

# MARVEL-40M+: Multi-Level Visual Elaboration for High-Fidelity Text-to-3D Content Creation

Sankalp Sinha<sup>1\*</sup> Mohammad Sadil Khan<sup>1\*†</sup> Muhammad Usama<sup>1</sup> Shino Sam<sup>1</sup>

Didier Stricker<sup>1</sup> Sk Aziz Ali<sup>2</sup> Muhammad Zeshan Afzal<sup>1</sup>

<sup>1,2</sup>DFKI <sup>1</sup>RPTU Kaiserslautern-Landau <sup>1</sup>MindGarage <sup>2</sup>BITS Pilani, Hyderabad

sankalp.sinha@dfki.de mohammad.khan@dfki.de



Figure 1. **Left:** Examples of MARVEL annotations created using our proposed pipeline, which produces high-quality, domain-specific and multi-level text descriptions for 3D assets (Sec 3.1). **Right:** Qualitative results from MARVEL-FX3D, our two-stage text-to-3D pipeline, which can generate textured mesh from text within 15s (Sec 3.3). Please zoom in for details.

## Abstract

Generating high-fidelity 3D content from text prompts remains a significant challenge in computer vision due to the limited size, diversity, and annotation depth of the existing datasets. To address this, we introduce MARVEL-40M+, an extensive dataset with 40 million text annotations for over 8.9 million 3D assets aggregated from seven major 3D datasets. Our contribution is a novel multi-stage annotation pipeline that integrates open-source pretrained multi-view VLMs and LLMs to automatically produce multi-

level descriptions, ranging from detailed (150-200 words) to concise semantic tags (10-20 words). This structure supports both fine-grained 3D reconstruction and rapid prototyping. Furthermore, we incorporate human metadata from source datasets into our annotation pipeline to add domain-specific information in our annotation and reduce VLM hallucinations. Additionally, we develop MARVEL-FX3D, a two-stage text-to-3D pipeline. We fine-tune Stable Diffusion with our annotations and use a pretrained image-to-3D network to generate 3D textured meshes within 15s. Extensive evaluations show that MARVEL-40M+ significantly outperforms existing datasets in annotation quality and linguistic diversity, achieving win rates of 72.41% by GPT-4 and

\*Equally contributing first authors.

†Corresponding Author.

73.40% by human evaluators.

## 1. Introduction

Text-to-3D (TT3D) content generation has emerged as a pivotal area in computer graphics, vision, and AI, enabling the creation of complex 3D objects from textual prompts [32, 38, 62] by understanding the shape, material properties [71, 89], and complex visual elaborations [36, 77, 90]. This technology holds significant potential for various industries, including gaming, augmented reality (AR), virtual reality (VR), and film production [32, 38]. Recent advancements in text-to-image (TTI) synthesis [3, 21, 67, 69] have achieved remarkable realism and precise control over visual effects [19, 65, 67]. However, extending these capabilities to high-fidelity TT3D generation remains a significant challenge [22, 32, 38, 90]. This is due to the intricate nature of modeling 3D shapes [35, 36, 44, 76, 89], textures [43, 44, 77], colors [71, 89] and spatial relationships [22, 90] from text descriptions, a challenge further amplified by the scarcity of high-quality 3D captions.

Current TT3D datasets like CAP3D [53], 3D-Topia [28], CLAY [89] and Kabra et al [34] attempt to bridge this gap through automated annotations but often fall short due to their reliance on single-view VLMs [11, 39, 45, 46] or GPT-4 [60] for caption generation. This approach frequently results in contradictory or inconsistent captions [34, 54]. Moreover, the captions lack the necessary details for fine-grained 3D reconstruction. Additionally, their dependence on proprietary models like GPT-4 [60] introduces significant scalability and cost constraints. Manual annotation is also impractical for large-scale datasets like Objaverse [18] and Objaverse-XL [17]. These datasets contain a diverse range of 3D models—from characters and biological elements to historical artifacts and complex ambiguous structures—requiring domain-specific expertise for accurate annotation (See Figure 1 - Left). Beyond being time-consuming and expensive, CAP3D [53] has shown that human-generated captions may not necessarily surpass automated methods in quality.

To address the previously mentioned challenges, we introduce MARVEL(Multi-Level Visual ELAbORation), an automated and scalable 3D captioning pipeline. Our approach combines state-of-the-art multi-view VLM InternVL2 [13, 15] and Qwen 2.5 LLM [85] to generate high-quality captions for over 8.9 million 3D models across seven datasets [10, 16–18, 20, 73, 74, 80]. To ensure domain specific information into our captions and reduce VLM hallucinations, we integrate human metadata from source datasets into our pipeline. Following [12, 92], we identify five key aspects for fine-grained 3D reconstruction: object names and components, shape and geometry, texture and materials, colors, and contextual environments. Our pipeline pro-

gressively compresses these aspects to generate five levels of annotations, ranging from comprehensive descriptions ( $\sim 200$  words) for fine-grained 3D reconstruction to concise tags ( $\sim 10$  words) for quick modeling, resulting in 40+ million annotations. Our pipeline addresses three fundamental challenges in 3D captioning - detail, accuracy, and scalability. Through comprehensive experimental analysis, we show that MARVEL-40M+ has superior annotation quality, information density, and linguistic diversity compared to other methods [28, 34, 53].

To showcase the application of our dataset, we introduce MARVEL-FX3D (Fast eXecution for 3D), a two-stage pipeline designed for high-fidelity TT3D generation. In the first stage, we fine-tune Stable Diffusion (SD) 3.5 [3] with our annotations to improve its capability to produce images for suitable 3D reconstruction. In the second stage, we leverage the pre-trained Stable Fast 3D (SF3D) [7] for rapid image-to-3D conversion. This enables the creation of textured meshes from texts within 15s. Our approach is inspired by multi-stage TT3D pipelines [41, 58, 71], a promising direction [32, 38, 41] that addresses the limitation of existing Score Distillation Sampling (SDS)[62]-based methods like *janus problem* [43, 44, 62, 77], oversaturation [43], and lengthy per-prompt optimization [43, 44, 62, 76, 77, 91]. Our experiments demonstrate that MARVEL-FX3D outperforms current state-of-the-art TT3D methods in terms of prompt fidelity and overall preference.

Our **contributions** can be summarized as follows:

1. We present MARVEL, an automated, scalable annotation pipeline for generating high-quality 3D captions. To the best of our knowledge, MARVEL-40M+ is the largest 3D caption dataset to date.
2. We propose a multi-level annotation structure that spans from detailed descriptions for fine-grained 3D reconstruction to concise tags for quick modeling.
3. We incorporate human metadata from source datasets into our pipeline to inject domain-specific information in the text descriptions and reduce VLM hallucinations.
4. As a downstream task, we introduce MARVEL-FX3D, a two-stage framework for high-fidelity TT3D generation.
5. Thorough experiments demonstrate that MARVEL-40M+ achieves state-of-the-art performances in linguistic diversity, image-text alignment, caption accuracy, and high-fidelity TT3D generation.

## 2. Related Work

**3D-Text Data:** 3D datasets such as ShapeNet [10], Objaverse [17, 18], and Omniobject3D [80] have played a crucial role in advancing 3D understanding tasks such as single [29, 48, 49, 84] or multi-view [70, 86] 3D reconstruction, multi-view consistent image generation [27, 50, 87], and 3D object synthesis [31, 89]. However, they often lack

	ShapeNet	Pix3D	OmniObject3D	Toys4K	GSO	ABO	Objaverse	Objaverse-XL	Total 3D Objects	Total Captions
Cap3D [53]	X	X	X	X	X	6,400 [52]	785,150	221,632	1,013,182	1,013,182
3DTopia [28]	X	X	X	X	X	X	361,357	X	361,357	361,357
Kabra [34]	X	X	X	X	X	X	763,827	X	763,827	763,827
MARVEL	<b>51,209</b>	<b>735</b>	<b>5,878</b>	<b>4,000</b>	<b>1,030</b>	<b>7,953</b>	<b>798,759</b>	<b>8,031,637</b>	<b>8,901,201</b>	<b>44,506,005</b>

Table 1. Overview of datasets [10, 16–18, 20, 73, 74, 80] annotated using our MARVEL pipeline. MARVEL provides the most extensive 3D asset annotations to date, encompassing over 8.9M 3D objects and 40M captions.

meaningful language descriptions, with available metadata being either noisy or inadequate [47, 53]. This language-3D gap has been a major bottleneck in developing high-fidelity TT3D models [28, 34, 53]. Recent works like CAP3D [53] addresses this by proposing an automated pipeline. It starts with BLIP [40] for single-view captioning of 3D assets followed by refinement using CLIP [64] and caption aggregation by GPT-4 [60]. Subsequent works, Kabra et al. [34] introduced ScoreAgg and PaLI-X[11] to improve caption accuracy, while 3D-Topia [28] explored an alternative path with LLaVA [45, 46] and GPT-3.5. CLAY [89] took a more direct approach, leveraging GPT-4 [60] for multi-view caption generation. Yet, all these approaches face inherent trade-offs. Single-view VLM approaches [28, 34, 53, 54] often produce incomplete or inaccurate annotations [34, 54] for 3D models, while GPT-4-based methods [28, 53, 60, 89] struggle with scalability and cost[4]. Our work presents a novel solution to these challenges through three key innovations. First, we leverage open-source multi-view VLM InternVL2 [13, 15] and Qwen 2.5 LLM [85], achieving GPT-4 [60] comparable performance [2, 13, 15, 85] without its scalability and cost constraints. Second, instead of discarding human metadata from source datasets as done in previous works [28, 34, 53, 89], we recognize its value as domain-specific prior knowledge. We incorporate filtered versions of this metadata into our pipeline to inject relevant context and reduce VLM hallucinations. Finally, we introduce a hierarchical annotation framework with five distinct levels, ranging from detailed descriptions to abstract tags. This multi-level approach represents a significant departure from existing methods [28, 34, 53, 89], which typically provide only single-level annotations.

**Text-to-3D:** Current TT3D methodologies can be broadly categorized into two main approaches. One prominent direction is based on the seminal work of DreamFusion [62], which introduced Score Distillation Sampling (SDS) to learn a NeRF [57] representation by leveraging information from pretrained TTI models [5, 67, 69]. Subsequent studies have advanced this framework by improving training stability [43, 77], increasing output diversity [43, 77, 91] and geometry extraction [14, 44, 76, 88]. However, SDS-based methods face two key challenges: geometric inconsistencies known as the *Janus problem* [32, 37, 38] and slow optimization times. This issue has been partially addressed using amortization efforts [51, 82]. The second group of methods consists of multistage pipelines [24, 33,

41, 42, 58, 71]. The goal is to generate single or multi-view images from a TTI model [3, 5, 21, 67, 69], followed by view reconstruction into various 3D representations [7, 24, 29, 41, 57, 70]. These methods often fine-tune the TTI [3, 5, 21, 67, 69] models on TT3D datasets [34, 53] to align the output image with reconstruction needs. PointE [58] fine-tunes GLIDE [59] for TTI synthesis and uses a point diffusion transformer for 3D point cloud generation. Instant3D [41] fine-tunes SD [67] to produce a  $2 \times 2$  grid of multi-view images and uses LRM [29] for 3D Gaussian reconstruction. AssetGen [71] extends LRM towards high-quality 3D meshes with detailed textures and PBR materials. Our dataset, MARVEL-40M+, is uniquely positioned to advance this domain by providing comprehensive, high-quality, and domain-specific text annotations that bridge the gap between TTI generation and image-to-3D reconstruction. By fine-tuning on MARVEL-40M+, we develop MARVEL-FX3D, which demonstrates better performance for high-fidelity TT3D generation compared to existing state-of-the-art methods.

## 3. Methodology

### 3.1. Multi-Stage Annotation Pipeline

We now present our proposed MARVEL annotation pipeline, shown in Figure 2 (left). Our goal is to generate detailed and domain-specific captions, for both fine-grained and abstract 3D modeling cases. Through a carefully designed five-stage process, MARVEL produces a hierarchy of information-rich and domain-specific annotations. These annotations range from detailed descriptions of object names, shapes, textures, and contextual relationships to concise summaries. Starting with multi-view rendering, our pipeline processes each asset through sequential stages of human metadata refinement, dense description generation via InternVL2 [15], multi-level elaboration using Qwen 2.5 [85], and ethical filtering. Below, we detail each component of our pipeline.

**Multi-View Rendering:** We first generate 4 multi-view images of resolution  $512 \times 512$  for each 3D model using Blender [1]. We rotate the camera around the object with azimuth angle,  $\theta = \{\frac{\pi i}{2}\}_{i=1}^4$  and fixed elevation angle,  $\phi = 60$ . The camera distance is set to 1.5. The four images correspond to the front, back, left, and right sides of the 3D model. Unlike existing 3D captioning pipelines [28, 53], we focus solely on these standard viewpoints. This method

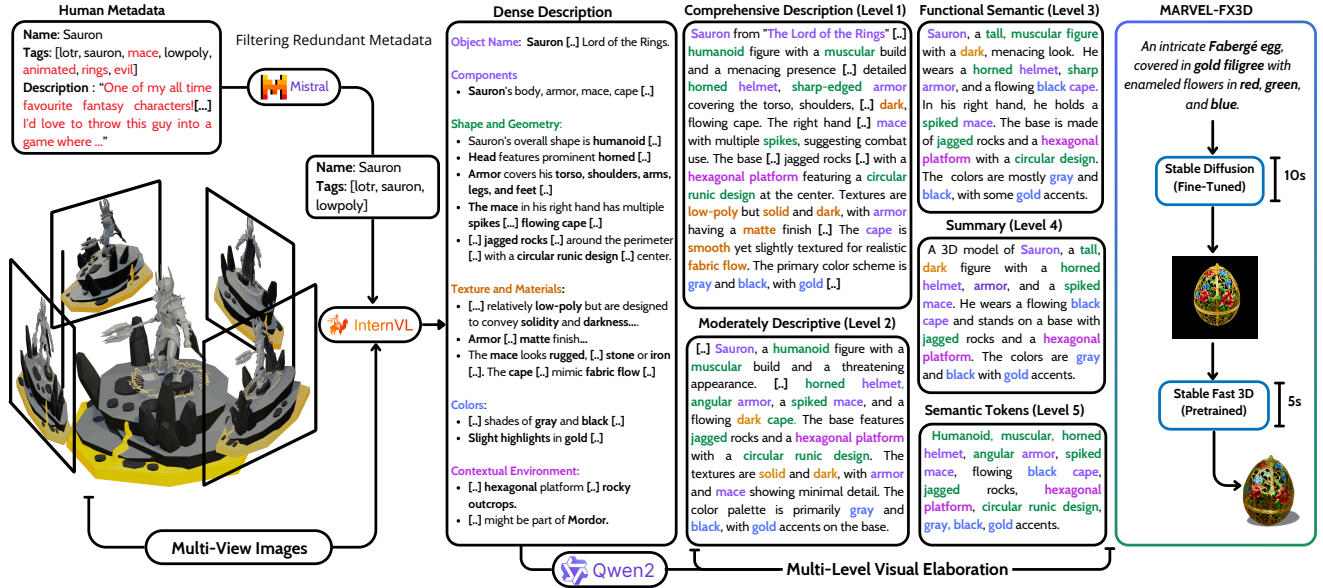


Figure 2. **Left:** MARVEL annotation pipeline for 3D assets. Our pipeline starts with human metadata [17, 18] and rendered multi-view images to create detailed visual descriptions using InternVL-2 [13]. These contain object names, shapes, textures, colors, and environments. Qwen2 [85] then processes these descriptions into five hierarchical levels, progressively compressing different aspects of the 3D assets. **Right:** Our Text-to-3D pipeline finetunes SD 3.5 [3, 21] with this dataset and uses pretrained SF3D [7] to generate a textured mesh in 15s.

aligns with recent studies [68, 79], which demonstrate that VLMs perform better on images from these viewpoints.

