LLM-Guided State Estimation for Partially Observable Task and Motion Planning

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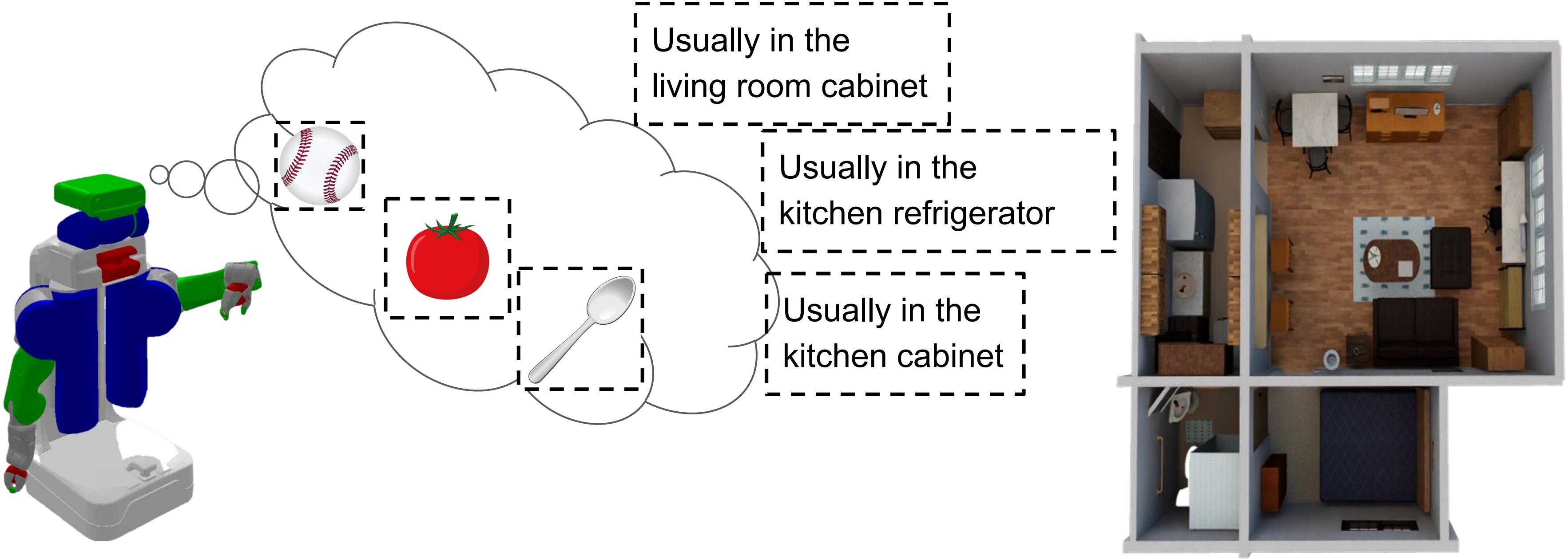
Motivation

Can we leverage **common sense** to solve partially observable TAMP problems?

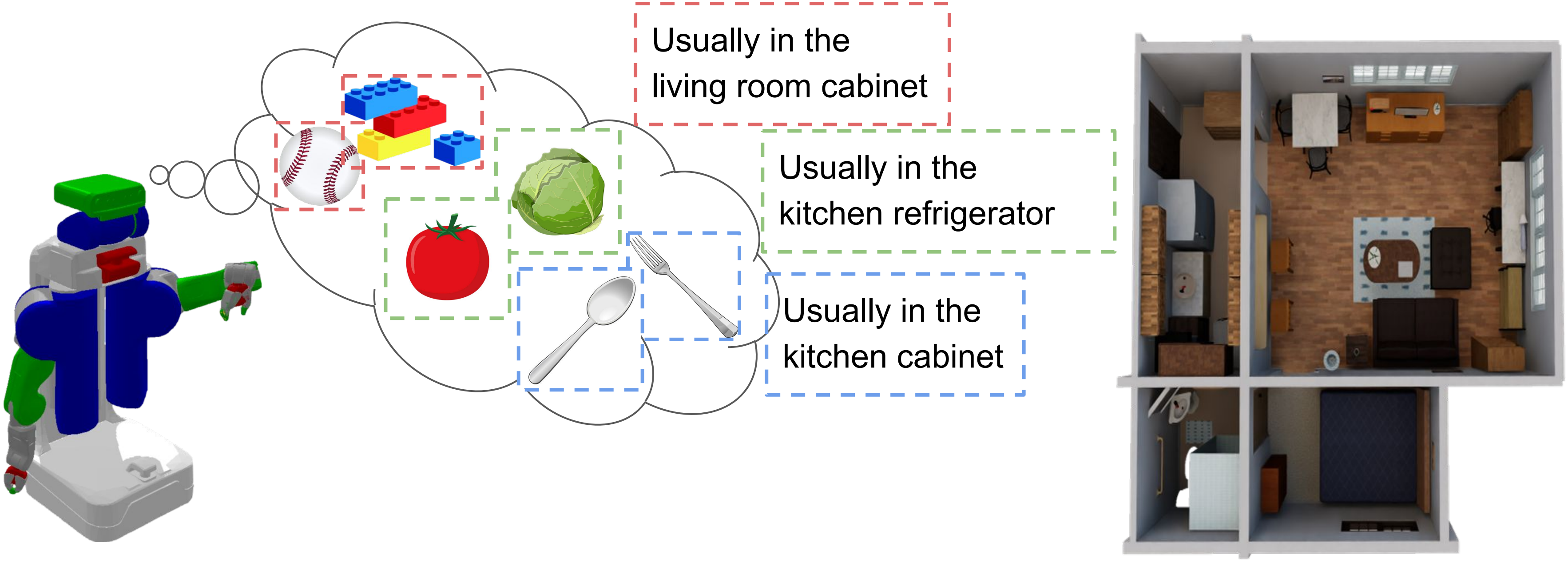
Common Sense 1. Certain objects are likely to be at certain locations.



