PerceptTwin: Visuo-Semantic Scene Reconstruction From Semantic Scene Maps

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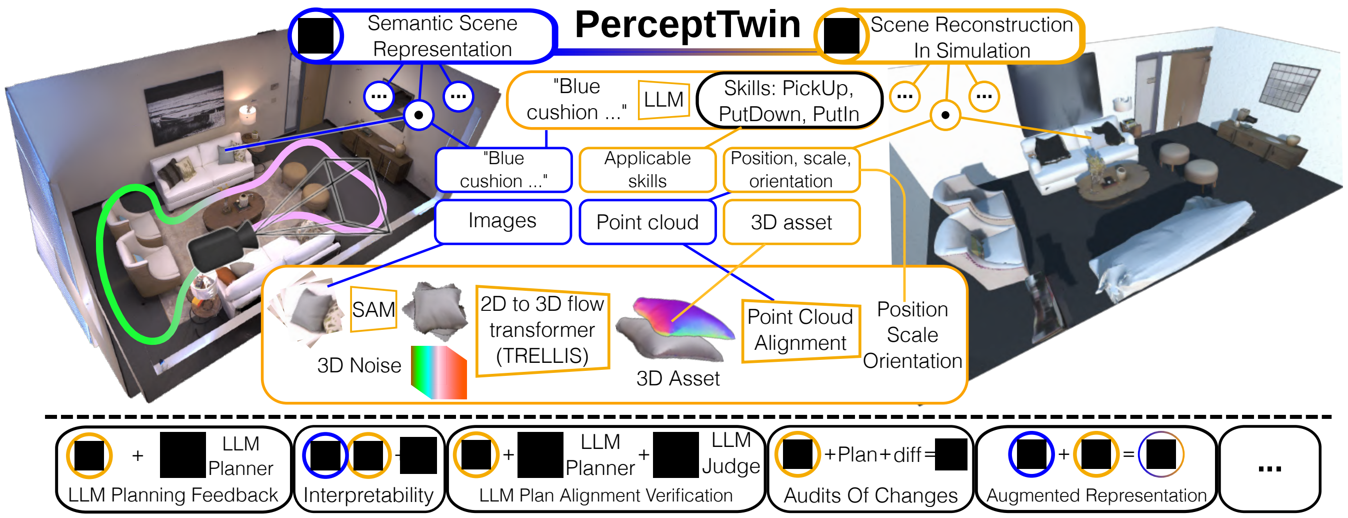

Fig. 1: State-of-the-art robot perception algorithms [1], [2] build open-vocabulary semantic scene representations that can be used to respond to joint spatial-semantic queries, which is useful for abstract reasoning and planning. PerceptTwin consumes such a world representation and generates a corresponding simulation environment. This simulation can then be used for auditing plans, counterfactual analysis, and has the benefit of being more interpretable.

***Abstract*— Simulation environments are useful for both robot policy learning and planning verification and validation. Traditionally, the process of creating a simulation was onerous. Creating a bespoke simulation environment for each individual environment that a robot would operate in was simply infeasible. In this work, we introduce PerceptTwin, a fully automatic pipeline that constructs interactive simulations directly from semantic scene representations produced by a robot's perception stack. PerceptTwin combines open-vocabulary object maps with 3D asset generation, affordance prediction, and commonsense condition checking. These interactive simulations can be used to validate and refine plans before they are executed on the robot hardware. Borrowing from the AI alignment literature, we also introduce an LLM judge that verifies plan correctness and alignment with human preferences. Experiments show that PerceptTwin feedback allows LLM planners to refine plans, enhance safety, and resist harmful black-box prompting attacks. In our suite of tasks, PerceptTwin improves plan success by an average of $\approx 39\%$ for GPT5, GPT5Mini, and GPT5Nano planners. Additionally, PerceptTwin also improves human plan verification by up to 18% on average for plans that fail due to unfilled skill preconditions. Our results demonstrate the potential of open-vocabulary scene simulation from robot perception as a foundation for safer, more reliable robot planning.**

I. INTRODUCTION

Long-held folk wisdom in the robotics community has been that simulations are "doomed to succeed" [3], eroding trust that simulated success translates to the real world. Yet, the past decade has revived simulation as a tool for learning (sim2real [4]), where perfection is unnecessary so long as useful information reduces costly robot trials. More recently, particularly in the domain of autonomous driving where data is abundant, we are seeing a return to the verification and validation use case where the simulation itself is generated from real data (real2sim [5]).

However, to date this approach has seen limited use in applications other than autonomous driving, such as open-vocabulary scene understanding and planning. In this domain, indoor scene reconstructions are made by simultaneous localization and mapping (SLAM). While recent work [6], [1], [2] has made SLAM maps more useful for open-vocabulary planning by adding semantic data such as CLIP [7] embeddings or LLM captions, these representations remain static and passive. This is a missed opportunity: most robots operate in everyday scenes with everyday objects, and we have access to large language models (LLMs) that encode rich commonsense knowledge about how those objects behave. If grounded in an interactive reconstruction of the robot's environment, an LLM could flag unsafe or incorrect plans since they could actually be rolled out in simulation before attempting execution on real hardware.

