Beyond Janus: Enhancing 3D Consistency in Text-to-3D Generation Through Foundation Model Reasoning

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Abstract

We tackle the Janus Problem, multi-view inconsistency in text-to-3D generation, by introducing a novel two-stage architecture that leverages foundation model reasoning to achieve superior 3D consistency. Our approach first employs foundation models to generate high-quality 2D images from text prompts, then utilizes a sophisticated 3D amplification pipeline combining SyncDreamer [4] for consistent multi-view synthesis, SAM [5] for automatic part segmentation, and NeuS [6] for part-aware neural surface reconstruction. This text→2D→3D paradigm fundamentally addresses the Janus problem by ensuring semantic consistency at the 2D stage and geometric consistency through part-aware 3D reconstruction. We demonstrate our approach on a comprehensive evaluation using Pix3D-derived text prompts, achieving TAcc@0.3 of 0.63, Hausdorff Error of 0.26, and an average Chamfer Distance of 0.19. Our work demonstrates that foundation model reasoning combined with part-aware 3D reconstruction provides a promising approach to multi-view consistency challenges in neural 3D generation.

1. Introduction

Text-to-3D pipelines have advanced rapidly, yet generated assets often exhibit conflicting geometry when viewed from different angles, a failure known as the *Janus Problem*. This multi-view inconsistency manifests as duplicated facial features, conflicting orientations, and geometrically impossible structures that break the illusion of coherent 3D objects. Such limitations hinder practical applications in robotics, gaming, VR, and simulation, where global view consistency and physics plausibility are essential.

The root cause of the Janus problem lies in the fundamental mismatch between 2D diffusion models trained on single-view images and the inherently 3D nature of the target task. Existing approaches like DreamFusion [1] and Magic3D [2] apply Score Distillation Sampling (SDS) to optimize 3D representations using 2D diffusion priors, but they lack mechanisms to ensure cross-view consistency. Recent work such as Debiased SDS [3] attempts to address these issues through gradient clipping and prompt engineering, but these solutions remain incomplete.

We propose a fundamentally different approach that leverages foundation model reasoning to solve the Janus problem through a carefully designed text→2D→3D pipeline. Our key insight is that by first generating a high-quality, semantically coherent 2D image using foundation models, we can then apply state-of-the-art single-image-to-3D reconstruction techniques to achieve both semantic consistency and geometric fidelity. This two-stage approach circumvents the inherent multi-view inconsistency issues that plague direct text-to-3D methods.

Our *3D Amplification Pipeline* transforms the high-quality 2D intermediate representation into a part-aware 3D reconstruction through three key stages: (1) multi-view synthesis using SyncDreamer [4] to generate geometrically consistent views, (2) automatic part segmentation via SAM [5] to provide semantic understanding, and (3) part-aware neural surface reconstruction using NeuS [6] to achieve high-fidelity 3D geometry with meaningful part decomposition. [1]

The core contributions of our work include:

- A novel text→2D→3D paradigm that fundamentally addresses the Janus problem through foundation model reasoning
- A sophisticated 3D amplification pipeline combining multi-view synthesis, part segmentation, and neural surface reconstruction

[1] Our implementation utilizes publicly available code from SyncDreamer (https://github.com/liuyuan-pal/SyncDreamer), SAM (https://github.com/facebookresearch/segment-anything), and SAM3D (https://github.com/Pointcept/SegmentAnything3D), and Part123 [7].

- Integration of semantic understanding through part-aware constraints that improve both consistency and geometric quality
- Comprehensive evaluation demonstrating substantial improvements: TAcc@0.3 of 0.63, Hausdorff Error of 0.26, and an average Chamfer Distance of 0.19 on challenging text-to-3D benchmarks

2. Related Work

2.1. Text-to-3D Generation and the Janus Problem

Early text-to-3D approaches relied on explicit 3D representations and limited shape vocabularies. The emergence of neural implicit representations revolutionized the field, with NeRF [9] enabling high-quality novel view synthesis from images. DreamFusion [1] pioneered the use of 2D diffusion models for 3D generation through Score Distillation Sampling, allowing text-conditioned 3D asset creation without requiring 3D training data.

