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Lifting Unlabeled Internet-level Data for 3D Scene Understanding

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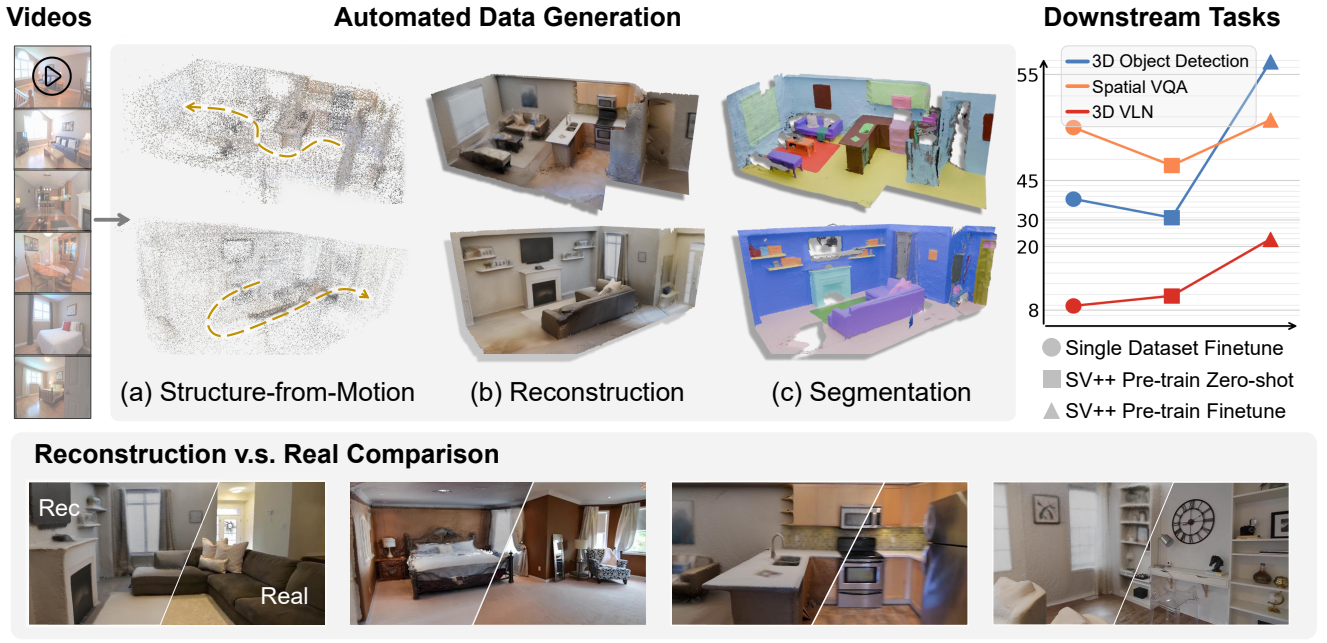


Figure 1. **Overview of SceneVerse++.** From unlabeled internet videos, we build automated data engines to create training data for comprehensive 3D scene understanding, realizing strong zero-shot performance on existing benchmarks, with further improvement after finetuning. This pinpoints future direction towards 3D spatial intelligence through improved automation on unlabeled, web-scale data.

Abstract

Annotated 3D scene data is scarce and expensive to acquire, while abundant unlabeled videos are readily available on the internet. In this paper, we demonstrate that carefully designed data engines can leverage web-curated, unlabeled videos to automatically generate training data, to facilitate end-to-end models in 3D scene understanding alongside human-annotated datasets. We identify and analyze bottlenecks in automated data generation, revealing critical factors that determine the efficiency and effectiveness of learning from unlabeled data. To validate our approach across different perception granularities, we evaluate on three tasks spanning low-level perception, i.e.*, 3D object detection and instance segmentation, to high-level reasoning,* i.e.*, 3D spatial Visual Question Answering (VQA) and Vision-Lanugage Navigation (VLN). Models trained on our generated data demonstrate strong zero-shot performance and show further improvement after finetuning. This demonstrates the viability of leveraging readily available web data as a path toward more capable scene understanding systems.*

1. Introduction

With the crucial role of 3D scene understanding in human and embodied intelligence, the field has made remarkable strides in recent years, spanning tasks from geometric perception (*e.g.*, depth estimation [24, 27, 31, 32, 35], camera

pose estimation [40, 90, 104, 105, 107]), semantic understanding (*e.g.*, 3D object detection [28, 57, 77] and segmentation [50, 92, 99]) to high-level reasoning (*e.g.*, 3D visual grounding [1, 16, 123] and spatial reasoning [3, 6, 72, 113]). The success of deep learning in this domain is fundamentally tied to the availability of large-scale, annotated, real-world 3D datasets [8, 26, 73, 114].

While methods [74, 105, 106] in 3D scene understanding continue to improve, progress in 3D scene data with high-quality annotations, on the contrary, has largely stagnated. Unlike 2D images [14, 91], which can be easily scraped and annotated from the web, capturing and labeling 3D data is far more challenging. The common procedure for 3D scene data curation involves recording thousands of frames with specialized hardware, *e.g.*, RGB-D sensors or LiDAR, reconstructing 3D meshes, and manually labeling 3D structures for dense semantic annotations. In fact, academia has not seen a quantitative leap in 3D data scaling since the pioneering ScanNet [26]; instead, efforts have focused on simplifying the procedure to get more scenes, *e.g.*, ARKitScenes [8] with 2x real-world sites at the cost of coarser scans and labeling, or improving data quality on a manageable number of scans, *e.g.*, ScanNet++ [114].