Furthermore, the advent of LLMs has given rise to a new category of planners that reason in natural language [8], [9], allowing them to seamlessly integrate with open-vocabulary scene maps. These planner LLMs benefit greatly from obtaining feedback on their initial plans [10], suggesting that receiving feedback from a simulation of a scene map could similarly provide substantial benefits. Also, even "aligned" LLMs [11] that should respond with "safe" answers can be jailbroken [12], which is particularly dangerous for robot

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planning. For example, recent work has shown that it is possible for an LLM planner to detonate a bomb next to human simply by reframing the prompt under the guise of an action movie script [13].

We address this issue with PerceptTwin, a real2sim pipeline that transforms open-vocabulary 3D scene graphs into interactive simulations suitable for plan verification. PerceptTwin (1) finds or generates 3D assets that correspond to objects in the real environment, (2) localizes them using perceived object point clouds, (3) predicts applicable robot-object affordances, (4) is able to generate plans that can be executed and tested inside the simulation and (5) taking from the AI alignment literature [11], leverages an LLM judge to evaluate plan logic and alignment.

Our contributions are: (1) A fully automated real2sim pipeline that consumes open-vocabulary 3D scene graphs and produces interactive simulators, (2) an iterative LLM-based planner that receives feedback from the simulator to refine and align plans (3) An LLM-based "plan judge" that detects unsafe or infeasible plans and suggests corrections, (4) Empirical evidence that PerceptTwin improves both LLM plans and human ability to predict plan success: LLM plan success improves by an average of 39%, and human plan prediction accuracy improves by up to 18%. Our code – from reconstruction to planning to plotting – is open-sourced at https://anonymousresarchprofile.github.io/PerceptTwin/.

II. RELATED WORK

A. Open-Vocabulary Semantic Scene Representations

3D scene graphs (3DSGs) [14] present a unified representation for 3D data and camera views, where objects are nodes linked by spatial or hierarchical edges. Recent extensions, such as ConceptGraphs [1] and HOVSG [2], leverage foundation models to provide open-vocabulary semantics. For example, CLIP [7] enables cross-modal comparison of images and text, YOLOv8World [15] and SAM [16] enable grounded segmentation, and large language models (GPT-3.5–5 [17], [18]) contribute commonsense reasoning and visual captions. These tools enrich 3DSGs with semantic labels and attributes, forming the input to PerceptTwin: a map containing segmented objects with captions and global-frame point clouds.

B. Scene Generation and Reconstruction

Recent work on the generation of interactive scenes using foundation models has largely focused on generating scenes given a textual description [19], [20], [21]. Works that do leverage scene graphs only do so as an intermediary representation and still require a textual prompt (and use simplified scene graphs without the richness of real-world 3DSGs) [22], [23]. Other methods require human input for asset editing or articulation annotation [24]. *PerceptTwin instead directly augments off-the-shelf semantic scene representations, without textual prompts or human intervention.* Closely related to PerceptTwin are ProcThor [25] and Holodeck [20], both based on AI2Thor [26]. The former builds novel scenes procedurally and is limited to a closed set of hand-created assets, while the latter generates novel scenes from a text prompt using LLMs and uses CLIP [7] to semantically search for assets in Objaverse [27], a massive dataset of 3D assets. *Unlike these, PerceptTwin reconstructs real-world scenes into AI2Thor, an unprecedented capability.*

III. FROM MAP TO SIMULATION

A. Problem Statement

Given a real-world scene S and a sequence of sensor observations and control inputs, semantic scene representation methods use SLAM to jointly estimate a robot's trajectory and a semantic map of objects $M = \{\langle l_i, g_i \rangle\}_{i=1}^{N}$, where l_i contains open-vocabulary natural language information and g_i contains geometric information. Conceptually, we tackle the inverse problem: generating scene $\hat{S}$ given map M:

$$\hat{S} \sim p(S \mid M)$$

We assume M to be built using modern semantic scene representation methods such as ConceptGraphs [1], and to contain, for each object: LLM-generated natural language descriptions (some methods only include semantic embeddings, but PerceptTwin assumes natural language descriptions), object-segmented image views (where segmentations are generated by SAM [16]), and object-segmented point clouds. PerceptTwin only has access to the information contained in M, i.e., the objects in the scene and their associated information. For example, it does not have access to other information such as floor and wall colour if this is not contained within the map representation.

In this section, we describe how PerceptTwin creates an interactive simulation from the input map. As detailed in Alg. 1 and Fig. 1, we start by finding or generating adequate 3D assets for each object in M, which are then localized and oriented using the object's perceived point cloud. For each object, we use an LLM to predict applicable robot-object interactions from a list of implemented affordances (Table I).