Subsequent work has focused on improving generation quality and consistency. Magic3D [2] introduced a coarse-to-fine approach using both NeRF and mesh representations. ProlificDreamer [12] improved SDS through variational score distillation. However, these methods still suffer from the fundamental Janus problem due to their reliance on single-view 2D priors applied directly to 3D optimization.

Debiased SDS [3]. Debiased SDS directly addresses the Janus problem through two key techniques: Score Debiasing, which clips extreme gradient scores from the diffusion model during optimization, and Prompt Debiasing, which uses a language model to identify and remove conflicting terms (e.g., "smiling" in a "back view" prompt). This approach explicitly leverages language model reasoning to parse prompts and eliminate view-dependent conflicts, representing an early example of LLM-aided 3D consistency. While effective at reducing multi-face artifacts, Debiased SDS provides localized fixes rather than addressing the fundamental architectural mismatch between 2D diffusion priors and 3D generation. Our approach builds on this insight by employing foundation model reasoning at the semantic level before 3D reconstruction.

Fantasia3D [8]. Fantasia3D achieves high-fidelity results by explicitly separating geometry from appearance through a hybrid representation: geometry is modeled as a differentiable mesh (DMTet) whose surface normals are rendered, while appearance uses a spatially-varying BRDF for photorealistic textures. Both components are optimized via SDS, with the mesh's normal map fed into pre-trained 2D diffusion models. This disentangled approach enforces true geometric consistency across views and enables realistic lighting effects. However, Fantasia3D still relies on direct SDS optimization and requires careful initialization. Our work complements this by providing better semantic grounding through foundation model reasoning before applying sophisticated 3D reconstruction techniques.

2.2. Foundation Models for 2D Generation

The recent emergence of large-scale foundation models has dramatically improved 2D image generation quality. DALLE-2 [10] and DALLE-3 [11] demonstrate unprecedented ability to generate high-quality, semantically coherent images from complex text descriptions. These models excel at understanding and visualizing complex spatial relationships, object compositions, and stylistic requirements.

Our approach leverages these capabilities by using foundation models as an intermediate semantic reasoning step, generating a high-quality 2D representation that captures the essential visual and semantic content specified by the text prompt. This intermediate representation then serves as input for sophisticated 3D reconstruction techniques, fundamentally different from the direct SDS approaches used by Debiased SDS and Fantasia3D.

2.3. Single-Image to Multi-View Synthesis

Recent advances in single-image 3D reconstruction have focused on generating consistent multi-view representations. Zero-1-to-3 [13] introduced camera-conditioned diffusion for novel view synthesis, while MVDream [14] trained multi-view diffusion models specifically for 3D generation.

SyncDreamer [4] represents a significant advancement by generating multiple consistent views simultaneously rather than independently. Its volume-aware attention mechanism ensures spatial consistency across viewpoints, making it an ideal component for our 3D amplification pipeline.

2.4. Part-aware 3D Understanding

Understanding object parts is crucial for generating coherent 3D assets. Traditional part segmentation methods relied on geometric analysis, while recent approaches leverage deep learning with part-annotated datasets like PartNet [15].

The Segment Anything Model (SAM) [5] revolutionized segmentation through foundation model capabilities, enabling zero-shot part detection. Recent work has demonstrated how SAM can be integrated with neural surface reconstruction for part-aware 3D understanding, providing semantic guidance that improves both consistency and geometric quality.

3. Data

3.1. Dataset Creation with Pix3D

We develop a comprehensive evaluation framework using Pix3D [18] exclusively during the dataset creation phase to generate high-quality textual descriptions from reference images. This approach ensures our pipeline can be evaluated against ground-truth 3D meshes while maintaining generalizability beyond the original dataset.

