

RoboTidy : A 3D Gaussian Splatting Household Tidying Benchmark for Embodied Navigation and Action

Xiaoquan Sun^{1*} Ruijian Zhang^{1*} Kang Pang¹ Bingchen Miao⁴ Yuxiang Tan¹
 Zhen Yang² Ming Li⁵ Jiayu Chen^{2,3†}

¹Huazhong University of Science and Technology ²The University of Hong Kong

³INFIFORCE Intelligent Technology Co., Ltd. ⁴Zhejiang University ⁵Guangming Lab, Shenzhen

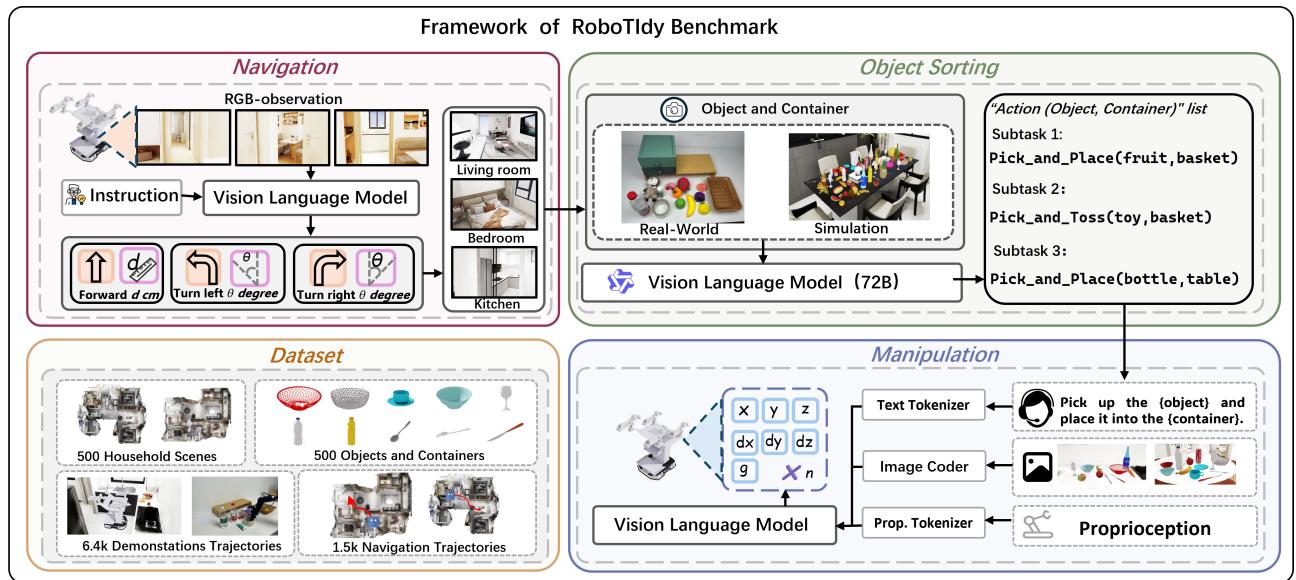


Figure 1. **Overview of RoboTidy Benchmark framework and dataset.** It spans Navigation, Object Sorting, and Manipulation: Qwen2.5-VL parses observations into an "Action (Object, Container)" list executed as manipulation actions. Our dataset offers 500 3DGS household scenes, 500 objects and containers, 6.4k manipulation trajectories and 1.5k navigation trajectories for sim2real evaluation.

Abstract

Household tidying is an important application area, yet current benchmarks neither model user preferences nor support mobility, and they generalize poorly, making it hard to comprehensively assess integrated language-to-action capabilities. To address this, we propose RoboTidy, a unified benchmark for language-guided household tidying that supports Vision-Language-Action (VLA) and Vision-Language-Navigation (VLN) training and evaluation. RoboTidy provides 500 photorealistic 3D Gaussian Splatting (3DGS) household scenes (covering 500 objects and containers) with collisions, formulates tidying as an "Action (Object,

Container)" list, and supplies 6.4k high-quality manipulation demonstration trajectories and 1.5k naviagtion trajectories to support both few-shot and large-scale training. We also deploy RoboTidy in the real world for object tidying, establishing an end-to-end benchmark for household tidying. RoboTidy offers a scalable platform and bridges a key gap in embodied AI by enabling holistic and realistic evaluation of language-guided robots.

1. Introduction

In recent years, household tidying has emerged as a prominent research avenue within indoor embodied intelligence. Fueled by rapid advances in Multimodal Large Language

¹Xiaoquan Sun and Ruijian Zhang contributed equally to this work.

²Corresponding author: Jiayu Chen, jiayuc@hku.hk

Models (MLLMs) and substantial gains in the capabilities of Vision-Language-Navigation (VLN) [7, 18, 46] and Vision-Language-Action (VLA) [2, 14, 47], an increasing number of studies now deploy and evaluate these models in real world environments to accomplish language-to-action tidying tasks in household scenes.

In household tidying, the key task is to place every object into a suitable container. Traditional methods [32, 44] often require users to explicitly specify a target container for every object, a process that is cumbersome and computationally inefficient. Alternatively, they learn non-personalized “typical placement” rules by averaging across users, thereby ignoring individual differences [42, 43]. TidyBot [40] infers from few-shot user preferences; it works in specific scenes but lacks robustness and generalization. To move beyond such per-user heuristics toward deployable policies, VLN and VLA models must be trained in environments with realistic visuals and physics.

However, collecting data in real-world environments for training VLA and VLN is costly and often of limited quality, prompting widespread adoption of the sim-to-real paradigm to obtain large-scale, high-quality datasets. To better bridge the sim-to-real gap, household scene representations have progressed from RGB-D-based scanned meshes such as Matterport3D [3] and HM3D [31] to 3D Gaussian Splatting (3DGS) [17], which offers superior photorealism and cross-view consistency, thereby providing more stable visual conditions for policy learning in VLN and VLA.

We introduce RoboTidy, a unified benchmark for language-guided tidying that jointly supports VLA and VLN. We formalize tidying as an *“Action (Object, Container)” list* with four manipulation actions and realize closed-loop execution in a physically realistic, photorealistic simulator; across-room navigation and multi-modal sensing are integrated for training and evaluation. On the data side, based on InteriorGS [36], we build 500 3DGS household scenes with convex-decomposed collision meshes and provide 6k manipulation demonstrations, 400 real world manipulation demonstrations and 1.5k navigation trajectories with language instructions.