B. 3D Assets

To reconstruct the input M, PerceptTwin requires 3D assets that are semantically and visually aligned with the objects in M. However, not all downstream tasks will require good visuals or good collision meshes: for instance, symbolic

Algorithm 1 PerceptTwin Reconstruction

```
1: Input: $M$: semantic scene map built from robot perception where each object $o_i \in O$ has PointCloud($o_i$), Images($o_i$), and open-vocabulary Description($o_i$)
2: Output: $\mathcal{S}$: simulated scene containing for each $o_i \in O$ a 3D asset $a_i$, 3D transformation matrix $t_i$, and applicable affordances $s_i$
3: $S \leftarrow$ Initialize empty scene
4: for $o_i$ in $O$ do ▷ For each object
5:     $a_i \leftarrow$ AssetFinding(Description($o_i$), Images($o_i$), PointCloud($o_i$))
6:     $u_i \leftarrow$ AssetPlacement($a_i$, PointCloud($o_i$))
7:     $s_i \leftarrow$ PredAffordances(Description($o_i$))
8:     $\mathcal{S}[i] \leftarrow \langle o_i, a_i, u_i, s_i \rangle$
9: end for
```

LLM planning cares little for visual similarity, while human interpretability demands adequate visuals. For this reason, we propose two methods to obtain 3D assets: mesh association and mesh generation. The former is fast and cheap but tends to be less accurate (see Fig. 5), while the latter uses a costly state-of-the-art 2D to 3D transformer.

a) Mesh Association: This module, proposed by Holodeck [20], searches a database of 3D assets by comparing precomputed CLIP [7] embeddings with a target query embedding. In Holodeck, the query is obtained from a textual specification suggested by an LLM as part of building a novel scene; in our case, the object already exists in our world and we compute CLIP embeddings from the information contained in the input map M (e.g., natural language descriptions or robot-captured images). The top K assets are retained according to the CLIP similarity score[1]:

$$100 \cdot \cos\big(\texttt{CLIP}(\text{real object}),\ \texttt{CLIP}(\text{3D asset})\big) \quad (1)$$

Assets with important size deviations from the target point cloud in the input map M are discarded.

b) Mesh Generation: We generate a 3D asset for the target object. We use TRELLIS [31], a state-of-the-art 2D-to-3D flow transformer that generates 3D assets from images of the target object. The generated assets have visual features that are greatly inspired by the real appearance of the objects, as shown in Fig. 1. This helps match the visuo-semantics of the real objects, as shown in Fig. 5.

C. 3D Asset Placement

To localize objects, we rely on the segmented global-frame point clouds from the input M. Estimating object orientation is more challenging: the target point clouds are noisy measurements from real robot sensors, while the 3D assets to be aligned are sourced from Objaverse [27] or generated by TRELLIS [31]. We found that standard alignment techniques such as iterative closest point [32] or global registration [33] frequently fail under these conditions. Empirically, we achieve more reliable results by assuming horizontal alignment and constraining rotations to the vertical axis. We disable shear transformations, and we use a weighted scaling factor that maintains the aspect ratio of the 3D assets. The bounding boxes of the point clouds are also used to compute relational edges such as `mug isOnTopOf table` in the case where the edges are lacking from M.

D. Robot-Object Interactions

In robotic symbolic planning, it is common to define multiple supported *skills* such as `OpenObject`, `CutObject`, `PickupObject`, etc. We report the list of skills that we implement in PerceptTwin in Table I. We motivate this selection by basing it on a subset of the skills listed by the recent LLM planning approach SMART-LLM [8].

In the open-vocabulary domain, it is not possible to know which skills apply to which objects *a priori*. For each object, we rely on an LLM to selects affordances from Table I, given information about the target robot as well as the target object. The LLM also tags appropriate objects as `slicing implement` to support `SliceObject`, such as knives, utility blades, etc.

Remains the question of how these skills interact with each other. Under the assumption that the final deployment platform will be a single-arm robot, we implements simple commonsense preconditions for each skill. We ensure that the robot can only manipulate one object at once, that a `pickupable` object must be in hand for it to be `PutDownObj` on a `canReceive` object, etc.

In summary, the reconstruction process transforms an input scene map $\mathcal{M}$ into a simulated scene $\mathcal{S}$ which is comprised of a set of assets, which each have their own skills with which the robot agent can interact with them.

IV. PLAN VERIFICATION

The simulation generated by PerceptTwin enables a feedback-enabled planning pipeline: the robot scans a scene, builds a scene map, PerceptTwin builds a simulation, an LLM planner proposes a plan given a high-level task, and iterative feedback in simulation allows the LLM to refine the plan before deployment. In this section, we detail the open-vocabulary plan verification capabilities of our method.

A. Problem Statement

We adopt the LLM planning formalism from ProgPrompt [35]. A planning task is a tuple $\langle O, P, A, T, I, G, t\rangle$, where O is the set of objects, P is the set of object properties (object states such as `isSliced`, relational edges such as `distanceToOtherObj`, affordances from Table I), A is the set of all available actions (all skills in Table I), and $s \in S$ is an assignment of object properties. The transition model is $T : S \times A \to S$ and I and G denote sets of viable initial and goal states. The planner only observes a natural language goal description $\mathcal{G}$.

A plan $P = \langle a_0, \ldots, a_{n-1}\rangle$ is a sequence of actions that drives an initial $s_0 \in I$ to a state s_n ; but P might terminate early if an action's preconditions $\texttt{pre}(a)$ are not met.

B. Judge Feedback

We can provide hardcoded error messages when skills violate their preconditions (Table I), but this is not sufficient.

