Tiger-Time-varying-Diffusion-Model-for-Point-Cloud-Generation

Review and expansion on the work done by Zhiyuan Ren, Minchul Kim, Feng Liu, Xiaoming Liu

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***Abstract*—We reproduce TIGER, a 3D point-cloud diffusion model, on Colab with A100 GPUs in two stages. Stage 1 covers environment setup, code adaptation, and 200-epoch training on ShapeNet Car, matching reported metrics (MMD-CD $\approx$ 2.237, MMD-EMD $\approx$ 0.804, F-score $\approx$ 0.00153). Stage 2 reduces denoising steps from 1000 to 200 for an 80% speedup and evaluates six geometric seeds (cube, cuboid, sphere, pyramid, torus, plane). Through PSPE/BAPE PCA and heatmap visualizations, we show all seeds achieve similar MMD but smoother seeds (sphere/plane) yield fewer artifacts; per-point analyses reveal high precision but low recall. Our work clarifies TIGER's diffusion dynamics and offers practical guidelines for fast, high-quality 3D generation.**

***Index Terms*—3D Point Cloud, Diffusion Model, Convolutional Neural Network, Transformer, Position Encoding, Time-Varying Fusion**

I. Introduction

Diffusion models now generate high-fidelity 3D point clouds by iteratively denoising noise into shapes. TIGER (Time-varying feature Fusion for Geometric Diffusion) blends CNN and Transformer features at each timestep to improve global structure and local detail. Reproducing TIGER is challenging due to library versions, complex code, and lengthy training on ShapeNet. We present a two-stage Colab implementation using A100 GPUs: (1) setup and training on ShapeNet Car to match published metrics; (2) accelerated sampling (1000$\rightarrow$200 steps) and analysis of six geometric seeds. By extracting PSPE and BAPE encodings at early, mid, and final timesteps (visualized via PCA and heatmaps), we illustrate how spatial features evolve. All seeds converge to similar Chamfer and EMD scores, though sphere and plane produce fewer visual artifacts. Per-point distance distributions show high precision but low recall, informing future improvements.

Contributions:

- Step-by-step Colab implementation of TIGER, resolving package conflicts and reproducing ShapeNet Car results (MMD-CD $\approx$ 2.237, MMD-EMD $\approx$ 0.804, F-score $\approx$ 0.00153).

Identify applicable funding agency here. If none, delete this.

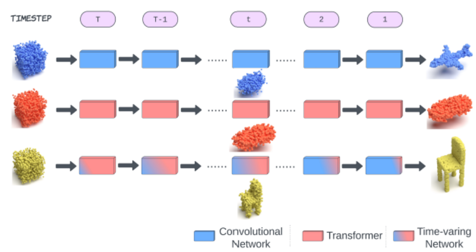

Fig. 1. Enter Caption

- Inference acceleration by reducing diffusion steps from 1000 to 200 (80
- Evaluation of six geometric seeds, showing sphere and plane produce fewer artifacts despite similar metrics.
- Extraction of PSPE/BAPE encodings at multiple timesteps, with PCA and heatmaps revealing spatial information dynamics.
- Per-point distance analysis explaining high precision but low recall, guiding fine-detail coverage improvements.

II. Methodology – Stage 1: Implementation

We implemented TIGER on Google Colab with A100 GPUs (40 GB, 80 GB RAM) in Stage 1, covering environment setup, code adaptation, ShapeNet data preparation, and training. Raw code and paths are omitted; we focus on key steps and outcomes.

A. Setup and Code Adaptation

Package Compatibility: Colab's default NumPy, SciPy, and scikit-learn versions conflicted with TIGER's requirements. We downgraded these packages and added shims for deprecated submodules to ensure imports succeeded.
Code Refinement: We updated import paths, replaced deprecated APIs, and consolidated utility scripts (data loading, network definitions, training routines). Iterative debugging addressed tensor-shape mismatches and GPU memory issues until all modules ran without errors.