Our experiments cover representative baselines for VLA and VLN. We observe that the VLN success rate on RoboTidy is markedly lower than that on R2R (Val-Unseen) [18], underscoring the increased difficulty and realism of our benchmark; pretrained VLA models fine-tuned in our framework exhibit improved robustness in unseen scenes and with unseen objects, highlighting the role of diverse data and physics-aware simulation. We further validate sim2real transfer via real world mobile bimanual tidying experiments.

In summary, our key contributions are as follows.

- **Object Sorting.** We create an *“Action (Object, Container)” list*, and use Qwen2.5-VL to automatically infer placement rules from observations and decide the actions.

- **3DGS household scenes.** We provide photorealistic 3DGS household scenes that cover 500 objects and containers. We also release 6.4k manipulation demonstration trajectories and 1.5k navigation trajectories to support training.
- **RoboTidy benchmark.** We evaluate representative VLA and VLN methods on our benchmark to assess generalization, and develop robot tidying in the real world to demonstrate sim2real transfer.

2. Related work

Early household benchmarks [8, 27, 28, 35, 37] typically evaluate object placement and rearrangement by requiring robots to move objects toward the pre-specified target position [10, 16, 39]. However, these methods rely heavily on per-object goal annotations, which make large-scale training and evaluation prohibitively expensive. More recently, TidyBot [40] infers preferences via LLMs from few examples; however, it does not provide a scalable, physically realistic benchmark and shows limited robustness across varied environments.

Recent embodied AI benchmarks have explored household tasks from different perspectives, including semantic planning [27, 28, 35], multi-task manipulation [4, 5, 11, 12], and large-scale activity suites [20, 29]. However, these platforms mostly target generic task execution, offering neither a unified focus on tidying organization nor a joint evaluation of high-level reasoning and low-level, feedback-driven control under photorealistic, physically realistic conditions.

Our **RoboTidy** benchmark targets household tidying by combining photorealistic 3DGS household scenes with Isaac Sim 5.0 [26]. It unifies manipulation and navigation through an *“Action (Object, Container)” list* and navigation trajectories, supporting both VLA [2, 14, 47] and VLN [7, 18, 46]. RoboTidy enables modular and feedback-aware evaluation with built-in trajectory logging and photorealistic execution.

3. Method

3.1. Overview

We formulate our problem as performing structured organization of objects in household scenes, automatically generating an *“Action (Object, Container)” list*, executing cross-room tidying, and continuously logging data that supports VLA and VLN training and evaluation. In this paper, we present RoboTidy, a unified benchmark for language-guided tidying that jointly supports VLA and VLN for household scenes. Methodologically, we build a modular framework in NVIDIA Isaac Sim [26] with physical and photorealistic simulation: the system takes multi-view ob-

Table 1. Comparison of various frameworks and benchmarks. ✓ indicates presence; ✗ indicates absence; “–” indicates not reported.

Feature	RoboTidy	tidybot [40]	Habitat 2.0 [37]	arnold [11]	RLBench [15]	Behavior-1K [20]	Teach [27]	ManiSkill 2 [12]	LIBERO [21]	CALVIN [24]
Manipulation	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓
Navigation	✓	✓	✓	✗	✗	✓	✓	✓	✗	✗
Household Scenes	✓	✓	✓	✗	✗	✓	✓	✗	✗	✗
Realistic Object Physics	✓	✗	✗	✓	✓	✓	✓	✗	✓	✗
Photorealism	✓	✓	✓	✗	✗	✓	✗	✓	✓	✗
Num Scenes	500	96	1	15	1	50	3	–	20	1

servations as input, uses Qwen2.5-VL [1] to extract category and attribute semantics of objects and containers, and for newly encountered items directly selects a target container and one of four manipulation actions (*Pick and Place*, *Pick and Toss*, *Open the Container*, *Close the Container*).

Our benchmark, RoboTidy, consists of four key modules detailed in the following sections: a) Tidying module that places objects into target containers according to the induced rules and updates the list; b) Manipulation action module that employs an inverse kinematics (IK) controller to generate feasible trajectories, executes the action, and logs vision-action data for VLA training and evaluation; c) Navigation module that performs path planning and across-room navigation while recording navigation trajectories to support VLN training and evaluation.; d) Sensor module that supports multimodal RGB-D and LiDAR sensing and handles data collection in simulation.

3.2. Object Sorting

We propose a preference tidying method that does not require additional input. At first the system passively scans the containers on the current workspace and their contents to obtain the existing “Object → Container”. Leveraging a Vision Language Model (VLM), it extracts object semantics and attributes, and automatically converts these observations into a parsable, code-style prompt. On this basis, an LLM abstracts the observed object → container correspondences into a personalized object sorting “*Action (Object, Container)*” list and for newly observed items that are not yet covered by the induced rules, jointly decides both the target container and the action to execute. We design a minimal set of four manipulation actions:

- *Pick and Place*: Use the gripper to grasp the object at its detected center, move the gripper to a pose just above the selected receptacle, and place the object at the target position.
- *Pick and Toss*: Use the gripper to grasp the object at its detected center, then swing the arm and release the grip-

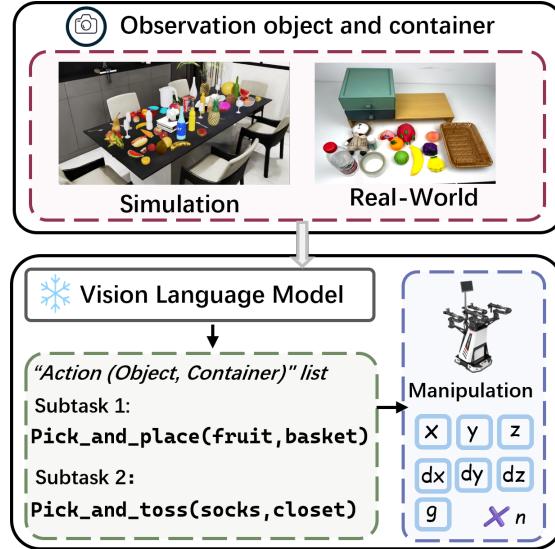


Figure 2. **Object Sorting Pipeline.** From workspace observations, Qwen2.5-VL [1] identifies objects and containers and produces an *Action (Object, Container)* list, which the system executes manipulation actions to complete sorting.

per with appropriate timing to toss the grasped object into the selected receptacle [45].

- *Open the Container*: Switch the container (e.g., drawer / cabinet) from closed to open.
- *Close the Container*: Switch the container(e.g., drawer / cabinet) from open to closed.