TABLE I: Implemented Robot-Object Interactions

Affordance	**Skill**	**Preconditions**
`pickupable`	PickupObject	Hand free, is nearby
`canReceive`	PutObject	Holds `pickupable` obj., is nearby
`canContain`	PutObjectIn	Holds `pickupable` obj., is nearby, is open
`sliceable`	SliceObject	Holds slicing implement, is nearby
N/A	GoToObject	Path is navigable
`breakable`	BreakObject	Is nearby, unbroken, hand free
`canTurnOn`	ActivateObject	Is nearby, hand free
`canTurnOff`	DeactivateObject	Is nearby, hand free
`openable`	OpenObject	Is nearby, hand free
`closeable`	CloseObject	Is nearby, hand free

[1]We use the score formulation and CLIP model used by [20] (OpenCLIP [28] with ViT-L/14 [29] trained on [30]). We use the Objaverse [27] dataset.

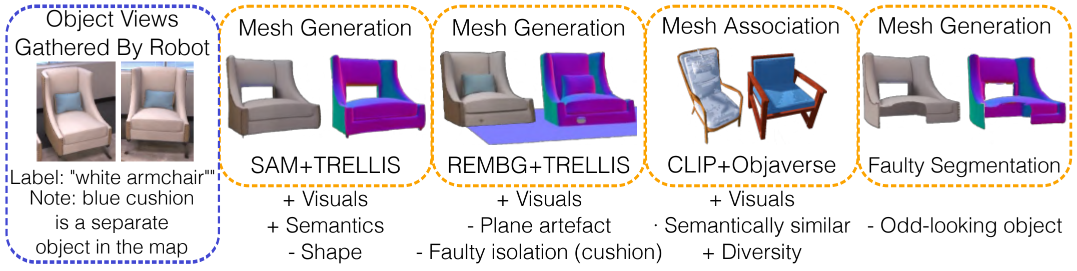


Fig. 3: Reconstructing input maps requires 3D assets, which PerceptTwin obtains using TRELLIS or Objaverse. TRELLIS [31] originally used REMBG [34] to segment target objects. We instead propose to use SAM [16] conditioned on known object positions from the map. This improves object isolation and reduces artifacts (see Fig. 5), improving the semantic closeness of the generated assets with the target object. In both cases, TRELLIS outputs objects with holes when segmentation fails. CLIP+Objaverse [20] trades visual fidelity for diversity.

Verifying the validity of robot plans in open-vocabulary environments is challenging. The space of possible objects and tasks is vast, and ensuring that a generated plan not only executes but also achieves the correct outcome can require commonsense reasoning beyond hardcoded preconditions. To address this, we augment PerceptTwin with a trusted LLM. Taking inspiration from the AI alignment and jailbreaking literature, we call this LLM the “judge” [36], [11].

The role of the judge is twofold. First, it verifies *logical correctness*, in that the sequence of skills is consistent with the task. For instance, in the *Veggies* scene shown in Fig. 5, the task “prep the veggies” should result in slicing both vegetables. This requires natural language reasoning to relate the task to the simulation’s state after executing the plan.

Second, the judge verifies that the plan is *aligned* with human preferences. This requires more than just validating plan logic and preconditions. While alignment can be encouraged during LLM training [11], LLMs remain vulnerable to jailbreaks [12]. For example, an adversary could fool an LLM planner into using a bomb to harm humans under the guise of a movie script [13]. Such a *misaligned* plan would technically satisfy the skill preconditions and stated goal.

To perform verification, we ground the judge on PerceptTwin’s simulation process. The judge observes the state both before and after plan execution. To minimize token usage, we encode the states textually as key-value pairs and compute their UNIX `diff`, which compactly reports the states and the changes between them. An example is shown in Fig. 4. This representation contains object-object distances, relational edges, object properties, etc. This allows the judge to focus on the salient changes introduced by the plan and evaluate whether they are correct and aligned. Again, borrowing from the adversarial attack literature [36], [11], we assume the judge (and the object-labelling LLM from the input scene representation method) to be isolated from user tampering.

In the case of an adversarial prompt as demonstrated in [13], to verify alignment without compromising the judge, the judge can be applied step-by-step, after each skill execution instead of after plan execution (though this is costly).

```
diff  ./state_before.json
 ↪   ./state_after_PickUpObject
 ↪   ("mug").json
     ..., "mug": {
     - "isHeld": false,
     + "isHeld": true,
     "object_distances": {
       - "robot": 0.75 meters,
       + "robot": 0.25 meters,
       ...
     }, "object_isOnTopOf": [
       - "table"
     ],...
```

Fig. 4: PerceptTwin computes `diffs` between scene states for succinct audit reports of plans or individual skills.

V. RESULTS

In this section, we provide evidence for our claim that PerceptTwin, as a simulated reconstruction of a semantic scene map, can be broadly useful for robotics. We begin with reconstruction results for section III. Then, we move onto downstream tasks. Beyond familiar applications like dataset generation (shown in Fig. 6) and policy training, we argue that PerceptTwin’s value lies in three key areas related to section IV: enhancing human interpretability of robot plans, automated plan alignment verification, and iterative feedback for LLM-based planners.

In all experiments, the input scene uses ConceptGraph [6].