**Human Metadata Filtering:** High-quality 3D annotation requires capturing both visual characteristics (e.g. shape, color, texture) and semantic properties (e.g. domain-specific nomenclature and object identification). This dual focus ensures that descriptions are not only visually precise but also contextually relevant within specific domains. A significant challenge in this process is the tendency of pre-trained VLMs [40] to hallucinate when dealing with complex datasets, such as Objaverse [17, 18], due to the inherent 2D-3D domain gap [34]. To address this, we use the user-generated metadata from source datasets, which provides valuable domain-specific names and descriptions that can guide VLMs [13, 15] toward generating more precise and informative annotations. However, this metadata often contains noise, including personalized or sensitive information [17, 18], which can compromise annotation quality. To mitigate this, we use Mistral-Nemo-Instruct-2407 [72] to filter the metadata, removing random, redundant, and sensitive content to ensure that only information relevant to 3D attributes is passed to the annotation pipeline. It is worth noting that our pipeline functions independently of human metadata, with it serving purely as an optional enhancement to add domain-specific terminology in the captions.

**Dense Description Generation:** In this stage, InternVL2 [13, 15] processes the 4 rendered multi-view images along with our metadata-augmented prompt to gen-

erate a dense description of the 3D models. This description contains several key requirements for fine-grained 3D model reconstruction: (1) *structural decomposition* with object identification and relative positions, (2) *geometric properties*, analyzing shape characteristics, symmetry axes, and proportional relationships, (3) *surface characteristics*, addressing texture and material properties and tactile qualities such as roughness and reflectivity; (4) *chromatic analysis*, mapping colors across primary objects and sub-components, including patterns and transitions (5) *environmental context*, capturing spatial relationships and its interaction with other elements.

To efficiently scale this process for large-scale annotation, we select InternVL2-40B [13, 15] for its balance of speed, accuracy, and prompt adherence. Recent studies show that InternVL2-40B [13, 15] performs comparably [2, 13, 15] to GPT-4o [60] with significantly lower annotation cost\*.

**Multi-Level Visual Elaboration:** This stage focuses on generating multi-level visual elaborations using Qwen2.5-72B [85] by compressing different aspects of 3D reconstructions at varying levels of detail. This hierarchical approach allows for flexible and adaptive 3D modeling outputs optimized for different use cases, such as scenarios where only key details—like *object name* and *colors*—are specified, but *texture* is excluded or where simplified *semantic tags* is necessary for rapid prototyping. While a direct prompting method will be to specify which aspects

\*InternVL2-40B [13, 15] ranked third on the Huggingface Open-VLM Leaderboard [2] during our project.

to compress, we found that this strategy often constrains the model’s ability to create rich and meaningful captions, aligning with findings from recent studies [75, 78]. To overcome these challenges, we develop a hierarchical prompting strategy that specifies the essential content for each level of elaboration, balancing detail and brevity. Below, we describe each level:

1. **Comprehensive Description (Level 1):** A detailed description covering all aspects of the 3D model, including precise geometric specifications, materials, spatial relationships, and structural details, in 150-200 words.
2. **Moderately Descriptive (Level 2):** Description of the model’s primary structures, components, and key geometric features. This level focuses on the overall shape and main features of the model in 100-150 words.
3. **Functional-Semantic Description (Level 3):** Basic description about the model’s functional aspects, general form, and primary characteristics in 50-100 words.
4. **Summary (Level 4):** A brief description of the object, highlighting its basic form, purpose, and most notable features, similar to existing datasets in 30 words.
5. **Concise tags (Level 5):** A list of distinct concepts of the 3D model for rapid 3D modeling in 10-20 words.

An example of multi-level visual elaboration is illustrated in Figure 2 (left), where Qwen 2.5 [85] compresses texture information progressively from Level 1 to Level 4. By Level 5, the output shifts to a concise format, highlighted with colored words representing key semantic tags and core attributes. To assess the effectiveness of this hierarchical compression, we conduct an ablation study in Section 4.3 B, measuring how well semantic information is retained across all the levels.

**Ethical Filtering:** Given the diverse metadata sources in our annotation pipeline, there is a risk of ethically problematic content being included in the multi-level descriptions. To mitigate this, we use the Qwen 2.5-14B [85] model with a targeted prompt for ethical filtering. This prompt removes meaningless or offensive words, personal names (unless they are famous or contextually relevant), and overly specific identifiers. Importantly, it retains well-known terms, scientific and cultural references, preserving valuable context. This filtering step maintains annotation quality, prevents the leakage of sensitive or inappropriate information, and upholds the integrity of the dataset. For details, please refer to the supplementary material.

### 3.2. Caption Generation

**Datasets:** We aggregate 8.9M 3D assets from seven diverse sources [10, 16–18, 20, 73, 74, 80]. For human metadata injection, we use the *name*, *tags* and *description* from Objaverse 1.0 [18] (Sketchfab) and *metadata* from Objaverse-XL [18] (thingiverse and github). Samples from Objaverse-XL [17] containing the file extension

*.ply* were excluded from the dataset. For the rest of the six datasets [10, 16, 20, 73, 74, 80], we use the class categories as metadata. Any samples that do not have renderable multi-views or lack textual information post-annotation are removed from the dataset. The final details of the dataset are provided in Table 1, with additional preparation information available in the supplementary materials.

**Implementation Details:** Our MARVEL annotation pipeline is optimized for large-scale processing, achieving a throughput of  $\sim 24,000$  samples per day. For human metadata filtering, we run the Mistral-Nemo-Instruct-2407 [72] on a single NVIDIA RTX 4090 GPU. Both InternVL2-40B [13, 15] for dense description generation and the Qwen2.5-72B [85] with 8-bit quantization for multi-level visual elaboration, runs on a single NVIDIA H100 GPU. For the final ethical filtering stage, we run Qwen 2.5-14B [85] on a single NVIDIA RTX A6000 GPU. For complete details including hyperparameter details, please refer to the supplementary material.

### 3.3. MARVEL-FX3D Architecture

In this section, we present MARVEL-FX3D, a two-stage pipeline that demonstrates the practicality of the MARVEL-40M+ dataset for TT3D synthesis. By leveraging our dataset’s comprehensive text descriptions and diverse 3D assets [18], MARVEL-FX3D generates high-quality textured 3D meshes from text descriptions that can specify multiple objects, scenes, geometric properties, colors, and textures. The pipeline consists of (1) TTI generation using fine-tuned Stable Diffusion [21], followed by (2) single-view 3D reconstruction with a pretrained view reconstruction model [7]. This entire process generates high quality 3D assets in 15s, as illustrated in Figure 2 (right).

**Fine-Tuning TTI Model:** The objective of this stage is to generate high-quality, diverse images from text prompts that can be effectively converted into 3D textured meshes using pretrained image-to-3D methods [7, 83]. A primary challenge in multi-stage TT3D pipelines [41, 42, 55, 58, 71] is the inherent 2D-3D domain gap, where reconstructing accurate and geometrically consistent 3D models from 2D images is hindered by the ambiguity between background and foreground information [42, 55]. To address this, some methods have fine-tuned TTI [5, 67] models on TT3D datasets [28, 34, 53, 89]. Following this approach, we fine-tune Stable Diffusion 3.5 [3, 21] using the LORA [30] strategy to bridge this domain gap and generate images similar to the training distribution of the image-to-3D methods [7].

**Image-to-3D Generation:** In the second stage, the background is removed from the generated image using DIS [63]. The refined image is then processed by pretrained SF3D [7] to generate a high-quality textured mesh within 5s. Further details can be found in the supplementary.

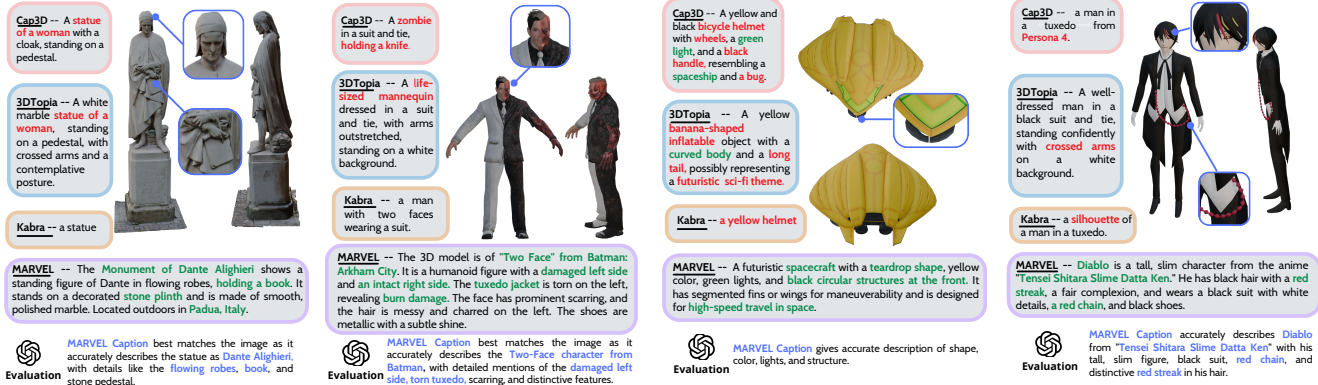


Figure 3. Qualitative Annotation Comparison: From top to bottom Cap3D [53], 3DTopia [28], Kabra [34], MARVEL (Level-4) annotations and GPT-4 [60] evaluation. MARVEL consistently provides the most comprehensive and precise annotations, capturing intricate details such as object names, color, structure, and specific attributes. Red is for wrong captions.

## 4. Experiment

The experiment section is divided into two parts. In Sec.4.1, we evaluate the quality of our annotations in comparison to the baseline datasets [28, 34, 53]. While Sec. 4.2 presents the performance evaluation of MARVEL-FX3D against current state-of-the-art methods [33, 43, 62, 91]. Both experiments are conducted on Objaverse [18] dataset.

### 4.1. Annotation Evaluation

**Experimental Setup and Metrics:** We assess annotation quality through (1) Linguistic Assessment, (2) Image-Text Alignment, and (3) Caption Accuracy.

The linguistic assessment evaluates annotation richness and diversity using the Measure of Textual Lexical Diversity (MTLD) [56] and N-gram analysis [8]. The MTLD metric calculates the average segment length at which the type-token ratio (TTR) drops below a threshold (typically 0.72), with higher MTLD scores indicating more diverse annotations. We randomly select 50K annotations for analysis.

Image-text alignment is measured using both GPT-4 [60] and human evaluators who review four multi-view images of each 3D model and select the best-matching caption. 5,000 samples are evaluated using GPT-4 and 1,000 samples by five human reviewers with each assigned 200 samples. Level 4 annotations from MARVEL-40M+ are used for fair comparison due to their similar average length to baseline datasets [28, 34, 53] as shown in Table 2.

Caption accuracy is separately assessed, where GPT-4 and human reviewers evaluate whether all the 3D attributes mentioned in the captions accurately correspond to the 3D models using four multi-view images. For MARVEL-40M+, Level 1 annotations are used, which are detailed and form the foundation for subsequent levels. GPT-4 evaluates 1,000 samples, while human reviewers assess 250 samples due to the evaluation’s time demands. More details are provided in the supplementary section.

Dataset	Average Length	MTLD [56] (@50K)	Unigram (@50K)	Bi-Gram (@50K)	GPT4 (@5K)	Human (@1K)
Cap3D [53]	16	39.71	15,189	123,071	14.55	9.50
3D-Topia [28]	29	41.43	10,329	95,856	10.80	14.00
Kabra [34]	5	25.85	3,862	19,753	2.24	3.10
MARVEL (Level 4)	<b>44</b>	<b>47.43</b>	<b>27,659</b>	<b>239,052</b>	<b>72.41</b>	<b>73.40</b>

Table 2. Quantitative comparison of annotation quality across datasets. MARVEL surpasses existing datasets [28, 34, 53] in all metrics, showcasing superior linguistic diversity, vocabulary coverage, and significantly higher ratings from GPT-4 and humans.

**Linguistic Assessment:** Table 2 (left) shows the MTLD [56] score and N-Gram analysis [8]. MARVEL demonstrates a notable improvement, achieving an MTLD score approximately 83% higher than Kabra [34] 19% higher than Cap3D [28] and 14% higher than 3D-Topia[53] signifying richer caption diversity. In addition, MARVEL shows a significantly higher unigram vocabulary size, surpassing Kabra [34], Cap3D [53] and 3D-Topia [28] by factors of approximately 7.1, 1.8 and 2.6 respectively. The trend extends to bigram analysis and average word length as well, showing MARVEL’s superior linguistic diversity and information density. Figure 3 also illustrates that MARVEL’s annotations contain more unique words, particularly focusing on object names, colors, textures, and attributes.