To account for diverse household tidying preferences, we annotate for each object the set of acceptable containers and, when multiple options exist, a priority order specifying the primary container and its equivalents, using the following criteria:

- **Attribute:** Sort objects by observable attributes such as material or size (e.g., put plastic objects in one container and metal ones in a different container).
- **Function:** Sort objects by purpose or usage context (e.g., put clothes here and socks there).
- **Safety:** Sort objects by safety risk and fragility (e.g., keep sharp tools in a closed container).
- **Hygiene:** Sort objects by cleanliness and contamination risk (e.g., put waste into a trash bin and place clean clothes in a wardrobe).

When multiple criteria are applied, the primary container is chosen according to the preset priority and the remaining options are included in the correct set as equivalent containers. All annotations are frozen before evaluation.

3.3. Navigation Module

The navigation module comprises a path planner and a low-level controller. During data generation, we run the A* planner [13] on the InteriorGS [36] 2D semantic map to

plan reference paths, time-parameterize and discretize them into waypoints; a PID controller tracks the trajectory using the robot’s real time pose, outputs velocity commands, and logs full navigation trajectories for VLN training and evaluation. During VLM evaluation, no map is supplied camera images and language instructions form a multimodal input that drives the VLM to directly predict velocity commands for navigation. For low-level control, a Proximal Policy Optimization (PPO) [34] policy converts velocity commands into joint-level motor actions to drive the robot.

3.4. Manipulation Module

We use an inverse kinematics (IK) solver together with a motion planner to plan and execute trajectories for the manipulation actions, and we collect demonstration trajectories for VLA training and evaluation. Given an object’s 6D pose and the position of the target container, the system automatically generates the pre-grasp, grasp, pre-place, and place; the IK solver proposes candidate joint waypoints, and the motion planner computes collision-free trajectories under joint limits, velocity, acceleration, and environment collision constraints. The gripper employs a closed-loop width-threshold criterion to determine grasp and release. We synchronously log multi-view RGB images, joint configurations and gripper states, along with the corresponding action-primitive labels, producing trajectories directly usable for VLA training and evaluation.

3.5. Sensors Module

Our benchmark supports multimodal data collection using RGB-D cameras and LiDAR scanning. In the simulation environment, new sensors are integrated by mounting them on the robot or within the scene, configuring their parameters, and referencing their prim paths in the main configuration. In the real-world environment, the number of cameras and LiDAR units is constrained by compute resources, I/O throughput, and interface bandwidth.

3.6. Metrics

Object Placement Accuracy (OPA). We treat placement as the selection from a scene’s closed set of candidate containers. For a scene s and the set of all scenes S , the per scene OPA(s) and overall OPA are:

$$\text{OPA}(s) = \frac{C(s)}{N(s)}, \quad \text{OPA} = \frac{1}{|S|} \sum_{s \in S} \text{OPA}(s).$$

Valid Sorting Success Rate (VSSR). An object counts as a success if its predicted container is valid (same rule as OPA) and its required actions finish successfully.

For a scene s , let $v_j(s) \in \{0, 1\}$ indicate success for

object j . Each scene VSSR(s) and the overall VSSR are:

$$\text{VSSR}(s) = \frac{1}{N(s)} \sum_{j=1}^{N(s)} v_j(s), \quad \text{VSSR} = \frac{1}{|S|} \sum_{s \in S} \text{VSSR}(s).$$

where s denotes a household scene, S denotes the set of all household scenes, $N(s)$ denotes the total number of objects in s , and $C(s)$ denotes the number of objects whose predicted container is judged correct. Predictions that fail to parse as a valid container, or that are not in the scene’s candidate container set, are counted as incorrect. For **VSSR**, $v_j(s) = 1$ iff $c_j(s) = 1$ and $d_j(s) = 1$; $c_j(s) = 1$ denotes a valid container prediction (predictions outside the candidate set count as 0), and $d_j(s) = 1$ denotes completion of the required manipulation actions (failures or aborts count as 0).

4. Experiment

4.1. Benchmark Dataset

3DGs household scenes. Building on InteriorGS [36], We construct 500 household scenes across *living room*, *bedroom*, and *kitchen*. Although 3DGs assets are appearance-only, each scene is authored as a 3DGs–mesh hybrid [25]: 3DGs (USDZ via 3DGUT [41]) remains visible for high-fidelity rendering, and artist-created triangle meshes are convex-decomposed with CoACD [38] to produce per-object collision bodies. We assemble USDA scenes with these collision shapes authored as invisible rigid bodies, enabling accurate contact and dynamics in Isaac Sim 5.0 [26].

Object Assets. We create an extensive collection of 3D assets for daily items to meet diverse scene construction needs. This collection covers categories such as fruits, beverages, containers, tableware and decorations. These assets are sourced from online 3D model repositories Sketchfab and TurboSquid, and have undergone standardized format processing. Our screening process involves removing low-precision models and those with appearance defects to ensure the high-quality presentation of the assets.

Demonstration Trajectories. We collected demonstration trajectories for four manipulation actions. For each action, data were gathered in two household scenes, covering five object–container categories and three rooms (*kitchen*, *bedroom*, *living room*). For every ”category–scene–room” combination, we recorded 100 demonstration trajectories, yielding 6k manipulation trajectories in total. For navigation, we fuse an occupancy grid with a 2D semantic map to construct a navigation map that is both traversability-aware and semantically grounded, and run an A*-based planner [13] to generate paths. Across 500 household scenes, we instantiate one trajectory for each pair among the three rooms, resulting in 1.5k navigation trajectories.

Language Instructions. We employ template-based commands for four manipulation actions with slots for the ob-

ject and container; controlled lexical variants increase diversity while preserving semantics (e.g., “*pick up the [object] and place into the [container]*”, “*pick up the [object] and toss into [container]*”). For navigation, For navigation, we adopt a hierarchical method [25]. High-level instructions align with realistic intents and are landmark-grounded via relative spatial relations; low-level instructions comprise basic actions (e.g., *move forward*, *turn left or right*); for each path, an LLM produces one high-level instruction and an associated sequence of low-level action steps as the final instruction.

4.2. Baselines

We benchmark across three task types: object sorting, manipulation, and navigation. For the object sorting task, we test RoBERTa [22], CLIP [30], and TidyBot [40]. For the manipulation task, we adopt ACT [47], RDT [2], and $\pi_{0.5}$ [14]. For the navigation task, we adopt VLN-CE [18], NaVid [46] and NaVILA [7].

Object Sorting Baseline.