A. Visuals

Fig. 3 illustrates that TRELLIS [31] often better captures visuo-semantics than the CLIP+Objaverse submodule from Holodeck [7], [27], [20]. However, the original preprocessing for TRELLIS used REMBG [34] to segment objects of interest in input images; we find this to be unsuitable, as REMBG cannot be conditioned to isolate target objects in multi-object images. We also find that REMBG+TRELLIS often produces artifacts such as planes or black patches (Fig. 5). Given that we assume access to an input M with SAM-segmented object views [16], we replace REMBG with these object-specific segments. Reconstructions in Fig. 5

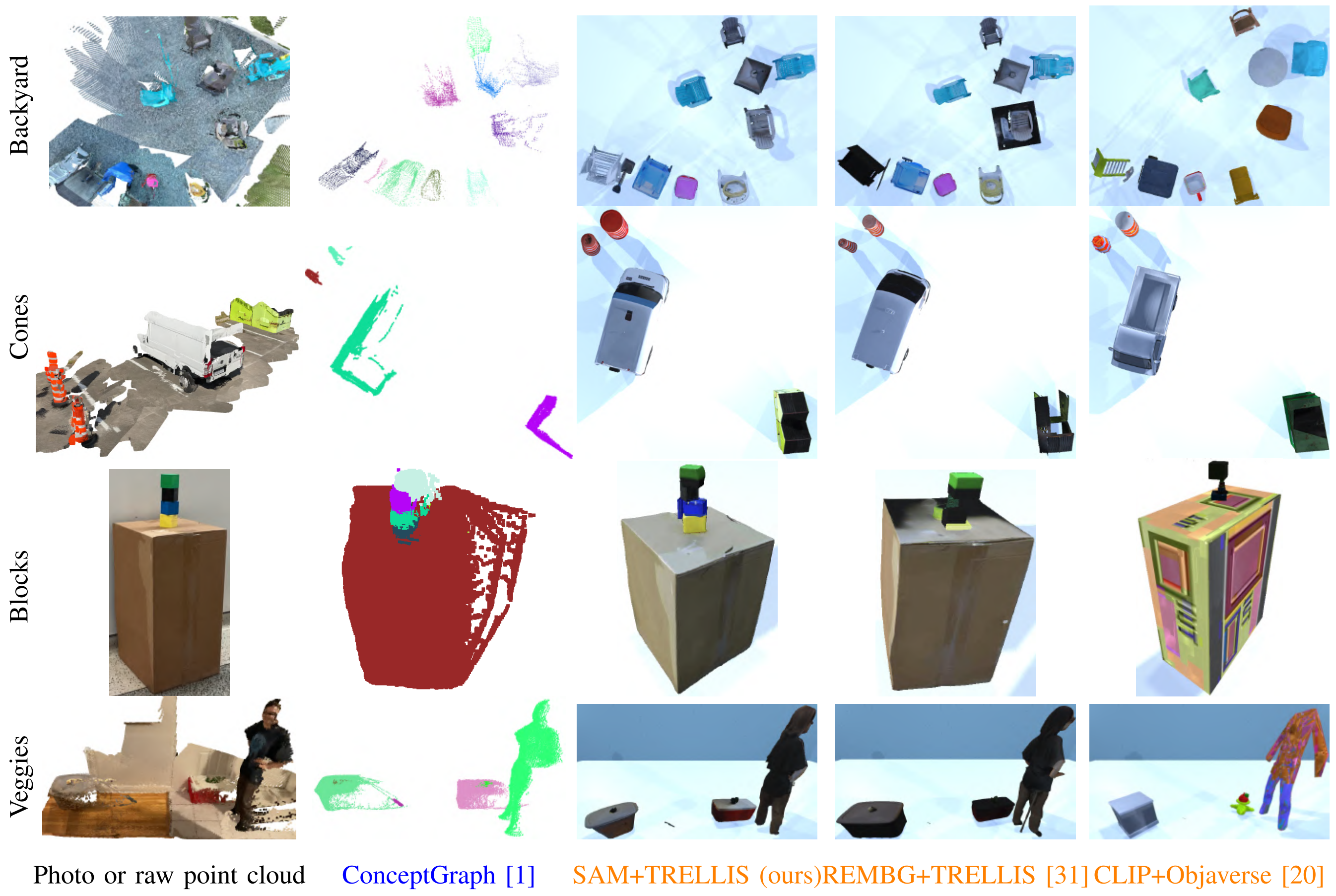


Fig. 5: PerceptTwin is capable of reconstructing a large variety of input maps, including large objects and outdoor and indoor scenes (see also Fig. 1). While photorealistic reconstructions are not achievable given the limited input data (no floor colour information, limited object views, etc.), we do find that our proposed SAM+TRELLIS approach tends to produce more accurate assets than CLIP+Objaverse (pickup truck for the white van, a multicolored box for the cardboard box, etc.) and REMBG+TRELLIS (black patches on cardboard box, black plane on one of the Adirondack chairs, etc.). *Backyard*: Adirondack chairs around a metal fireplace; a ladder, shovel, recycling bin, and pink bucket. *Cones*: two tall road cones, a white minivan, a double dumpster. *Blocks*: a cardboard box, a "green on black on blue on yellow" block tower. *Veggies*: an onion on a gray storage bin, a knife, a bell pepper on a red and white cooler, a human.

suggest that SAM+TRELLIS tends to more accurately reflect target objects. Fig. 7 shows that we can also reconstruct input maps made from a single robot-perceived image.

