Università degli Studi di Padova

3D GAN for Voxel-based Shape Generation

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Introduction & Project Overview

Motivation: 3D Content Creation

Goal: Generate 3D Chairs from Noise

Key Tech: Generative Adversarial Network (GAN)

Fig 1. 3D Shapes Generated by GANs [1, 2]

3D Data Representation: Voxels

Voxels: 3D Pixels (Volumetric Grid)

Pros: Directly compatible with 3D CNNs

Cons: Blocky Appearance, High Memory

Dataset: ShapeNet (Chairs Subset)

Technical Env:

Software: Python, Pytorch, Pygame, Numpy

Hardware: NVIDIA GTX 1660ti

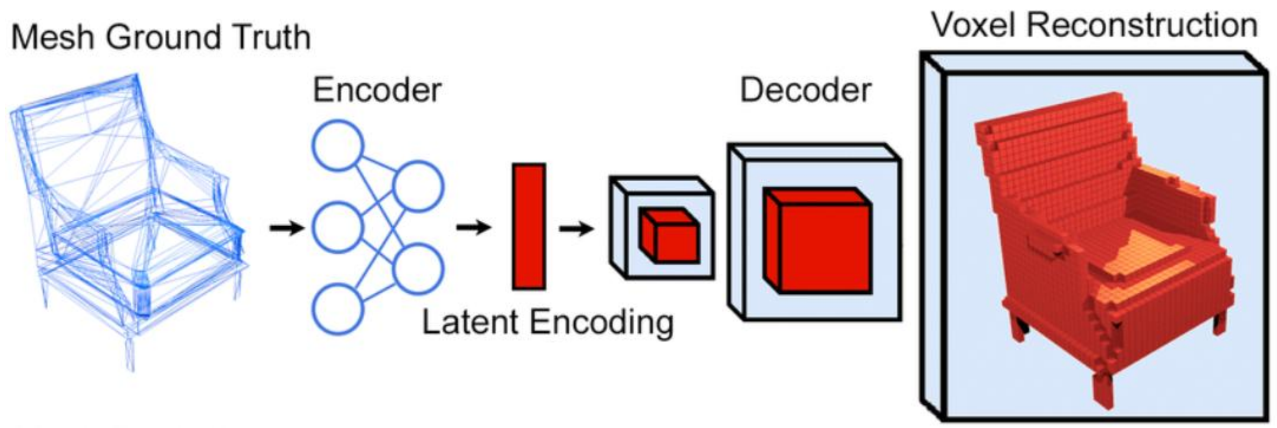

Fig 2. Mesh to Voxel Reconstruction Pipeline [3]

Understanding GANs

The Core Idea: Two Networks competing

Generator (G): Creates Fake Data

Discriminator (D): Distinguishes Real vs. Fake

The Adversarial Game: Minimax Objective

Analogy: Art Forger vs. Art Critic

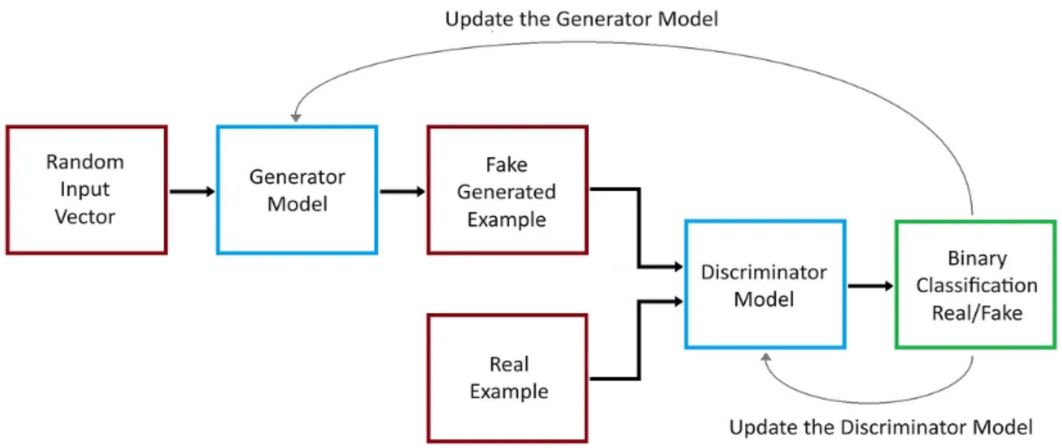

Fig 3. Generative Adversarial Network Framework [4]

