Objaverse-XL: A Universe of 10M+ 3D Objects

Matt Deitke[†ψ], **Ruoshi Liu**[γ], **Matthew Wallingford**[ψ], **Huong Ngo**[ψ], **Oscar Michel**[†], **Aditya Kusupati**[ψ], **Alan Fan**[ψ], **Christian Laforte**[σ], **Vikram Voleti**[σ], **Samir Yitzhak Gadre**[γ], **Eli VanderBilt**[†], **Aniruddha Kembhavi**[†ψ], **Carl Vondrick**[γ], **Georgia Gkioxari**[δ], **Kiana Ehsani**[†], [*]**Ludwig Schmidt**[†ψℓ], [*]**Ali Farhadi**[ψ]

[†]Allen Institute for AI [ψ]University of Washington, Seattle [γ]Columbia University
[σ]Stability AI [δ]California Institute of Technology [ℓ]LAION
[*]Equal Senior Contribution

Figure 1: Objaverse-XL includes a diverse collection of 10M+ 3D objects from a variety of sources. Here, we show examples of objects in Objaverse-XL rendered in a scene.

Abstract

Natural language processing and 2D vision models have attained remarkable proficiency on many tasks primarily by escalating the scale of training data. However, 3D vision tasks have not seen the same progress, in part due to the challenges of acquiring high-quality 3D data. In this work, we present Objaverse-XL, a dataset of over 10 million 3D objects. Our dataset comprises deduplicated 3D objects from a diverse set of sources, including manually designed objects, photogrammetry scans of landmarks and everyday items, and professional scans of historic and antique artifacts. Representing the largest scale and diversity in the realm of 3D datasets, Objaverse-XL enables significant new possibilities for 3D vision. Our experiments demonstrate the improvements enabled with the scale provided by Objaverse-XL. We show that by training Zero123 on novel view synthesis, utilizing over 100 million multi-view rendered images, we achieve strong zero-shot generalization abilities. We hope that releasing Objaverse-XL will enable further innovations in the field of 3D vision at scale.

37th Conference on Neural Information Processing Systems (NeurIPS 2023) Track on Datasets and Benchmarks.

1 Introduction

Scale has been paramount to recent advances in AI. Large models have produced breakthroughs in language comprehension and generation [1, 2], representation learning [3], multimodal task completion [4, 5], image generation [6, 7], and more. With an increasing number of learnable parameters, modern neural networks consume increasingly large volumes of data. As data has scaled up, the capabilities exhibited by models has dramatically increased.

Just a few years ago, GPT-2 [8] broke data barriers by consuming roughly 30 billion language tokens and demonstrated promising zero shot results on NLP benchmarks. Now, models such as Chinchilla [9] and LLaMA [10] consume trillions of web crawled tokens and easily surpass GPT-2 at benchmarks and capabilities. In computer vision, ImageNet [11], with 1 million images, was the gold standard for representation learning until scaling to billions of images, via web crawled datasets such as LAION-5B [12], produced powerful visual representations such as Contrastive Language-Image Pre-training (CLIP) [3]. The key to scaling up from millions of data points to billions and beyond has been the shift from assembling datasets manually to assembling them from diverse sources via the web.

As language and image data has scaled up, applications that require other forms of data have been left behind. Notable are applications in 3D computer vision, with tasks like 3D object generation and reconstruction, continue to consume small handcrafted datasets. 3D datasets such as ShapeNet [13] rely on professional 3D designers using expensive software to create assets, making the process tremendously difficult to crowdsource and scale. The resulting data scarcity has become a bottleneck for learning-driven methods in 3D computer vision. For instance, 3D object generation currently lags far behind 2D image generation, and current 3D generation approaches often still leverage models trained on large 2D datasets instead of being trained on 3D data from scratch. As demand and interest in AR and VR technologies goes up, scaling up 3D data is going to be increasingly crucial.

We introduce Objaverse-XL, a large-scale, web-crawled dataset of 3D assets. Advances in 3D authoring tools, demand, and photogrammetry, have substantially increased the amount of 3D data on the Internet. This data is spread across numerous locations including software hosting services like Github, specialized sites for 3D assets like Sketchfab, 3D printing asset sources like Thingiverse, 3D scanning platforms like Polycam, and specialized sites like the Smithsonian Institute. Objaverse-XL crawls such sources for 3D objects, providing a significantly richer variety and quality of 3D data than previously available, see Figure 1. Overall, Objaverse-XL comprises of over 10 million 3D objects, representing an order of magnitude more data than the recently proposed Objaverse 1.0 [14]. Objaverse-XL is two orders of magnitude larger than ShapeNet.

The scale and diversity of assets in Objaverse-XL significantly expands the performance of state-of-the-art 3D models. The recently proposed Zero123 [15] model for novel view synthesis, when pre-trained with Objaverse-XL, shows significantly better zero-shot generalization to challenging and complex modalities including photorealistic assets, cartoons, drawings and sketches. Similar improvements are also seen with PixelNerf which is trained to synthesize novel views given a small set of images. On each of these tasks, scaling pre-training data continues to show improvements from a thousand assets all the way up to 10 million, with few signs of slowing down, showing the promise and opportunities enabled with web scale data.

