla T4.

4. RESULTS & ABLATION

4.1 Pre-trained Results (4 Datasets)

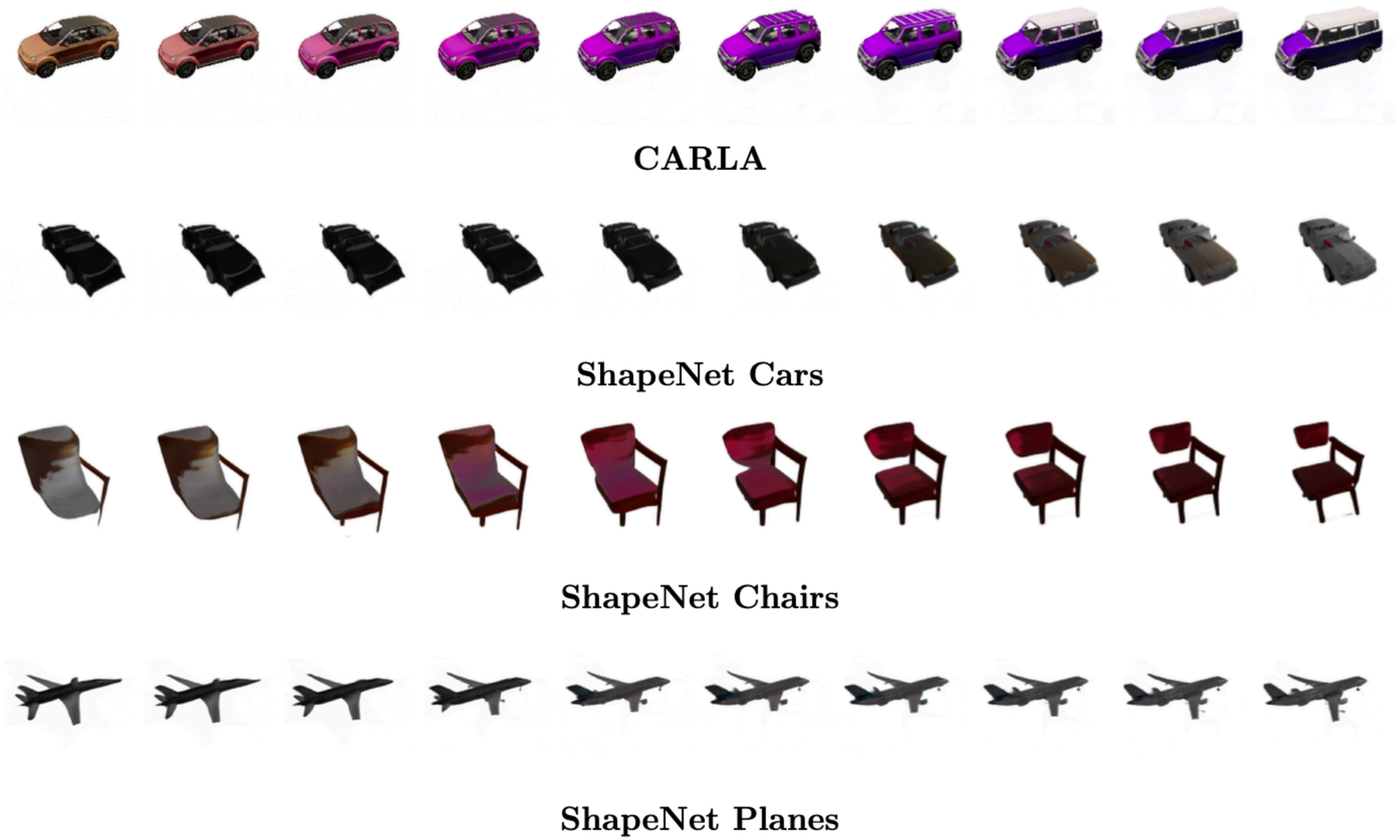


Figure 3: Latent space interpolation using official pre-trained weights. The transitions represent the theoretical upper bound of smoothness achievable by the architecture.

4. RESULTS & ABLATION

4.2 Qualitative Baseline Results (4 Datasets)

- Successfully reproduced on CARLA, ShapeNet Cars, Planes, Chairs.
- **Observations:**
  - **Cars:** Solid volumes.
  - **Planes:** Thin wings captured (Hardest task).
  - **Chairs:** Complex topology/negative space handled well.