**Image-Text Alignment:** As shown in Table 2, MARVEL achieves notably higher ratings in image-text alignment, with win rates of 72.41% from GPT-4 [81] and 73.40% from human evaluators, outperforming prior methods. This reflects MARVEL’s superior alignment of captions with 3D models. Figure 3 highlights this through examples, showing that MARVEL’s detailed descriptions capture nuances, such as the “*flowing robes and book-holding posture of a historical statue*”, even at Level 4. In contrast, baselines [28, 34, 53] produce simpler, more generic descriptions. MARVEL’s integration of filtered human-annotated metadata further enhances the identification of complex, domain-specific entities like “*Monument of Dante*



Figure 4. Visual results of high fidelity TT3D generation. Left to right, the reconstructed 3D assets from Shap-E [33], DreamFusion [62], Lucid-Dreamer [43], HIFA [91] and MARVEL-FX3D.

*Alighieri*”, “*Two Face*”, and “*Diablo*”.

**Caption Accuracy:** Table 3 shows the caption accuracy results, where MARVEL (Level 1) achieves the highest scores—84.70% in GPT-4 evaluation and 82.80% in human evaluation—demonstrating superior consistency compared to other methods. Baseline datasets with shorter captions, like Kabra [34] and others [28, 53], tend to capture objects semantically (e.g., “*a statute*”, “*a man in a tuxedo*”) but lack detailed descriptions. Although longer captions increase the risk of errors, MARVEL (Level 1) maintains high accuracy with an average length of 170 words (34× that of Kabra [34], 10× that of Cap3D [53], and 5× that of 3D-Topia [28]), effectively balancing detail and correctness. As shown in Figure 3, MARVEL captures both domain-specific names and intricate features, exemplified by captions like “*The Monument of Dante Alighieri... flowing robes, holding a book. It stands on a decorated stone plinth and is made of smooth, polished marble...*”

Method	Average Length	Correct	
		GPT4 Evaluation (@1k)	Human Evaluation (@250)
Cap3D [53]	16	76.00	72.80
3D-Topia [28]	29	54.60	44.80
Kabra [34]	5	83.40	78.20
MARVEL (Level 1)	170	<b>84.70</b>	<b>82.80</b>

Table 3. Comparison of caption accuracy using GPT-4V [60] and humans, highlighting MARVEL’s (Level 1) superior consistency despite significantly higher caption length.

## 4.2. Text-to-3D Generation

**Implementation Details:** We fine-tune SD 3.5 [3, 21] using the Objaverse [18] dataset, which includes 798,759 3D assets, split into training, validation, and test sets in a

90 : 5 : 5 ratio. Fine-tuning is conducted in half-precision for 5 epochs with a batch size of 8, using a single NVIDIA H100 GPU, with LoRA [30] rank and alpha set to 4. Further details are provided in the supplementary section.

**Baselines:** To evaluate MARVEL-FX3D’s performance in high-fidelity TT3D generation, we compare it with Shap-E [33], Dreamfusion [62], Luciddreamer [43], and HIFA [91]. We use the official implementations and pre-trained models for Shap-E and Luciddreamer, training the latter for 3k steps. Dreamfusion and HIFA are trained using the open-source threestudio [23] implementation, with 10k and 24k steps, respectively, under default settings. Due to the slower optimization of Dreamfusion, HIFA, and Luciddreamer, we limit comparisons to 50 randomly selected samples from the Objaverse [18] test set. Instant3D [41] and Assetgen [71] are excluded due to unavailable code.

**User Study:** We conducted a human evaluation to assess the geometric consistency, visual quality, prompt fidelity, and overall preference of reconstructed 3D assets. Geometric consistency measures realism and physical plausibility, identifying issues like the *janus problem*. Prompt fidelity evaluates alignment with input text, while visual quality considers aesthetic elements such as colors and textures. Five users were presented with the text prompt and videos of the rendered 3D assets generated by the baseline methods and MARVEL-FX3D. The users scored each asset separately from 1 to 10 based on these criteria, and the final scores were averaged across all users.

	Time↓	Geometric Consistency	Visual Quality	Prompt Fidelity	Overall
Shap-E [33]	5s	3.31 ± 0.71	2.25 ± 0.43	2.65 ± 0.51	2.41 ± 0.50
DreamFusion [62]	30m	4.88 ± 0.47	3.74 ± 0.80	4.22 ± 0.79	4.09 ± 0.81
HiFA [91]	>1h	6.59 ± 0.57	6.42 ± 0.26	6.88 ± 0.46	6.44 ± 0.35
Lucid-Dreamer [43]	45m	<b>7.25 ± 0.60</b>	6.47 ± 1.24	6.62 ± 1.37	6.59 ± 0.86
MARVEL-FX3D	15s	7.20 ± 0.91	<b>6.58 ± 0.86</b>	<b>7.71 ± 0.68</b>	<b>6.94 ± 0.71</b>

Table 4. Quantitative evaluation focusing on time and human evaluation criteria: geometric consistency, visual quality, prompt fidelity, and overall preference.

**Results:** Table 4 presents the quantitative comparison of MARVEL-FX3D against the baselines [33, 43, 62, 91]. MARVEL-FX3D shows notable improvements, achieving the highest prompt fidelity (7.71) and overall preference (6.94), indicating strong alignment with input descriptions and balanced performance across criteria. It also tops visual quality with a score of 6.58, slightly ahead of Lucid-Dreamer [43] (6.47), which marginally exceeds MARVEL-FX3D in geometric consistency (7.25 vs. 7.20) due to occasional flat outputs from SF3D [7]. Despite this, MARVEL-FX3D’s processing time is significantly faster, completing in just 15s compared to Lucid-Dreamer’s 45 minutes, HiFA’s over 1 hour, and DreamFusion’s 30 minutes. Shap-E [33], while the quickest at 5 seconds, shows considerably lower performance across all metrics. Figure 4 includes

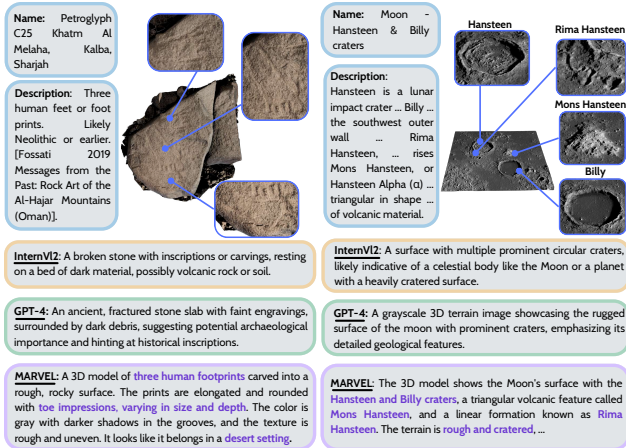


Figure 5. MARVEL uses human-generated metadata from source datasets to create detailed, accurate captions (e.g., names of the lunar craters, detection of human footprints) and reduce hallucinations. Without metadata, VLMs like GPT-4 [60] and InternVL2 [15] generate vague or speculative descriptions.

some qualitative examples.

### 4.3. Ablation Study

#### A. Effect of Human Metadata on Annotation Quality:

Human-generated metadata is vital in the MARVEL annotation pipeline, enriching text captions with domain-specific details. While quantitative analysis would require specialized expertise, we provide qualitative evidence of its impact. As shown in Figure 5, MARVEL accurately identifies specific details, such as “*three human footprints on a rocky surface*”, which both InternVL-2 [13, 15] and GPT-4 [60] miss, producing only generic descriptions. Similarly, MARVEL annotations include detailed identifiers like specific lunar craters, which are absent in outputs from InternVL-2 and GPT-4. This highlights how integrating human metadata enhances the context in annotations. Additional examples spanning other domains (e.g. biological elements, historical sites) are detailed in the supplementary material.

#### B. Inter-Level Semantic Retention Evaluation:

This ablation study measures how well semantic information is retained across MARVEL-40M+ annotation levels as they progress from detailed descriptions to concise tokens. To evaluate this, we report the semantic similarity (cosine similarity of embeddings) between levels using sentence-BERT [66] and the compression ratio (word count ratio) [6]. Results in Table 5 show strong semantic retention from Levels 1-4, demonstrating effective compression while preserving meaning. However, the shift to Level 5 results in lower similarity, reflecting the transition to a list of concepts at the expense of cohesive descriptions.

Source Level	Target Level	Semantic Similarity	Compression Ratio
Level 1	Level 2	0.91	0.30
Level 2	Level 3	0.92	0.27
Level 3	Level 4	0.88	0.47
Level 4	Level 5	0.72	0.22

Table 5. Ablation study results showing SCS across MARVEL-40M levels, illustrating strong semantic retention through Levels 1-4 and reduced detail at Level 5.

## 5. Limitation

Our analysis reveals some limitations in MARVEL annotation pipeline and MARVEL-FX3D. First, the underlying VLMs and LLMs exhibit inherent weaknesses in numerical precision [9, 61] and directional understanding [26] in complex scenes with multiple objects and occlusion. Second, InternVL-2 struggles with very thin objects, often misidentifying their side-views as different objects entirely. Finally, without metadata support, the caption accuracy becomes generic for complex 3D structures, particularly in scenes with fragmented geometries like architectural interiors. Additionally, MARVEL-FX3D sometimes generates flat 3D objects due to depth ambiguity in the input image. In supplementary section, some visual examples are provided. Despite these challenges, it is important to note that the strengths of our proposed pipeline and architecture remain significant, as they are both model-agnostic and adaptable to future enhancements.

## 6. Conclusion

In this work, we introduced MARVEL-40M+, the largest 3D captioning dataset to date, comprising over 40 million high-quality text annotations for 8.9 million 3D assets across seven major 3D datasets. Our primary contributions include a scalable, multi-stage annotation pipeline that combines open-source pretrained multi-view VLMs and LLMs with filtered human metadata to reduce hallucinations and introduce domain-specific information. Our pipeline produces five levels of annotations for diverse 3D modeling needs, from detailed reconstruction descriptions to rapid prototyping tags. Additionally, we introduce MARVEL-FX3D, a two-stage architecture that leverages fine-tuned Stable Diffusion on our dataset and pretrained Stable Fast 3D to generate high-quality, textured 3D meshes in just 15 seconds. Through extensive experimentation, we demonstrated both MARVEL-40M+’s superior annotation quality and linguistic depth, and MARVEL-FX3D’s state-of-the-art performance in high fidelity text-to-3D generation. We believe that MARVEL-40M+ will serve as a foundational resource for future advancements in text-to-3D content creation, inspiring further research to address the current limitations and expand the dataset’s applications.



## 7. Acknowledgement

This work was in parts supported by the EU Horizon Europe Framework under grant agreement 101135724 (LUMINOUS).