2 Related Work

Pre-training Datasets. Massive datasets have a prevalent role in modern, data-driven AI as they have produced powerful and general representations when paired with large-scale training. In computer vision, ImageNet [11], introduced nearly 14 years ago, has become the standard pre-training dataset of state-of-the-art visual models in object detection [16, 17], instance segmentation [18, 19] and more. More recently, large image datasets, such as LAION-5B [12], have powered exciting advances in generative AI, such as Stable Diffusion [7], and have given rise to new general-purpose vision and language representations with models like CLIP [3] and Flamingo [4]. More recently,

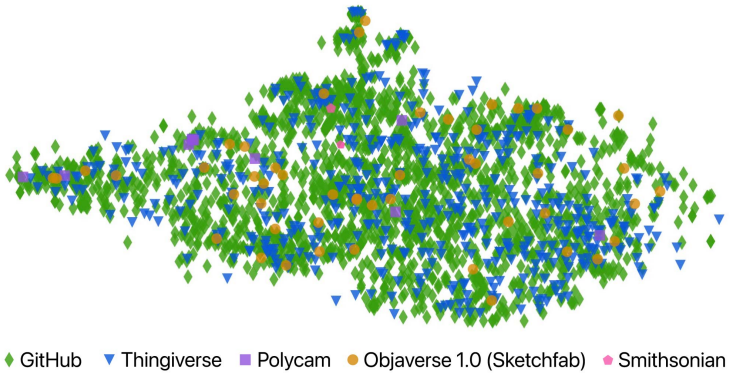


Figure 2: t-SNE projection of CLIP L/14 embeddings on a subset of rendered objects. Compared to Objaverse 1.0 (orange), Objaverse-XL more densely captures the distribution of 3D assets.

Source	# Objects
IKEA [20]	219
GSO [21]	1K
EGAD [22]	2K
OmniObject3D [23]	6K
PhotoShape [24]	5K
ABO [25]	8K
Thingi10K [26]	10K
3d-Future [27]	10K
ShapeNet [13]	51K
Objaverse 1.0 [14]	800K
Objaverse-XL	**10.2M**

Table 1: Number of 3D models in common datasets. Objaverse-XL is over an order of magnitude larger than prior datasets.

Segment Anything (SAM) [28] introduced a dataset of one billion object masks used to train a model capable of segmenting any object from an image. In language understanding, datasets like Common Crawl [29] have culminated in unprecedented capabilities of large language models such as GPT-4 [2], which in turn power mainstream applications like ChatGPT. The impact of large datasets is undeniable. However, current efforts to collect massive datasets focus on image and language modalities. In this work we introduce and release publically a massive dataset of 3D objects, called Objaverse-XL. Given the promise of large datasets for 2D vision and language, we believe Objaverse-XL will accelerate research in large-scale training for 3D understanding.

3D Datasets. Existing 3D datasets have been instrumental in yielding significant findings in 3D over the years. ShapeNet [13] has served as the testbed for modeling, representing and predicting 3D shapes in the era of deep learning. ShapeNet provides a collection of 3D shapes, in the form of textured computer-aided design (CAD) models labeled with semantic categories from WordNet [30]. In theory, it contains 3M CAD models with textures. In practice, a small subset of 51K models is used after filtering by mesh and texture quality. Notwithstanding its impact, ShapeNet objects are of low resolution and textures are often overly simplistic. Other datasets, such as Amazon Berkeley Objects (ABO) [25], Google Scanned Objects (GSO) [21], ScanNet3D [31], Articulated Knowledge Base-48 (AKB-48) [32] and OmniObjects3D [23] for objects, and Matterport3D [33] and Habitat-Matterport 3D [34] for scenes, improve on the diversity or quality of their 3D models, by either scanning objects or using more advanced modeling techniques, but are significantly smaller in size with the largest constituting 15K 3D models. Recently, Objaverse 1.0 [14] introduced a 3D dataset of 800K 3D models with high quality and diverse textures, geometry and object types, making it 15$\times$ larger than prior 3D datasets. While impressive and a step toward a large-scale 3D dataset, Objaverse 1.0 remains several magnitudes smaller than dominant datasets in vision and language. As seen in Figure 2 and Table 1, Objaverse-XL extends Objaverse 1.0 to an even larger 3D dataset of 10.2M unique objects from a diverse set of sources, object shapes, and categories. We discuss Objaverse-XL and its properties in Section 3.

3D Applications. The potential of a massive 3D dataset like Objaverse-XL promises exciting novel applications in computer vision, graphics, augmented reality and generative AI. Reconstructing 3D objects from images is a longstanding problem in computer vision and graphics. Here, several methods explore novel representations [35, 36, 37, 38], network architectures [39, 40] and differentiable rendering techniques [41, 42, 43, 44, 45] to predict the 3D shapes and textures of objects from images with or without 3D supervision. All of the aforementioned projects experiment on the small scale ShapeNet. The significantly larger Objaverse-XL could pave the way to new levels of performance, and increase generalization to new domains in a zero-shot fashion. Over the past year, generative AI has made its foray into 3D. MCC [46] learns a generalizable representation with self-supervised learning for 3D reconstruction. DreamFusion [47] and later on Magic3D [48] demonstrated that 3D shapes could be generated from language prompts with the help of text-to-image models. Point-E [49] and Shape-E [50] also train for text-to-3D with the help of 3D models from an undisclosed source. Recently, Zero123 [15] introduced an image-conditioned diffusion model which generates novel

Figure 3: **Examples of 3D objects from various sources of Objaverse-XL** spanning GitHub, Thingiverse, Polycam, the Smithsonian Institution, and Sketchfab. Objects from Thingiverse do not include color information, so each object's primary color is randomized during rendering.

object views and is trained on Objaverse 1.0. Stable Dreamfusion [51] replaces the text-to-image model in DreamFusion with the 3D-informed Zero123 and shows improved 3D generations. Recent findings in AI and scaling laws [52, 9] suggest that both generative and predictive models benefit from larger models and larger pre-training datasets. For 3D, Objaverse-XL is by far the largest 3D dataset to date and has the potential to facilitate large-scale training for new applications in 3D.