- **RoBERTa** [22]: A Sentence-BERT [33] name embeddings map each unseen object to the receptacle of its cosine-nearest seen neighbor.
- **CLIP** [30]: A CLIP-based name-embedding method that embeds object names with CLIP’s text encoder and maps each unseen object to the receptacle of its nearest seen neighbor in the shared semantic space using cosine similarity.
- **TidyBot** [40]: A few-shot preference–summarization approach that uses an LLM to infer user-specific rules from textual examples and grounds the summarized categories with open-vocabulary image classification.

Manipulation Baseline.

- **ACT** [47]: A CVAE-based imitation learner that chunks actions to predict future action sequences and uses temporal ensembling for smooth, stable execution.
- **RDT** [2]: A diffusion-augmented transformer [2] for bi-manual manipulation that unifies the action space and fuses multimodal inputs, enabling data-efficient few-shot learning across diverse tasks.
- $\pi_{0.5}$ [14]: A scalable VLA policy with semantic planning and flow-matching control for open-world long-horizon mobile manipulation in unseen homes.

Navigation Baseline.

- **VLN-CE** [18]: An instruction-guided navigation benchmark in continuous, photo-realistic 3D environments with crowdsourced language and unconstrained agent control.
- **NaVid** [46]: A video-based large VLM that maps on-the-fly monocular RGB streams to next-step actions without maps/odometry/depth, encoding spatio-temporal history for instruction following.
- **NaVILA** [7]: A two-level framework that couples VLA planning with locomotion skills for navigation—issuing

high-level language commands while a real-time locomotion policy handles obstacle avoidance.

4.3. Object Sorting Task

Setting details. Each scene contains a set of objects and 2–5 containers. We evaluate two object sorting settings: Zero-Shot (**ZS**), in which the model receives only scene observations without examples and must predict the target container for unseen objects, and Few-Shot (**FS**), in which the same scene is augmented with the seen examples (two per container, 4–10 per scene) to induce preferences and predict the remaining unseen objects. We use Qwen2.5-VL-72B [1] as Vision Language Model backbone.

Evaluation results. Table 2 shows that our method achieves state-of-the-art performance under both **ZS** and **FS** settings, significantly outperforming all baselines [22, 30, 40]. This stems from our use of a powerful VLM [1], which abstracts object sorting rules through multimodal understanding even without demonstrations, it accurately predicts containers for unseen objects. In contrast, RoBERTa [22] and CLIP [30] rely on single modal features and struggle to model the semantic-perceptual relationships in the scene, while TidyBot [40], though effective in specific scene, lacks robustness in complex environments. As shown in Table 4, we compare Qwen2.5-VL [1] with different parameter sizes and find that while the **OPA** metric improves with increasing model size, the improvement is not linear.

4.4. Manipulation Task

Setting details. To assess the utility and generalization challenge of the RoboTidy benchmark, we compare three policies: ACT [47], RDT [2], and $\pi_{0.5}$ [14]. All VLA methods are fine-tuned per primitive starting from their released pretrained weights. Experiments are conducted on four manipulation tasks using an aloha-agilex robot. For each task, we train on 100 demonstration trajectories and evaluate on unseen household scenes, objects and containers to measure robustness to environment. Additionally, under these unseen scenes, objects and containers conditions, we run 100 evaluation trials per action task and report the success rate (%); Object sorting correctness is not assessed; we only measure whether the action task completes successfully.

Evaluation results. Table 5 presents results across four action tasks. Non-pretrained model (ACT [47]) performs poorly on unseen households scenes and objects; in contrast, the pretrained models (RDT [2], $\pi_{0.5}$ [14]) maintain stronger robustness across different household scenes and objects, indicating that VLA pretraining provides effective priors for cross-domain generalization. Under our evaluation setup, $\pi_{0.5}$ [14] achieves the best overall performance. Overall, these findings corroborate that the diverse, background-rich trajectories provided by the RoboTidy Benchmark complement the limited coverage of existing

Table 2. Comparison among different object sorting methods. We report **OPA** (%) for each method under **ZS** and **FS** setting, with mean and standard deviation over 3 random seeds.

Room	RoBERTa [22]		CLIP [30]		TidyBot [40]		RoboTidy (ours)	
	ZS	FS	ZS	FS	ZS	FS	ZS	FS
Livingroom	71.5 \pm 1.2	78.4 \pm 1.7	79.6 \pm 2.6	84.5 \pm 1.9	94.5 \pm 0.7	95.1 \pm 2.4	89.5 \pm 0.6	92.4 \pm 2.0
Kitchen	77.3 \pm 0.7	84.5 \pm 0.9	83.1 \pm 1.8	87.3 \pm 2.0	88.5 \pm 1.6	90.1 \pm 0.9	96.3 \pm 2.8	97.1 \pm 1.4
Bedroom	76.3 \pm 0.9	79.1 \pm 1.6	81.2 \pm 1.3	85.3 \pm 2.5	89.3 \pm 1.7	71.9 \pm 0.6	92.3 \pm 1.2	94.1 \pm 1.3
Average OPA	75.1 \pm 0.7	80.6 \pm 1.2	81.9 \pm 1.8	85.6 \pm 2.1	90.7 \pm 1.4	85.7 \pm 1.8	92.7 \pm 1.9	94.6 \pm 1.7

Table 3. Comparison of VLN methods on the RoboTidy benchmark. We report **SR**, **OSR**, and **SPL** for each method, with mean \pm standard deviation over 3 random seeds.

Metric	CMA [18]	InternVL-2.5-8B [6]	Llama-3.2-11B [9]	NaVid-base [46]	NaVILA-base [7]	Navid-R (ours)	NaVILA-R (ours)
SR	0.09 \pm 0.01	0.08 \pm 0.01	0.12 \pm 0.01	0.11 \pm 0.02	0.22 \pm 0.04	0.16 \pm 0.01	0.26 \pm 0.01
OSR	0.11 \pm 0.01	0.11 \pm 0.02	0.16 \pm 0.03	0.12 \pm 0.00	0.12 \pm 0.00	0.14 \pm 0.01	0.15 \pm 0.02
SPL	0.10 \pm 0.03	0.12 \pm 0.01	0.13 \pm 0.00	0.11 \pm 0.01	0.20 \pm 0.02	0.15 \pm 0.00	0.23 \pm 0.02

Table 4. Comparison among different sizes of Qwen2.5-VL [1] in terms of **OPA** (%) under both **ZS** and **FS** settings. Results are reported as mean \pm standard deviation over 3 random seeds. Here, “B” denotes billions.