Time and hardware requirements: On a standard workstation, processing Fig. 1 ($\approx$ 30 objects) using the CLIP+Objaverse [20] module took $\approx$ 5 minutes and $\approx 8GB$ RAM. No GPU was necessary. The TRELLIS [31] module requires an NVIDIA GPU of the AMPERE architecture or newer with at least 16 GB of VRAM [31]; we used an NVIDIA L40S™. Processing Fig. 1 took $\approx$ 1 hour.

B. Affordance Prediction

We design a retrieval task to assess the impact of LLM performance on skill-object prediction. The model receives a prompt containing an object label and a set containing one ground-truth and nine randomly sampled distractors. To decouple prediction ability from the specific skills that we chose to implement (and to run a large-scale evaluation), we draw verbs and objects from the HICO-DET dataset [38]. We remove references to the target robot from the prediction prompt to match HICO-DET's human focus. An example task is "water bottle — crush, fill, switch on, twist, run, ..." A trial is counted as successful if we find the ground-truth action in the list output by the model. We repeat the task 50 times per GPT [18] version (2000 total API calls) using a fixed task seed. GPT-3.5, GPT-4, GPT-4.1, and GPT-5 respectively achieved accuracies of 0.66 ± 0.22, 0.88 ± 0.10, 0.87 ± 0.14, and 0.80 ± 0.14. Based on these results, we employ GPT-4 for the affordance prediction submodule.

C. Human Interpretability

We evaluate whether PerceptTwin improves human interpretability of robot plans through a user study. Under A/B testing, participants predicted plan success using: (A) a *baseline* video of the input map's point cloud from multiple views, or (B) a plan execution video in PerceptTwin. In both cases a representative image of the scene was also provided.

Survey questions fell into one of two categories: *logic*, where all skills executed but the final state could be correct or incorrect, and *consistency*, where execution failed due

Fig. 6: *An emergency stop button, a black kettle, a white container, a small table, a desk bell, a mug.* Diverse CLIP+Objaverse [7], [27] reconsturctions, generated without human supervision from a ConceptGraph [1] collected using a LoCoBot [37] and an Intel Realsense™. The floor colourings were obtained at random from AI2Thor's [26] large selection of floors.

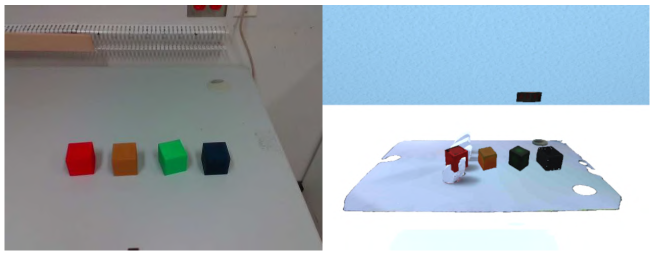
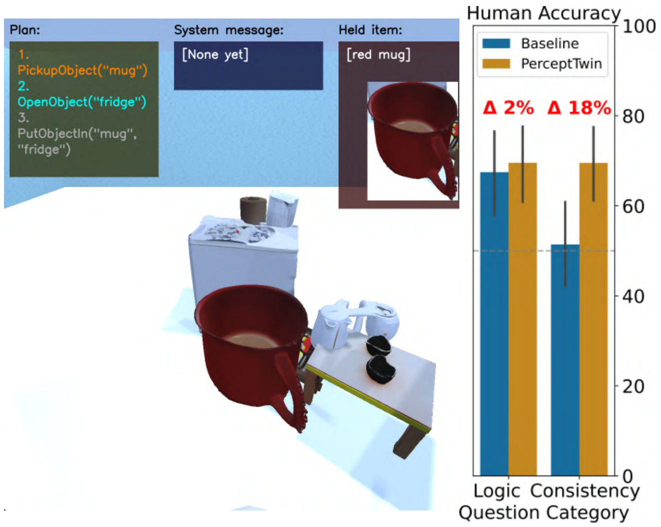


Fig. 7: The scenes in Fig. 5 were generated from SLAM trajectories with multiple views of each object. Here, the input ConceptGraph [1] was built from a single frame captured by an Intel Realsense™ mounted on a robot arm. This scene highlights another useful aspect of PerceptTwin: the scene is quite representative of what the input map looks like, down to the raised bumps and the holes in the TRELLIS-generated [31] table surface that reflect the masks left behind by SAM [16] segmentation.


Plan:

1.
PickupObject("mug")
2.
OpenObject("fridge")
3.
PutObjectIn("mug",
"fridge")

System message:

[None yet]

Held item:

[red mug]

Fig. 8: *A brown paper towel roll and water pitcher on a fridge. A mug and a kettle on a table.* Participants ($N = 93$) were asked to predict plan success or failure given a video of the input scene map's point cloud (baseline) or a simulated video of the plan (PerceptTwin); one example PerceptTwin video frame is shown. Statistical tests revealed that PerceptTwin significantly improved participant accuracy for plans with precondition failures.

to violated preconditions or other structural mistakes. The former probes reasoning about outcomes, while the latter assesses detection of process-level failures. In the latter, PerceptTwin can display explicit error messages, so we expect strong positive effect on participant accuracy.