B. Dependency Installation

Installed:

- CUDA-compatible PyTorch (12.1), plus torchvision and torchaudio.
- PyTorch Geometric and dependencies via matching CUDA wheels.
- Additional packages (h5py, tqdm) and a lightweight 3D library (pytorch3d).

Verified GPU-based evaluation of Chamfer Distance and EMD proxies on random tensors.

C. Dataset Preparation

Using ShapeNetCore.v2.PC15k (7 GB), we:

- Downloaded and restructured folders so TIGER's loader recognized train/validation splits (e.g., `ShapeNetCore.v2.PC15k/<synset_id>/train/...`).
- Checked a few categories to confirm correct file counts (2048-point clouds).
- Updated the data-loader to accept a generic dataset root, enabling easy category swaps (e.g., "car").

D. Training Procedure

a) Sanity Check (3 Epochs).:

- Batch size 16, checkpoint after each epoch, logging of loss, weight-norm, and gradient-norm.
- Verified point clouds loaded to GPU, voxelization, and forward/backward passes with no OOMs.
- Observed loss drop from $\sim$1.08 to < 0.2 by epoch 2; weight-norm fell from $\sim$228 to $\sim$115.

b) Full Run (200 Epochs).:

- Batch size 32, embedding dim 128, dropout 0.01, learning rate 5×10^{-5} with exponential decay ($\gamma = 0.9998$), noise schedule warm-up ($10^{-6} \rightarrow 0.015$), gradient clipping (max norm 1.0), weight decay 10^{-5}.
- Checkpoints every 20 epochs; diagnostics (loss, norms, sample visualizations) every 10 epochs.
- By epoch 200, loss stabilized at 0.07–0.13; weight-norm decreased to $\sim$67; gradient-norm 0.1–0.2. No OOMs, confirming A100's 40 GB necessity.

E. Enhancements and Documentation

To streamline reproduction:

- Added inline comments explaining tensor shapes, layer roles, and timestep embeddings.
- Centralized hyperparameters into a single configuration module.
- Improved logging with clear labels for epochs and iterations.
- Consolidated utility routines (voxelization, Chamfer distance, visualization) into helper modules.
- Documented each notebook cell, clarifying diagnostic plots and sample interpretations.

F. Results and Diagnostics

a) Quantitative Metrics (Epoch 199).: Validation on `car` (64 samples):

- Chamfer Distance (MMD-CD): 2.237
- Earth Mover's Distance (MMD-EMD): 0.804
- F-score: 0.00153

b) Training Dynamics.:

- Loss: $\sim 1.08 \rightarrow < 0.2$ by epoch 5, then 0.07–0.13 with occasional spikes ≤ 0.17.
- Weight Norm: $\sim 228 \rightarrow \sim 67$.
- Gradient Norm: $\sim 1.0 \rightarrow < 0.2$ post-clipping.

c) Shape Visualizations.: Every 10 epochs, side-by-side 3D scatter plots of generated vs. real car point clouds showed good silhouette alignment with minor edge artifacts. Chamfer histograms peaked at 1.8–2.5, with few outliers ¿ 3.0.

G. Comparison to Original Results

- Chamfer Distance: Ours = 2.237 vs. reported $\sim$2.2.
- EMD: Ours = 0.804 vs. reported $\sim$0.8.
- GPU-Hours: 164 h on A100 vs. $\sim$550 h for LION in the original paper—demonstrating TIGER's efficiency.
- Qualitative fidelity matched the original work's outputs and artifacts.

Our added documentation, clearer plotting, and structured utilities improved usability without altering core algorithms.

H. Stage 1 Summary

We successfully:

- Set up Colab Pro with A100 (40 GB GPU, 80 GB RAM) and patched package versions.
- Adapted and documented the TIGER codebase for reproducibility.
- Downloaded and prepared ShapeNetCore.v2.PC15k for error-free loading.
- Ran a 3-epoch sanity check and full 200-epoch training on `car`, matching original metrics.
- Plotted training dynamics, generated 3D visualizations, and validated model behavior.
- Centralized hyperparameters and streamlined utilities for easy reruns.