VLM Model	params	ZS	FS
Qwen2.5-VL	0.5B	92.6 \pm 1.7	94.9 \pm 3.2
Qwen2.5-VL	7B	93.7 \pm 3.1	95.2 \pm 3.6
Qwen2.5-VL	72B (ours)	94.0 \pm 2.9	95.6 \pm 2.6

Table 5. Comparison among different VLA methods on our RoboTidy benchmark and report the success rate (%) \pm standard deviation over 3 random seeds.

Action Task	ACT [47]	RDT [2]	$\pi_{0.5}$ [14]
Pick and Place	24.2 \pm 1.2	95.1 \pm 2.9	98.0 \pm 0.0
Pick and Toss	6.2 \pm 2.2	73.7 \pm 2.0	85.2 \pm 1.4
Open the Container	14.0 \pm 1.0	83.2 \pm 2.0	93.1 \pm 2.9
Close the Container	21.3 \pm 0.8	85.9 \pm 1.2	96.2 \pm 2.6

household datasets, thereby improving generalization and robustness.

4.5. Navigation Task

Setting details. For each household scene, we consider bidirectional navigation tasks between three rooms (*living room, kitchen* and *bedroom*). The robot is equipped with an onboard, egocentric RGB camera with resolution 640×480 . Each episode is automatically terminated if any of the following occurs: (1) the simulation time reaches 120 seconds; (2) the robot remains stationary beyond a predefined timeout or becomes unstable; (3) the robot reaches the goal region. We fine-tune on 300 household

Table 6. Comparison among different VLN methods on VLN-CE benchmark [18] under **R2R Val-Unseen** setting. Results are reported as **SR**, **OSR** and **SPL**.

Methods	R2R Val-Unseen		
	SR	OSR	SPL
Seq2Seq [19]	0.25	0.37	0.22
InstructNav [23]	0.42	0.29	0.12
Navid-base [46]	0.22	0.32	0.17
NaVILA-base [7]	0.29	0.38	0.27
Navid-R (ours)	0.27	0.34	0.19
NaVILA-R (ours)	0.31	0.41	0.28

scenes (0.9k trajectory–instruction pairs) and evaluate on the remaining scenes. Our experiments consider two backbones: Navid [46] (navid-7b-full-224) and NaVILA [7] (navila-siglip-llama3-8b-v1.5-pretrain). We refer to the pre-trained checkpoints as **Navid-base** and **NaVILA-base**, and to their RoboTidy-finetuned counterparts as **Navid-R** and **NaVILA-R** (“R” denotes RoboTidy). We report navigation metrics: Success Rate (**SR**), Oracle Success Rate (**OSR**), and Success weighted by Path Length (**OSR**).

Evaluation results. As shown in Table 3, we report results for several MLLMs and VLN models on our RoboTidy benchmark. Apart from NaVILA [7], the recent SOTA VLN model, the SR values of the remaining models are all below 0.2. Taking NaVid-base as an example, the model achieves 0.22 SR on VLN-CE [18] R2R Val-Unseen, yet on our benchmark its SR decreases to 0.16. The results demonstrate that the proposed RoboTidy benchmark presents a more challenging setting for current VLN models. Table 6 reports the VLN-CE results of NaVid-R and NaVILA-R

trained exclusively on our datasets. Relative to the baselines, the two models achieve marked improvements in robustness, highlighting the advantages brought by our diverse 3DGS household scenes.

4.6. Sim2Real Transfer Experiment

We investigate a key question: *what extent can robot trained in RoboTidy generalize to the real world?* To evaluate Sim2Real transfer, we conduct two real-world manipulation experiments: **(E1)** under a fixed setting with one object and one container, evaluating four manipulation actions: *Pick and Place*, *Pick and Toss*, *Open the Container* and *Close the Container*; **(E2)** workbench multi-object sorting, performing a household tidying task with 12 objects and 3 containers.

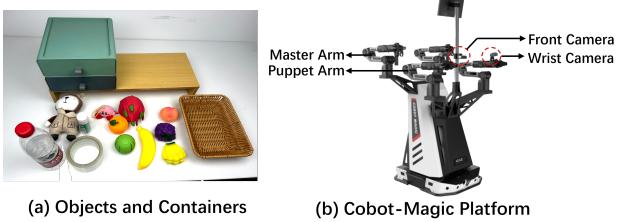


Figure 4. Real-world Experimental setup. (a) Workspace with objects and containers. (b) Cobot-Magic dual-arm mobile manipulation platform.

Setting details. As shown in Figure 4, we set up a real-world testbed using a Cobot-Magic dual-arm mobile platform equipped with four Piper manipulators (two masters and two puppets). The system captures RGB images at 480×640 resolution at 30 Hz. We compare three training settings: (1) 50 real-world demonstrations. (2) a combined set of 50 real-world and 100 RoboTidy synthetic demonstrations (**FS**). (3) 100 RoboTidy synthetic demonstrations only (**ZS**). Both experiments adopt RDT [2] as the VLA policy for manipulation and use Qwen2.5-VL [1] as the VLM backbone for object sorting. For **(E1)** we evaluate each manipulation action 10 times per setting and report **SR**, and for **(E2)** we report **SR** and **VSSR**.

Evaluation results. As shown in Figure 5 and Table 7, incorporating RoboTidy synthetic demonstration trajectories into training substantially improves the real-world manipulation success rate. With 100 RoboTidy demonstration trajectories, the **FS** setting outperforms training on 50 real-world demonstrations alone, yielding gains of approximately 20% on *Pick and Place* and 10% on *Pick and Toss*, *Open the Container* and *Close the Container*. Real-world stowing success also increases across the board. In the **ZS** setting trained solely on RoboTidy demonstrations, the policy still maintains competitive performance, matching the 50 real-world demonstrations on *Pick and Toss*. In real-world evaluation, the **ZS** setting reaches 4/12 overall suc-

cesses, versus 5/12 for the **FS** setting, and matches the 50 real-world demonstrations, indicating a small performance gap. Overall, these findings indicate that RoboTidy’s physics-consistent simulation and diverse object and container configurations effectively narrow the sim2real gap. These results indicate that our 3DGS household scenes provide photorealistic visual fidelity and physical consistency, thereby enabling reliable sim2real transfer.

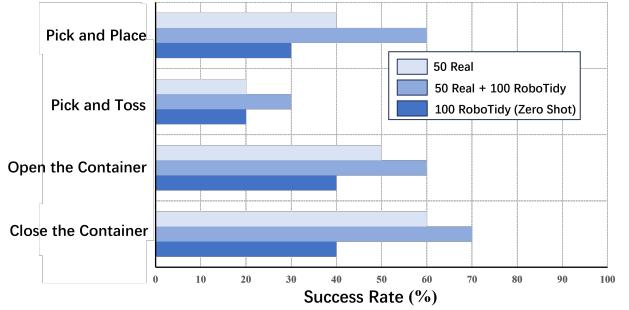


Figure 5. Real-world experimental results (E1). We report success rates for four manipulation action tasks under three different settings.