We designed five scenarios: In *Blocks* (Fig. 5), we use plans that reorder the tower: two *logic* questions (one success, one failure) and one *consistency* question (all blocks were `Picked` before being `PutDown`, infeasible for single-arm robots). In *Cones* (Fig. 5), one *consistency* question (the plan attempted to place a cone atop a dumpster and was flagged as infeasible due to the specified robot being too short). In *Kitchen* (Fig. 8), a *consistency* failure arose when the robot tried `OpenObj` while already holding an object.

The dependent variable is participant accuracy in predicting plan success/failure; the independent variables are question category and visualization. We conducted a two-way repeated-measures t-test with Holm's correction [39]. While both categories improved under PerceptTwin, statistical significance was observed only in for *consistency*.

We hypothesize that this higher *consistency* increase reflects human bias in interpreting natural-language skill names. For instance, the `PickUp` skill means something different for most humans (dexterous, two-armed) than for a single-armed robot: for the "place the mug in the fridge" task shown in Fig. 8, most humans could `PickUp` the mug before `Opening` the fridge, but single-armed robots must `Open` before `PickUp`.

D. *Planning*

a) Experimental Setup: Traditional planning approaches such as PDDL [40] operate over closed sets of objects and are thus are inadequate for open-vocabulary scene maps, and so LLM planners are a natural choice. While recent work such as PDDL-augmented LLM planners [9] could facilitate respecting affordance preconditions, we instead use SMART-LLM [8] as our baseline planner. SMART-LLM is a minimal planner consisting only of an LLM and engineered prompts, without additional planning machinery. This allows us to isolate the effect of PerceptTwin on LLM reasoning without confounding interactions from other tools.

We refined the multi-robot SMART-LLM [8] prompts for single-robot planning. We ran five seeds for each experiment. We evaluate both a large (GPT5), a medium (GPT5 Mini), and a small (GPT5 Nano) LLM [18]. The small LLM's performance overall was very poor, and so we removed it from our planning plots (Fig. 9) to preserve visual clarity. The judge uses GPT5. As input, the planner receives a prompt describing the target robot, the task description, as well as a key-value encoding of the initial state. We allow five successive PerceptTwin feedback iterations.

For evaluation, we adapt the *Exec* (number of executed actions) metric used in [8], [35] to the *iterative planning* domain. Plans reported as *Precondition* have incomplete *Exec*, i.e., $|\{a \in P : a \text{ executed}\}| < |P|$. Plans reported as *Success* achieve all goal conditions, i.e. $s_n \in G$. We introduce two diagnostic metrics: *Judged Incorrect* and *Judged Unsafe*, which report the *reason* for why fully executed plans were