Motivation

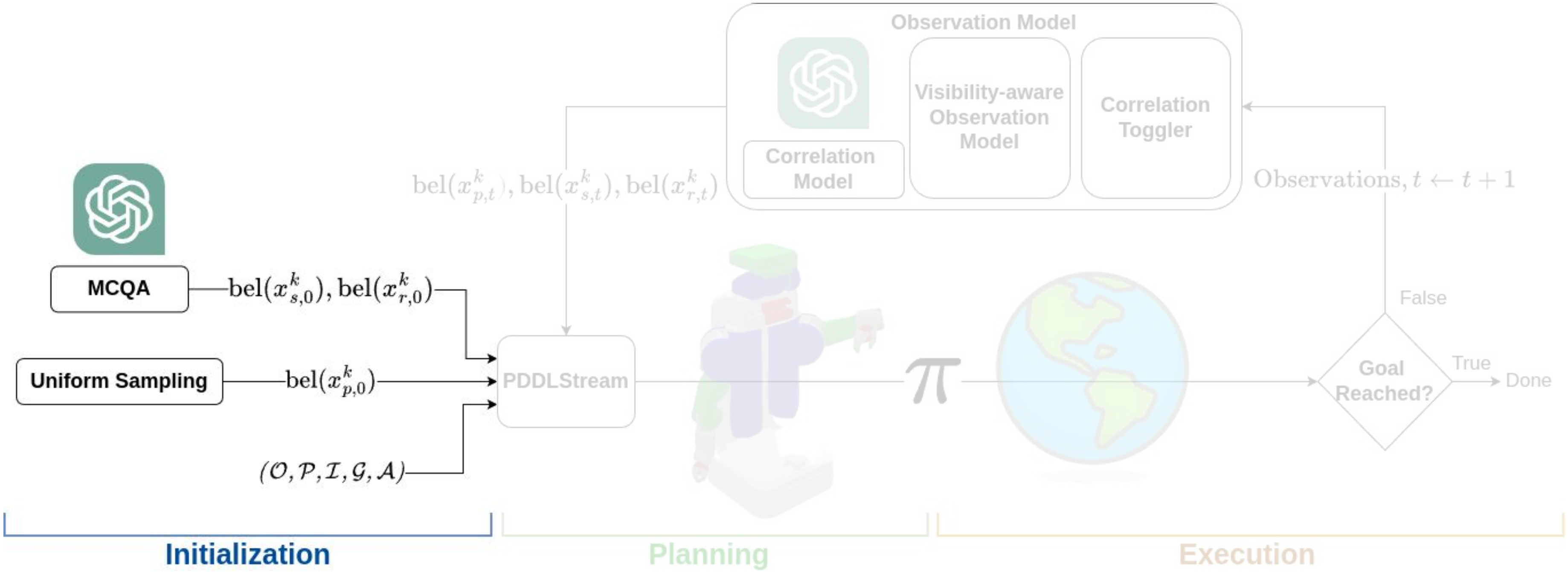
Can we leverage common sense to solve partially observable TAMP problems?

Common Sense 2. Similar objects are likely to be collocated, dissimilar objects are not likely to be placed together.