Table 7. Real-world experimental results (E2). We report **SR** and **VSSR** for household tidying task under three different settings.

Metric	50 Real	50 Real + 100 RoboTidy	100 RoboTidy
SR	5/12	8/12	4/12
VSSR	5/12	7/12	4/12

4.7. Ablation Studies

Setting details. We conduct an ablation that isolates instruction semantics as the independent variable: one variant requires object sorting and the other does not. We use RDT [2] as the VLA policy and keep all other components fixed. In simulation, we perform tidying tasks in three rooms in each of ten unseen household scenes and evaluate under the **ZS** and **FS** settings. The real-world experiments follow the same setup as **E2** and are evaluated under the **ZS** and **FS** settings.

Evaluation results. As shown in Table 8, altering only the instruction semantics by requiring object sorting yields consistent gains. In simulation **ZS** setting, SR (+7.9%) and VSSR (+11.5%); in simulation **FS** setting, SR (+11.2%) and VSSR (+11.3%). In the real world, both **ZS** and **FS** settings also show improvements, indicating that clear sorting rules shrink the search space under perception noise and reduce failures. Overall, removing the object sorting rules degrades performance; making object sorting rules explicit at the instruction level is key to accurate container selection

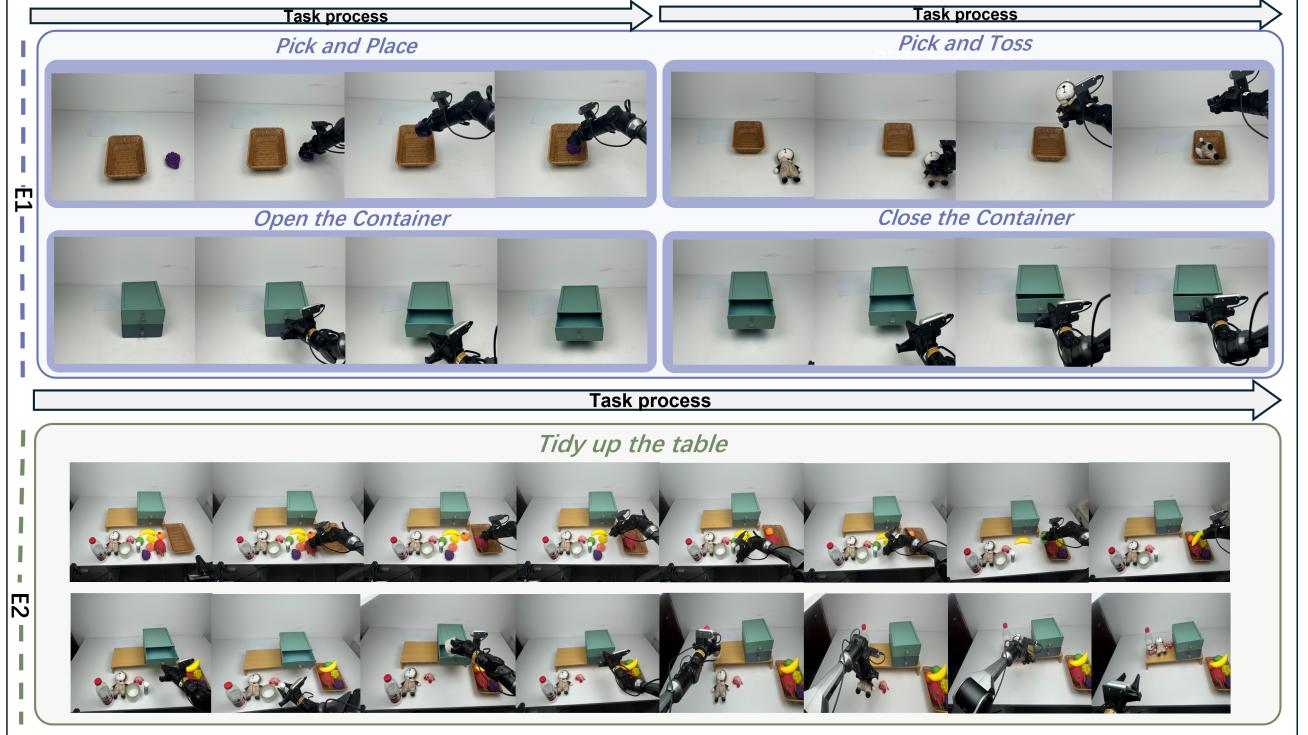


Figure 3. **Visualization of real-world tasks.** **E1:** four manipulation action tasks (*Pick and Place*, *Pick and Toss*, *Open the Container* and *Close the Container*). **E2:** household tidying task where the policy follows an “*Action (Object, Container)*” list to sort objects. Task progresses from left to right.

Table 8. Ablation with and without object sorting under **ZS** and **FS** settings. In simulation, we report **SR(%)** and **VSSR(%)** as the mean and standard deviation over 3 random seeds; in the real-world, results are counts over 12 objects and 3 containers.

Method	Simulation (ZS)		Simulation (FS)		Real-world (ZS)		Real-world (FS)	
	SR	VSSR	SR	VSSR	SR	VSSR	SR	VSSR
RDT [2]	68.4 ± 1.4	59.3 ± 0.6	70.1 ± 0.9	63.2 ± 1.1	4/12	7/12	5/12	7/12
RDT w/ object sorting	76.3 ± 0.3	70.8 ± 1.4	81.3 ± 2.1	74.5 ± 1.8	5/12	5/12	7/12	8/12

and higher end to end success, with the same trend under both **ZS** and **FS** settings.

5. Conclusion

We introduced RoboTidy, a language-guided benchmark for household tidying that evaluates embodied agents in both VLA and VLN. The benchmark combines photorealistic 3DGS household scenes with physics collisions, manipulation demonstrations and cross-room navigation trajectories, and an “*Action (Object, Container)*” list that captures user-interpretable placement preferences. It also provides language instructions and standardized evaluation metrics, enabling fair and consistent comparison. Building on this design, we conducted representative baselines for VLA and VLN and validated sim2real transfer in the real world. RoboTidy supports sim2real transfer and emphasizes reproducibility and extensibility. We expect RoboTidy to serve as

a foundation for future work on richer long horizon actions and interactive manipulation, and broader sim2real studies.