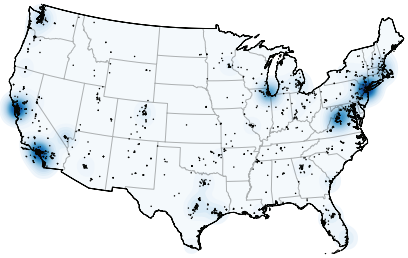
3 Objaverse-XL

Objaverse-XL is a web scale 3D object dataset composed of a highly diverse set of 3D data sources on the internet. In this section, we discuss the sources, metadata of the objects, and provide an analysis of the objects.

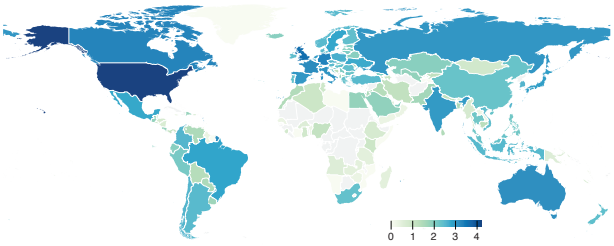
3.1 Composition

Objaverse-XL is composed of 3D objects coming from several sources, including GitHub, Thingiverse, Sketchfab, Polycam, and the Smithsonian Institution. We detail each source below.

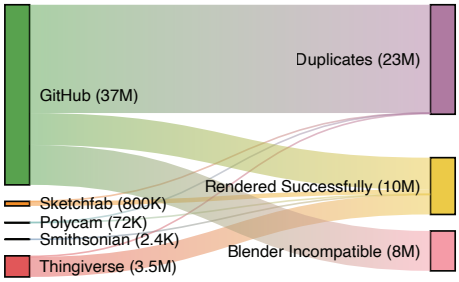
GitHub is a popular online platform for hosting code. We index 37M public files that contain common 3D object extensions; in particular, `.obj`, `.glb`, `.gltf`, `.usdz`, `.usd`, `.usda`, `.fbx`, `.stl`, `.dae`, `.ply`, `.abc`, and `.blend`. These extensions were chosen as they are best supported in Blender, which we use to render 2D images of the 3D objects. We only index objects that come from "base"



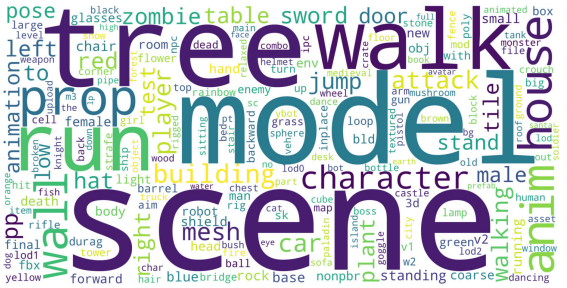
(a) Object location density in the United States



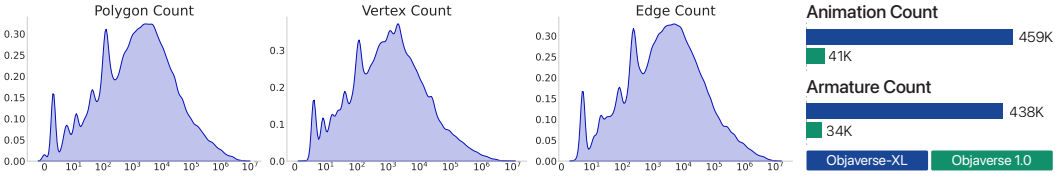
(b) Choropleth map of objects per country (log scale)



(c) Sankey diagram of Objaverse-XL sources



(d) Word cloud of file names for GitHub



(e) Statistics of the metadata extracted from the 3D objects.

Figure 4: **Analysis of metadata from Objaverse-XL.** Locations of geotagged objects in (a) the United States and (b) around the world. (c) Various sources and their contribution to Objaverse-XL. (d) Frequency of filenames of GitHub objects. (e) Further statistics of collected 3D objects.

GitHub repositories (*i.e.* non-forked repos, excluding forks that had more stars than the original repo). In total, the files come from over 500K repositories.

Across all of Objaverse-XL, objects are deduplicated by file content hash, which removes approximately 23 million files. Among the remaining files, we were able to import and successfully render 5.5 million of those files. Files that were not successfully rendered were either caused by import compatibility issues (*i.e.* FBX ASCII files are not natively importable to Blender), no meshes are in the files, or the file is not a valid 3D file (*e.g.* an `.obj` file may be a C compiler file instead of a Wavefront Object file). Moving forward, we expect a solution for converting 3D file formats into a consolidated representation may yield several million more unique 3D objects.

Thingiverse is a platform for sharing objects most commonly used for 3D printing. We index and download around 3.5 million objects from the platform, which are predominantly released under Creative Commons licenses. The vast majority of the objects are STL files, which are often watertight meshes that are untextured, and serve as useful data for learning a shape prior. During rendering, we randomize the colors to broaden the distribution of the images.

Sketchfab is an online platform where users can publish and share 3D models, encompassing a broad variety of categories. The data sourced from Sketchfab for our project is specifically from Objaverse 1.0, a dataset of 800K objects consisting of Creative Commons-licensed 3D models. Each model is distributed as a standardized GLB file. The 3D models are freely usable and modifiable, covering an array of object types, from real-world 3D scans to intricate designs created in 3D software.

Polycam is a 3D scanning mobile application designed to facilitate the acquisition and sharing of 3D data. One of its salient features is the *explore* functionality, which enables members of the user

community to contribute their 3D scans to a publicly accessible database. In the context of our dataset, we focus specifically on the subset of objects within the explore page that are designated as savable. These savable objects are governed by a Creative Commons Attribution 4.0 International License (CC-BY 4.0). We indexed 72K objects that were marked as savable and licensed under a CC-BY 4.0 license. Following deduplication, we obtain 71K unique objects.