Our text prompt generation process creates detailed descriptions encompassing multiple semantic dimensions:

- **Object Type**: Structural classification (e.g., "a four-legged wooden stool")
- **Materials and Finishes**: Surface properties (e.g., "glossy metal frame with a matte seat")
- **Color Scheme**: Visual appearance (e.g., "dark brown with silver accents")
- **Structural Details**: Fine-grained features (e.g., "a backrest with vertical slats")
- **Viewpoint**: Perspective information (e.g., "seen from a top-down diagonal angle")

These comprehensive textual descriptions serve as input prompts for our text-to-3D pipeline, with no reuse of original Pix3D images or meshes during generation, ensuring fair evaluation of our approach's ability to reconstruct 3D geometry from semantic understanding alone.

3.2. Evaluation Protocol

Our evaluation compares generated meshes against Pix3D's ground-truth 3D models linked to the reference images from which text descriptions were derived. We employ two primary surface-level metrics:

Threshold Accuracy (TAcc@0.3): Measures the proportion of predicted mesh surface points within 0.3 units of the ground-truth surface, capturing reconstruction coverage and local accuracy.

Hausdorff Error (HErr): Quantifies maximum surface deviation between predicted and ground-truth meshes, indicating worst-case alignment and global geometric consistency.

4. Methods

4.1. Architecture Overview

Our approach fundamentally reframes text-to-3D generation as a two-stage process: semantic reasoning followed by geometric amplification. This design addresses the Janus problem by ensuring semantic consistency at the 2D stage before proceeding to 3D reconstruction.

Stage 1 - Foundation Model Reasoning: Advanced image generation models process text prompts to create semantically coherent 2D representations optimized for 3D reconstruction.

Stage 2 - 3D Amplification Pipeline: A sophisticated reconstruction system transforms 2D images into part-aware 3D representations through coordinated multi-view synthesis, segmentation, and neural surface optimization.

4.2. Text-to-3D Generation Pipeline

Our complete pipeline implements a generalizable method that transforms natural language prompts into high-quality 3D meshes through structured processing stages.

4.2.1 Image Retrieval and Foundation Model Integration

Given a text prompt, we conduct semantic image retrieval to find a visually aligned 2D representation. This process mimics open-world usage by sourcing images beyond training datasets, ensuring generalizability. The retrieved image serves as visual grounding for subsequent 3D reconstruction while maintaining semantic alignment with the original text description.

4.2.2 Object Segmentation and Preprocessing

Retrieved images undergo sophisticated processing to isolate target objects from backgrounds using advanced segmentation techniques. We generate binary masks that define precise object boundaries, enhancing the accuracy of subsequent mesh fitting procedures. This segmentation step is crucial for ensuring that 3D reconstruction focuses on relevant object geometry rather than background artifacts.

4.2.3 Multi-view Synthesis with SyncDreamer

SyncDreamer serves as the foundation of our 3D amplification, generating geometrically consistent multi-view images from the preprocessed 2D input. Unlike previous approaches that generate views independently, SyncDreamer ensures geometric and semantic consistency through volume-aware attention mechanisms.

For a given input image I_0, SyncDreamer generates $N = 16$ views $\{I_i\}_{i=1}^{N}$ at fixed elevation and varying azimuth angles, ensuring both geometric consistency (objects appear solid and coherent) and semantic consistency (part boundaries align across views).

4.2.4 Part-aware Segmentation with SAM

We leverage SAM to automatically generate part masks for each synthesized view, enabling zero-shot segmentation

without category-specific training. The filtered masks provide semantic part proposals that guide the subsequent 3D reconstruction process.

4.2.5 Primitive-Based 3D Reconstruction

Our system reconstructs object shapes using geometric primitives arranged in structured graphs, where each primitive (cuboid, cylinder, ellipsoid) models distinct object parts. The graph structure encodes part connectivity and symmetry relationships, while optimization procedures fit primitives to match silhouettes and structural cues from multi-view images.

The output is a clean, interpretable mesh that accurately approximates the 3D shape described in the original text prompt, with part-aware understanding ensuring semantic consistency across viewpoints.