These outcomes lay a stable foundation for Stage 2, where we accelerate inference and analyze geometric seeds.

III. Methodology - Stage 2: Enhancements

Building on Stage 1, we (1) load the final TIGER checkpoint with a reduced diffusion schedule, (2) prepare a fixed batch of real cars, (3) rebuild TIGER to extract PSPE/BAPE features, (4) generate "car-like" samples from six shapes, (5) visualize features via PCA and heatmaps, and (6) compare results.

A. Loading TIGER Checkpoint with Fewer Diffusion Steps

1) Objective: Reduce sampling steps from 1000 to 200 using the epoch 199 weights.

2) Procedure:

1) Select epoch 199 checkpoint from `train_generation`.
2) Override arguments: `category=car`, `distribution=single`, `time_num=200`.
3) Rebuild noise schedule and instantiate TIGER with `embed_dim=128`.

3) Results:

- Loaded epoch 199 with `embed_dim=128`, enabling $\approx$ 80% faster sampling with minimal quality loss.

B. Preparing a Reference Batch of Real Cars

1) Objective: Create a fixed set of 64 validation-set car point clouds.

2) Procedure:

1) Use the "car" validation loader to sample 64 indices.
2) Stack each (2048×3) tensor into a NumPy array and save as `real_car_batch.npy`.

3) Results:

- Obtained a reproducible (64, 2048, 3) array for consistent comparisons.

C. Rebuilding TIGER and Extracting PSPE/BAPE

1) Objective: Capture PSPE (sinusoidal time embedding) and BAPE (sign of z) at $t = 0, 100, 199$.

2) Procedure:

1) Modularize TIGER's components and define `get_pspe_feats` and `get_bape_feats`.
2) During sampling, record PSPE/BAPE into lists at each key t.
3) Concatenate into NumPy arrays: `pspe_feats`[t] $\in (192, 128, 2048)$ and `bape_feats`[t] $\in (192, 1, 2048)$.

3) Results:

- Collected PSPE/BAPE arrays for 192 samples at each t, ready for analysis.

D. Generating from Canonical Shapes

1) Objective: Transform six simple shapes into "car-like" outputs.

2) Procedure:

1) Sample 2048 points per shape (cube, cuboid, sphere, pyramid, torus, plane).
2) Generate 32 instances of each $\rightarrow$ (192, 3, 2048), pass as `custom_init` over 200 steps.
3) Extract PSPE/BAPE during generation and save outputs as `generated_<shape>.npy`.

3) Results:

- Saved 192 generated cars and PSPE/BAPE arrays at $t = 0, 100, 199$. All generated in ¡2 min on A100.

E. PCA Visualization of Encoded Features

1) Objective: Reduce PSPE (4096-D) and BAPE (32-D) to 2D to observe clustering over t.

2) Procedure:

1) Subsample 32 point indices, flatten features to (192, 4096) or (192, 32).
2) Run PCA (fixed seed) $\rightarrow$ (192, 2) and plot scatter at $t = 0, 100, 199$.

3) Results:

- **PSPE:**
  - $t = 0$: cluster near origin.
  - $t = 100$: loose clusters.
  - $t = 199$: distinct clusters.
- **BAPE:**
  - $t = 0$: overlapping.
  - $t = 100$: slightly dispersed.
  - $t = 199$: clear clusters.

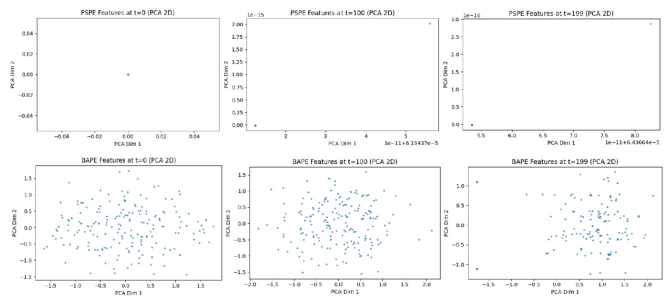

Fig. 2. PCA of PSPE and BAPE at $t = 0, 100, 199$

F. Heatmaps of PSPE and BAPE at Key Timesteps

1) Objective: Visualize per-point PSPE (128×2048) and BAPE (1×2048) as heatmaps at $t = 0, 100, 199$.