In this paper, we show that leveraging carefully designed data engines to generate training data from unlabeled, web-scale videos is a promising approach to address the scarcity of annotated 3D scenes. These data engines, often modularized, draw upon prior knowledge from existing foundation models [7, 61, 86] or scene-specific optimization methods that target particular aspects of general scene understanding, *e.g.*, reconstruction [52, 76, 78, 80], instance segmentation [36, 59, 111], and open-set semantics [53, 65, 82]. Since these submodular methods vary in representation, methodology, and technical focus, design choices for automatic data generation are non-trivial. The effectiveness of scaling generated data is task-dependent and strongly influenced by both quality and efficiency considerations.

To this end, we systematically analyze the bottlenecks in creating automated data engines for 3D scene understanding, provide guidelines on how to scale end-to-end (E2E) models, and pinpoint what submodular models should prioritize in future development. From Internet videos, we curate SceneVerse++ of 6,687 real-world scenes with images, camera poses, dense reconstructions, instance segmentations and high-level reasoning annotations. We demonstrate the effectiveness of internet-scale data by empowering three exemplar tasks in 3D scene understanding:

- 3D detection and segmentation. The models trained on SceneVerse++ realize strong zero-shot performance on ScanNet and ARKitscenes, and further significantly improve after finetuning (+20.6 for F1@.25).
- 3D spatial Visual Question Answering (VQA): Training on SceneVerse++ significantly improves the spatial reasoning performance of Vision-Language Models (VLMs), achieving zero-shot performance comparable to models trained on ground-truth 3D scenes.
- 3D Vision-Lanugage Navigation (VLN): We examine the zero-shot transfer from real-world videos to navigation in simulation, and demonstrate SceneVerse++ brings an extra 14% navigation success rate after finetuning.

2. Related Work

2.1. 3D Scene Understanding and Datasets

Early work in 3D scene understanding primarily focuses on tasks such as semantic segmentation [83, 108, 118], instance segmentation [50, 92, 99, 124], and object detection from images [10, 19, 28] or point clouds [5, 57, 74, 77]. Beyond geometry-centric perception, there has been growing interest in vision-language tasks within 3D scenes, including object referral [1, 16, 119], captioning [17, 18, 21, 117], spatial reasoning [6, 20, 45, 72, 113], and navigation [3, 44, 58, 85]. The shift is driven by the popularity of E2E VLMs [7, 22, 81, 100], offering advantages in multi-tasking [56] and scaling [49, 51, 97] in both model architecture and training data.

The success of these E2E models relies critically on 3D datasets [54, 73, 87, 101, 115, 121] with detailed annotation, such as pioneering ScanNet [26], later ARKitScenes [8] captured with portable devices, and ScanNet++ [114] with higher-quality scans. However, unlike their 2D counterparts, the scaling of the 3D datasets faces significant bottlenecks in capture and labeling costs that hinder further expansion. In the meantime, the internet contains orders of magnitude more unlabeled data that captures our 3D world.

In this paper, we advocate for advancing comprehensive 3D scene understanding by leveraging these unlabeled internet videos. We build upon methods that address intermediate problems in scene understanding, achieved by leveraging pre-trained models in a training-free [25, 70, 106, 111] or weakly-supervised manner [36, 67, 93, 95] to inject knowledge into 3D, *e.g.*, open-vocabulary 3D segmentation by lifting 2D results [99]. We build automated data engines on top of these submodules, leveraging their complementary strengths while mitigating limitations, achieving an efficiency-efficacy balance in internet-level data scaling.

2.2. Leveraging Internet-level Videos

Recognizing the scarcity of 3D datasets, an emerging direction is to harness video data to lift 2D content into 3D annotations for training. For instance, Miao et al. [75] proposes using existing 2D single-view datasets with estimated depth to generate 3D annotations. However, their data generation is bound to existing datasets [64, 94] with 2D segmentation annotations and operates at the single-image level, presenting a significant gap towards whole-

scene understanding. The abundant internet videos present an attractive, untapped resource, and recent work has begun to explore this direction, but mostly on training generative video [2, 43, 68, 71, 103] or novel-view synthesis (NVS) [29, 66, 69, 89] models. In pursuit of scalable 3D scene understanding [63, 96, 112], RoomTour3D [39] generates video instructions for navigation through summarization and candidate view selection, while NaVILA [23] incorporates real video trajectories into training to improve instruction-following in Vision-Lanugage Navigation (VLN). However, they remain confined to the navigation domain, without addressing broader spatial reasoning or scene understanding. Moreover, they often treat the multi-module data generation pipeline as given, offering little analysis of which components are most critical or where errors propagate. In contrast, our work addresses comprehensive 3D scene understanding tasks, from low-level perception to high-level reasoning, and provides systematic analyses, examining both the efficiency and efficacy of transforming internet-scale data for task-specific training.