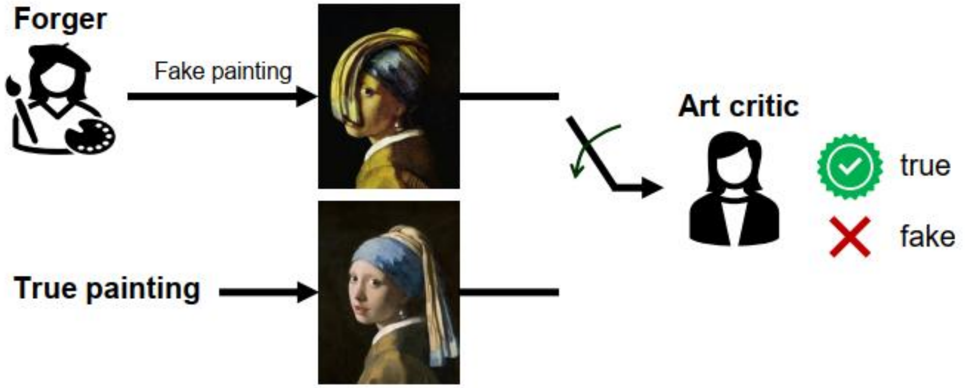

Fig 4. Forger-Critic Example [5]

Vanilla GAN Training & Its Pitfalls

Training Setup:

BCE Loss

Adam Optimizer

Problems:

Training Instability: Discriminator Domination

Mode Collapse: Limited Diversity

Vanishing\Exploding Gradients

Result: Incoherent & Non-Diverse 3D Shapes

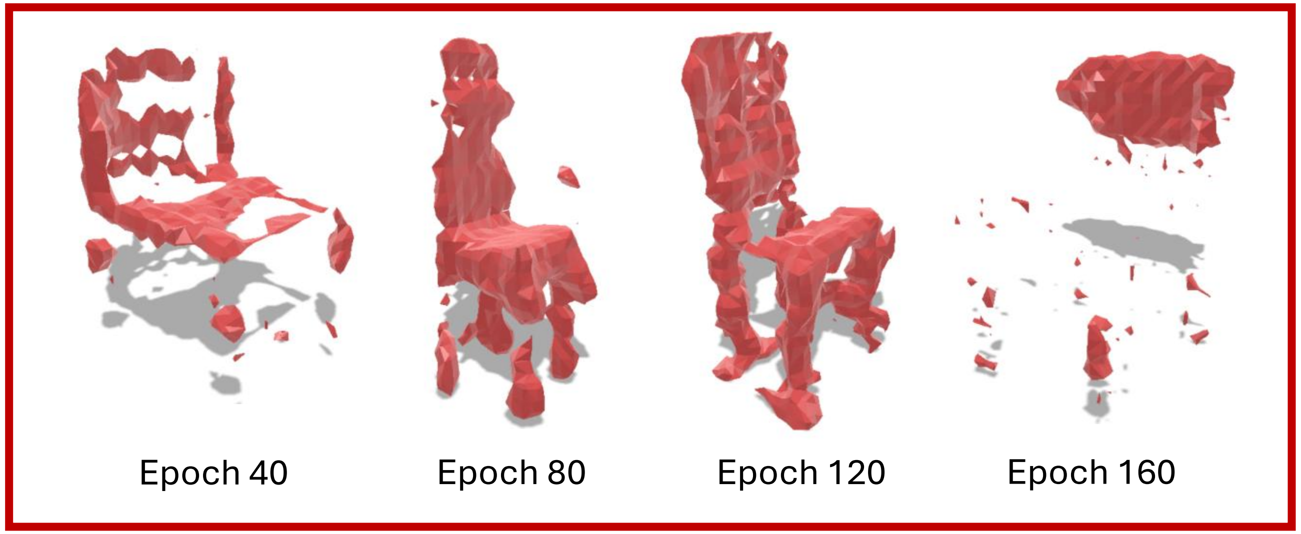

Fig 5. Visual progression of 3D chair generation during Vanilla GAN training

Epoch	40	80	120	160
D_Loss	1.3863	1.0066	1.3863	1.3863
G_Loss	0.6931	0.6931	0.6931	0.6931
D (Real)	0.5	0.7310	0.5	0.5
D (Fake)	0.5	0.5	0.5	0.5

Table 1. Vanilla GAN training log

WGAN-GP: The Robust Solution

Why WGAN-GP?