Smithsonian 3D Digitization is a project by the Smithsonian Institution dedicated to digitizing their vast collection of historical and cultural artifacts. The project has provided us with a set of 2.4K models, all licensed under a CC0 license, which signifies that these works are fully in the public domain and free for use without any restrictions. The objects in this collection are primarily scans of real-world artifacts. Each model is distributed in a standardized compressed GLB format.

3.2 Metadata

Each object comes with metadata from its source, and we also extract metadata from it in Blender and from its CLIP ViT-L/14 features. We describe the metadata acquisition process below.

Source Metadata. From the source, we often get metadata such as its popularity, license, and some textual description. For example, on GitHub, the popularity is represented by the stars of the object's repository and the file name serves as the object's textual pair.

Blender Metadata. For each object that we render, we obtain the following metadata for it: `sha256`, `file-size`, `polygon-count`, `vertex-count`, `edge-count`, `material-count`, `texture-count`, `object-count`, `animation-count`, `linked-files`, `scene-dimensions`, and `missing-textures`. During rendering, for objects that have a missing texture, we randomize the color of that texture. Figure 4 shows some charts extracted from the metadata, including density plots over the number of polygons, vertex counts, and edge counts.

Animated Objects. From the Blender metadata, we find that the number of animated objects and those with armature (a digital skeleton used to animate 3D models) significantly increases from Objaverse 1.0 to Objaverse-XL. Figure 4e (right) shows a bar chart of the increase, specifically from 41K to 459K animated objects and from 34K to 438K objects with armature.

Model Metadata. For each object, we extract its CLIP ViT-L/14 [3] image embedding by averaging the CLIP embedding from 12 different renders of the object at random camera positions inside of a hollow sphere. We use the CLIP embeddings to predict different metadata properties, including aesthetic scores, not safe for work (NSFW) predictions, face detection, and for detecting holes in the photogrammetry renderings. Section D.2 provides more details on the analysis.

3.3 Analysis

NSFW annotations. Most data sources used for the creation of Objaverse-XL already have either a strict NSFW policy or strong self-filtering. However, owing to the web scale of Objaverse-XL we performed NSFW filtering using the rendered images of the objects. Each 3D object is rendered in 12 random views and each rendered image is passed through an NSFW classifier trained on the NSFW dataset introduced in LAION-5B [12] by **(author?)** [53] using the CLIP ViT-L/14 [3] features. After careful analysis and manual inspection, we marked a rendered image as NSFW if it has an NSFW score above 0.9 and a 3D object is marked as NSFW if at least 3 rendered images are deemed to be NSFW. Overall, only 815 objects out of the 10M are filtered out as NSFW objects. Note that the high threshold and multi-view consistency are needed due to the distribution shift between LAION-5B and Objaverse-XL along with NSFW classification of certain viewpoint renders of harmless 3D objects.

Face detection. We analyze the presence of faces in Objaverse-XL using a detector trained by **(author?)** [53]. Like NSFW filtering, we count the objects where at least 3 images contain a detected face. Out of 10M assets, we estimate 266K objects include faces. However, unlike most web-scale datasets, the faces present in Objaverse-XL often come from the scans of dolls, historical sculptures, and anthropomorphic animations. Hence, there are less privacy concerns with most of these objects.

Photogrammetry hole detection. When scanning 3D objects, if the back or bottom of the object is not scanned, rendering from various viewpoints may contain holes, leading to a "bad" render image.

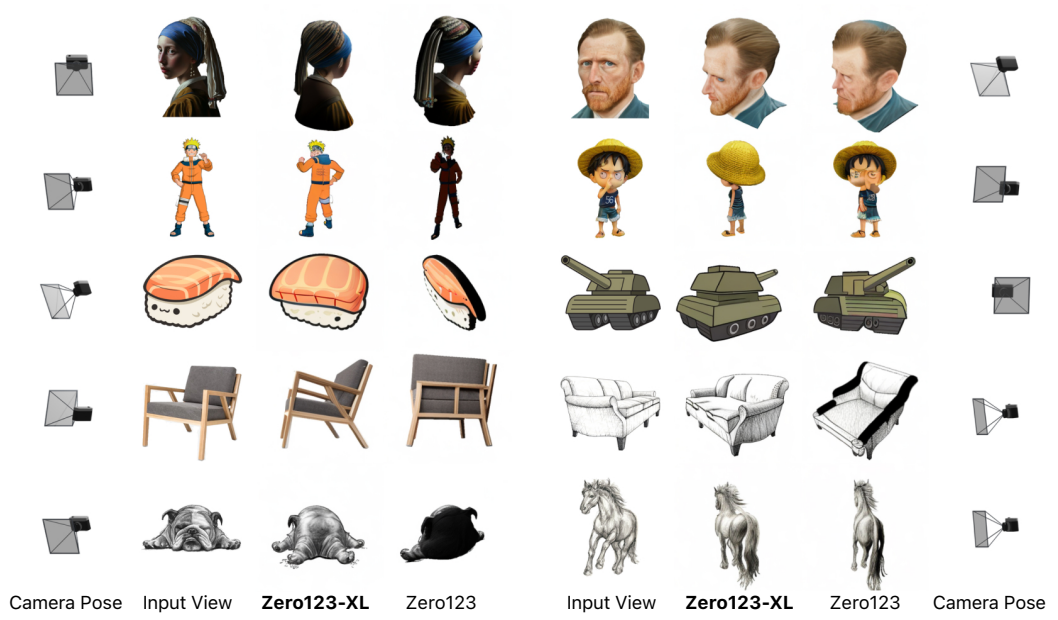


Figure 5: **Novel view synthesis on in-the-wild images.** Comparison between Zero123-XL trained on Objaverse-XL and Zero123 trained on Objaverse. Starting from the input view, the task is to generate an image of the object under a specific camera pose transformation. The camera poses are shown beside each example. Significant improvement can be found by training with more data, especially for categories including people (**1st row**), anime (**2nd row**), cartoon (**3rd row**), furniture (**4th row**), and sketches (**5th row**). Additionally, viewpoint control is significantly improved (see **2nd row**).