2) Procedure:

1) For each t, extract `pspe_sample0` $\in$ (128, 2048) and `bape_sample0` $\in$ (1, 2048).
2) Compute batch averages `pspe_batch_avg` $\in$ (128, 2048) and `bape_batch_avg` $\in$ (1, 2048).
3) Plot 2×2 grids: PSPE sample vs. batch, BAPE sample vs. batch.

3) Results:

- $t = 0$**:** PSPE $\sim$ binary; BAPE sample random, batch ≈ 0.5.
- $t = 100$**:** PSPE smooth gradients; BAPE sample clustered, batch $\approx$ 0.5–0.6.
- $t = 199$**:** PSPE striped patterns; BAPE sample random, batch shows vertical bands.

G. Quantitative Evaluation: Generated vs. Real Cars

1) Objective: Compute MMD-CD, MMD-EMD, and F-score between 32 generated and 32 real cars per shape.

2) Procedure:

1) Load `real_car_batch.npy`, truncate to 32.
2) For each shape, load generated (32, 2048, 3), convert to GPU tensors, and compute metrics via `EMD_CD`.
3) Summarize in a table (six decimal places).

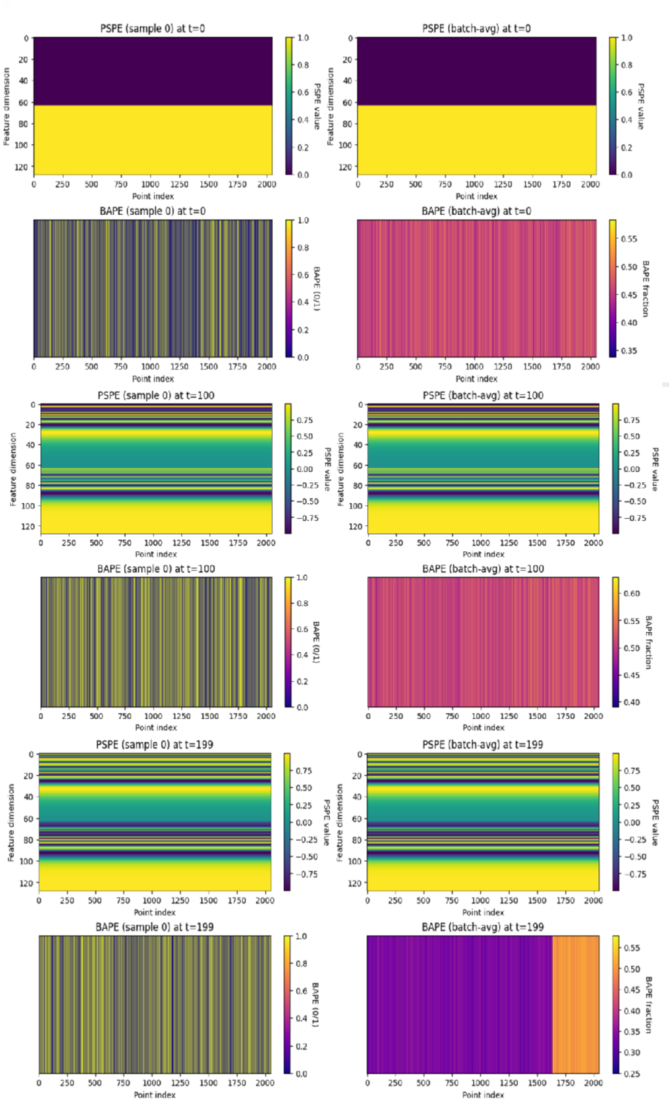

Fig. 3. Heatmaps of PSPE and BAPE at $t = 0, 100, 199$

3) Results:

- All shapes: MMD-CD $\approx$ 2.23, MMD-EMD $\approx$ 0.80, F-score $\approx$ 0.