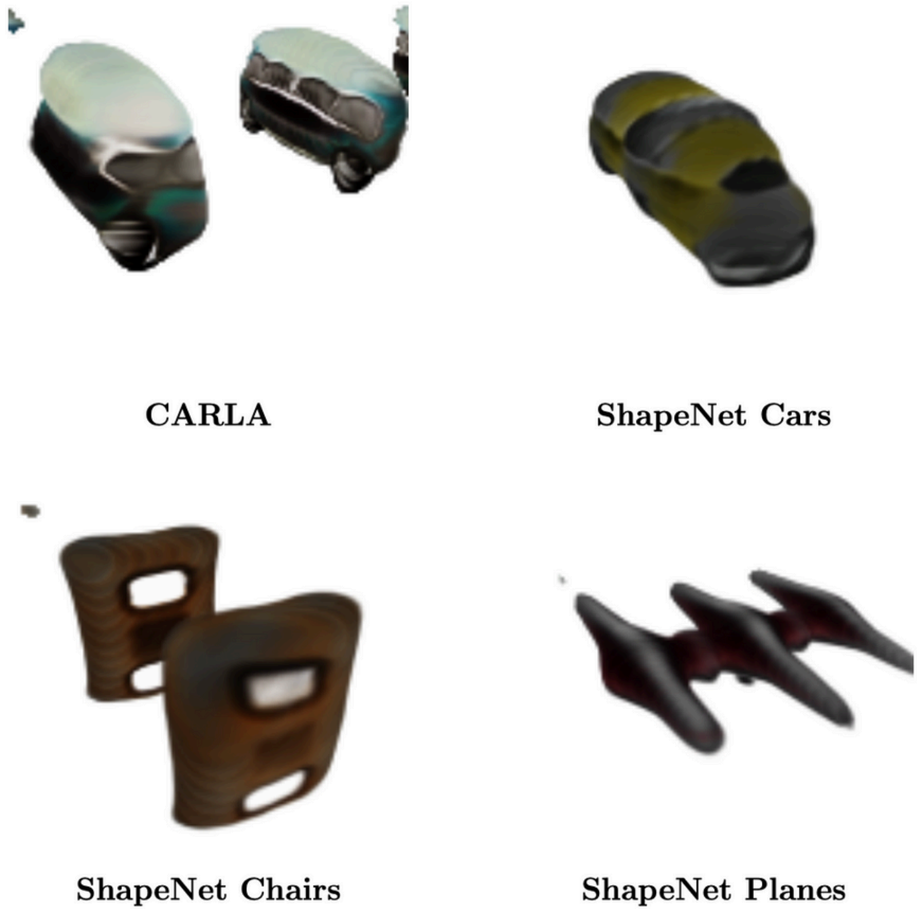


Figure 4: Baseline qualitative results of HyperNeRFGAN across different datasets. Each image shows a randomly sampled object rendered from a fixed viewpoint.

4. RESULTS & ABLATION

4.3 Manifold Continuity (Interpolation)

- Linear Interpolation: $z_{new} = (1 - \alpha)z_1 + \alpha z_2$.
- **Result:** Smooth transitions (e.g., Chair leg thickness changes gradually).
- **Proof:** The model learns the **structure**, not memorization.

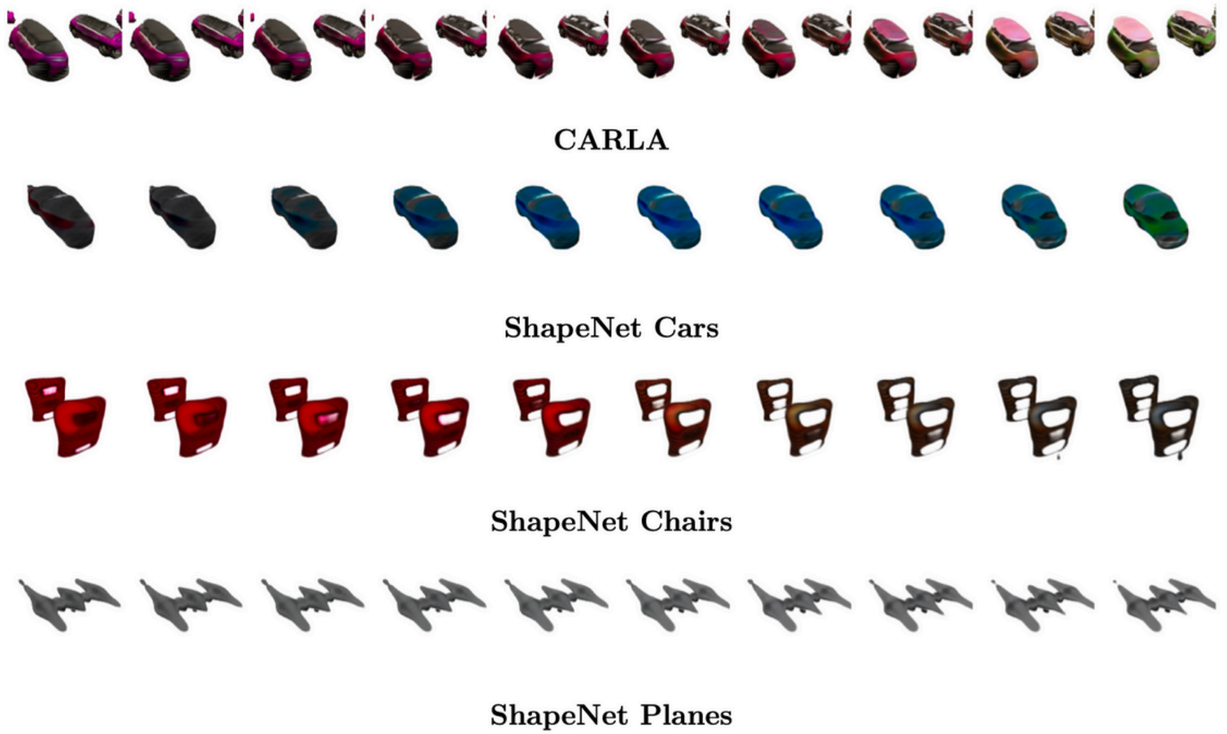


Figure 5: Linear latent space interpolation results. Each row shows interpolation between two latent codes, demonstrating smooth transitions in object identity and viewpoint.

