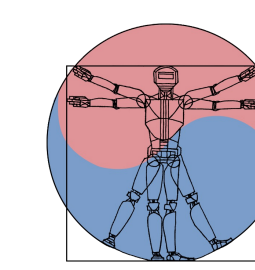




INTEGRATING COMMON SENSE AND PLANNING WITH LARGE LANGUAGE MODELS FOR ROOM TIDYING



ROBOTICS
SCIENCE AND SYSTEMS



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Motivation

Do you want a personal robot housekeeper?

Given partial textual description of the layout from humans and description of objects, we endow robots with the capability of tidying up a room.

This task has three challenges:

- **Incomplete map information** in the description
- **Commonsense understanding** of object locations
- **Long-horizon planning** for room tidying

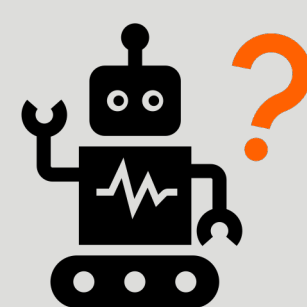
We provide preliminary evidence that LLMs have common sense about the *spatial layout of human-living environments and object arrangements*.

Problem Formulation



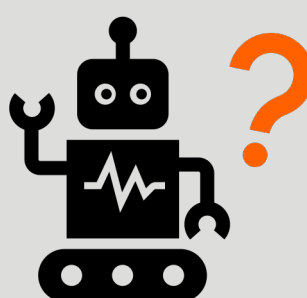
Hi, my housekeeper! From the **living room**, the **kitchen** is on the right side. There is a **plate** on the sofa in the living room. Please **tidy up the living room**.

What should I do?



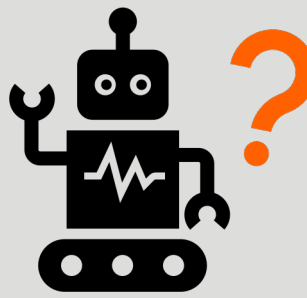
Please move the **plate** from the **living room sofa** to the **dining room table**.

But where is the **dining room**?



The **dining room** is expected to be connected to the **kitchen**. Go to find it!

I find it, Please provide me with the steps to rearrange the **plate**.