3. Data Curation for SceneVerse++

Our work focuses on 3D scene understanding for static indoor scenes. The first step for task-specific 3D scene understanding is to curate internet videos and convert them to a basic 3D representation consisting of camera poses and sparse 3D geometry. Inspired by prior work on internet data processing [2, 39, 63], our data pipeline combines video curation with Structure-from-Motion (SfM) [40], encompassing shot splitting, filtering, key frame extraction, pixel matching, global bundle adjustment, and quality check.

We use TransNetV2 [98] to detect shots in long-form videos and discard very short clips. The filtering process removes low-quality or unsuitable content, including pure black screen, visual noise, humans [41], and outdoor scenes [122]. To handle potentially long-duration internet videos, we select keyframes based on parallax rather than uniform sampling [39], ensuring well-constrained triangulation with redundancy control. For sparse reconstruction and camera pose estimation, we adopt a dense pixel matching and bundle adjustment approach, which provides more robust camera poses and sparse point clouds than existing feed-forward methods [105, 106]. The overall pipeline resembles Mast3R-SFM [30], and we introduce optimized pseudo-track pixels to improve memory efficiency for long-term videos (*e.g.*, >300 frames) and incorporate relative image similarity to address the false-positive bias in existing pixel matching models [60]. Finally, we filter out the scenes with small spatial coverage, relatively empty space, or wrong SfM results. This can be achieved by existing VLMs [7, 81, 100], but we resort to human annotation (<10 seconds/scene) to ensure data quality for downstream tasks.

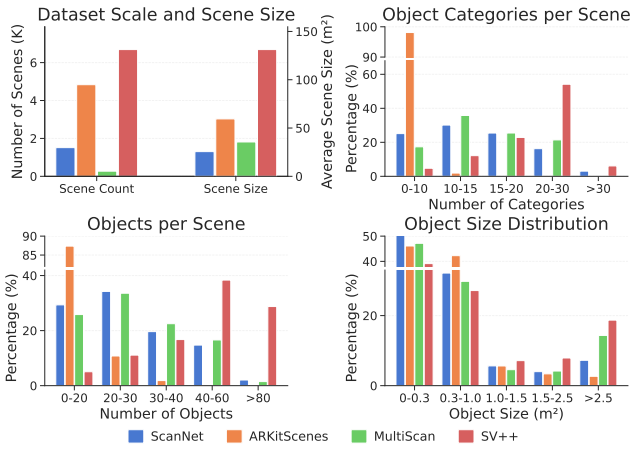


Figure 2. **Statistics comparison.** SceneVerse++ encompasses more scenes, larger areas, and greater object diversity compared with existing real-world datasets.

Statistics The dataset statistics are shown in Fig. 2, with comparison with ScanNet [26], MultiScan [73] and ARKitScenes [8]. Starting from 8,217 videos from the open internet platforms, we obtain 6,687 scenes, exceeding ARKitScenes captured with portable devices. SceneVerse++ contains multi-floor, multi-room scans from long-range videos, producing scenes significantly larger[1] than existing room-scale or lab-based datasets. More details about data curation, SfM methods, and examples with camera trajectories and sparse geometry are presented in *supplementary*.

4. SceneVerse++ for 3D Scene Understanding

In this section, we present how to leverage SceneVerse++ to generate training data and improve on three representative tasks in 3D scene understanding.

4.1. 3D Object Detection and Segmentation

Task and Benchmark The 3D object detection and segmentation task aims to localize distinct objects within a 3D scene, assigning each a precise geometric boundary and a semantic label. This task serves as a bridge between low-level 3D reconstruction and high-level scene understanding. In the following, we first introduce the data engine that generates 3D instance annotations, and then evaluate its effectiveness on real-world benchmarks.

Data Generation To obtain the complete reconstructed meshes and instance-level annotations from the sparse outputs of SfM, we design a reconstruction and segmentation pipeline, as illustrated in Fig. 3. It transforms internet images into 3D scenes, considering both efficiency and effectiveness in large-scale data generation.

[1] Scene area is approximated by the product of extents along x-y plane.