4. RESULTS & ABLATION

4.4 Quantitative Analysis (Convergence)

Table 2: FID-1k convergence progress across reproduced datasets (0 to 200 kimg).

Dataset	Initial FID ($kimg = 0$)	Final FID ($kimg = 200$)	Improvement (%)	Training Time
CARLA (Baseline)	339.9	155.4	**54.3%**	$\approx$ 4h 18m
ShapeNet Cars	341.3	136.2	**60.1%**	$\approx$ 5h 17m
ShapeNet Planes	294.8	182.8	38.0%	$\approx$ 5h 19m
ShapeNet Chairs	296.8	169.2	43.0%	$\approx$ 5h 14m

- **Table:** FID improvement over 200 kimg.
- **Key Findings:**
  - **ShapeNet Cars: 60.1%** improvement (Best).
  - **ShapeNet Planes: 38.0%** improvement (Lowest - Thin structures need high N_s).
- **Baseline FID:** CARLA reached **155.4**.

4. RESULTS & ABLATION

4.5 Ablation: The Geometry-Memory Trade-off

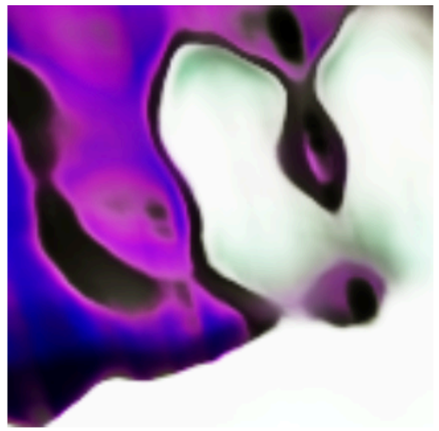
Experiment 1: Sparse Sampling (num_sample=8).

- Visual: Cloudy/Ghost-like.
- FID: **+104.7 degradation.**
- Reason: Numerical integration failure (Slide 7).

Experiment 2: Small Patch (patch_size=8).

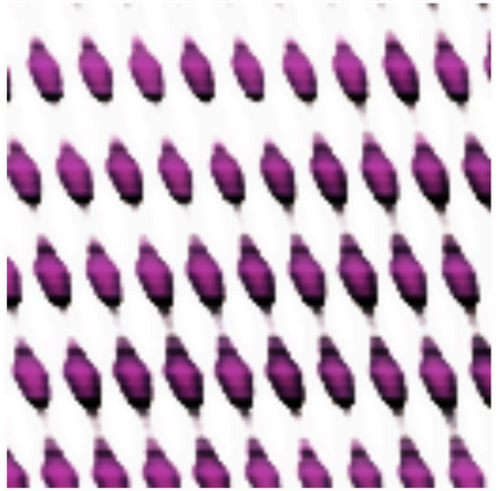
- Visual: Fragmented parts.
- FID: **+169.0 degradation.**
- Reason: D loses global context.

(a) Baseline ($N_s = 32$)



(b) Sparse Sampling ($N_s = 8$)

(a) Baseline ($P_s = 32$)



(b) Small Patch ($P_s = 8$)

4. RESULTS & ABLATION

4.6 Ablation: Stability & Mode Collapse

Experiment 3: No Augmentation (p=0.0).

- **Paradox:** FID (-0.5) is "better", BUT...
- Visual: **Mode Collapse** (All cars look the same).
- Reason: Discriminator overfitting → Generator memorizes "safe" modes.

(a) Baseline (Diverse)

(b) No Augment (Collapsed)

Experiment 4: Reduced Reg (γ=0.5).

- Visual: High-frequency artifacts.
- FID: **+39.4 degradation.**

(a) Baseline ($\gamma = 1.0$)

(b) Reduced Reg. ($\gamma = 0.5$)

5. CONCLUSION

- **1. The "Memory Wall":** There is a hard lower bound (num_samples >= 32) for 3D illusion.
- **2. Hypernetwork Efficacy:** Works across diverse topologies (Solid, Thin, Complex).
- **3. View-Independence:** A robust feature for unposed data, at the cost of specular reflections.
- **Final Verdict:** HyperNeRFGAN is viable on consumer hardware with careful tuning.

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Thank you for your attention

Ho Chi Minh City, December 28, 2025