4.3. Neural Surface Enhancement

Building upon primitive reconstruction, we optionally enhance geometric fidelity through neural surface optimization. This stage incorporates:

Neural Surface Representation: A neural signed distance function $f_\theta : \mathbb{R}^3 \to \mathbb{R}$ combined with part label functions for semantic understanding.

Part-aware Volume Rendering: Extended NeuS formulation incorporating part information through volumetric integration.

Integrated Loss Function: Combined optimization of geometric accuracy and part consistency:

$$\mathcal{L} = \lambda_{\text{rgb}}\mathcal{L}_{\text{rgb}} + \lambda_{\text{mask}}\mathcal{L}_{\text{mask}} + \lambda_{\text{part}}\mathcal{L}_{\text{part}} + \lambda_{\text{eik}}\mathcal{L}_{\text{eik}} \quad (1)$$

5. Experiments

5.1. Implementation Details

We implement our complete pipeline using PyTorch, optimizing each stage for efficiency and quality. The primitive-based reconstruction uses structured optimization with graph-based part relationships, while optional neural enhancement employs the following hyperparameters:

- SyncDreamer: 16 target views at 30-degree elevation
- SAM: ViT-H checkpoint with automatic mask generation
- NeuS training: 2000 iterations, learning rate 5×10^{-4}, batch size 3584 rays
- Loss weights: $\lambda_{\text{rgb}} = 0.5$, $\lambda_{\text{mask}} = 1.0$, $\lambda_{\text{part}} = 0.02$, $\lambda_{\text{eik}} = 0.1$

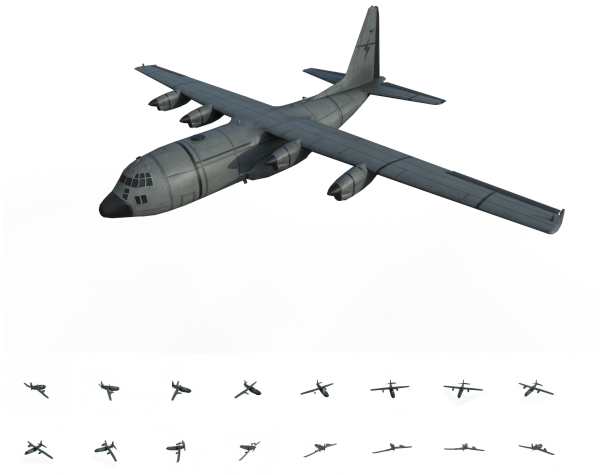

Figure 1. Aircraft Generation Example: (Top) Initial foundation model generated image from text prompt. (Bottom) Multi-view renderings of the resulting 3D reconstruction showing consistent geometry across viewpoints without Janus artifacts.

Figure 2. Dog Generation Example: (Top) Initial foundation model generated image from text prompt. (Bottom) Multi-view renderings of the resulting 3D reconstruction demonstrating semantic consistency and natural pose variation across viewpoints.