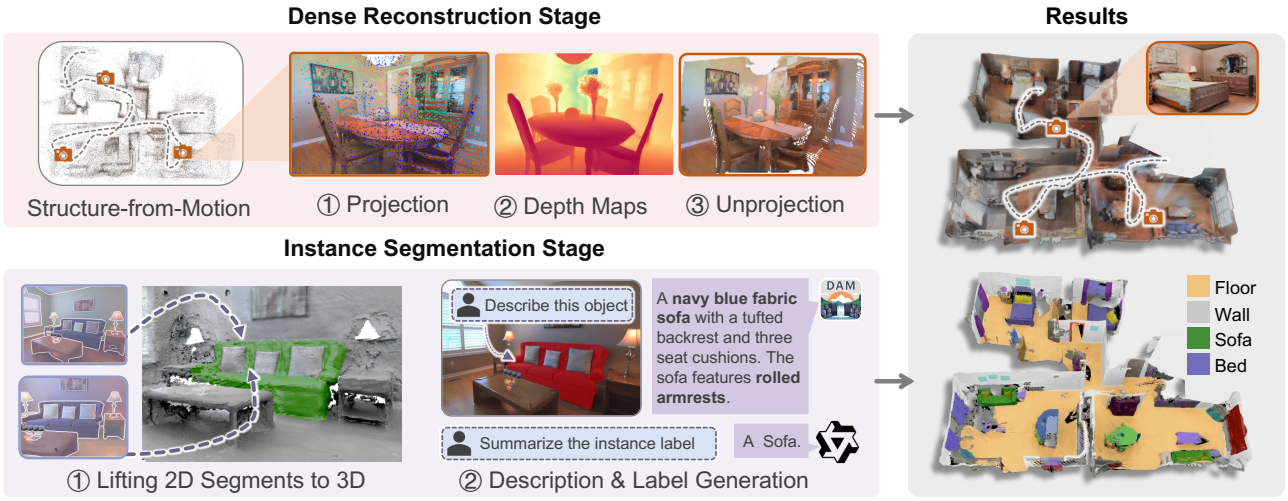


Figure 3. **Overview of data generation.** The pipeline leverages a modular design for automatic 3D reconstruction and segmentation.

Dense Reconstruction. Recent advances in 3D reconstruction introduce various approaches with different trade-offs between quality and efficiency. Neural rendering methods [15, 38, 47, 78–80, 116] produce photo-realistic rendering and recover detailed geometry, but they require dense computation for per-scene optimization, especially for large and complex environments. End-to-end reconstruction frameworks [105, 106] enable dense point cloud reconstruction directly from images, providing convenience and speed; however, they struggle with long videos due to memory constraints and often exhibit obvious artifacts in multi-view consistency and geometry distortion.

To balance efficiency and reconstruction quality, we design a reconstruction pipeline based on metric depth estimation that effectively leverages SfM outputs from Sec. 3. Specifically, we project the reconstructed sparse 3D points onto the image plane to obtain sparse depth maps, which serve as priors for PriorDA [109] to predict dense metric depth maps. The predicted depths are then fused using a Truncated Signed Distance Function (TSDF) representation to produce watertight 3D meshes. During fusion, unreliable large depth values are truncated, and radius- and statistical-based filters further remove floating noisy points. This design achieves stable, high-quality reconstructions with reduced computational cost, enabling efficient processing of large-scale internet videos while maintaining sufficient accuracy for downstream tasks. Qualitative results and computation time comparison are shown in Fig. 4.

Instance Segmentation. Recent advances in per-scene 3D segmentation have also explored different paradigms. For example, image-based approaches, such as the SAM series [55, 88], effectively identify 2D object masks across frames, but do not explicitly leverage 3D spatial information. When applied to long video sequences, they often produce duplicated instances due to incorrect cross-view associations. In contrast, feature-lifting methods [9, 36, 95] exploit spatial correspondences across multiple views through rendering [52, 76], but their performance is affected by the rendering quality and typically requires substantial computational resources and processing time for long videos.

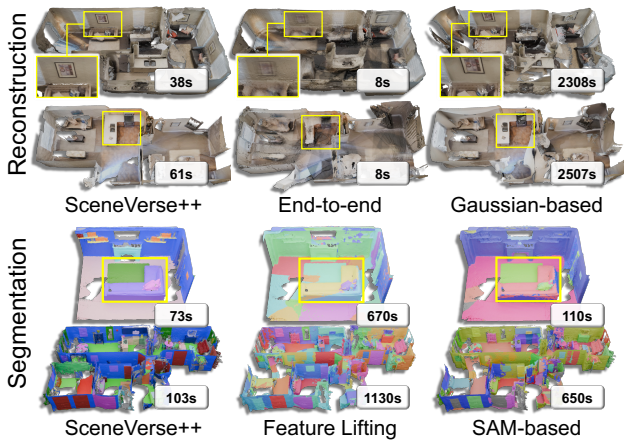


Figure 4. **Reconstruction and segmentation comparison**, where SceneVerse++ features a balance in quality and efficiency.

To overcome these challenges, we choose to lift 2D masks to 3D using the dense reconstruction results. Specifically, we first apply CropFormer [84] to obtain per-frame segmentation masks, which are then aggregated in 3D space based on neighboring-frame view consensus [111] and spatial agreement. Finally, we employ Describe Anything [62] and Qwen2-VL [7] to automatically generate textual descriptions for each 3D instance and align their semantic labels to the ScanNet category set. The segmentation comparison is shown in Fig. 4.

Statistics In practice, the average runtime for each scene is 71 seconds for dense reconstruction and 96 seconds for segmentation. On average, each scene in SceneVerse++ has 49 objects across 21 distinct categories, both surpassing existing datasets as shown in Fig. 2. This reflects the greater diversity of object types and richer scene compositions in our data. In addition, the object size distribution in SceneVerse++ closely aligns with that of real-world datasets, indicating that our reconstructed scenes preserve realistic scale and spatial relationships.

Performance We validate the effectiveness of our dataset on 3D object detection with SpatialLM [74] and 3D instance segmentation with Mask3D [92]. The quantitative results are summarized in Tab. 2.