## References

- [1] Blender - a 3d modelling and rendering software. <https://www.blender.org.3>
- [2] OpenVLM leaderboard - a hugging face space. [https://huggingface.co/spaces/opencompass/open\\_vlm\\_leaderboard.3,4](https://huggingface.co/spaces/opencompass/open_vlm_leaderboard.3,4)
- [3] Stable diffusion 3.5 large - huggingface. <https://huggingface.co/stabilityai/stable-diffusion-3.5-large.2,3,4,5,7,14>
- [4] Mohammed Aldeen, Joshua Luo, Ashley Lian, Venus Zheng, Allen Hong, Preethika Yetukuri, and Long Cheng. ChatGPT vs. human annotators: A comprehensive analysis of chatGPT for text annotation. In *2023 International Conference on Machine Learning and Applications (ICMLA)*, pages 602–609. IEEE, 2023. 3
- [5] DeepFloyd Lab at StabilityAI. DeepFloyd IF: a novel state-of-the-art open-source text-to-image model with a high degree of photorealism and language understanding. <https://www.deepfloyd.ai/deepfloyd-if>, 2023. Retrieved on 2023-11-08. 3, 5
- [6] Timothy Bell, Ian H Witten, and John G Cleary. Modeling for text compression. *ACM Computing Surveys (CSUR)*, 21(4):557–591, 1989. 8
- [7] Mark Boss, Zixuan Huang, Aaryaman Vasishta, and Varun Jampani. Sf3d: Stable fast 3d mesh reconstruction with uv-unwrapping and illumination disentanglement, 2024. 2, 3, 4, 5, 7
- [8] Peter F Brown, Stephen A Della Pietra, Vincent J Della Pietra, Jennifer C Lai, and Robert L Mercer. An estimate of an upper bound for the entropy of english. *Computational Linguistics*, 18(1):31–40, 1992. 6
- [9] Declan Campbell, Sunayana Rane, Tyler Giallanza, Nicolò De Sabbata, Kia Ghods, Amogh Joshi, Alexander Ku, Steven M. Frankland, Thomas L. Griffiths, Jonathan D. Cohen, and Taylor W. Webb. Understanding the limits of vision language models through the lens of the binding problem, 2024. 8
- [10] Angel X. Chang, Thomas A. Funkhouser, Leonidas J. Guibas, Pat Hanrahan, Qi-Xing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, Jianxiong Xiao, L. Yi, and Fisher Yu. Shapenet: An information-rich 3d model repository. *ArXiv*, abs/1512.03012, 2015. 2, 3, 5, 14, 23
- [11] Xi Chen, Josip Djolonga, Piotr Padlewski, Basil Mustafa, Soravit Changpinyo, Jialin Wu, Carlos Riquelme Ruiz, Sebastian Goodman, Xiao Wang, Yi Tay, Siamak Shakeri, Mostafa Dehghani, Daniel Salz, Mario Lucic, Michael Tschannen, Arsha Nagrani, Hexiang Hu, Mandar Joshi, Bo Pang, Ceslee Montgomery, Paulina Pietrzyk, Marvin Ritter, AJ Piergiovanni, Matthias Minderer, Filip Pavetic, Austin Waters, Gang Li, Ibrahim Alabdulmohsin, Lucas Beyer, Julien Amelot, Kenton Lee, Andreas Peter Steiner, Yang Li, Daniel Keysers, Anurag Arnab, Yuanzhong Xu, Keran Rong, Alexander Kolesnikov, Mojtaba Seyedhosseini, Anelia Angelova, Xiaohua Zhai, Neil Houlsby, and Radu Soricut. Pali-x: On scaling up a multilingual vision and language model, 2023. 2, 3
- [12] Yixin Chen, Junfeng Ni, Nan Jiang, Yaowei Zhang, Yixin Zhu, and Siyuan Huang. Single-view 3d scene reconstruction with high-fidelity shape and texture. In *2024 International Conference on 3D Vision (3DV)*, pages 1456–1467. IEEE, 2024. 2
- [13] Zhe Chen, Jiannan Wu, Wenhai Wang, Weijie Su, Guo Chen, Sen Xing, Muyan Zhong, Qinglong Zhang, Xizhou Zhu, Lewei Lu, Bin Li, Ping Luo, Tong Lu, Yu Qiao, and Jifeng Dai. Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks. *arXiv preprint arXiv:2312.14238*, 2023. 2, 3, 4, 5, 8, 14, 15
- [14] Zilong Chen, Feng Wang, Yikai Wang, and Huaping Liu. Text-to-3d using gaussian splatting, 2024. 3
- [15] Zhe Chen, Weiyun Wang, Hao Tian, Shenglong Ye, Zhangwei Gao, Erfei Cui, Wenwen Tong, Kongzhi Hu, Jiapeng Luo, Zheng Ma, et al. How far are we to gpt-4v? closing the gap to commercial multimodal models with open-source suites. *arXiv preprint arXiv:2404.16821*, 2024. 2, 3, 4, 5, 8, 14
- [16] Jasmine Collins, Shubham Goel, Kenan Deng, Achleshwar Luthra, Leon Xu, Erhan Gundogdu, Xi Zhang, Tomas F Yago Vicente, Thomas Dideriksen, Himanshu Arora, Matthieu Guillaumin, and Jitendra Malik. Abo: Dataset and benchmarks for real-world 3d object understanding. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022. 2, 3, 5, 14, 25
- [17] Matt Deitke, Ruoshi Liu, Matthew Wallingford, Huong Ngo, Oscar Michel, Aditya Kusupati, Alan Fan, Christian Laforte, Vikram Voleti, Samir Yitzhak Gadre, Eli VanderBilt, Aniruddha Kembhavi, Carl Vondrick, Georgia Gkioxari, Kiana Ehsani, Ludwig Schmidt, and Ali Farhadi. Objaverse-XL: A universe of 10m+ 3d objects. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023. 2, 4, 5, 13
- [18] Matt Deitke, Dustin Schwenk, Jordi Salvador, Luca Weihs, Oscar Michel, Eli VanderBilt, Ludwig Schmidt, Kiana Ehsani, Aniruddha Kembhavi, and Ali Farhadi. Objaverse: A universe of annotated 3d objects. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13142–13153, 2023. 2, 3, 4, 5, 6, 7, 13, 14, 21
- [19] Ankit Dhiman, Manan Shah, Rishubh Parihar, Yash Bhargat, Lokesh R Boregowda, and R Venkatesh Babu. Reflecting reality: Enabling diffusion models to produce faithful mirror reflections. *arXiv preprint arXiv:2409.14677*, 2024. 2
- [20] Laura Downs, Anthony Francis, Nate Koenig, Brandon Kinman, Ryan Hickman, Krista Reymann, Thomas B. McHugh, and Vincent Vanhoucke. Google scanned objects: A high-quality dataset of 3d scanned household items, 2022. 2, 3, 5, 13, 14, 26

- [21] Patrick Esser, Sumith Kulal, Andreas Blattmann, Rahim Entezari, Jonas Müller, Harry Saini, Yam Levi, Dominik Lorenz, Axel Sauer, Frederic Boesel, Dustin Podell, Tim Dockhorn, Zion English, Kyle Lacey, Alex Goodwin, Yan-nik Marek, and Robin Rombach. Scaling rectified flow transformers for high-resolution image synthesis, 2024. 2, 3, 4, 5, 7, 14
- [22] Chongjian Ge, Chenfeng Xu, Yuanfeng Ji, Chensheng Peng, Masayoshi Tomizuka, Ping Luo, Mingyu Ding, Varun Jampani, and Wei Zhan. Compgs: Unleashing 2d compositionality for compositional text-to-3d via dynamically optimizing 3d gaussians, 2024. 2
- [23] Yuan-Chen Guo, Ying-Tian Liu, Ruizhi Shao, Christian Laforte, Vikram Voleti, Guan Luo, Chia-Hao Chen, Zi-Xin Zou, Chen Wang, Yan-Pei Cao, and Song-Hai Zhang. threestudio: A unified framework for 3d content generation. <https://github.com/threestudio-project/threestudio>, 2023. 7
- [24] Junlin Han, Jianyuan Wang, Andrea Vedaldi, Philip Torr, and Filippos Kokkinos. Flex3d: Feed-forward 3d generation with flexible reconstruction model and input view curation. *arXiv preprint arXiv:2410.00890*, 2024. 3
- [25] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance, 2022. 14
- [26] Nils Hoehing, Ellen Rushe, and Anthony Ventresque. What’s left can’t be right – the remaining positional incompetence of contrastive vision-language models, 2023. 8
- [27] Lukas Höllein, Aljaž Božič, Norman Müller, David Novotny, Hung-Yu Tseng, Christian Richardt, Michael Zollhöfer, and Matthias Nießner. Viewdiff: 3d-consistent image generation with text-to-image models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2024. 2
- [28] Fangzhou Hong, Jiayang Tang, Ziang Cao, Min Shi, Tong Wu, Zhaoxi Chen, Shuai Yang, Tengfei Wang, Liang Pan, Dahua Lin, and Ziwei Liu. 3dtopia: Large text-to-3d generation model with hybrid diffusion priors, 2024. 2, 3, 5, 6, 7, 14, 16, 17, 18, 19, 20
- [29] Yicong Hong, Kai Zhang, Jiuxiang Gu, Sai Bi, Yang Zhou, Difan Liu, Feng Liu, Kalyan Sunkavalli, Trung Bui, and Hao Tan. Lrm: Large reconstruction model for single image to 3d. *arXiv preprint arXiv:2311.04400*, 2023. 2, 3
- [30] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021. 5, 7
- [31] Ka-Hei Hui, Aditya Sanghi, Arianna Rampini, Kamal Rahimi Malekshan, Zhengzhe Liu, Hooman Shayani, and Chi-Wing Fu. Make-a-shape: a ten-million-scale 3D shape model. In *Proceedings of the 41st International Conference on Machine Learning*, pages 20660–20681. PMLR, 2024. 2
- [32] Chenhan Jiang. A survey on text-to-3d contents generation in the wild. *arXiv preprint arXiv:2405.09431*, 2024. 2, 3
- [33] Heewoo Jun and Alex Nichol. Shap-e: Generating conditional 3d implicit functions, 2023. 3, 6, 7, 28, 29
- [34] Rishabh Kabra, Loic Matthey, Alexander Lerchner, and Niloy J. Mitra. Leveraging vlm-based pipelines to annotate 3d objects. In *Proceedings of the 41st International Conference on Machine Learning*. PMLR, 2024. 2, 3, 4, 5, 6, 7, 14, 16, 17, 18, 19, 20
- [35] Mohammad Sadil Khan, Elona Dupont, Sk Aziz Ali, Kseniya Cherenkova, Anis Kacem, and Djamilia Aouada. Cad-signet: Cad language inference from point clouds using layer-wise sketch instance guided attention. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4713–4722, 2024. 2
- [36] Mohammad Sadil Khan, Sankalp Sinha, Talha Uddin Sheikh, Didier Stricker, Sk Aziz Ali, and Muhammad Zeshan Afzal. Text2cad: Generating sequential cad models from beginner-to-expert level text prompts. In *Advances in Neural Information Processing Systems*, 2024. 2
- [37] Min-Seop Kwak, Donghoon Ahn, Ines Hyeonsu Kim, Jin-Hwa Kim, and Seungryong Kim. Geometry-aware score distillation via 3d consistent noising and gradient consistency modeling, 2024. 3
- [38] Chenghao Li, Chaoning Zhang, Atish Waghvase, Lik-Hang Lee, Francois Rameau, Yang Yang, Sung-Ho Bae, and Choong Seon Hong. Generative ai meets 3d: A survey on text-to-3d in aigc era. *arXiv preprint arXiv:2305.06131*, 2023. 2, 3
- [39] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *ICML*, 2022. 2
- [40] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. BLIP-2: bootstrapping language-image pre-training with frozen image encoders and large language models. In *ICML*, 2023. 3, 4
- [41] Jiahao Li, Hao Tan, Kai Zhang, Zexiang Xu, Fujun Luan, Yinghao Xu, Yicong Hong, Kalyan Sunkavalli, Greg Shakhnarovich, and Sai Bi. Instant3d: Fast text-to-3d with sparse-view generation and large reconstruction model, 2023. 2, 3, 5, 7
- [42] Xinyang Li, Zhangyu Lai, Linning Xu, Jianfei Guo, Lijuan Cao, Shengchuan Zhang, Bo Dai, and Rongrong Ji. Dual3d: Efficient and consistent text-to-3d generation with dual-mode multi-view latent diffusion, 2024. 3, 5
- [43] Yixun Liang, Xin Yang, Jiantao Lin, Haodong Li, Xiaogang Xu, and Yingcong Chen. Luciddreamer: Towards high-fidelity text-to-3d generation via interval score matching. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6517–6526, 2024. 2, 3, 6, 7, 28, 29
- [44] Chen-Hsuan Lin, Jun Gao, Luming Tang, Towaki Takikawa, Xiaohui Zeng, Xun Huang, Karsten Kreis, Sanja Fidler, Ming-Yu Liu, and Tsung-Yi Lin. Magic3d: High-resolution text-to-3d content creation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 2, 3
- [45] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. In *NeurIPS*, 2023. 2, 3
- [46] Haotian Liu, Chunyuan Li, Yuheng Li, Bo Li, Yuanhan Zhang, Sheng Shen, and Yong Jae Lee. Llava-next: Improved reasoning, ocr, and world knowledge, 2024. 2, 3
- [47] Minghua Liu, Ruoxi Shi, Kaoming Kuang, Yin hao Zhu, Xu-anlin Li, Shizhong Han, Hong Cai, Fatih Porikli, and Hao

- Su. Openshape: Scaling up 3d shape representation towards open-world understanding. *Advances in neural information processing systems*, 36, 2024. 3
- [48] Minghua Liu, Chao Xu, Haian Jin, Linghao Chen, Mukund Varma T, Zexiang Xu, and Hao Su. One-2-3-45: Any single image to 3d mesh in 45 seconds without per-shape optimization. *Advances in Neural Information Processing Systems*, 36, 2024. 2
- [49] Ruoshi Liu, Rundi Wu, Basile Van Hoorick, Pavel Tokmakov, Sergey Zakharov, and Carl Vondrick. Zero-1-to-3: Zero-shot one image to 3d object, 2023. 2
- [50] Yuan Liu, Cheng Lin, Zijiao Zeng, Xiaoxiao Long, Lingjie Liu, Taku Komura, and Wenping Wang. Syncdreamer: Generating multiview-consistent images from a single-view image. *arXiv preprint arXiv:2309.03453*, 2023. 2
- [51] Jonathan Lorraine, Kevin Xie, Xiaohui Zeng, Chen-Hsuan Lin, Towaki Takikawa, Nicholas Sharp, Tsung-Yi Lin, Ming-Yu Liu, Sanja Fidler, and James Lucas. Att3d: Amortized text-to-3d object synthesis. *The International Conference on Computer Vision (ICCV)*, 2023. 3
- [52] Tiange Luo, Honglak Lee, and Justin Johnson. Neural shape compiler: A unified framework for transforming between text, point cloud, and program. 2022. 3
- [53] Tiange Luo, Chris Rockwell, Honglak Lee, and Justin Johnson. Scalable 3d captioning with pretrained models. In *Advances in Neural Information Processing Systems*, pages 75307–75337. Curran Associates, Inc., 2023. 2, 3, 5, 6, 7, 14, 16, 17, 18, 19, 20
- [54] Tiange Luo, Justin Johnson, and Honglak Lee. View selection for 3d captioning via diffusion ranking. *arXiv preprint arXiv:2404.07984*, 2024. 2, 3
- [55] Yiwei Ma, Yijun Fan, Jiayi Ji, Haowei Wang, Xiaoshuai Sun, Guannan Jiang, Annan Shu, and Rongrong Ji. X-dreamer: Creating high-quality 3d content by bridging the domain gap between text-to-2d and text-to-3d generation, 2024. 5
- [56] Philip M. McCarthy and Scott Jarvis. MtlD, vocd-d, and hdd: A validation study of sophisticated approaches to lexical diversity assessment. *Behavior Research Methods*, 42:381–392, 2010. 6
- [57] Ben Mildenhall, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, and Ren Ng. Nerf: Representing scenes as neural radiance fields for view synthesis. In *Computer Vision – ECCV 2020*, 2020. 3
- [58] Alex Nichol, Heewoo Jun, Prafulla Dhariwal, Pamela Mishkin, and Mark Chen. Point-e: A system for generating 3d point clouds from complex prompts. *arXiv preprint arXiv:2212.08751*, 2022. 2, 3, 5
- [59] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models, 2022a eprint=2112.10741, archivePrefix=arXiv, primaryClass=cs.CV, url=https://arxiv.org/abs/2112.10741,. 3
- [60] Josh OpenAI, Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023. 2, 3, 4, 6, 7, 8, 14, 15
- [61] Letitia Parcalabescu, Albert Gatt, Anette Frank, and Iacer Calixto. Seeing past words: Testing the cross-modal capabilities of pretrained v&l models on counting tasks, 2021. 8
- [62] Ben Poole, Ajay Jain, Jonathan T. Barron, and Ben Mildenhall. Dreamfusion: Text-to-3d using 2d diffusion. *arXiv*, 2022. 2, 3, 6, 7, 28, 29
- [63] Xuebin Qin, Hang Dai, Xiaobin Hu, Deng-Ping Fan, Ling Shao, and Luc Van Gool. Highly accurate dichotomous image segmentation. In *ECCV*, 2022. 5
- [64] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision, 2021. 3
- [65] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *International conference on machine learning*, pages 8821–8831. Pmlr, 2021. 2
- [66] N Reimers. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*, 2019. 8
- [67] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022. 2, 3, 5
- [68] Shouwei Ruan, Yinpeng Dong, Hanqing Liu, Yao Huang, Hang Su, and Xingxing Wei. Omniview-tuning: Boosting viewpoint invariance of vision-language pre-training models, 2024. 4
- [69] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in neural information processing systems*, 35:36479–36494, 2022. 2, 3
- [70] Yichun Shi, Peng Wang, Jianglong Ye, Long Mai, Kejie Li, and Xiao Yang. MVDream: Multi-view diffusion for 3d generation. In *The Twelfth International Conference on Learning Representations*, 2024. 2, 3
- [71] Yawar Siddiqui, Tom Monnier, Filippos Kokkinos, Mahendra Kariya, Yanir Kleiman, Emilien Garreau, Oran Gafni, Natalia Neverova, Andrea Vedaldi, Roman Shapovalov, and David Novotny. Meta 3d assetgen: Text-to-mesh generation with high-quality geometry, texture, and pbr materials. *arXiv*, 2024. 2, 3, 5, 7
- [72] Sharath Turuvekere Sreenivas, Saurav Muralidharan, Raviraj Joshi, Marcin Chochowski, Mostofa Patwary, Mohammad Shoeybi, Bryan Catanzaro, Jan Kautz, and Pavlo Molchanov. Llm pruning and distillation in practice: The minitron approach, 2024. 4, 5
- [73] Stefan Stojanov, Anh Thai, and James M. Rehg. Using shape to categorize: Low-shot learning with an explicit shape bias. 2021. 2, 3, 5, 13, 14
- [74] Xingyuan Sun, Jiajun Wu, Xiuming Zhang, Zhoutong Zhang, Chengkai Zhang, Tianfan Xue, Joshua B Tenenbaum, and William T Freeman. Pix3d: Dataset and methods for