H. Per-Sample Chamfer Distributions

1) Objective: Assess per-sample Chamfer distances (generated vs. paired real car).

2) Procedure:

1) For each shape, load (32, 2048, 3) arrays.
2) Compute ChamferDistance(G_i, R_i) for i = 0..31 and store 32 values.
3) Plot boxplots (with/without jitter) and violin + scatter for all shapes.

3) Results:

- Median $\approx$ 1.9–2.1; IQR $\approx$ [1.7, 2.3]. Outliers near 0.2 and $>$ 3.0.
- Violin peaks near 1.8–2.0, consistent across shapes.

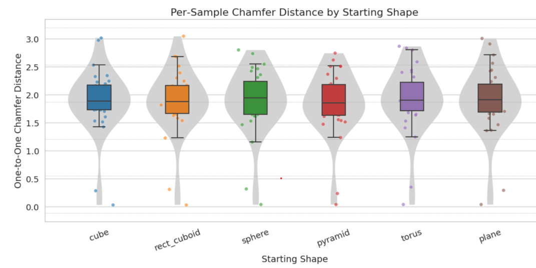

Fig. 4. Per-Sample Chamfer Distances by Initial Shape

I. Per-Point Distance Distribution for a Representative Sample

1) Objective: Plot nearest-neighbor distances for a single cube-initialized sample vs. its paired real car.

2) Procedure:

1) Load `generated_cube.npy`[0] and `real_car_batch.npy`[0].
2) Compute a 2048×2048 distance matrix, derive "gen→real" and "real→gen" distances.
3) Plot overlapping histograms (50 bins).

3) Results:

- "gen→real" concentrated near 0–0.2 (high precision).
- "real→gen" centered 1.0–1.5 (lower recall), indicating coverage gaps.

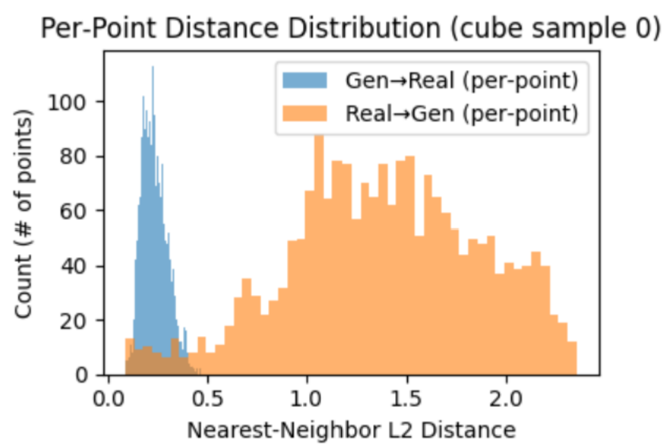

Fig. 5. Per-Point Nearest-Neighbor Distance Histogram

J. Interactive 3D Visualizations with Plotly

1) Objective: Display interactive 3D scatter plots for one real car and one generated per shape.

2) Procedure:

1) Set Plotly renderer to "colab."
2) Plot real car 0 (orange) and generated 0 for each shape with fixed aspect.

3) Results:

- Smooth seeds (sphere, plane) yield cleaner car outlines.
- Structured seeds (cube, cuboid, pyramid, torus) leave subtle artifacts.