Limitations and Future Work. Although we focus on building photorealistic simulated household environments, a gap to the real world remains. We will expand the breadth of objects and scenes. In our real world experiments, the complexity of lighting and background variation meant that some challenging household scenes were not covered. Going forward, we will enrich the set of manipulation actions and continue to scale up demonstration data to improve robustness and generalization in more challenging environments. We will also incorporate scenarios with human interference and moving obstacles to evaluate policies under dynamic conditions. These additions will stress test closed loop recovery and safety and bring the benchmark closer to real deployments, thereby advancing embodied intelligence more effectively. In addition, we will apply stronger domain randomization for illumination, textures, and clutter, and we will report standardized

diagnostics of failure modes to guide future research.

References

- [1] Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025. 3, 5, 6, 7
- [2] Anthony Brohan, Noah Brown, Justice Carbajal, Yevgen Chebotar, Joseph Dabis, Chelsea Finn, , et al. Rt-1: Robotics transformer for real-world control at scale. *Proceedings of Robotics: Science and Systems*, 2023. 2, 5, 6, 7, 8
- [3] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niebner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from rgb-d data in indoor environments. In *2017 International Conference on 3D Vision (3DV)*, pages 667–676. IEEE Computer Society, 2017. 2
- [4] Jiayu Chen, Dipesh Tamboli, Tian Lan, and Vaneet Aggarwal. Multi-task hierarchical adversarial inverse reinforcement learning. In *International Conference on Machine Learning*, pages 4895–4920. PMLR, 2023. 2
- [5] Tianxing Chen, Zanxin Chen, Baijun Chen, Zijian Cai, Yibin Liu, Zixuan Li, Qiwei Liang, Xianliang Lin, Yiheng Ge, Zhenyu Gu, et al. Robotwin 2.0: A scalable data generator and benchmark with strong domain randomization for robust bimanual robotic manipulation. *arXiv preprint arXiv:2506.18088*, 2025. 2
- [6] Zhe Chen, Weiyun Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Erfei Cui, Jinguo Zhu, Shenglong Ye, Hao Tian, ZhaoYang Liu, et al. Expanding performance boundaries of open-source multimodal models with model, data, and test-time scaling. *arXiv preprint arXiv:2412.05271*, 2024. 6
- [7] An-Chieh Cheng, Yandong Ji, Zhaojing Yang, Zaitian Gongye, Xueyan Zou, Jan Kautz, Erdem Biyik, Hongxu Yin, Sifei Liu, and Xiaolong Wang. Navila: Legged robot vision-language-action model for navigation. *arXiv preprint arXiv:2412.04453*, 2024. 2, 5, 6
- [8] Jae-Woo Choi, Youngwoo Yoon, Hyobin Ong, Jaehong Kim, and Minsu Jang. Lota-bench: Benchmarking language-oriented task planners for embodied agents. *arXiv preprint arXiv:2402.08178*, 2024. 2
- [9] Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv e-prints*, pages arXiv–2407, 2024. 6
- [10] Kiana Ehsani, Winson Han, Alvaro Herrasti, Eli VanderBilt, Luca Weihs, Eric Kolve, Aniruddha Kembhavi, and Roozbeh Mottaghi. Manipulathor: A framework for visual object manipulation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 4497–4506, 2021. 2
- [11] Ran Gong, Jiangyong Huang, Yizhou Zhao, Haoran Geng, Xiaofeng Gao, Qingyang Wu, Wensi Ai, Ziheng Zhou, Demetri Terzopoulos, Song-Chun Zhu, et al. Arnold: A benchmark for language-grounded task learning with continuous states in realistic 3d scenes. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 20483–20495, 2023. 2, 3
- [12] Jiayuan Gu, Fanbo Xiang, Xuanlin Li, Zhan Ling, Xiqiang Liu, Tongzhou Mu, Yihe Tang, Stone Tao, Xinyue Wei, Yunchao Yao, et al. Maniskill2: A unified benchmark for generalizable manipulation skills. *arXiv preprint arXiv:2302.04659*, 2023. 2, 3
- [13] Peter E Hart, Nils J Nilsson, and Bertram Raphael. A formal basis for the heuristic determination of minimum cost paths. *IEEE transactions on Systems Science and Cybernetics*, 4(2):100–107, 1968. 3, 4
- [14] Physical Intelligence, Kevin Black, Noah Brown, James Darpinian, Karan Dhabalia, Danny Driess, Adnan Esmail, Michael Equi, Chelsea Finn, Niccolo Fusai, et al. $\pi_{0.5}$: A Vision–Language–Action model with Open-World generalization. *arXiv preprint arXiv:2504.16054*, 2025. 2, 5, 6
- [15] Stephen James, Zicong Ma, David Rovick Arrojo, and Andrew J Davison. Rlbench: The robot learning benchmark & learning environment. *IEEE Robotics and Automation Letters*, 5(2):3019–3026, 2020. 3
- [16] Yash Kant, Arun Ramachandran, Sriram Yenamandra, Igor Gilitschenski, Dhruv Batra, Andrew Szot, and Harsh Agrawal. Housekeep: Tidying virtual households using commonsense reasoning. In *European Conference on Computer Vision*, pages 355–373. Springer, 2022. 2
- [17] Bernhard Kerbl, Georgios Kopanas, Thomas Leimkühler, and George Drettakis. 3d gaussian splatting for real-time radiance field rendering. *ACM Trans. Graph.*, 42(4):139–1, 2023. 2
- [18] Jacob Krantz, Erik Wijmans, Arjun Majumdar, Dhruv Batra, and Stefan Lee. Beyond the nav-graph: Vision-and-language navigation in continuous environments. In *European Conference on Computer Vision*, pages 104–120. Springer, 2020. 2, 5, 6
- [19] Jacob Krantz, Erik Wijmans, Arjun Majumdar, Dhruv Batra, and Stefan Lee. Beyond the nav-graph: Vision-and-language navigation in continuous environments. In *European Conference on Computer Vision*, pages 104–120. Springer, 2020. 6
- [20] Chengshu Li, Ruohan Zhang, Josiah Wong, Cem Gokmen, Sanjana Srivastava, Roberto Martín-Martín, Chen Wang, Gabriel Levine, Michael Lingelbach, Jiankai Sun, et al. Behavior-1k: A benchmark for embodied ai with 1,000 everyday activities and realistic simulation. In *Conference on Robot Learning*, pages 80–93. PMLR, 2023. 2, 3
- [21] Bo Liu, Yifeng Zhu, Chongkai Gao, Yihao Feng, Qiang Liu, Yuke Zhu, and Peter Stone. Libero: Benchmarking knowledge transfer for lifelong robot learning. *arXiv preprint arXiv:2306.03310*, 2023. 3
- [22] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019. 5, 6
- [23] Yuxing Long, Wenzhe Cai, Hongcheng Wang, Guanqi Zhan, and Hao Dong. Instructnav: Zero-shot system for generic