- SpatialLM, derived from a Multimodal Large Language Model (MLLM), generates structured 3D scene descriptions for object detection and is originally trained on a synthetic dataset of over 12,000 indoor scenes. We adopt the same base model and evaluate on two real-world benchmarks. Without fine-tuning, the model trained on SceneVerse++ achieves slightly better detection on ScanNet and ARKitScenes than training only on synthetic data. When fine-tuned on ScanNet, the model pretrained on SceneVerse++ achieves a substantial improvement, *i.e.*, F1@0.25 of 58.6 *vs*. 38.0; this shows SceneVerse++ better captures real-world distributions and provides a better initialization. Training from scratch on ScanNet fails to converge, as the adapter linking 3D encoder [110] to MLLM requires significant pretraining [48, 74].
- The results on 3D instance segmentation using Mask3D reveal a different trend: the model pretrained solely on SceneVerse++ does not transfer well to ScanNet, but it consistently improves performance across all metrics after finetuning compared with training from scratch. This drop stems from Mask3D's reliance on segment-level masks obtained from a graph-based segmentation [34], which is highly sensitive to sensor and reconstruction pipelines. This highlights a key factor in model scaling - their susceptibility to domain-specific bias.

More details, additional experiments and ablations, and further discussions are provided in *supplementary*.

4.2. 3D Spatial VQA

Task and Benchmark Visual-spatial intelligence [113] requires the combination of visual perception, linguistic understanding, temporal reasoning, and spatial reasoning [37, 42]. Despite being a critical capability for future embodied agents to explore and perform tasks in the 3D world, it remains a challenging frontier for current VLMs. To investigate how SceneVerse++ can improve the spatial reasoning ability of VLM, we focus on 3D spatial Visual Question Answering (VQA), which requires a model to answer questions about 3D space by inferring spatial relations from 2D visual input. We evaluate on VSI-Bench [113], a 3D spatial understanding benchmark constructed from egocentric videos in ScanNet, ScanNet++, and ARKitScenes. It contains over 5,000 question-answering (QA) pairs spanning eight task types, presented as Multiple-Choice Answers (MCA) or Numerical Answers (NA). MCA performance is measured by mean accuracy, while NA performance is calculated using relative accuracy across multiple confidence thresholds.

Table 1. **Testing SpatialLM on 3D object detection.** Performance is reported under different pretraining and finetuning configurations with the same model architecture.

Benchmark	Pretrain	Finetune	F1@.25	F1@0.5
ARKitScenes	SpatialLM	-	35.1	21.2
	SceneVerse++	-	35.8	20.7
ScanNet	-	ScanNet	2.9	0.7
	SpatialLM	-	29.0	19.7
	SceneVerse++	-	30.9	21.3
	SpatialLM	ScanNet	38.0	28.7
	SceneVerse++	ScanNet	**58.6**	**45.4**

Table 2. **Testing Mask3D on 3D instance segmentation**. It presents reliance on data-specific bias that hurts model scaling.

Benchmark	Pretrain	Finetune	AP_{25}	AP_{50}	AP
ScanNet	-	ScanNet	36.1	31.8	22.8
	SceneVerse++	-	15.4	13.0	8.3
	SceneVerse++	ScanNet	**38.5**	**32.9**	**23.6**

Data Generation We generate general spatial QAs by transferring the geometry and semantic information in 3D scenes (Sec. 4.1) to 3D scene graphs [4, 49, 102], following VLM-3R [33]. Each node in the scene graph represents a distinct 3D object instance, and edges represent pairwise spatial relations. Leveraging these structured semantics, QA pairs are automatically generated for *Object Counting, Relative Distance, Relative Direction, Object Size, Absolute Distance*, and *Room Size* by designing task-specific templates [33]. For the *Route Planning* task, we generate QA pairs by employing a VLM [7] to summarize the navigation trajectories within 3D environments (introduced in Sec. 4.3). The summary is then transformed into fill-in-the-blank Multiple-Choice questions by masking specific actions. The *Appearance Order* task is not included following the setting of VLM3R.

Statistics Applying the automatic generation pipeline to the reconstructed scenes in SceneVerse++ yields 632K spatial VQA data following the VSI-Bench format. It comprises 391K samples for MCA and 241K samples for NA, respectively. More details on data generation and question type distribution are in *supplementary*.

Table 3. **Evaluation results on VSI-Bench.** Performance is reported on both the full set and ARKitScenes subset: 1) zero-shot test (-); 2) trained on SceneVerse++ (SV++); 3) trained on VLM-3R data from ScanNet and ScanNet++ (SN, SN++); and 4) trained on the combination of 2) and 3) (All). The figures of "SN, SN++" and "All" on the full set indicate in-domain (ID) results, while others are out-of-domain (OOD) results. SceneVerse++ is more effective in improving general spatial knowledge but less in domain-specific knowledge.