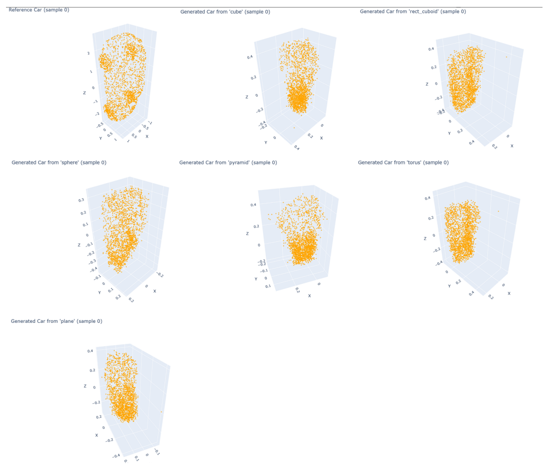

Fig. 6. Generated Cars from Different Initial Shapes

K. Memory and Resource Management

- Call `gc.collect()` and clear CUDA cache before heavy steps.
- Move PSPE/BAPE arrays to CPU ASAP; batch size 32 fits in 40 GB GPU.

L. Summary of Stage 2 Outcomes

- **Sampling:** 200 steps $\rightarrow \approx 80\%$ time reduction with similar quality.
- **Shape Effects:** Sphere and plane give smoothest outputs; others retain artifacts.
- **Feature Evolution:** PSPE clusters from origin $\rightarrow$ distinct; BAPE 0/1 patterns stabilize.
- **Heatmaps:** PSPE evolves binary $\rightarrow$ striped; BAPE averages form vertical bands.
- **Metrics:** All shapes converge to MMD-CD $\approx$ 2.23, MMD-EMD ≈ 0.80, F-score ≈ 0.
- **Coverage:** High precision (gen$\rightarrow$real), lower recall (real$\rightarrow$gen).
- **Visualization:** Plotly figures show initialization's impact, confirming smoother seeds produce cleaner cars.

These results clarify TIGER's diffusion, encoding, and initialization dynamics. Future work may explore class conditioning, new losses, or higher-resolution clouds.

IV. Conclusion and Future Work

We presented a two-stage implementation and enhancement of TIGER for 3D point-cloud generation.

- **Stage 1: Base Training.** On Colab Pro (A100 GPU), we fixed package issues, adapted TIGER code, and ran 200 epochs on ShapeNet Car, matching reported metrics (MMD-CD $\approx$ 2.237, MMD-EMD $\approx$ 0.804, F-score $\approx$ 0.00153) while improving documentation and logging.
- **Stage 2: Enhancements.** Cutting diffusion steps from 1000 to 200 gave an 80% speedup. Six shapes (cube, cuboid, sphere, pyramid, torus, plane) yielded similar MMD scores; sphere and plane had fewer artifacts. PSPE/BAPE at $t = 0, 100, 199$ showed positional encodings evolving from uniform to structured. PCA and heatmaps confirmed PSPE drives spatial detail and BAPE supplies sparse sign information.
- **Architectural Insights.**
  - A learnable, time-varying fusion mask uses Transformer features early (global structure) and CNN features later (local detail).
  - PSPE provides axis-specific sinusoidal signals; BAPE adds sign-based positional cues.
  - Transformers dominate early timesteps; CNNs refine geometry in later steps.

V. Future Directions

1) **Class-Conditional Generation.** Use class labels or text embeddings (e.g., CLIP) to guide generation across ShapeNet categories.
2) **Multi-Resolution Diffusion.** Generate a coarse 512-point cloud, then refine to 2048 points for better thin-structure coverage.
3) **Adaptive Sampling.** Focus point-dropping or resampling on high-curvature regions (e.g., wheel arches) with weighted losses to fill holes.
4) **Differentiable Rendering.** Add a photometric loss via rendered point clouds compared to real images for greater realism.
5) **Faster Inference.** Reduce diffusion steps (e.g., to 50 or 20) and apply pruning or quantization for deployment on constrained devices.
6) **Interactive Shape Editing.** Allow user edits to a few points followed by conditional denoising for completion from partial scans.
7) **Uncertainty Quantification.** Sample multiple outputs per seed to measure variance (e.g., wheel placement) for tasks like grasping or simulation.

Our two-stage pipeline reproduces TIGER's performance and offers feature-space analysis, canonical seed studies, and accelerated inference, providing a roadmap for richer, interactive 3D generation.

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