Method

Initialization: The initial beliefs about the semantic locations of objects are derived from LLMs, while the initial beliefs about their poses, are uniformly distributed across all surfaces



Method

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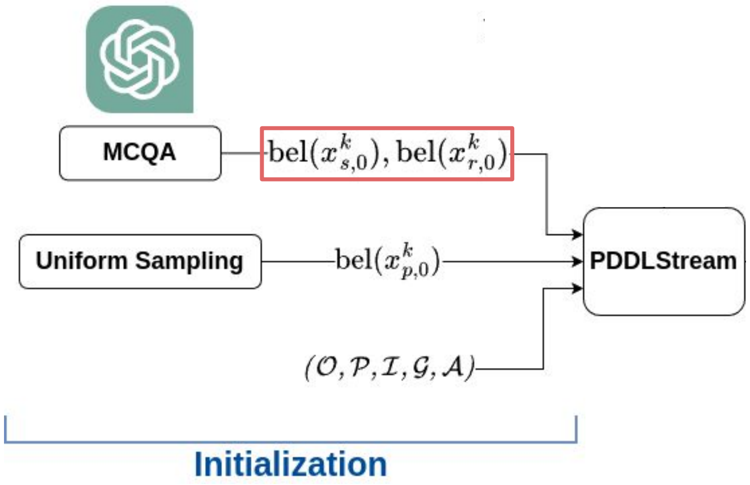
1. Use MCQA to generate categorical distribution over rooms and surfaces via next token prediction.

$$\mathrm{bel}(x^k_{s,0}) = \{\mathrm{Dishwasher} : 0.05, \mathrm{Cabinet} : 0.25, \mathrm{Counter} : 0.4, \mathrm{Table} : 0.3\}$$
$$\mathrm{bel}(x^k_{r,0}) = \{\mathrm{Kitchen} : 0.95, \mathrm{Bathroom} : 0.01, \mathrm{Livingroom} : 0.02, \mathrm{Garage} : 0.02\}$$



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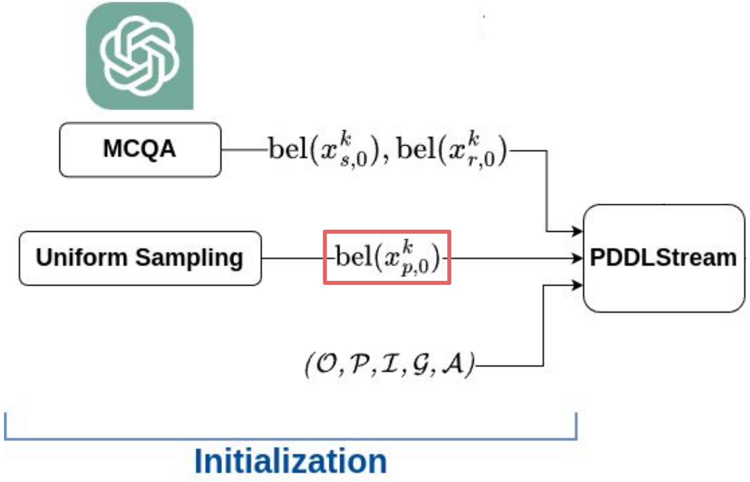
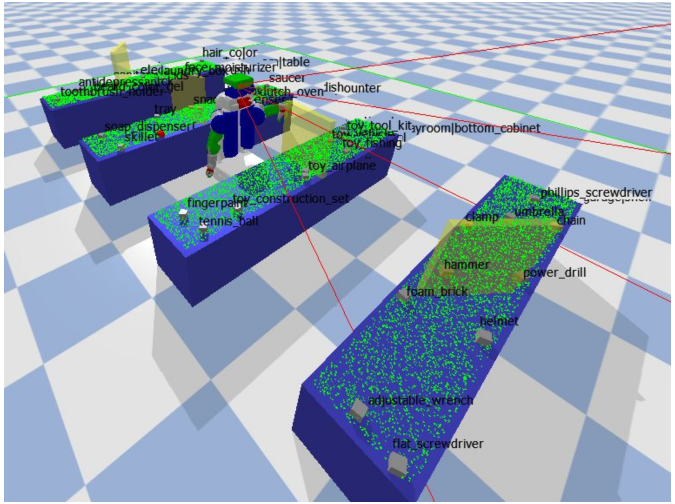
2. Sample object poses uniformly across all surfaces.