- single-image 3d shape modeling. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. [2](#), [3](#), [5](#), [13](#), [14](#), [27](#)
- [75] Zhi Rui Tam, Cheng-Kuang Wu, Yi-Lin Tsai, Chieh-Yen Lin, Hung-yi Lee, and Yun-Nung Chen. Let me speak freely? a study on the impact of format restrictions on performance of large language models. *arXiv preprint arXiv:2408.02442*, 2024. [5](#)
- [76] Christina Tsalicoglou, Fabian Manhardt, Alessio Tonioni, Michael Niemeyer, and Federico Tombari. Textmesh: Generation of realistic 3d meshes from text prompts. In *International conference on 3D vision (3DV)*, 2024. [2](#), [3](#)
- [77] Zhengyi Wang, Cheng Lu, Yikai Wang, Fan Bao, Chongxuan Li, Hang Su, and Jun Zhu. Prolificdreamer: High-fidelity and diverse text-to-3d generation with variational score distillation. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2023. [2](#), [3](#)
- [78] Jules White, Quchen Fu, Sam Hays, Michael Sandborn, Carlos Olea, Henry Gilbert, Ashraf Elnashar, Jesse Spencer-Smith, and Douglas C Schmidt. A prompt pattern catalog to enhance prompt engineering with chatgpt. *arXiv preprint arXiv:2302.11382*, 2023. [5](#)
- [79] Sangmin Woo, Jaehyuk Jang, Donguk Kim, Yubin Choi, and Changick Kim. Ritual: Random image transformations as a universal anti-hallucination lever in lvlms, 2024. [4](#)
- [80] Tong Wu, Jiarui Zhang, Xiao Fu, Yuxin Wang, Liang Pan Jiawei Ren, Wayne Wu, Lei Yang, Jiaqi Wang, Chen Qian, Dahua Lin, and Ziwei Liu. Omniobject3d: Large-vocabulary 3d object dataset for realistic perception, reconstruction and generation. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. [2](#), [3](#), [5](#), [13](#), [14](#), [22](#)
- [81] Tong Wu, Guandao Yang, Zhibing Li, Kai Zhang, Ziwei Liu, Leonidas Guibas, Dahua Lin, and Gordon Wetzstein. Gpt-4v(ision) is a human-aligned evaluator for text-to-3d generation, 2024. [6](#)
- [82] Kevin Xie, Jonathan Lorraine, Tianshi Cao, Jun Gao, James Lucas, Antonio Torralba, Sanja Fidler, and Xiaohui Zeng. Latte3d: Large-scale amortized text-to-enhanced3d synthesis. *The 18th European Conference on Computer Vision (ECCV)*, 2024. [3](#)
- [83] Jiale Xu, Weihao Cheng, Yiming Gao, Xintao Wang, Shenghua Gao, and Ying Shan. Instantmesh: Efficient 3d mesh generation from a single image with sparse-view large reconstruction models. *arXiv preprint arXiv:2404.07191*, 2024. [5](#)
- [84] Xinchun Yan, Jimei Yang, Ersin Yumer, Yijie Guo, and Honglak Lee. Perspective transformer nets: Learning single-view 3d object reconstruction without 3d supervision. *Advances in neural information processing systems*, 29, 2016. [2](#)
- [85] An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. Qwen2 technical report, 2024. [2](#), [3](#), [4](#), [5](#)
- [86] Jiayu Yang, Ziang Cheng, Yunfei Duan, Pan Ji, and Hongdong Li. Consistnet: Enforcing 3d consistency for multi-view images diffusion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7079–7088, 2024. [2](#)
- [87] Yunhan Yang, Yukun Huang, Xiaoyang Wu, Yuan-Chen Guo, Song-Hai Zhang, Hengshuang Zhao, Tong He, and Xi-hui Liu. Dreamcomposer: Controllable 3d object generation via multi-view conditions. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 8111–8120, 2024. [2](#)
- [88] Taoran Yi, Jiemin Fang, Junjie Wang, Guanjun Wu, Lingxi Xie, Xiaopeng Zhang, Wenyu Liu, Qi Tian, and Xinggang Wang. Gaussiandreamer: Fast generation from text to 3d gaussians by bridging 2d and 3d diffusion models, 2024. [3](#)
- [89] Longwen Zhang, Ziyu Wang, Qixuan Zhang, Qiwei Qiu, Anqi Pang, Haoran Jiang, Wei Yang, Lan Xu, and Jingyi Yu. Clay: A controllable large-scale generative model for creating high-quality 3d assets. *ACM Transactions on Graphics (TOG)*, 43(4):1–20, 2024. [2](#), [3](#), [5](#)
- [90] Xiaoyu Zhou, Xingjian Ran, Yajiao Xiong, Jinlin He, Zhiwei Lin, Yongtao Wang, Deqing Sun, and Ming-Hsuan Yang. Gala3d: Towards text-to-3d complex scene generation via layout-guided generative gaussian splatting. *arXiv preprint arXiv:2402.07207*, 2024. [2](#)
- [91] Junzhe Zhu and Peiye Zhuang. Hifa: High-fidelity text-to-3d generation with advanced diffusion guidance, 2023. [2](#), [3](#), [6](#), [7](#), [28](#), [29](#)
- [92] Peiye Zhuang, Songfang Han, Chaoyang Wang, Aliakhsandr Siarohin, Jiaxu Zou, Michael Vasilkovsky, Vladislav Shakhrai, Sergey Korolev, Sergey Tulyakov, and Hsin-Ying Lee. Gtr: Improving large 3d reconstruction models through geometry and texture refinement. *arXiv preprint arXiv:2406.05649*, 2024. [2](#)

# MARVEL-40M+: Multi-Level Visual Elaboration for High-Fidelity Text-to-3D Content Creation

## Supplementary Material

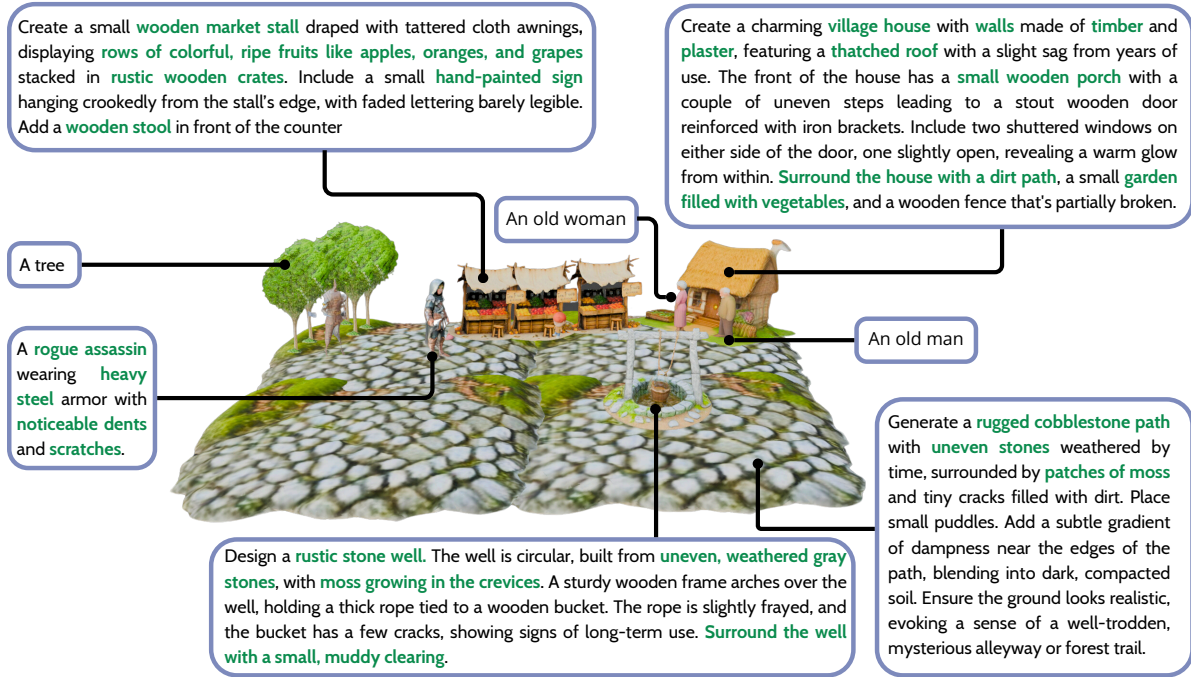


Figure 6. An example use case of MARVEL-FX3D, demonstrating how multiple prompts can be combined to create a detailed and complex 3D scene, with each prompt contributing specific elements such as characters, structures, and environmental details. Please zoom in for details.

This supplementary material provides additional details and results to support the main paper. Section 8 outlines the captioning process, including dataset preparation and implementation specifics. Sections 9 and 10 delve deeper into MARVEL annotations and MARVEL-FX3D results, offering more examples, discussions, and insights into their applications and limitations.

## 8. Additional Details on Captioning Process

### 8.1. Dataset Preparation

**Objaverse:** Objaverse<sup>†</sup> [18] contains 798,759 3D assets, with metadata (e.g., *name*, *tags*, *description*) available for ~93% samples after filtering. From ObjaverseXL [17], we rendered 8,031,637 assets, of which ~3.7M included metadata. After filtering, around 3M samples are retained as valid metadata.

**ShapeNet:** For the ShapeNet dataset, which contains

<sup>†</sup><https://objaverse.allenai.org/objaverse-1.0>

51,209 samples, we use the ShapeNet taxonomy as its metadata (e.g., *airplane*, *bowl*, *cap*, *clock*, etc.).

**Pix3D:** For the Pix3D<sup>‡</sup> [74] dataset, which contains 735 samples, we use the associated category tag as its metadata (e.g., *bed*, *table*, *desk*, *chair*, etc.).

**OmniObject3D:** The Omni-Object-3D<sup>§</sup> [80] dataset, which contains 5,878 samples, we use the folder names (e.g., *bed*, *table*, *desk*, *chair*, etc.) as our metadata.

**Toys4K:** For the Toys4K<sup>¶</sup> [73] dataset, which contains 4,000 samples, we use the folder names (e.g., *car*, *airplane*, *train*, *robot*, etc.) as our metadata.

**GSO:** The GSO (Google Scanned Objects)<sup>||</sup> [20] dataset, which contains 1,030 samples, we use the folder names (e.g., *lamp*, *sofa*, *vase*, *refrigerator*, etc.) as our metadata.

<sup>‡</sup><http://pix3d.csail.mit.edu/>

<sup>§</sup><https://omniobject3d.github.io/>

<sup>¶</sup><https://github.com/rehg-lab/lowshot-shapebias/tree/main/toys4k>

<sup>||</sup><https://goo.gle/scanned-objects>

**ABO:** The ABO (Amazon Berkeley Objects)\*\*[16] dataset, which contains 7,953 samples, provides metadata through listings information. Since these listings are multilingual, we first use the nllb-200†† model to translate the listings to English. The translated English listings are then used as our metadata.

## 8.2. Implementation Details

For human metadata filtering, we use the Mistral-Nemo-Instruct-2407 model with a temperature of 0.3 and a top-p value of 0.95. For dense description generation, we employ InternVL2-40B, configured with a temperature of 0.70, a top-p value of 0.95, and a repetition penalty of 1.10, with multinomial sampling enabled. For multi-level visual elaboration, we utilize Qwen2.5-72B with 8-bit quantization, a temperature of 0.70, a top-p value of 0.80, and a repetition penalty of 1.05. Finally, the Qwen2.5-14B model, used for the ethical filtering stage, is configured with a temperature of 0 and a top-p value of 0.90.

For human evaluations in our paper, we developed a Gradio app to compare our captions with those from baseline datasets, including Cap3D, 3DTopia, and Kabra, as well as to evaluate FX3D results against text-to-3D baselines. The evaluations were conducted by a panel of five human experts.

## 9. Additional details on MARVEL annotations

### 9.1. More Results on Effects of Human Metadata

Figure 7 showcases examples where human-provided metadata from source datasets reduce VLM hallucination and enhances annotations with domain-specific information. To generate captions using InternVL2 [13, 15] and GPT-4 [60], we input the same multi-view images used for MARVEL annotations, instructing them to produce concise descriptions that include names, shapes, textures, colors, and contextual environments.