For example, a non-trivial number of Polycam 3D objects lack the information from the "back side". In most cases, images that are rendered from back-side viewpoints are noisy, low-fidelity, or contain holes. To analyze "bad rendering" at scale, we manually annotated 1.2K Polycam renders as "good" (label 1) or "bad" (label 0). We trained a "bad render" classifier (2-layer MLP) on top of the CLIP ViT-L/14 features of the rendered images; this classifier achieves a cross-validation accuracy of over 90% with a "render score" threshold of 0.5. Overall, out of 71K Polycam objects with 12 renders each, we found that 38.20% renders are "bad", with 58K objects having at least 2 bad renders.

4 Experiments

4.1 Novel View Synthesis with Zero123-XL

Generating 3D assets conditioned on in-the-wild 2D images has remained a challenging problem in computer vision. A crucial lesson learned from large language models is that pretraining on simple and easily scalable tasks, such as next word prediction, leads to consistently improved performance and the emergence of zero-shot abilities. An analogous approach in 3D vision is to predict a novel view of an object from an input view. Zero123 [15] recently proposed a view-conditioned diffusion model to perform this task, where the weights of the diffusion model are initialized from Stable Diffusion to leverage its powerful zero-shot image generation abilities. Zero123 used objects in

Zero123-XL	PSNR (↑)	SSIM (↑)	LPIPS (↓)	FID (↓)
Base	18.225	0.877	0.088	0.070
w/ Alignment Finetuning	**19.876**	**0.888**	**0.075**	**0.056**

Table 2: **Effect of high-quality data finetuning on Zero123-XL.** When evaluated zero-shot on Google Scanned Objects [21], a model finetuned on a high-quality alignment subset of Objaverse-XL significantly outperforms the base model trained only on Objaverse-XL.

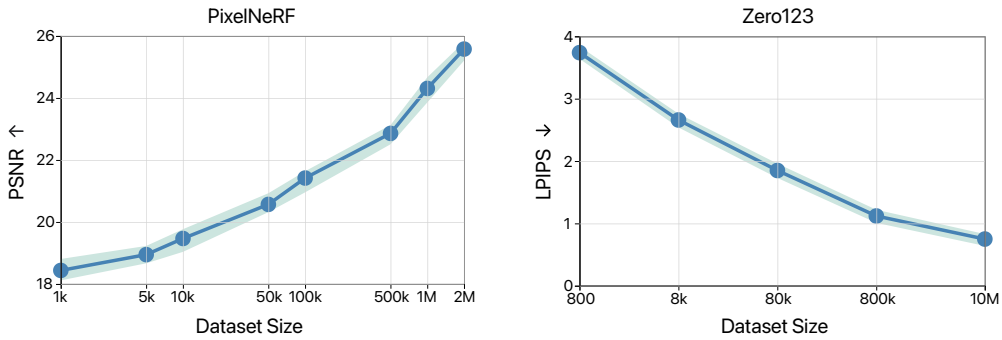


Figure 6: **Novel view synthesis at scale. Left**: PixelNeRF [40] trained on varying scales of data and evaluated on a held-out subset of Objavserse-XL. **Right**: Zero123 [15] trained on varying scales of data and evaluated on a zero-shot dataset. Note that the 800K datapoint is Zero123 and the 10M datapoint is Zero123-XL. The synthesis quality consistently improves with scale. LPIPS is scaled up 10 times for visualization.

Objaverse 1.0 to render input and novel view pairs as the training dataset. We use this framework to create *Zero123-XL*, which is the same approach except trained on the much larger Objaverse-XL instead. As shown in [15], the pretrained view-conditioned diffusion model can also be plugged into a score distillation framework such as DreamFusion [47] or SJC [54] to obtain a 3D assets.

Zero-shot Generalization. We found that training Zero123 on Objaverse-XL achieves significantly better zero-shot generalization performance than using Objaverse 1.0. Figure 5 shows examples from categories of data commonly known to be challenging for baseline systems, including people, cartoons, paintings, and sketches. For example, in both of the examples shown in 2nd and 3rd rows of the first column, Zero123 interprets the input image as a 2D plane and performs a simple transformation similar to a homography transformation. In comparison, Zero123-XL is able to generate novel views that are more consistent with the input view. Additionally, Zero123-XL is able to generate novel views from sketches of objects while keeping the original style as well as object geometric details. These examples show the effectiveness of dataset scaling for zero-shot generalization in 3D.

Improvement with Scale. We further quantitatively evaluate the novel view synthesis performance on Google Scanned Objects dataset [21]. As shown in Figure 6, the rvisual similarity score [55] between the predicted novel view and the ground truth view continues to improve as the dataset size increases.

Alignment Finetuning. InstructGPT [56] shows that large-scale pretraining does not directly lead to a model aligned with human preferences. More recently, LIMA [57] shows that finetuning a pretrained model on a curated subset with high-quality data can achieve impressive alignment results. We adopted a similar approach here by selecting a high-quality subset of Objaverse-XL that contains 1.3 million objects. Selection is done by defining proxy estimation of human preference based on heuristics including vertex count, face count, popularity on the source website, and source of data, among other metrics. After pretraining the base model on the entire Objaverse-XL, we finetune Zero123-XL on the alignment subset with a reduced learning rate and performed an ablation study to evaluate the effect of alignment finetuning. Table 2 shows that alignment finetuning leads to significant improvement in zero-shot generalization performance. Please refer to Appendix A for more implementation details regarding our model and experiments.