Model	Dataset Source	VSI-Bench Fullset$_{SN, SN++, ARKit}$ App. Ord.	Abs. Dist.	Obj. Cnt.	Rel. Dist.	Obj. Size	Room Size	Route Plan	Rel. Dir.	Avg.	Subset$_{ARKit}$ Avg.
Qwen2.5 -VL-3B	-	27.3	17.4	25.2	37.2	16.5	26.2	28.4	45.4	27.9	28.1
	SV++	26.1	30.2	61.8	49.3	49.8	43.9	33.6	47.8	42.8	48.0
	SN, SN++	32.4	39.6	67.4	48.9	64.0	53.8	38.7	44.9	48.7	49.0
	All	27.2	39.3	67.5	50.3	63.5	54.0	36.6	55.8	49.3	51.3
Qwen2.5 -VL-7B	-	34.5	21.0	41.5	38.6	50.5	36.7	29.4	41.0	36.6	39.4
	SV++	43.4	28.9	63.8	48.9	57.0	46.4	35.1	48.0	46.4	49.1
	SN, SN++	37.7	38.8	68.3	52.8	64.8	53.0	37.1	47.3	50.0	48.8
	All	29.8	38.3	67.1	51.7	65.8	53.5	41.2	57.3	50.7	50.5

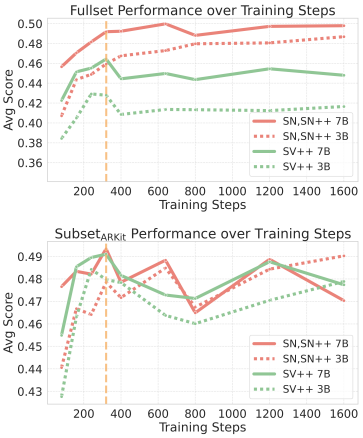


Figure 5. **Training dynamics.**

Performance We evaluate the performance of Qwen2.5-VL after LoRA fine-tuning [46] on VSI-Bench, which spans ScanNet (SN), ScanNet++ (SN++), and ARKitScenes (ARKit). Given the domain discrepancy between datasets, we regard training and testing on SN and SN++ as in-domain (ID), and out-of-domain (OOD) otherwise. For fairness, we sample 202K data from SceneVerse++ for training, comparable with 206K samples on SN and SN++ from VLM3R [33]. We report quantitative results in Tab. 3 and key observations as follows:

- **Spatial reasoning enhancement.** SceneVerse++ can improve the spatial reasoning capability of the base VLMs, yielding +14.9 for the 3B model and +9.8 for 7B on VSI-Bench full set. This highlights SceneVerse++ as a reliable and promising data source for advancing existing VLMs.
- **Domain generalization.** We observe comparable performance between SceneVerse++ and SN/SN++ on the VSI-Bench ARKit subset, indicating their comparable domain generalizability, despite that SN and SN++ have groundtruth annotations. This contrasts with the performance gap observed on the VSI-Bench full set, reflecting a larger-than-expected domain gap across datasets. Training on all data sources (All) further improves performance on both the full set and ARKit subset, showing the benefit of a broader domain covered in SceneVerse++.
- **Category-wise difference.** Per-category analysis reveals that SceneVerse++ delivers greater improvement on categories concerning *general spatial knowledge* such as *Relative Distance* and *Relative Direction*, which are less susceptible to domain-specific distribution. In contrast, it exhibits worse results on categories highly relying on *domain-specific knowledge* such as *Object Count* and *Room Size*, likely due to variations in object and scene distributions, as illustrated in Fig. 2.
- **Training dynamics.** We visualize the evolution of evaluation results within one training epoch in Fig. 5. A distinct turning point (green dashed line) emerges: model performance consistently improves before this point, after which in-domain training (SN, SN++ curves on full set) continues to rise while others plateau or decline. This provides further evidence of domain gap and overfitting to *domain-specific knowledge*, aligning with findings from concurrent works [11, 12].

4.3. 3D Vision-Lanugage Navigation (VLN)

Task and Benchmark The goal of VLN is to enable embodied agents to follow natural language instructions and navigate toward specified goals within 3D environments. Room-tour videos from the internet provide a valuable proxy for natural human navigation in real indoor spaces. Unlike prior work [23, 63], we focus on the key factors to provide rich, continuous trajectories that can bridge the gap between model navigation and real-world embodied behaviour. We adopt the widely used Room-to-Room (R2R) benchmark [3] built on Matterport3D [13] environments, where an agent receives a sequence of rendered egocentric observations and a goal-directed instruction as input, and outputs a sequence of discrete navigation actions. The action space consists of fixed translation and rotation steps, where movements are discretized into three distance bins of [25, 50, 75] cm and rotations into [15°, 30°, 45°].

Data Generation R2R establishes a controlled and standardized setting for instruction-following navigation, but its simulated trajectories differ from how humans naturally explore real environments. Specifically, VLN trajectories are goal-directed shortest paths with all forward-facing movements, whereas room-tour videos capture free-form exploration in the environment, often exhibiting *irregular camera motion*, *redundancy*, and *backtracking*, shown in Fig. 7. These discrepancies introduce challenges in deriving navigation-consistent trajectories from room-tour videos for VLN model learning. To bridge this gap, we analyze human motion patterns in real videos and design a three-stage pipeline to convert room-tour camera trajectories to navigation trajectories as in Fig. 6.