Examples 1, 2, and 3 demonstrate how the inclusion of simple metadata (e.g. “*La Cava Window*”, “*Mount St. Helens*”) significantly reduces VLM hallucination, resulting in more accurate captions. Example 4 illustrates how metadata can support the generation of highly domain-specific information (e.g. “*alpha-helices and beta sheets*”, “*N-terminus, middle, and C-terminus*”).

### 9.2. More 3D Captioning Results

We provide more qualitative comparisons of annotations, highlighting differences between the baseline [28, 34, 53]

\*\*<https://amazon-berkeley-objects.s3.amazonaws.com/index.html>

††<https://huggingface.co/facebook/nllb-200-distilled-600M>

and our proposed MARVEL-40M+ dataset. For consistency, we used only Level 4 annotations, as their length closely matches that of the baselines. To improve clarity, we further categorized examples into distinct domains.

- **Figure 9** showcases 3D models of automotive designs (e.g., *cars, planes*) and CAD models.
- **Figure 10** features iconic characters from *anime, movies, and video games*.
- **Figure 11** illustrates biological elements such as *animals, plants, and molecules*.
- **Figure 12** includes diverse items ranging from *everyday objects, essentials, food to luxury items*.
- **Figures 13 and 14** depict historical artifacts (e.g., *statues, memorials*) and various scenes (e.g. *digital elevation maps, realistic and animated scenes*) respectively.

As illustrated in the figures, MARVEL annotations offer more precise and domain-specific descriptions, leveraging accurate nomenclature and contextual terminology, surpassing the quality of the baseline datasets.

### 9.3. More Multi-Level Examples

We present additional qualitative results showcasing our multi-level annotations across all seven datasets [10, 16, 18, 20, 73, 74, 80], with two examples per dataset - **Objaverse** (Figure 15), **OmniObject3D** (Figure 16), **ShapeNet** (Figure 17), **Toys4k** (Figure 18), **ABO** (Figure 19) and **GSO** (Figure 20).

### 9.4. Failure Cases

Figure 8 presents examples of the failure cases discussed in Section 5 of the main paper, illustrating the challenges associated with using pretrained VLMs to generate dense descriptions of 3D models.

## 10. Additional results of MARVEL-FX3D

### 10.1. More Implementation Details

As discussed in the main paper, MARVEL-FX3D is a two-stage pipeline. In the first stage, Stable Diffusion 3.5 [3, 21] is fine-tuned. During each epoch, one annotation is sampled from five levels and paired with a randomly selected multi-view image for MSE loss calculation. During inference, CFG [25] is set to 7.5, and 30 steps are used to balance speed and output diversity.

### 10.2. More Text-to-3D Results

Figures 22 and 23 showcase visual results of TT3D generation on unseen prompts. Using GPT-4 [60], we generated 10 random prompts focused on shape and scene descriptions. As demonstrated, MARVEL-FX3D produces higher-fidelity 3D models from text prompts compared to the baseline methods.

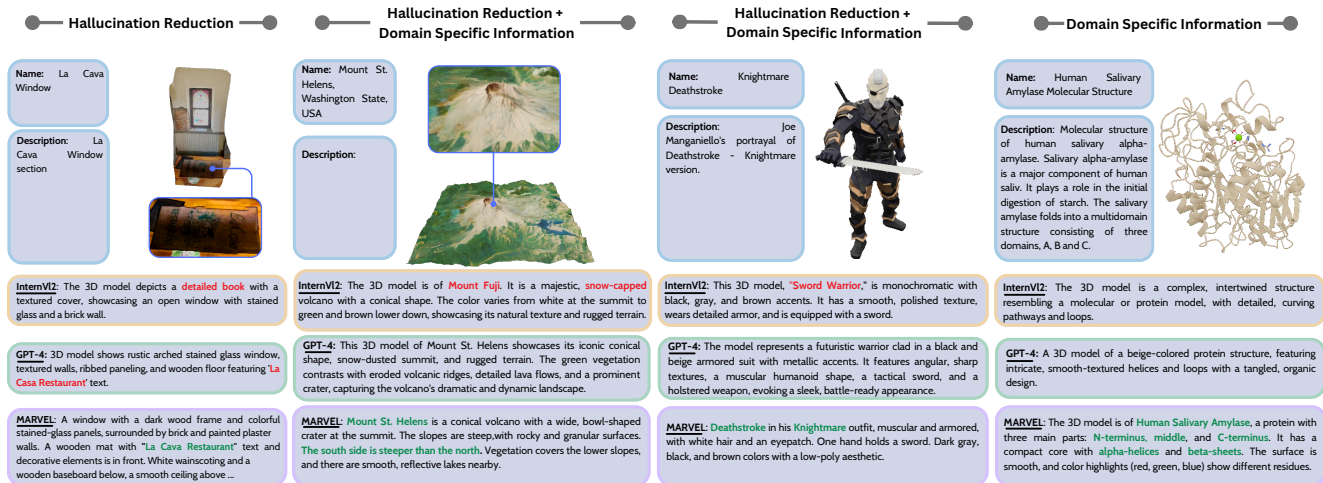


Figure 7. Effect of including human metadata, highlighting improvements in descriptive accuracy and contextual relevance compared to outputs generated without metadata, even when using state-of-the-art models like GPT-4 [60] and InternV12 [13]. Metadata inclusion helps reduce hallucinations and enhances domain-specific understanding.

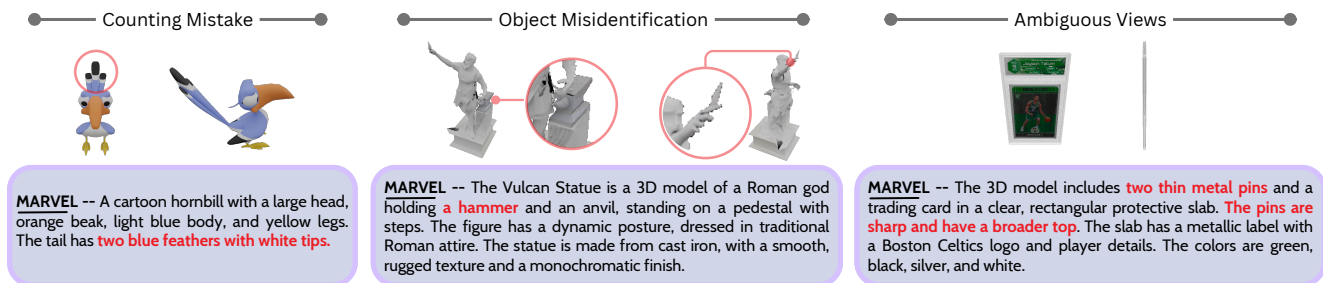


Figure 8. Failure cases of the MARVEL annotation pipeline. From left to right, the examples illustrate errors such as counting mistakes, object misidentification, and challenges with ambiguous views.

### 10.3. Discussion on Application of MARVEL

The MARVEL-40M+ dataset, with its scale and diversity, serves as a powerful resource for text-to-3D tasks such as reconstruction, multi-view consistency, and compositional scene generation. A notable real-world use case, illustrated in Figure 6, demonstrates how MARVEL-FX3D which is trained on MARVEL dataset enables rapid prototyping of diverse 3D objects from complex, fine-grained or simple text prompts. This capability facilitates the creation of intricate scenes, making it particularly valuable for applications in gaming, AR, and VR.



Figure 9. Qualitative comparison of 3D annotations across baselines [28, 34, 53] and the proposed MARVEL-40M+ for automotive (cars, planes, etc) and CAD models. MARVEL-40M+ provides more accurate and domain-specific annotations, compared to the baselines. Incorrect captions are highlighted in red, while important captions are highlighted in green.



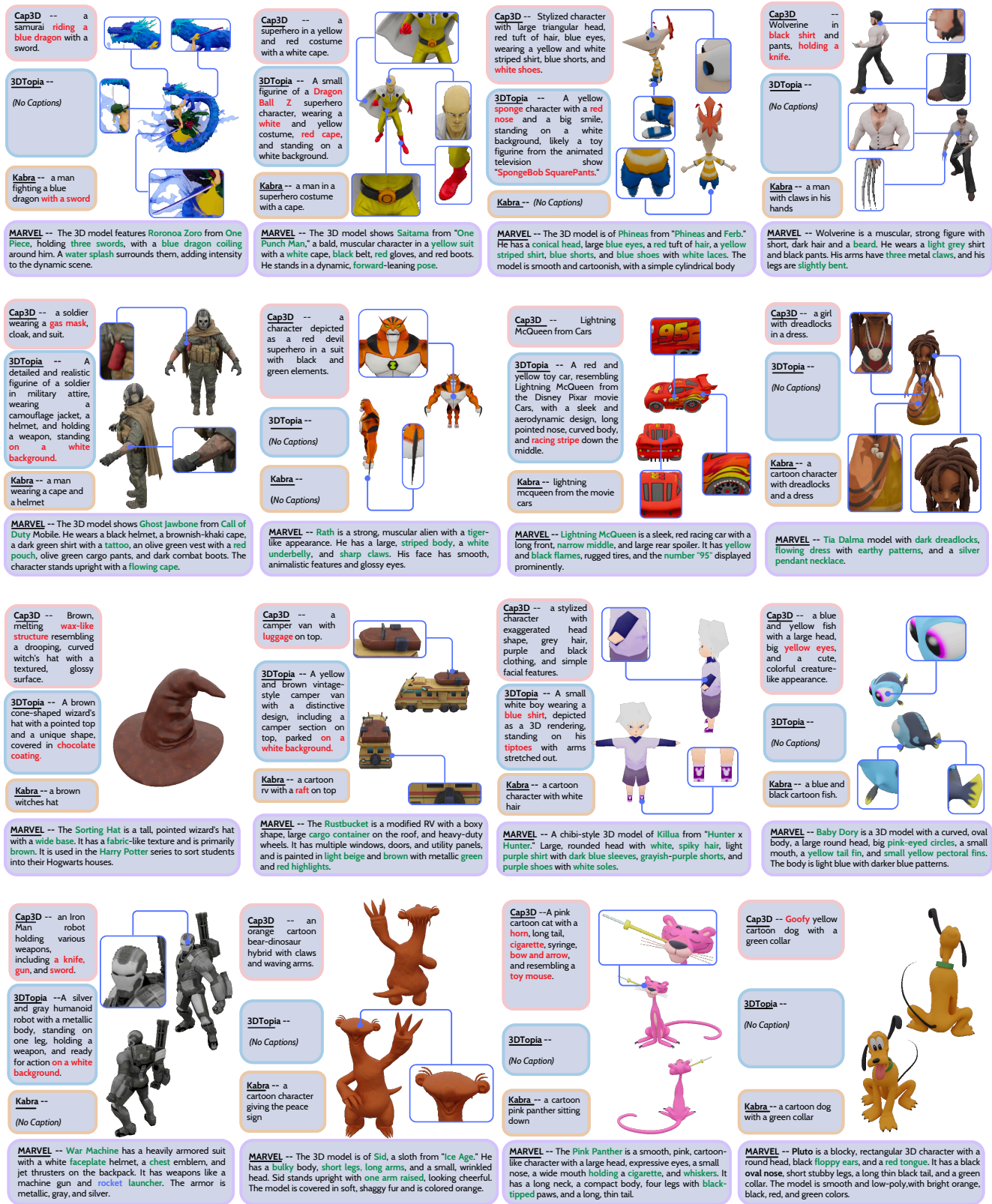


Figure 10. Qualitative comparison of 3D annotations across baselines [28, 34, 53] and the proposed MARVEL-40M+ for popular anime, movie, and cartoon characters. MARVEL-40M+ provides more accurate and domain-specific annotations, compared to the baselines. Incorrect captions are highlighted in red, while important captions are highlighted in green.



Figure 11. Qualitative comparison of 3D annotations across baselines [28, 34, 53] and the proposed MARVEL-40M+ for biological objects, including animals, plants, and molecular models. MARVEL-40M+ provides more accurate and domain-specific annotations, compared to the baselines. Incorrect captions are highlighted in red, while important captions are highlighted in green.



Figure 12. Qualitative comparison of 3D annotations across baselines [28, 34, 53] and the proposed MARVEL-40M+ for diverse items including daily objects, essentials. MARVEL-40M+ provides more accurate and domain-specific annotations, compared to the baselines. Incorrect captions are highlighted in red, while important captions are highlighted in green.

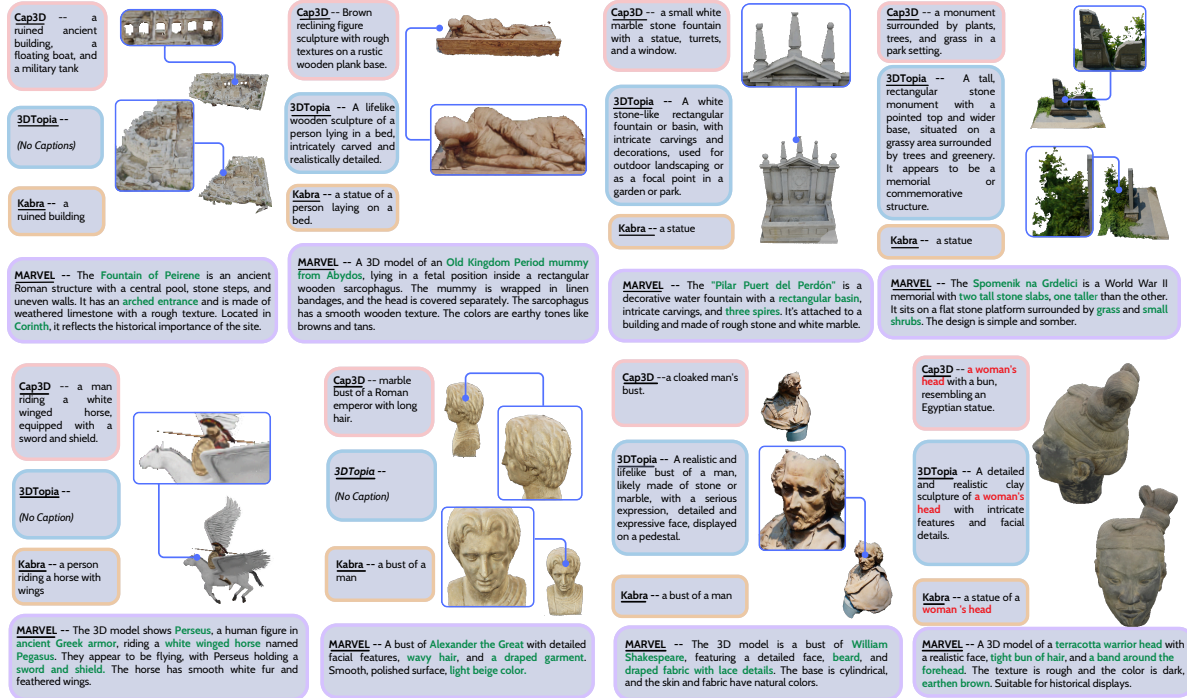


Figure 13. Qualitative comparison of 3D annotations across baselines [28, 34, 53] and the proposed MARVEL-40M+ for *historical elements including statues, places, memorials, etc.* Incorrect captions are highlighted in red, while important captions are highlighted in green.