- instruction navigation in unexplored environment. *arXiv preprint arXiv:2406.04882*, 2024. 6
- [24] Oier Mees, Lukas Hermann, Erick Rosete-Beas, and Wolfram Burgard. Calvin: A benchmark for language-conditioned policy learning for long-horizon robot manipulation tasks. *IEEE Robotics and Automation Letters (RA-L)*, 7(3):7327–7334, 2022. 3
- [25] Bingchen Miao, Rong Wei, Zhiqi Ge, Xiaoquan Sun, Shiqi Gao, Jingzhe Zhu, Renhan Wang, Siliang Tang, Jun Xiao, Rui Tang, Juncheng Li, et al. Towards physically executable 3d gaussian for embodied navigation. *arXiv preprint arXiv:2510.21307*, 2025. 4, 5
- [26] NVIDIA. Isaac Sim. <https://github.com/isaacsim/IsaacSim>, 2025. 2, 4
- [27] Aishwarya Padmakumar, Jesse Thomason, Ayush Shrivastava, Patrick Lange, Anjali Narayan-Chen, Spandana Gella, Robinson Piramuthu, Gokhan Tur, and Dilek Hakkani-Tur. Teach: Task-driven embodied agents that chat. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 2017–2025, 2022. 2, 3
- [28] Xavier Puig, Kevin Ra, Marko Boben, Jiaman Li, Tingwu Wang, Sanja Fidler, and Antonio Torralba. Virtualhome: Simulating household activities via programs. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. IEEE, 2018. 2
- [29] Wilbert Pumacay, Ishika Singh, Jiafei Duan, Ranjay Krishna, Jesse Thomason, and Dieter Fox. The colosseum: A benchmark for evaluating generalization for robotic manipulation. In *RSS 2024 Workshop: Data Generation for Robotics*. 2
- [30] 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. 5, 6
- [31] Santhosh Kumar Ramakrishnan, Aaron Gokaslan, Erik Wijmans, Oleksandr Maksymets, Alexander Clegg, John M 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. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*. 2
- [32] Robin Rasch, Dennis Sprute, Aljoscha Pörtner, Sven Battermann, and Matthias König. Tidy up my room: Multi-agent cooperation for service tasks in smart environments. *Journal of Ambient Intelligence and Smart Environments*, 11(3): 261–275, 2019. 2
- [33] Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, page 3982. Association for Computational Linguistics, 2019. 5
- [34] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017. 4
- [35] Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Rozbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. Alfred: A benchmark for interpreting grounded instructions for everyday tasks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10740–10749, 2020. 2
- [36] Manycore Tech Inc. SpatialVerse Research Team. InteriorGS: A 3d gaussian splatting dataset of semantically labeled indoor scenes. <https://huggingface.co/datasets/spatialverse/InteriorGS>, 2025. 2, 3, 4
- [37] Andrew Szot, Alexander Clegg, Eric Undersander, Erik Wijmans, Yili Zhao, John Turner, Noah Maestre, Mustafa Mukadam, Devendra Singh Chaplot, Oleksandr Maksymets, et al. Habitat 2.0: Training home assistants to rearrange their habitat. *Advances in neural information processing systems*, 34:251–266, 2021. 2, 3
- [38] Xinyue Wei, Minghua Liu, Zhan Ling, and Hao Su. Approximate convex decomposition for 3d meshes with collision-aware concavity and tree search. *ACM Transactions on Graphics (TOG)*, 41(4):1–18, 2022. 4
- [39] Luca Weihs, Matt Deitke, Aniruddha Kembhavi, and Rozbeh Mottaghi. Visual room rearrangement. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5922–5931, 2021. 2
- [40] Jimmy Wu, Rika Antonova, Adam Kan, Marion Lepert, Andy Zeng, Shuran Song, Jeannette Bohg, Szymon Rusinkiewicz, and Thomas Funkhouser. Tidybot: Personalized robot assistance with large language models. *Autonomous Robots*, 47(8):1087–1102, 2023. 2, 3, 5, 6
- [41] Qi Wu, Janick Martinez Esturo, Ashkan Mirzaei, Nicolas Moenne-Loccoz, and Zan Gojcic. 3dgut: Enabling distorted cameras and secondary rays in gaussian splatting. *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2025. 4
- [42] Zhi Yan, Nathan Crombez, Jocelyn Buisson, Yassine Ruichck, Tomas Krajnik, and Li Sun. A quantifiable stratification strategy for tidy-up in service robotics. In *2021 IEEE international conference on advanced robotics and its social impacts (ARSO)*, pages 182–187. IEEE, 2021. 2
- [43] Zhi Yan, Nathan Crombez, Jocelyn Buisson, Yassine Ruichck, Tomas Krajnik, and Li Sun. A quantifiable stratification strategy for tidy-up in service robotics. In *2021 IEEE international conference on advanced robotics and its social impacts (ARSO)*, pages 182–187. IEEE, 2021. 2
- [44] Zhi Yan, Nathan Crombez, Jocelyn Buisson, Yassine Ruichck, Tomas Krajnik, and Li Sun. A quantifiable stratification strategy for tidy-up in service robotics. In *2021 IEEE international conference on advanced robotics and its social impacts (ARSO)*, pages 182–187. IEEE, 2021. 2
- [45] Andy Zeng, Shuran Song, Johnny Lee, Alberto Rodriguez, and Thomas Funkhouser. Tossingbot: Learning to throw arbitrary objects with residual physics. *IEEE Transactions on Robotics*, 36(4):1307–1319, 2020. 3
- [46] Jiazhao Zhang, Kunyu Wang, Rongtao Xu, Gengze Zhou, Yicong Hong, Xiaomeng Fang, Qi Wu, Zhizheng Zhang, and He Wang. Navid: Video-based vlm plans the next step for vision-and-language navigation. *arXiv preprint arXiv:2402.15852*, 2024. 2, 5, 6

- [47] Tony Z. Zhao, Vikash Kumar, Sergey Levine, and Chelsea Finn. Learning fine-grained bimanual manipulation with low-cost hardware. In *Proceedings of Robotics: Science and Systems*, 2023. [2](#), [5](#), [6](#)