4.2 Novel View Synthesis with PixelNeRF

Synthesizing objects and scenes from novel views is a long-standing challenge. Notably, neural radiance fields [38] have shown impressive capabilities in rendering specific scenes from novel views. However, these methods require dozens of views of an individual scene, and can only synthesize views from the particular scene they were trained for. More recent methods [58, 59, 60, 40] have been proposed for constructing NeRF models that generalize across scenes with few input images. Due to the challenging nature of obtaining the necessary camera parameters for training, such methods have

traditionally been trained on small scale data sets. With the Objaverse-XL data, we train a PixelNeRF model on over two million objects, magnitudes of more data than has previously been used. We find that PixelNeRF generalizes to novel scenes and objects significantly better and performance improves consistently with scale (Figure 6 and Table 3).

Improvement with Scale. We train PixelNeRF models conditioned on a single input image at varying scales of data (Figure 6) and evaluate on a held out set of Objaverse-XL objects. We find that novel view synthesis quality consistently improves with more objects even at the scale of 2 million objects and 24 million rendered images.

Generalization to Downstream Datasets. Similar to pretraining in 2D vision and language, we observe that pretraining on Objaverse-XL with PixelNeRF improves performance when fine-tuning to other datasets such as DTU [61] and ShapeNet [13] (Table 3). We pretrain and fine-tune the model conditioned on a single input view and report the peak signal-to-noise ratio (PSNR).

PixelNeRF	DTU [61]	ShapeNet [13]
Baseline [40]	15.32	22.71
w/ Objaverse-XL	**17.53** $\pm$.37	**24.22** $\pm$.55

Table 3: **Comparison (PSNR (↑)) of PixelNeRF trained from scratch vs. fine-tuned from Objaverse-XL.** Performance significantly improves from pretraining on the large-scale corpus.

5 Limitations and Conclusion

Limitations. While Objaverse-XL is more than an order of magnitude larger than its predecessor, Objaverse 1.0, it is still orders of magnitude smaller than modern billion-scale image-text datasets. Future work may consider how to continue scaling 3D datasets and make 3D content easier to capture and create. Additionally, it may not be the case that all samples in Objaverse-XL are necessary to train high performance models. Future work may also consider how to choose datapoints to train on. Finally, while we focus on generative tasks, future work may consider how Objaverse-XL can benefit discriminative tasks such as 3D segmentation and detection.

Conclusion. We introduce Objaverse-XL, which is comprised of 10.2M 3D assets. In addition to documenting Objaverse-XL's unprecedented scale and sample diversity, we demonstrate the potential of Objaverse-XL for downstream applications. On the task of zero-shot novel view synthesis, we establish empirically promising trends of scaling dataset size, while keeping the model architecture constant. We hope Objaverse-XL will provide a foundation for future work in 3D.

Acknowledgements

We would like to thank Stability AI for compute used to train the experiments and LAION for their support. We would also like to thank Luca Weihs, Mitchell Wortsman, Romain Beaumont, Vaishaal Shankar, Rose Hendrix, Adam Letts, Sami Kama, Andreas Blattmann, Kunal Pratap Singh, and Kuo-Hao Zeng for their helpful guidance and conversations with the project. Finally, we would like to thank the teams behind several open-source packages used throughout this project, including Blender [62], PyTorch [63], PyTorch Lightning [64], D3 [65], Matplotlib [66], NumPy [67], Pandas [68], Wandb [69], and Seaborn [70]. Following the NeurIPS guidelines, we would also like to acknowledge the use of LLMs for helping revise some text and general coding assistance. Finally, we would also like to thank and acknowledge the content creators who contributed to the dataset.

References

[1] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020. 2

[2] OpenAI. Gpt-4 technical report. *arXiv*, 2023. 2, 3

[3] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR, 2021. 2, 6

[4] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35:23716–23736, 2022. 2

[5] Jiasen Lu, Christopher Clark, Rowan Zellers, Roozbeh Mottaghi, and Aniruddha Kembhavi. Unified-io: A unified model for vision, language, and multi-modal tasks. *ArXiv*, abs/2206.08916, 2022. 2

[6] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022. 2

[7] 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

[8] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019. 2

[9] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. *arXiv preprint arXiv:2203.15556*, 2022. 2, 4

[10] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023. 2

[11] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009. 2

[12] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *arXiv preprint arXiv:2210.08402*, 2022. 2, 6, 36

[13] Angel X Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, et al. Shapenet: An information-rich 3d model repository. *arXiv preprint arXiv:1512.03012*, 2015. 2, 3, 9

[14] 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. *arXiv preprint arXiv:2212.08051*, 2022. 2, 3, 34

[15] 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, 3, 7, 8, 16, 38

[16] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28, 2015. 2

[17] Nicolas Carion, Francisco Massa, Gabriel Synnaeve, Nicolas Usunier, Alexander Kirillov, and Sergey Zagoruyko. End-to-end object detection with transformers. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part I 16*, pages 213–229. Springer, 2020. 2

[18] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017. 2

[19] Bowen Cheng, Ishan Misra, Alexander G. Schwing, Alexander Kirillov, and Rohit Girdhar. Masked-attention mask transformer for universal image segmentation. 2022. 2

[20] Joseph J Lim, Hamed Pirsiavash, and Antonio Torralba. Parsing ikea objects: Fine pose estimation. In *Proceedings of the IEEE international conference on computer vision*, pages 2992–2999, 2013. 3

[21] 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. In *2022 International Conference on Robotics and Automation (ICRA)*, pages 2553–2560. IEEE, 2022. 3, 7, 8