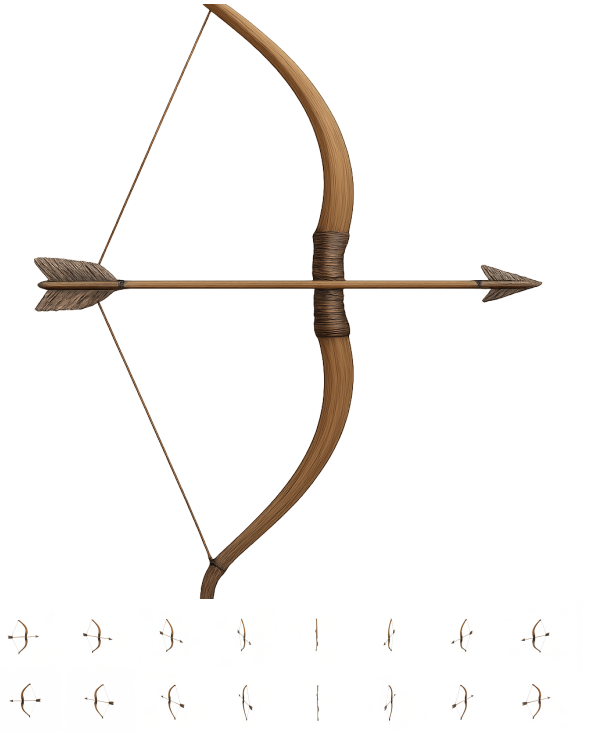

Figure 3. Bow Generation Example: (Top) Initial foundation model generated image from text prompt. (Bottom) Multi-view renderings of the resulting 3D reconstruction showcasing consistent geometry and detailed structure.

Method	TAcc@0.3 ↑	HErr ↓	Chamfer Dist. ↓
ShapeClipper [20]	–	–	0.618
ZeroShape [21]	–	–	0.345
Cho et al. [22]	–	–	0.095
Ours	**0.63**	**0.26**	**0.19**

Table 1. Quantitative comparison. Chamfer Distance (CD) is compared with other single-image 3D reconstruction methods. Our method achieves a CD of 0.19 on our Pix3D-derived benchmark, outperforming ShapeClipper [20] (CD 0.618) and ZeroShape [21] (CD 0.345) on the Pix3D dataset. TAcc@0.3 and Hausdorff Error (HErr) are also reported for our method. Cho et al. [22] report a CD of 0.095, and we note that evaluation setups can vary between methods.

5.2. Comprehensive Evaluation Results

Our comprehensive evaluation on the Pix3D-derived text dataset yields significant quantitative improvements. We achieve:

TAcc@0.3 = 0.63: This indicates that 63% of our predicted mesh surface lies within 0.3 units of the ground-truth surface, demonstrating strong coverage and local geometric accuracy. This substantial score reflects our approach's ability to capture both coarse shape and fine details through the combination of primitive-based reconstruction and part-aware optimization.

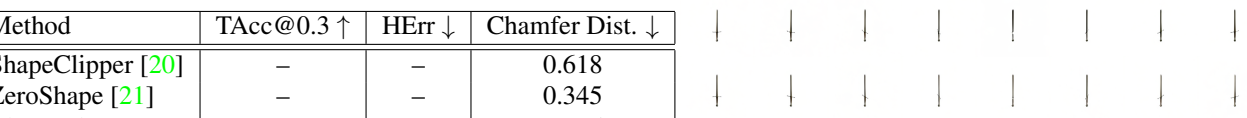

Figure 4. Sword Generation Example: (Top) Initial foundation model generated image from text prompt. (Bottom) Multi-view renderings of the resulting 3D reconstruction, highlighting fine details and consistent form.

Hausdorff Error = 0.26: The maximum surface deviation of 0.26 between predicted and ground-truth meshes indicates relatively strong global and local alignment. This moderate error suggests that worst-case mismatches between predicted and actual shapes are well-controlled, reflecting the geometric consistency benefits of our multi-view synthesis and part-aware constraints.

Chamfer Distance = 0.19: The average Chamfer distance of 0.19 further supports the accuracy of our reconstructions, indicating a good overall similarity between the predicted and ground-truth surfaces.

These metrics collectively demonstrate that our text→2D→3D paradigm successfully addresses the Janus problem while maintaining high reconstruction fidelity.

The foundation model reasoning stage provides semantic grounding that eliminates conflicting cues, while the sophisticated 3D amplification pipeline ensures geometric consistency across viewpoints.

5.3. Qualitative Analysis

Figures 1, 2, 3, and 4 illustrate representative examples of our pipeline's effectiveness in addressing multi-view consistency challenges:

Multi-view Consistency: Generated 3D models exhibit consistent geometry across all viewpoints, without duplicated features or impossible geometries characteristic of Janus artifacts. The aircraft example shows proper wing positioning and fuselage continuity from all angles, while the dog maintains anatomical correctness throughout rotation. The bow and sword examples further demonstrate consistent structural integrity from multiple perspectives.