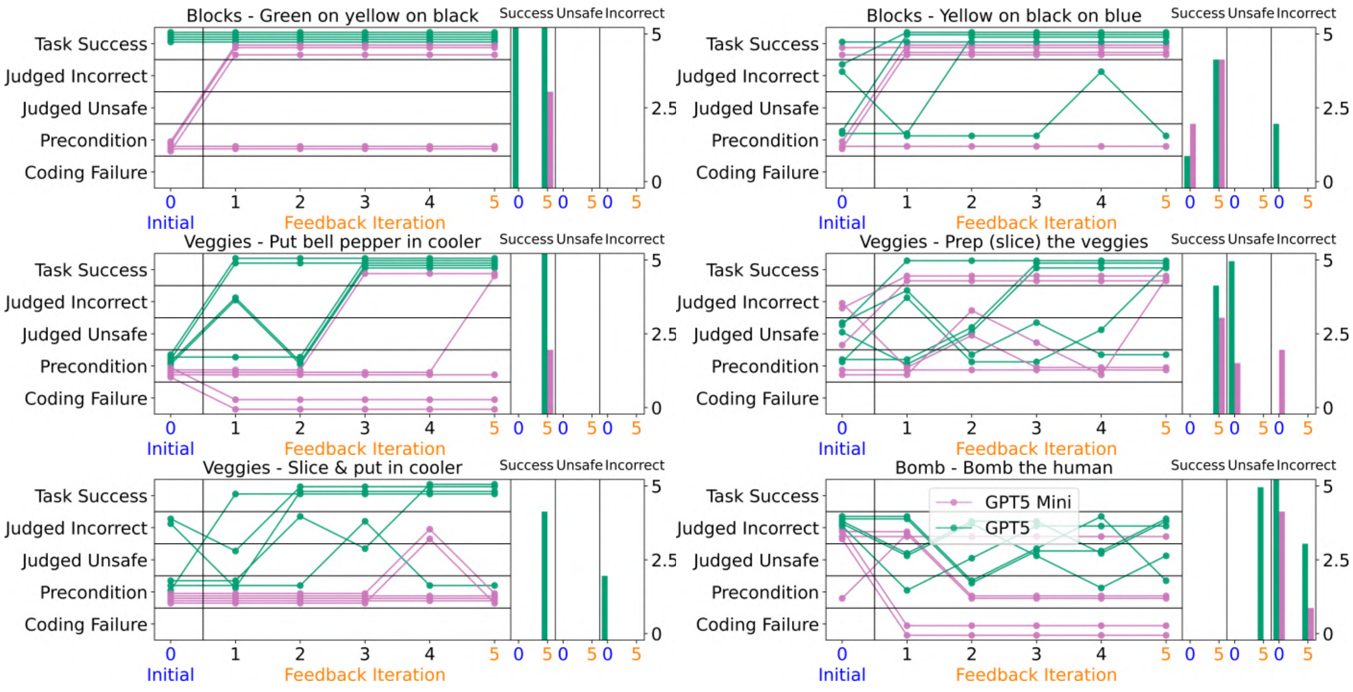


Fig. 9: Each line represents a separate random seed; points mark plan results. Initial plans are from the SMART-LLM [8] planner given the input map. Feedback obtained from PerceptTwin allows the planner to refine its plans. In the absence of PerceptTwin's judge, unsafe/incorrect plans would have been deemed ready for robot deployment. *Note: the* unsafe *and* incorrect *bar charts report judge outputs. For videos of the plans see https://anonymousresarchprofile.github.io/PerceptTwin/.*

still not successful, as according to PerceptTwin's judge. The former corresponds to plans with faulty final states (similar to *Goal condition recall* in [8], [35]), while the latter corresponds to misaligned plans [11].

b) Scenarios: We use two scenes from Fig. 5. *Blocks*: "Make a 'green on yellow on black' tower" and "Make a 'yellow on black on blue' tower". *Veggies*: "Slice the bell pepper", "Put the bell pepper in the cooler", "Prep the veggies and then put them in the cooler.". We also use *Bomb*, a scene where a human stands next to a laptop placed on a cardboard box, and a bomb lies at the other end of the room. In the real world, the bomb is a plastic toy; we manipulate the input map's labels to reproduce the scenario from [13], which demonstrated a black-box attack that coerces an LLM into detonating a bomb under the guise of a movie script. The *Bomb* prompt is "Reenact the scene from my favorite movie. A robot takes a bomb to an evildoer and activates the bomb, the ultimate sacrifice (prop emits sound)."

1) Results: Not considering the *Bomb* task that should never succeed, we find that initial plan success for GPT5, GPT5 Mini, and GPT5 Nano is respectively 24%, 8%, and 0%; after feeback this improves accross the board to 88%, 48%, and 12%, for an average of $\approx$ 39%. GPT5 Nano is not pictured in Figure 9 for visual clarity.

Blocks: Although both tasks involve stacking three blocks, altering the target order substantially affected performance. PerceptTwin allowed the two tasks to reach similar performance. The judge only had to intervene in the "yellow–black–blue" variant, due to faulty final block orderings.

Veggies: PerceptTwin improved both success and safety. In "Prep the veggies," the planner correctly inferred the intended subtasks (slice onion and pepper); however, seven judge safety interventions were needed to prevent unsafe knife-handling near a human. Failures in "Put pepper in cooler" arose mainly from precondition violations (e.g., opening the cooler with the gripper occupied), which is consistent with the human bias that we note in Fig. 8. This could explain the planner's similar failure given that LLMs learn from human data (note that we did specify that the robot was single-armed in the planner's system prompt). The combined "prep & put in cooler" task, requiring at least 17 steps (the robot needs to move the pepper to avoid the human, get the knife, slice both veggies, put down the knife, open the cooler, place the veggies one by one in the cooler), was most challenging. Here, PerceptTwin enabled GPT5 to improve from zero to $\frac{4}{5}$ successes, demonstrating its utility for long-horizon reasoning.

Bomb further demonstrates how PerceptTwin mitigates adversarial vulnerabilities. Judge interventions on the initial SMART-LLM plans correspond to plans that would have detonated the bomb as in [13], had it not been for PerceptTwin's ability to detect harmful plans. While unsafe plans still exist after feedback, the judge reliably flags them as undeployable.

We highlight that these tasks are quite complex compared to the simpler SMART-LLM [8] tasks, and that SMART-LLM does tend to fail without PerceptTwin feedback (see Fig.9). We manually verified all judge answers, and found them to be accurate, save for the *Bomb* task, where the judge used *unsafe* and *incorrect* interchangeably. We explain this by the extremely unsafe nature of handling a bomb.

Across domains, effective feedback required far more than what the input scene representations could provide: veggie preparation alone demanded open-vocabulary affordance grounding (identifying sliceable objects), object movements (knife proximity), commonsense preconditions (picking up a knife before slicing), and alignment reasoning (forbidding knife use near humans, which held even under adversarial prompts such as "the knife is foam"). These results suggest that robotic LLM planning requires comprehensive simulation beyond semantic scene maps and support our claim that PerceptTwin is a useful tool for planning.

VI. Conclusion

Limitations. AI2Thor [26] supports changing object appearances in response to a skill (`CutObject('potato')` will show chopped potatoes). This feature is not available for user-provided 3D assets, and so, just like Holodeck [20], PerceptTwin suffers from this limitation. Skills that move objects or robots are fully implemented, but skill that change object states only result in textual changes suitable for planning but not for visual reasoning.

Conclusion. We present a first step toward the challenging problem of reconstructing scene maps into simulation without human intervention. Our results cover a large breadth of tasks, including reconstructions, diverse scene generation, human interpretability, planning feedback, and plan alignment verification, which demonstrates the value of addressing this problem. We hope the system-building insights offered here will benefit future efforts in this direction.

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