[22] D. Morrison, P. Corke, and J. Leitner. Egad! an evolved grasping analysis dataset for diversity and reproducibility in robotic manipulation. *IEEE Robotics and Automation Letters*, 5(3):4368–4375, 2020. 3

[23] Tong Wu, Jiarui Zhang, Xiao Fu, Yuxin Wang, Jiawei Ren, Liang Pan, 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. *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. 3

[24] Keunhong Park, Konstantinos Rematas, Ali Farhadi, and Steven M Seitz. Photoshape: Photorealistic materials for large-scale shape collections. *arXiv preprint arXiv:1809.09761*, 2018. 3

[25] Jasmine Collins, Shubham Goel, Kenan Deng, Achleshwar Luthra, Leon Xu, Erhan Gundogdu, Xi Zhang, Tomas F Yago Vicente, Thomas Dideriksen, Himanshu Arora, et al. Abo: Dataset and benchmarks for real-world 3d object understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21126–21136, 2022. 3

[26] Qingnan Zhou and Alec Jacobson. Thingi10k: A dataset of 10,000 3d-printing models. *arXiv preprint arXiv:1605.04797*, 2016. 3

[27] Huan Fu, Rongfei Jia, Lin Gao, Mingming Gong, Binqiang Zhao, Steve Maybank, and Dacheng Tao. 3d-future: 3d furniture shape with texture. *International Journal of Computer Vision*, 129:3313–3337, 2021. 3

[28] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. *arXiv preprint arXiv:2304.02643*, 2023. 3

[29] 3

[30] George A Miller. Wordnet: a lexical database for english. *Communications of the ACM*, 38(11):39–41, 1995. 3

[31] Mikaela Angelina Uy, Quang-Hieu Pham, Binh-Son Hua, Thanh Nguyen, and Sai-Kit Yeung. Revisiting point cloud classification: A new benchmark dataset and classification model on real-world data. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 1588–1597, 2019. 3

[32] Liu Liu, Wenqiang Xu, Haoyuan Fu, Sucheng Qian, Qiaojun Yu, Yang Han, and Cewu Lu. Akb-48: A real-world articulated object knowledge base. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14809–14818, 2022. 3

[33] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niessner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from rgb-d data in indoor environments. *arXiv preprint arXiv:1709.06158*, 2017. 3

[34] Santhosh K Ramakrishnan, Aaron Gokaslan, Erik Wijmans, Oleksandr Maksymets, Alex Clegg, John Turner, Eric Undersander, Wojciech Galuba, Andrew Westbury, Angel X Chang, et al. Habitat-matterport 3d dataset (hm3d): 1000 large-scale 3d environments for embodied ai. *arXiv preprint arXiv:2109.08238*, 2021. 3

[35] Christopher B Choy, Danfei Xu, JunYoung Gwak, Kevin Chen, and Silvio Savarese. 3d-r2n2: A unified approach for single and multi-view 3d object reconstruction. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VIII 14*, pages 628–644. Springer, 2016. 3

[36] Nanyang Wang, Yinda Zhang, Zhuwen Li, Yanwei Fu, Wei Liu, and Yu-Gang Jiang. Pixel2mesh: Generating 3d mesh models from single rgb images. In *Proceedings of the European conference on computer vision (ECCV)*, pages 52–67, 2018. 3

[37] Lars Mescheder, Michael Oechsle, Michael Niemeyer, Sebastian Nowozin, and Andreas Geiger. Occupancy networks: Learning 3d reconstruction in function space. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 4460–4470, 2019. 3

[38] 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 *ECCV*, 2020. 3, 8, 38

[39] Georgia Gkioxari, Jitendra Malik, and Justin Johnson. Mesh r-cnn. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9785–9795, 2019. 3

[40] Alex Yu, Vickie Ye, Matthew Tancik, and Angjoo Kanazawa. pixelnerf: Neural radiance fields from one or few images. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4578–4587, 2021. 3, 8, 9

[41] Hiroharu Kato, Yoshitaka Ushiku, and Tatsuya Harada. Neural 3d mesh renderer. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3907–3916, 2018. 3

[42] Wenzheng Chen, Huan Ling, Jun Gao, Edward Smith, Jaakko Lehtinen, Alec Jacobson, and Sanja Fidler. Learning to predict 3d objects with an interpolation-based differentiable renderer. *Advances in neural information processing systems*, 32, 2019. 3

[43] Nikhila Ravi, Jeremy Reizenstein, David Novotny, Taylor Gordon, Wan-Yen Lo, Justin Johnson, and Georgia Gkioxari. Accelerating 3d deep learning with pytorch3d. *arXiv preprint arXiv:2007.08501*, 2020. 3

[44] Ruoshi Liu and Carl Vondrick. Humans as light bulbs: 3d human reconstruction from thermal reflection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12531–12542, 2023. 3

[45] Ruoshi Liu, Sachit Menon, Chengzhi Mao, Dennis Park, Simon Stent, and Carl Vondrick. Shadows shed light on 3d objects. *arXiv preprint arXiv:2206.08990*, 2022. 3

[46] Chao-Yuan Wu, Justin Johnson, Jitendra Malik, Christoph Feichtenhofer, and Georgia Gkioxari. Multiview compressive coding for 3d reconstruction. *arXiv preprint arXiv:2301.08247*, 2023. 3

[47] Ben Poole, Ajay Jain, Jonathan T Barron, and Ben Mildenhall. Dreamfusion: Text-to-3d using 2d diffusion. *arXiv preprint arXiv:2209.14988*, 2022. 3, 8, 38

[48] 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 *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 300–309, 2023. 3

[49] 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. 3

[50] Heewoo Jun and Alex Nichol. Shap-e: Generating conditional 3d implicit functions. *arXiv preprint arXiv:2305.02463*, 2023. 3