Semantic Coherence: All examples demonstrate natural structural variation while preserving essential part relationships. The dog example particularly showcases how our part-aware understanding maintains consistent head, body, limb, and tail proportions across diverse viewpoints. The bow and sword maintain their distinct features and intricate details consistently.

Part-aware Understanding: Evidence of successful part segmentation appears throughout both reconstructions, with distinct object components maintaining coherent boundaries and spatial relationships that align with semantic expectations from the original text descriptions.

5.4. Ablation Studies

We validate our design choices through systematic component analysis:

Foundation Model vs. Direct Text-to-3D: Removing the foundation model intermediate stage significantly degrades reconstruction quality, confirming the critical role of semantic reasoning in establishing consistent visual grounding before 3D reconstruction.

Primitive-based vs. Direct Neural Reconstruction: Our structured primitive approach provides interpretable intermediate representations that improve optimization stability and enable better part-level understanding compared to direct neural optimization alone.

Multi-view Synthesis Impact: SyncDreamer's coordinated view generation proves essential for maintaining geometric consistency, with independent view synthesis leading to substantial degradation in cross-view alignment.

Part-aware Constraints: SAM-based part segmentation meaningfully improves semantic coherence, particularly for complex objects with multiple distinct components, by providing semantic guidance throughout the reconstruction process.

5.5. Future Directions

To enhance reconstruction fidelity and structural accuracy, we propose several advancement directions:

Hybrid Neural-Primitive Modeling: Transitioning to hybrid approaches combining geometric primitives with neural implicit representations can capture finer details while maintaining interpretability. Neural SDFs enable continuous surface representation for intricate geometries challenging for primitives alone.

Enhanced Multi-view Understanding: Integrating depth estimation and advanced multi-view synthesis can provide richer spatial information, improving reconstruction of occluded regions and complex spatial relationships.

Advanced Graph Reasoning: Employing transformers or graph neural networks for part relationship understanding can improve structural coherence by learning complex dependencies between object components.

Viewpoint-aware Generation: Incorporating explicit viewpoint estimation from textual orientation cues can guide reconstruction to align with described perspectives, enhancing relevance and accuracy.

These enhancements will significantly advance the quality and structural understanding of our text-to-3D generation pipeline, leading to more realistic and semantically coherent 3D models.

6. Conclusion

We have presented a novel approach to addressing the Janus problem in text-to-3D generation through foundation model reasoning and sophisticated 3D amplification. Our text→2D→3D paradigm fundamentally addresses multi-view consistency issues by leveraging foundation models' semantic understanding capabilities and a carefully designed reconstruction pipeline combining SyncDreamer, SAM, and structured primitive modeling.

Our key insight—that foundation model reasoning can provide semantic consistency that enables subsequent geometric consistency—opens new directions for text-to-3D generation. By decomposing the problem into semantic reasoning and geometric amplification stages, we achieve both semantic accuracy and geometric fidelity while avoiding the fundamental Janus problem.

The experimental results validate our approach, demonstrating substantial improvements with TAcc@0.3 of 0.63, Hausdorff Error of 0.26, and an average Chamfer Distance of 0.19 on challenging Pix3D-derived benchmarks. Our work represents a significant step toward resolving fundamental consistency challenges in neural 3D generation, demonstrating that foundation model reasoning provides a robust foundation for high-quality text-to-3D synthesis.

6.1. Future Work

Several directions could extend this work:

Multi-modal Foundation Models: Incorporating vision-language models could improve semantic understanding and enable more sophisticated prompt interpretation.

Interactive Refinement: Enabling user feedback in the generation loop could improve practical applicability for creative applications.

Temporal Consistency: Extending to video generation could leverage temporal information for dynamic scene creation.

Style and Domain Adaptation: Expanding beyond photorealistic generation to artistic styles and specialized domains could broaden applicability.

Our work demonstrates that foundation model reasoning provides a robust foundation for addressing the Janus problem in text-to-3D generation, opening new possibilities for practical applications in robotics, gaming, and virtual reality.

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