Figure 14. Qualitative comparison of 3D annotations across baselines [28, 34, 53] and the proposed MARVEL-40M+ for *diverse scenes including digital elevation maps, places, realistic or animated scenes.* Incorrect captions are in red, while important captions are in green.

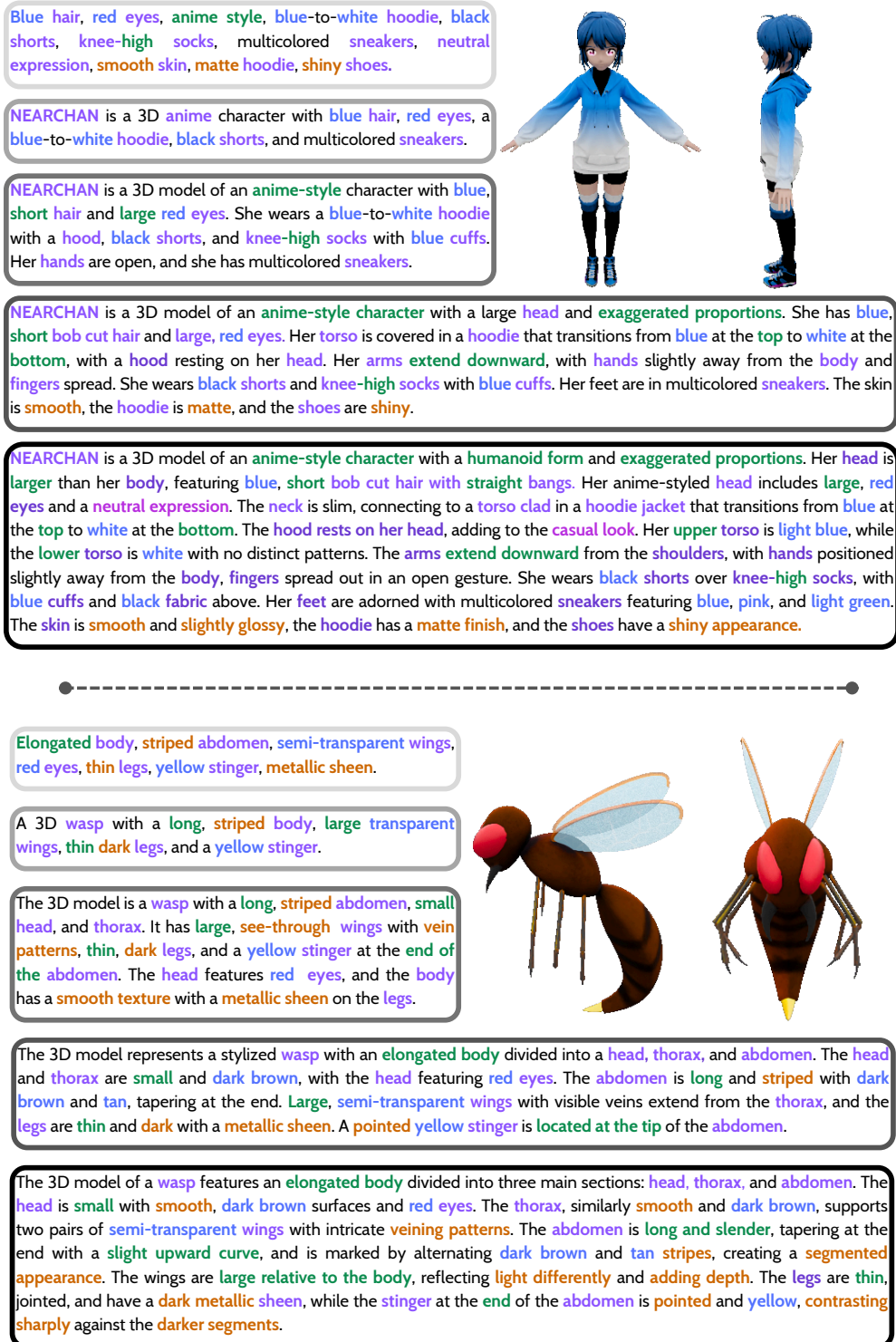
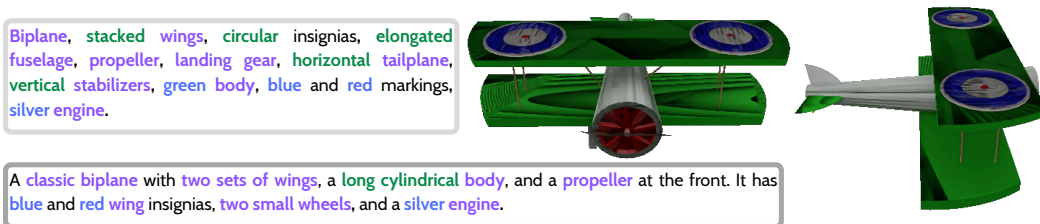


Figure 15. Multi-level annotation examples of MARVEL for the Objaverse [18] dataset. Words corresponding to Object and Components are highlighted in violet, Shape and Geometry in green, Texture and Materials in orange, Colors in blue, and Contextual Environment in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.



Figure 16. Multi-level annotation examples of MARVEL for the Omni-Object [80] dataset. Words corresponding to **Object and Components** are highlighted in violet, **Shape and Geometry** in green, **Texture and Materials** in orange, **Colors** in blue, and **Contextual Environment** in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.



Biplane, stacked wings, circular insignias, elongated fuselage, propeller, landing gear, horizontal tailplane, vertical stabilizers, green body, blue and red markings, silver engine.

A classic biplane with two sets of wings, a long cylindrical body, and a propeller at the front. It has blue and red wing insignias, two small wheels, and a silver engine.

The 3D model is a biplane with two sets of wings stacked on top of each other. The fuselage is long and cylindrical, narrowing at the back, with a propeller at the front. The wings have blue circular insignias with red dots. The landing gear consists of two small wheels under the fuselage. The control surfaces include a horizontal tailplane and vertical stabilizers at the rear. The plane is mainly green, with blue and red wing markings and a silver engine and propeller.

The 3D model is a biplane with a traditional layout. It features two sets of horizontally stacked wings, each adorned with circular blue insignias and red dots. The fuselage is elongated and cylindrical, tapering towards the rear, with a cylindrical engine and propeller at the front. The landing gear includes two small wheels at the bottom center of the fuselage. Control surfaces consist of a horizontal tailplane and vertical stabilizers at the rear. Struts and braces provide structural support between the upper and lower wings. The aircraft is primarily green, with blue and red wing insignias and a silver engine and propeller.

The 3D model represents a classic biplane with a detailed and symmetrical design. The main wings are horizontally stacked in a biplane configuration, each featuring circular blue insignias with red dots at their centers. The fuselage is elongated and cylindrical, tapering slightly towards the rear, with a cylindrical engine mounted on top and a prominent propeller at the front. The landing gear consists of two small wheels positioned near the bottom center of the fuselage. The control surfaces include a horizontal tailplane and vertical stabilizers at the rear. Struts and braces connect the upper and lower wings for structural support. The wings are rectangular with rounded tips, and the fuselage and engine housing exhibit a semi-matte finish, simulating lightweight materials like aluminum or wood. The engine and propeller blades have a metallic, slightly glossy appearance. The primary color of the aircraft is green, with blue and red accents on the wing insignias and silver for the engine and propeller.



Hammock, fabric body, wooden spreader bars, black pillow, vibrant colors, woven pattern, ropes, hooks, outdoor use, rectangular form, bilateral symmetry.

A colorful hammock with wooden spreader bars, a black pillow, and ropes for hanging. Suitable for outdoor relaxation.



The 3D model is a hammock with a colorful fabric body, two wooden spreader bars, and a black pillow. The fabric is an elongated rectangle that curves slightly and features vibrant patterns. The spreader bars keep the hammock open and rigid. The pillow, attached at one end, is soft and comfortable. Ropes and hooks are provided for hanging the hammock. The spreader bars are wood-colored, and the pillow is brownish-yellow. It is designed for outdoor use.

The 3D model is a hammock with a main fabric body, two wooden spreader bars, and a black pillow. The fabric is an elongated rectangle that curves slightly, with a woven pattern and vibrant colors including red, yellow, pink, and green. The spreader bars maintain the rectangular form and provide rigidity. The pillow, attached at one end, adds comfort. Ropes and hooks are included for secure suspension. The spreader bars are a natural wood color, and the pillow is brownish-yellow. The design is suitable for outdoor settings.

The 3D model represents a hammock with a main fabric body, two wooden spreader bars, and a black pillow. The fabric is an elongated rectangle that curves slightly, with a woven pattern suggesting a synthetic blend. The spreader bars, attached at the ends, maintain the rectangular form and provide rigidity. The hammock exhibits bilateral symmetry along its central axis, with open ends revealing the inner fabric and attachment points. The pillow, attached at one end, has a plush texture. Ropes and hooks are included for suspension, likely made of nylon or polyester. The fabric features vibrant red, yellow, pink, and green patterns, with the spreader bars in a natural wood color and the pillow in a brownish-yellow hue. The design is versatile for outdoor use, such as patios, gardens, or camping.

Figure 17. Multi-level annotation examples of MARVEL for the ShapeNet [10] dataset. Words corresponding to Object and Components are highlighted in violet, Shape and Geometry in green, Texture and Materials in orange, Colors in blue, and Contextual Environment in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.

Triceratops, large head, eye horns, nasal horn, frill with spikes, robust body, strong legs, long tapering tail, rough scaly skin, green body, lighter horns.

The 3D model is a Triceratops, a large dinosaur with a big head, two eye horns, a nasal horn, and a frill with spikes. It has a robust body, strong legs, and a long, tapering tail. The skin is rough and scaly, with a green body and lighter horns.



The 3D model is a Triceratops, known for its large head with two eye horns and a big nasal horn, and a frill with spikes. The body is robust and supported by strong legs. The tail is long and tapers. The skin is rough and scaly, with a green body and lighter horns. This model captures the essential features of a Triceratops, making it suitable for both educational and creative projects.

The 3D model is a Triceratops, featuring a large head with two eye horns and a prominent nasal horn, set against a frill with spikes. The body is robust and tapers into a shorter tail. Strong, sturdy legs support the heavy frame. The skin is rough and scaly, with raised bumps along the back. The horns and frill are smooth and slightly glossy, contrasting with the green body and lighter horns.

The 3D model represents a Triceratops, a large ornithomimid dinosaur. The head features two prominent horns above the eyes and a larger nasal horn, with a frill at the back adorned with spikes. The body is bulky and robust, transitioning into powerful hindquarters and a relatively short but thick neck. The tail is long and tapers backward, providing balance. The skin texture is rough and scaly, with raised bumps along the back, suggesting osteoderms. The horns and frill have a smooth, slightly glossy surface, possibly covered with keratinous material. The main body color is predominantly green with darker patches, while the horns and frill are a lighter, almost white shade.

Pug, traffic cone hat, round body, folded ears, small round eyes, flat snout, short sturdy legs, curled tail, bright yellow, brown eyes, matte texture, yellow and white stripes.

A pug dog with a round body and a traffic cone hat. The pug has folded ears, small round eyes, and a flat snout. The hat is yellow with white stripes. The body is bright yellow with brown eyes and nose. The texture is matte.

The 3D model is a pug dog wearing a traffic cone hat. The pug has a round, short body with a broad face and folded ears. Its eyes are small and round, and the snout is flat and large. The legs are short and sturdy, and the tail is small and curled. The traffic cone hat is yellow with white stripes and fits around the pug's head. The pug's body is mostly bright yellow, with brown areas for the eyes and nose. The texture is matte, and the model is simple.



The 3D model depicts a pug dog wearing a traffic cone hat. The pug has a rounded, short-statured body with a broad face and compact build. Its ears are folded downward, and the eyes are small and round, positioned slightly above mid-face level. The snout is flat and large, typical of pugs. The legs are short and sturdy, and the tail is small and curled up over the back. The traffic cone hat is conical with alternating yellow and white stripes, fitting around the pug's head. The pug's body is primarily bright yellow, with brownish areas for the eyes and nose. The texture is matte, and the model is in a low poly style.

The 3D model represents a pug dog adorned with a traffic cone hat. The pug's body is rounded and short-statured, with a broad face and compact build. The ears are folded downward, close to the sides of the face. The eyes are small and round, positioned slightly above mid-face level, with a glossy appearance, possibly indicating a glass or polished plastic material. The snout is flat and large, characteristic of pugs. The legs are short and sturdy, supporting the round body, while the tail is small and curled up over the back. The traffic cone hat is conical, featuring alternating yellow and white stripes, with a circular base that fits snugly around the pug's head. The pug's body is a uniform bright yellow, with brownish areas for the eyes, nose, and some parts of the face. The texture of the pug and the cone hat is matte, with no shiny highlights or reflections. The model is designed in a low poly style, with subtle geometric facets.

Figure 18. Multi-level annotation examples of MARVEL for the Toys4K dataset. Words corresponding to Object and Components are highlighted in violet, Shape and Geometry in green, Texture and Materials in orange, Colors in blue, and Contextual Environment in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.