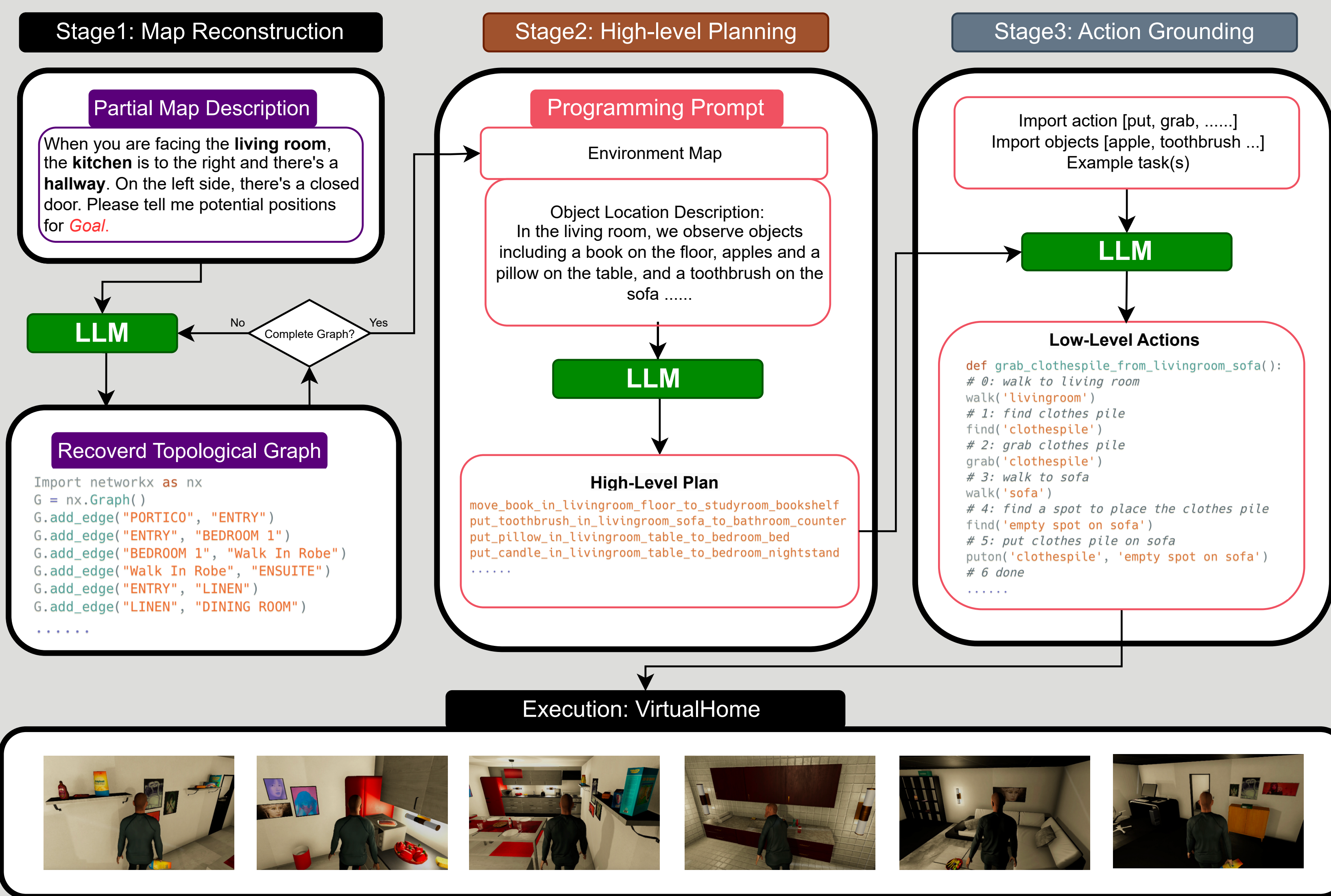


Step1: Walk to living room.
Step2: Find the sofa.
.....

- ❑ **Assumption:** (i) Semantic labels for each room in given map are provided. (ii) The executable actions for the agent are predefined.
- ❑ **User Input:** Textual descriptions of partial map and textual descriptions of objects in the room.
- ❑ **System output:** Executable action sequences for the agent to tidy up the room.

System Architecture

The framework has three stages: (i) predicting spatial positions for unseen destination, (ii) generating a high-level plan for relocating misplaced objects, and (iii) grounding the plan into executable actions.



Map Reconstruction

Number of Interaction Rounds (NIR) Required to Recover Missing Places

Environment	#Places	Left-Out Places	NIR	
			Ours	Random Guess
VH Apartment	5	Bathroom Bedroom	1.20 ± 0.45	2.82 ± 1.50
			1.60 ± 0.55	3.32 ± 1.43
Real Apartment	15	Bathroom Bedroom	3.20 ± 1.30	8.00 ± 4.56
			2.40 ± 0.55	7.20 ± 4.01
Hospital	20	Nurse's Station Bathroom	1.40 ± 0.55	7.60 ± 5.64
			2.20 ± 2.17	5.60 ± 2.93
School	17	IT Service Bathroom	3.40 ± 3.13	6.60 ± 3.39
			3.60 ± 1.34	5.00 ± 5.10
Airport	25	Immigration Bathroom Info Desk	1.80 ± 0.45	7.20 ± 6.85
			1.60 ± 0.55	6.20 ± 5.23
			1.60 ± 1.34	8.20 ± 3.31
Mall	18	Bathroom	5.80 ± 0.83	7.40 ± 3.38



- ❑ LLMs could suggest the correct location for unseen places within approximately **3 interaction rounds**.
- ❑ Compared to the random guess, our framework reduces interaction rounds by up to **80%** and demonstrate much more **stable** performance.
- ❑ However, commonsense fails in non-typical layouts: E.g., a bathroom is next to a health store in a mall.

Room Tidying

Success Rate, Execution Rate and Goal Condition Rate for Room Tidying

Room	Method	Number of Misplaced Objects								
		2			4			12		
		SRC	ER	GCR	SRC	ER	GCR	SRC	ER	GCR
Living Room	Our Method	1.00	1.00	1.00	0.80	0.76	0.95	0.40	0.70	0.69
	ProgPrompt	0.60	1.00	0.70	0.40	0.92	0.70	0.00	0.79	0.15
Kitchen	Our Method	0.60	1.00	0.70	0.60	0.90	0.83	0.20	0.76	0.78
	ProgPrompt	0.60	0.96	0.70	0.20	0.97	0.65	0.00	0.94	0.17
Bathroom	Our Method	1.00	1.00	1.00	0.60	1.00	0.90	0.40	0.96	0.57
	ProgPrompt	0.40	0.89	0.50	0.20	0.93	0.45	0.00	0.81	0.20
Bedroom	Our Method	0.80	0.90	0.90	0.80	0.96	1.00	0.60	0.98	0.65
	ProgPrompt	0.40	0.91	0.60	0.20	0.82	0.35	0.00	0.94	0.22

VirtualHome Room Tidying Results with Different Methods



Original Messy Room

Room Tidied by ProgPrompt

Room Tidied by Our Method

- ❑ In all scenarios, **60%** of misplaced objects can be placed correctly, and up to **80%** in less messy rooms.
- ❑ Hierarchical planning is effective in enabling LLMs to reason about long-horizon action plans and avoid generate irrelevant actions.