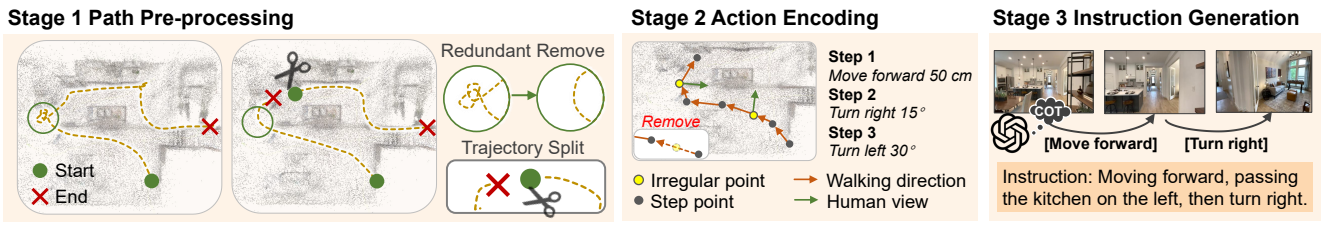


Figure 6. **Overview of the VLN data generation pipeline.** We construct VLN data from room-tour videos by (i) preprocessing trajectories to eliminate redundant local rotations and segmenting long paths into sub-paths suitable for instruction generation; (ii) converting camera transitions within each sub-path into R2R-style navigation actions; and (iii) generating instructions for each sub-path using VLMs.

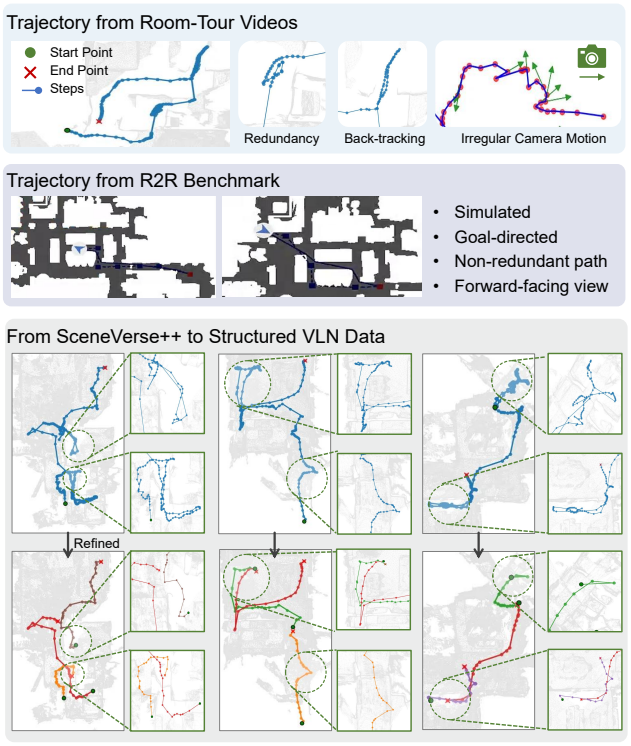


Figure 7. **Trajectory comparison.** Top: Room-tour videos show irregular and redundant camera motions. Middle: R2R trajectories are smooth and goal-directed. Bottom: raw videos are converted into VLN-compatible data. Different colors indicate sub-paths.

Path Pre-processing. The goal of this stage is to extract clean and coherent trajectories from room-tour videos using the SfM reconstructions described in Sec. 3. We first cluster camera positions within a 0.5m radius to merge nearby viewpoints, keeping one representative node per cluster to maintain trajectory continuity and remove redundant local rotations. Next, to eliminate backtracking, we split long trajectories into sub-paths. Specifically, we detect cluster centers along each trajectory and use them as potential break points—only when the two adjacent segments separated by a center exceed 15 steps do we perform a split. Finally, we filter out steps that involve rotations greater than 90° or translations larger than 70cm. The resulting trajectories are shown at the bottom of Fig. 7.

Action Encoding. Action encoding converts each structured trajectory into a sequence of discrete actions for VLN model training. We extract each node's 3D camera pose $(\mathbf{R}_i, \mathbf{t}_i)$ from the SfM reconstruction, project it onto the ground plane, and represent it as $p_i = [x_i, y_i, \theta_i]$, where (x_i, y_i) denotes the position and θ_i is the yaw angle derived from $\mathbf{R}_i$. As room-tour videos often contain irregular camera motions, we remove non-navigational "looking around motions" by removing actions whose viewing direction deviates from walking direction. Finally, the movement action is defined by the Euclidean distance between p_i and p_{i+1}, and rotation action by $\Delta\theta_i = \theta_{i+1} - \theta_i$. Both are discretized following the R2R convention for compatibility with existing VLN benchmarks.

Instruction Generation. We leverage VLM to generate natural language navigation instructions aligned with both motion and visual context, by providing both the corresponding images and encoded actions. The VLM first reasons about local motion changes using Chain-of-Thought (CoT) and then composes coherent instructions to describe the entire trajectory. To enhance linguistic diversity and improve generalization, we generate three stylistically varied instructions for each trajectory.

Statistics The VLN data derived from SceneVerse++ contains 9,631 trajectories, each averaging 12.8 meters in length and 15 steps. For each trajectory, we provide three instructions in formal, conversational, and narrative styles, averaging 42, 47, and 57 words, respectively. After discrete action encoding, forward and rotational movements account for 52% and 48%, reflecting a balanced motion distribution. R2R comprises 7,189 trajectories and 21,567 instructions averaging 29 words, collected from 29 simulated indoor scenes. Our dataset extends these benchmarks by incorporating richer linguistic diversity and natural, real-world motion patterns captured from internet videos.