Addresses Vanilla GAN Instability

Uses **Wasserstein Distance** for better gradients

Gradient Penalty for robust training

Key Improvements:

Stable Training Progression

Improved Visual Quality & Diversity

Recovery From Stagnation

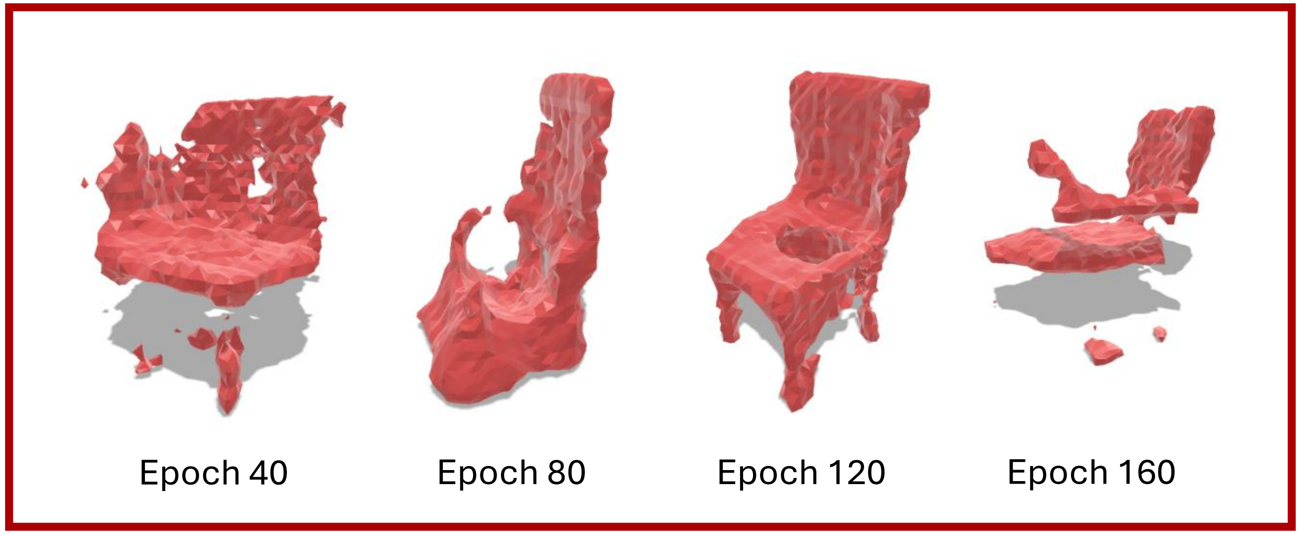

Fig 6. Visual progression of 3D chair generation during WGAN training

Epoch	40	80	120	160
D_Loss	-143.2665	-64.1949	-27.3979	-326.3633
G_Loss	-20.7126	-24.5052	-0.0296	-32.1574
D (Real)	279.1197	-217.1161	44.4026	588.9059
D (Fake)	116.2310	128.9184	4.7337	191.8284

Table 2. WGAN training log

Conclusion & Future Work

Project Summary:

implemented & trained WGAN-GP for 3D chair generation

Demonstrated WGAN-GP's superior stability & quality over Vanilla GAN

Gradient Penalty for robust training

Key Takeaway: Robust GAN Architectures are crucial for Complex 3D Tasks

Future Directions:

Higher Resolution Generation

3D CGAN Implementation

Exploring other 3D Representation

References

1. Wu, J., Zhang, C., Xue, T., Freeman, W. T., & Tenenbaum, J. B. (2020). *3D-GAN: Learning a Probabilistic Latent Space for 3D Object Generation*. arXiv.

2. Mariani, M. M. (n.d.). *marian42/shapegan*. GitHub. Retrieved [Current Date, e.g., July 5, 2025] from https://github.com/marian42/shapegan

3. David B. D. W. et al. (2019). *GEOMetrics: Exploiting Geometric Structure for Graph-Encoded Objects*. ResearchGate.

4. Del Pra, M. (2023, October 26). *Generative Adversarial Networks*. Medium. https://medium.com/@marcodelpra/generative-adversarial-networks-dba10e1b4424

5. Rossi, M., & Pegoraro, J. (2025). *Generative Adversarial Networks*. Neural Network and Deep Learning Course Slides, University of Padova.

Thanks for Listening