Blue ceramic cup, embossed flower patterns, tapered shape, smooth interior, deep blue color, lighter interior, gradient effect, symmetrical design, stable base.

A blue ceramic cup with embossed flower patterns on the outside and a smooth interior. It tapers from a wide top to a narrow base and is primarily deep blue with a lighter interior.



The 3D model is a blue ceramic cup with flower patterns. It has a standard cup shape, tapering slightly from a wide top to a narrow base. The exterior is textured with embossed flowers, while the interior and base are smooth. The cup is primarily deep blue, with a lighter shade inside. The flowers have a subtle gradient effect.

The 3D model is a blue ceramic cup with a flower pattern. It has a standard cup shape, slightly tapering from a wide opening at the top to a narrower base at the bottom. The exterior features embossed flower patterns, evenly distributed around the cylindrical body, creating a textured look. The interior and base are smooth, making it easy to clean and stable on surfaces. The primary color is deep blue, with a lighter shade inside. The flower patterns have a subtle gradient effect, with darker centers and lighter petals.

The 3D model represents a blue ceramic cup with a flower pattern. The cup has a standard shape, slightly tapering from a wider opening at the top to a narrower base at the bottom, ensuring stability. The geometry is symmetrical along its vertical axis, with equal proportions on all sides. The exterior surface features multiple embossed flower patterns, evenly distributed around the cylindrical body. Each pattern consists of concentric petals radiating outward from a central point, resembling a sunflower. The texture of the exterior is raised, providing a tactile quality. The interior and base surfaces are smooth, facilitating easy cleaning and enhancing stability. The primary color is deep blue, with a lighter shade of blue or off-white on the interior. The flower patterns have a subtle gradient effect, with darker centers and lighter petals, creating a harmonious visual contrast.

Ergonomic seat, high backrest, headrest, horizontal armrests, five-spoke base, caster wheels, smooth white upholstery, gray metal accents, minimalistic design.

Modern office chair with a curved seat, high backrest, and horizontal armrests. Five-spoke base with wheels. Smooth white upholstery, gray metal accents. Clean, minimalist design.



The office chair has a comfortable, slightly curved seat and a high, curved backrest with a headrest. Armrests are horizontal with slight upward curves. The base has five spokes with wheels. The chair is covered in smooth, white leather-like material with gray metal accents. It has a clean, modern look.

The office chair has an ergonomic design with a slightly curved, rectangular seat that tapers at the front. The high backrest curves gently and includes a headrest. Armrests are positioned mid-width and extend horizontally with slight upward curves. The base features five spokes with caster wheels. The chair is upholstered in a smooth, white leather-like material, with gray accents on the metal parts. The design is clean and minimalistic, ideal for modern offices.

The modern office chair features an ergonomic design with a slightly curved, rectangular seat that tapers at the front for leg comfort. The high backrest provides substantial lumbar support and gently curves from top to bottom, integrating a headrest. Armrests, positioned near the midpoint of the backrest width, extend horizontally with slight upward curves for optimal forearm rest and shoulder alignment. The base consists of five spokes converging into a central hub, each ending in a caster wheel for mobility. The chair is upholstered in a smooth, leather-like material, predominantly white, with subtle gray accents on the metal components, including the base and adjustment mechanisms. The design is minimalistic, with uniform colors and no patterns, making it suitable for modern office settings.

Figure 19. Multi-level annotation examples of MARVEL for the ABO (Amazon Berkeley Objects) [16] dataset. Words corresponding to Object and Components are highlighted in violet, Shape and Geometry in green, Texture and Materials in orange, Colors in blue, and Contextual Environment in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.

Cylindrical shape, beige fabric, horse print, light beige zipper, corner reinforcements, blue tag, flat base, stands upright, vibrant colors, symmetrical design.

A cylindrical pencil case with a beige fabric body and colorful horse print. Features a light beige zipper, corner reinforcements, and a blue tag. Stands upright on a flat base.



The Horse Print Pencil Case is a cylindrical pencil holder with a beige fabric body and a colorful horse print. It has a light beige zipper, corner reinforcements, and a blue tag near the zipper. The flat base allows it to stand upright. The design is clean and functional.

The Horse Print Pencil Case is a cylindrical, symmetrical object with a beige fabric body featuring a vibrant horse print. It includes a light beige zipper mechanism for opening and closing, and corner reinforcements to prevent damage. A blue rectangular tag is attached near the zipper. The flat base allows the case to stand upright.

The Horse Print Pencil Case is a cylindrical, symmetrical object designed to hold writing instruments. It features a beige fabric body with a vibrant horse print pattern, showcasing horses in various poses and colors such as black, brown, white, and blue. The case has a light beige zipper mechanism, likely made of metal with plastic components for ease of use. Corner reinforcements at both ends are made of sturdy material to prevent fraying and tearing, matching the main body's color for a seamless look. A blue rectangular tag, possibly fabric or plastic, is sewn onto one end near the zipper, providing additional branding or information. The flat base allows the case to stand upright, and the overall proportions are consistent throughout its length.

Blue, Nintendo 3DS XL, handheld gaming console, rounded rectangle, matte finish, two screens, black bezels, touchscreen, directional pad, action buttons, start/select buttons, strap holes, hinges, detachable upper cover, speaker slots, branding.

The 3D model is a blue Nintendo 3DS XL handheld gaming console with a rounded rectangular shape. It has two screens, a larger touchscreen on the bottom and a smaller screen above, both with black bezels. Controls include a directional pad, action buttons, and start/select buttons. The upper case is a detachable cover, and the backside has "Nintendo 3DS XL" branding.



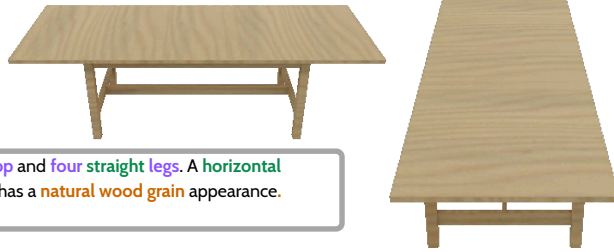
The 3D model is a blue Nintendo 3DS XL handheld gaming console. It has a slightly rounded rectangular shape with a matte finish. The console features two screens: a larger touchscreen on the bottom and a smaller screen above, both with black bezels. Controls include a directional pad, action buttons ('A', 'B', 'X', 'Y'), and start/select buttons. There are strap holes on the sides and hinges connecting the upper and lower parts. The upper case is a detachable cover, and the backside has "Nintendo 3DS XL" branding. The primary material is plastic, and the color scheme is bright blue with black accents.

The 3D model is a blue Nintendo 3DS XL handheld gaming console. The main body is a slightly rounded rectangle with a matte finish. It features two screens: a larger touchscreen on the bottom and a smaller screen above, both surrounded by black bezels. Controls include a directional pad, action buttons ('A', 'B', 'X', 'Y'), and start/select buttons, with a power button near the top-left corner. Strap holes are on the upper edges, and hinges connect the upper and lower parts. The upper case is a detachable cover, and speaker slots are on the sides of the upper case. The backside has "Nintendo 3DS XL" branding and regulatory text. The primary material is plastic, and the color scheme is bright blue with black accents.

The 3D model represents a blue Nintendo 3DS XL handheld gaming console. The main body is a slightly rounded rectangular shape with a matte finish, housing all internal components. Two screens are present: a larger touchscreen on the bottom and a smaller screen above, both surrounded by black bezels. Controls include a directional pad on the left, action buttons ('A', 'B', 'X', 'Y') on the right, and start/select buttons at the center, with a power button near the top-left corner. Strap holes are located on the upper edges of both sides. The closure mechanism features visible hinges where the upper and lower parts meet. The upper case is a detachable cover that folds over the main body, and the lower case houses the screens and controls. Speaker slots are visible on either side of the upper case, just below the hinge area. The backside displays "Nintendo 3DS XL" branding, along with regulatory text and logos. The primary material is plastic with a matte texture, offering a soft tactile feel, while control areas may have a slightly glossier finish. The predominant color is bright blue, with black accents for contrast.

Figure 20. Multi-level annotation examples of MARVEL for the GSO (Google Scanned Objects) [20] dataset. Words corresponding to Object and Components are highlighted in violet, Shape and Geometry in green, Texture and Materials in orange, Colors in blue, and Contextual Environment in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.

Rectangular tabletop, smooth wood grain, four straight legs, horizontal support beam, light brown color, natural wood appearance.



A rectangular wooden table with a smooth, light brown tabletop and four straight legs. A horizontal support beam runs underneath, connecting the legs. The table has a natural wood grain appearance.

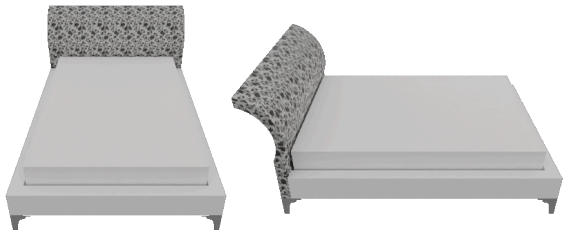
The 3D model is a rectangular wooden table. It has a flat, smooth tabletop with wood grain patterns. Four legs are positioned at each corner, and a horizontal support beam runs underneath, connecting the legs. The table is light brown with subtle wood grain, giving it a natural look.

The 3D model is a rectangular wooden table. The tabletop is flat and smooth with visible wood grain, indicating natural materials. Four legs, positioned at each corner, have a simple, straight shape and a slightly rounded texture. A horizontal support beam connects the legs underneath, running parallel to the longer edges of the table. The table has a light brown color with subtle variations in hue, creating a realistic wood grain effect.

The 3D model represents a rectangular wooden table. The tabletop is a flat, smooth surface with visible wood grain patterns, suggesting natural materials like plywood or solid wood veneer. The table measures significantly longer than it is wide, maintaining symmetry in leg placement and underframe design. Four legs, positioned at each corner, have a simple, straight shape with a slightly rounded texture, showing consistent wood grain patterns. A horizontal support beam connects two pairs of legs underneath the tabletop, running parallel to the longer edges, enhancing stability. All components share a light brown color with subtle variations in hue, creating a realistic wood grain effect.



Modern rectangular bed, white metal frame, slightly curved headboard, grayish floral pattern, plain white mattress, symmetric design, extended headboard, smooth matte finish.



A modern rectangular bed with a slightly curved headboard. The bed has a white metal frame and a grayish floral-patterned headboard. The mattress is plain white. The headboard extends slightly beyond the mattress width.

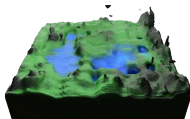
The bed with headboard is a modern, rectangular design. It has a sturdy white metal frame and a slightly curved headboard covered in grayish fabric with a floral pattern. The mattress is plain white and sits on top of the frame. The design is symmetric and well-proportioned, with the headboard extending slightly beyond the mattress width.

The bed with headboard is a modern, rectangular design. The base frame is made from a sturdy metal with a smooth, matte white finish. The headboard, which is slightly curved, is covered in a grayish fabric with a detailed floral pattern. The mattress is plain white and sits on top of the frame. The design is symmetric, with sharp, clean lines and a balanced proportion between the headboard and the bed's length. The headboard extends slightly beyond the width of the mattress. Ensure the mattress aligns perfectly with the headboard and maintain the smooth, matte finish of the frame.

The bed with headboard is a modern, rectangular design featuring a slightly curved headboard at one end. The base frame is constructed from a sturdy, sleek metal with a smooth, matte white finish. The headboard is covered in a grayish fabric with an intricate floral pattern, featuring small dark flowers and leaves. The fabric has a soft, slightly raised texture, adding depth and detail. The mattress, placed on top of the base frame, is covered in plain white fabric, suggesting a smooth, padded surface for comfort. The design is symmetric along both axes, with sharp, clean lines defining each side. The headboard extends beyond the width of the mattress, maintaining a balanced proportion with the bed's length. Ensure the mattress dimensions match those of the frame, aligning perfectly with the headboard. Pay close attention to the textures and proportions to achieve a faithful recreation.

Figure 21. Multi-level annotation examples of MARVEL for the Pix3D [74] dataset. Words corresponding to Object and Components are highlighted in violet, Shape and Geometry in green, Texture and Materials in orange, Colors in blue, and Contextual Environment in purple. From top to bottom, we go from level-5 (Concise Tags) captions to level-1 (Comprehensive Description) captions.

SHAP-E (5s)



DreamFusion (30m)



LucidDreamer (45m)



HiFA (1h)



MARVEL-FX3D (15s)



A lively **rainforest** with **tall trees**, dense foliage, and a **waterfall** cascading into a **pool** surrounded by **wildlife**.



A **gentle giant** with moss-covered **shoulders** and **vines** hanging from its body, resting in a **lush jungle**.



A **mischievous elf** with **pointy ears** and a playful grin, **holding a small bag** of tricks in a bustling marketplace.



A cozy **cabin** in the woods with **smoke coming** from the **chimney** and **snow covering** the roof and trees.



A cheerful **elf baker** with flour-dusted **apron** and a tray of **fresh cookies**, working in a **cozy kitchen**.

Figure 22. Qualitative Results for high fidelity TT3D generation on unseen prompts. From left to right, 3D models generated using Shap-E [33], DreamFusion [62], LucidDreamer [43], HiFA [91] and MARVEL-FX3D (ours).

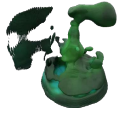
SHAP-E (5s)

DreamFusion (30m)

LucidDreamer (45m)

HiFA (1h)

MARVEL-FX3D (15s)



A shy fairy with transparent wings and a green dress, sitting on a lily pad in a pond.



A wise old wizard with an impressive white beard, reading a scroll in an ancient library.



A peaceful garden with a stone path, blooming roses, and a small fountain surrounded by benches.



A dark sorcerer with flowing black robes and glowing red eyes, holding an ancient spellbook.



A curious gnome with a bushy white beard and a pointy red hat, sitting on a mushroom in an enchanted forest.

Figure 23. Qualitative Results for high fidelity TT3D generation on unseen prompts. From left to right, 3D models generated using Shap-E [33], DreamFusion [62], LucidDreamer [43], HiFA [91] and MARVEL-FX3D (ours).