Performance We validate the effectiveness of our constructed VLN dataset using LLaVA-Video [120] as the base model. All experiments are evaluated on the validation set

Table 4. **VLN evaluation under different training settings**. TR denotes trajectory refinement, and IE for instruction enrichment.

Pretrain	Finetune	SR↑	OS↑	SPL↑	Dist↓	PL
-	R2R	0.088	0.133	0.076	8.031	5.222
R2R + SceneVerse++	-	0.188	0.262	0.150	8.117	10.496
SceneVerse++	–	0.107	0.194	0.074	9.418	14.097
SceneVerse++	R2R	**0.228**	**0.315**	**0.191**	**7.65**	11.642
SceneVerse++ (w/o IE)	–	0.022	0.043	0.016	8.978	2.333
SceneVerse++ (w/o IE)	R2R	0.074	0.111	0.062	8.175	5.009
SceneVerse++ (w/o TR)	–	0.036	0.045	0.032	8.662	2.521
SceneVerse++ (w/o TR)	R2R	0.177	0.298	0.130	8.23	11.949

of R2R [3]. To ensure a fair comparison, we use the same number of training epochs across all experiments. Evaluation follows standard VLN metrics, including *Distance to Goal* (Dist.), *Success Rate* (SR), *Oracle Success* (OS), *Success-weighted Path Length* (SPL) and *Path Length* (PL).

- **Domain Transfer and Training Strategies.** We investigate how incorporating real-world video data affects VLN performance on R2R. As shown in Tab. 4, training on SceneVerse++ yields a modest SR improvement (0.107 *vs*. 0.088) under zero-shot evaluation compared with training on R2R alone. The substantially longer path length (14.1 *vs*. 5.2) reflects that the richer and more complex trajectories in room-tour videos offer more diverse and challenging experiences to learn navigation behaviors, compared with the shortest paths in R2R. Further fine-tuning on R2R significantly boosts SR to 0.228, demonstrating that large-scale video pretraining provides valuable visual and linguistic priors for navigation tasks. In contrast, directly mixing SceneVerse++ with R2R during training yields weaker results, suggesting that the visual gap between real videos and simulator-rendered scenes makes naive mix-training less effective.
- **Data Quality.** To further investigate the impact of data quality on VLN performance, we conduct ablation experiments on two core components in data generation: trajectory refinement (TR) and instruction enrichment (IE). As shown in Tab. 4, removing either component results in a clear performance drop. Even after fine-tuning on R2R, models pretrained on these ablated datasets fail to fully recover, *e.g*., SR decreases from 0.228 to 0.177 when TR is removed. These results demonstrate that raw internet videos alone are insufficient for effective VLN training; task-specific data processing is essential. We additionally include comparisons with YouTube-based VLN data from NaVILA [23] in *supplementary*, where SceneVerse++ enables stronger model performance due to higher quality.

5. Discussion and Conclusion

In this paper, we investigate pathways to advance comprehensive 3D scene understanding across multiple tasks by leveraging unlabeled internet videos. We develop automated data engines to generate training data and demonstrate that high-quality data can benefit downstream tasks. We further offer the following discussions on data generation, benchmarks, and model scaling. Limitations and future work are discussed in *supplementary*.

Scaling capability of models. In our experiments, we observe clear differences in how models scale. Models that depend on task-specific, pre-computed segments are more sensitive to data distribution shifts and hyperparameter changes, resulting in limited scalability and weaker generalization in 3D instance segmentation (Sec. 4.1). In contrast, models that operate directly on raw and widely available modalities, *e.g*., 3D voxels or RGB-based MLLMs, exhibit more robust scaling behavior. This contrast is less evident in two-dimensional settings due to the uniformity of image inputs, but becomes increasingly pronounced when scaling 3D understanding.

Fair evaluation of capability and benchmarks. Existing benchmarks may not fully reflect a model's true capability, *e.g*., VSI-Bench exhibits strong QA distribution bias [11] and VLMs overfit to data-specific cues for in-domain evaluation (Sec. 4.2). To ensure fair assessment, future evaluation should emphasize zero-shot testing on existing benchmarks, avoiding data contamination and minimizing data distribution gap, or more benchmarks that accurately measure 3D scene understanding and generalization in the wild.

Understanding data and task-specific biases. Effective data scaling requires not only high-quality data, but also a careful examination of data distribution and task-specific or benchmark-specific characteristics. Performance is strongly affected by factors that remain hidden without deeper analysis, *e.g*., the discrepancy between natural camera motion in real-world videos and goal-directed navigation trajectories (Sec. 4.3). Identifying such mismatches is essential to avoid biases and to ensure that scaled data provides meaningful improvements for the intended task.

Advancing automated data generation. Building an automated data generation pipeline reveals significant challenges in using existing models to produce high-quality data for 3D scene understanding from in-the-wild videos. Modules such as SfM, instance segmentation, and language grounding are typically trained on task-specific or small-scale benchmarks, limiting their generalization capabilities and introducing sequential errors when combined together for in-the-wild spatial understanding. As a result, substantial effort is required for careful model selection and non-trivial coordination across modules. We advocate that future development of these sub-modules should align with the broader goal of enabling robust in-the-wild 3D understanding, with evaluation based not only on task-specific performance but also on their contribution to reliable automated data generation pipelines.

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