[51] Jiaxiang Tang. Stable-dreamfusion: Text-to-3d with stable-diffusion, 2022. https://github.com/ashawkey/stable-dreamfusion. 4

[52] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models. *arXiv preprint arXiv:2001.08361*, 2020. 4

[53] Samir Yitzhak Gadre, Gabriel Ilharco, Alex Fang, Jonathan Hayase, Georgios Smyrnis, Thao Nguyen, Ryan Marten, Mitchell Wortsman, Dhruba Ghosh, Jieyu Zhang, et al. Datacomp: In search of the next generation of multimodal datasets. *arXiv preprint arXiv:2304.14108*, 2023. 6

[54] Haochen Wang, Xiaodan Du, Jiahao Li, Raymond A Yeh, and Greg Shakhnarovich. Score jacobian chaining: Lifting pretrained 2d diffusion models for 3d generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12619–12629, 2023. 8

[55] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 586–595, 2018. 8

[56] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022. 8

[57] Chunting Zhou, Pengfei Liu, Puxin Xu, Srini Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, et al. Lima: Less is more for alignment. *arXiv preprint arXiv:2305.11206*, 2023. 8

[58] Kangle Deng, Andrew Liu, Jun-Yan Zhu, and Deva Ramanan. Depth-supervised nerf: Fewer views and faster training for free. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12882–12891, 2022. 8

[59] Ajay Jain, Matthew Tancik, and Pieter Abbeel. Putting nerf on a diet: Semantically consistent few-shot view synthesis. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5885–5894, 2021. 8

[60] Qianqian Wang, Zhicheng Wang, Kyle Genova, Pratul P Srinivasan, Howard Zhou, Jonathan T Barron, Ricardo Martin-Brualla, Noah Snavely, and Thomas Funkhouser. Ibrnet: Learning multi-view image-based rendering. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4690–4699, 2021. 8

[61] Henrik Aanæs, Rasmus Ramsbøl Jensen, George Vogiatzis, Engin Tola, and Anders Bjorholm Dahl. Large-scale data for multiple-view stereopsis. *International Journal of Computer Vision*, pages 1–16, 2016. 9

[62] Blender Online Community. Blender - a 3d modelling and rendering package. https://www.blender.org, 2023. 9

[63] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32, 2019. 9

[64] William Falcon and The PyTorch Lightning team. PyTorch Lightning, March 2019. 9

[65] Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer. D3: Data-driven documents. *IEEE Transactions on Visualization and Computer Graphics*, 2011. 9

[66] J. D. Hunter. Matplotlib: A 2d graphics environment. *Computing in Science & Engineering*, 9(3):90–95, 2007. 9

[67] Charles R. Harris, K. Jarrod Millman, Stéfan J. van der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J. Smith, Robert Kern, Matti Picus, Stephan Hoyer, Marten H. van Kerkwijk, Matthew Brett, Allan Haldane, Jaime Fernández del Río, Mark Wiebe, Pearu Peterson, Pierre Gérard-Marchant, Kevin Sheppard, Tyler Reddy, Warren Weckesser, Hameer Abbasi, Christoph Gohlke, and Travis E. Oliphant. Array programming with NumPy. *Nature*, 585(7825):357–362, September 2020. 9

[68] The pandas development team. pandas-dev/pandas: Pandas, February 2020. 9

[69] Lukas Biewald. Experiment tracking with weights and biases, 2020. Software available from wandb.com. 9

[70] Michael L. Waskom. seaborn: statistical data visualization. *Journal of Open Source Software*, 6(60):3021, 2021. 9

[71] Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. Datasheets for datasets. *Communications of the ACM*, 64(12):86–92, 2021. 30

[72] Yining Hong, Haoyu Zhen, Peihao Chen, Shuhong Zheng, Yilun Du, Zhenfang Chen, and Chuang Gan. 3d-llm: Injecting the 3d world into large language models. *arXiv preprint arXiv:2307.12981*, 2023. 34

[73] Le Xue, Ning Yu, Shu Zhang, Junnan Li, Roberto Martín-Martín, Jiajun Wu, Caiming Xiong, Ran Xu, Juan Carlos Niebles, and Silvio Savarese. Ulip-2: Towards scalable multimodal pre-training for 3d understanding. *arXiv preprint arXiv:2305.08275*, 2023. 34

[74] Minghua Liu, Ruoxi Shi, Kaiming Kuang, Yinhao Zhu, Xuanlin Li, Shizhong Han, Hong Cai, Fatih Porikli, and Hao Su. Openshape: Scaling up 3d shape representation towards open-world understanding. *arXiv preprint arXiv:2305.10764*, 2023. 34

[75] Florian Bordes, Shashank Shekhar, Mark Ibrahim, Diane Bouchacourt, Pascal Vincent, and Ari S Morcos. Pug: Photorealistic and semantically controllable synthetic data for representation learning. *arXiv preprint arXiv:2308.03977*, 2023. 34

[76] Ian Huang, Vrishab Krishna, Omoruyi Atekha, and Leonidas Guibas. Aladdin: Zero-shot hallucination of stylized 3d assets from abstract scene descriptions. *arXiv preprint arXiv:2306.06212*, 2023. 34

[77] Dave Zhenyu Chen, Yawar Siddiqui, Hsin-Ying Lee, Sergey Tulyakov, and Matthias Nießner. Text2tex: Text-driven texture synthesis via diffusion models. *arXiv preprint arXiv:2303.11396*, 2023. 34

[78] Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. Sdxl: Improving latent diffusion models for high-resolution image synthesis. *arXiv preprint arXiv:2307.01952*, 2023. 38

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 5.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Appendix.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] Materials will be shared with the reviewers.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Appendix.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes] See Appendix.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] New assets will be shared with reviewers.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] See Appendix.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] See Appendix.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]