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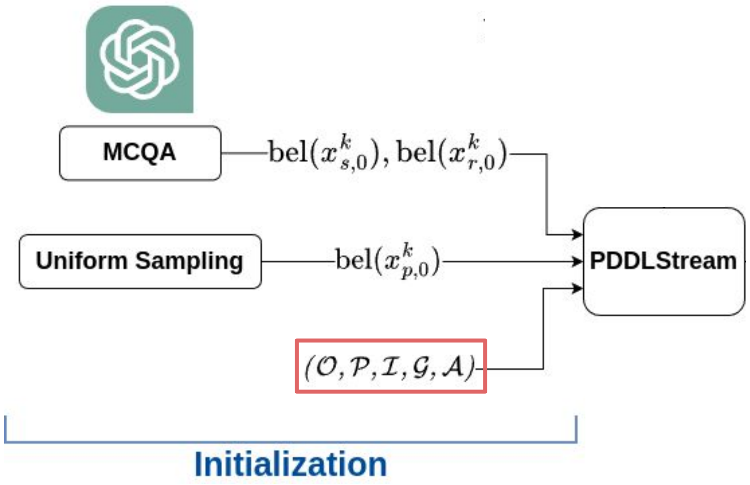
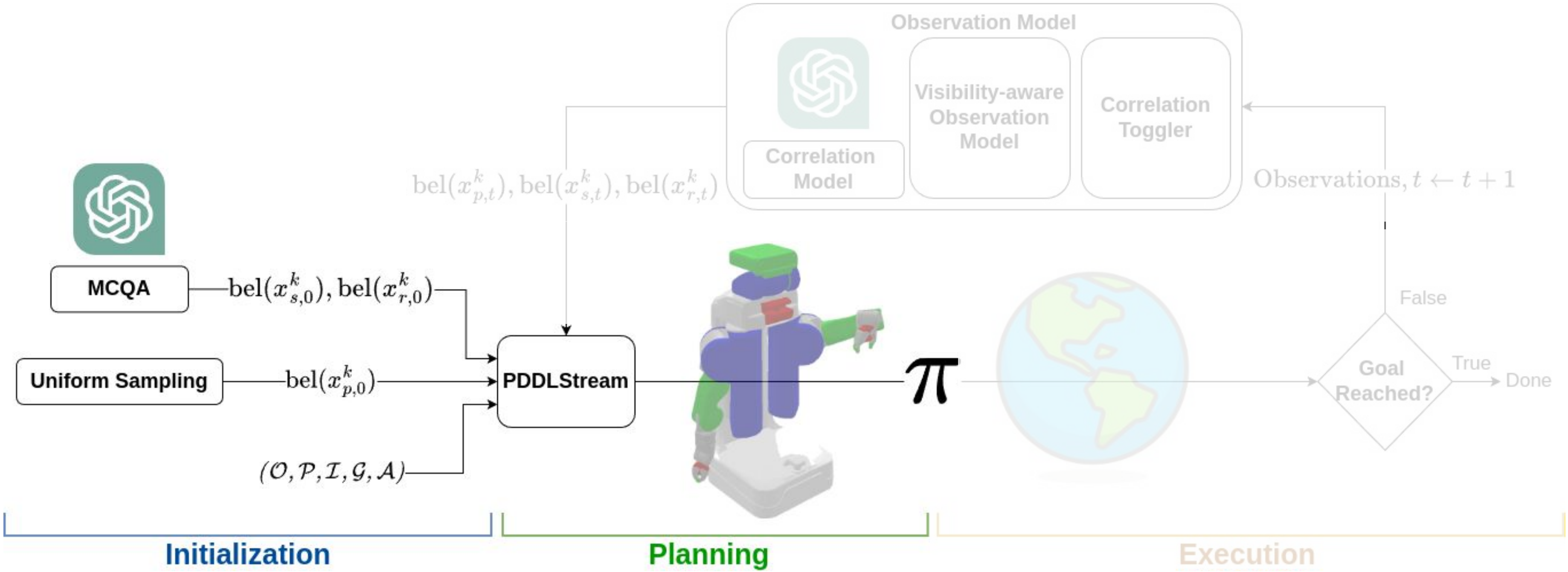


1. Use MCQA to generate categorical distribution over rooms and surfaces via next token prediction.
2. Sample object poses uniformly across all surfaces.
3. Create a TAMP problem description

$\mathcal{O}$: set of manipulable objects
$\mathcal{P}$: set of predicates
$\mathcal{I}$: initial state
$\mathcal{A}$: set of actions
$\mathcal{G}$: goal state

Method

Planning: Off-the-shelf TAMP planner solves a determinized partially observable TAMP problem.

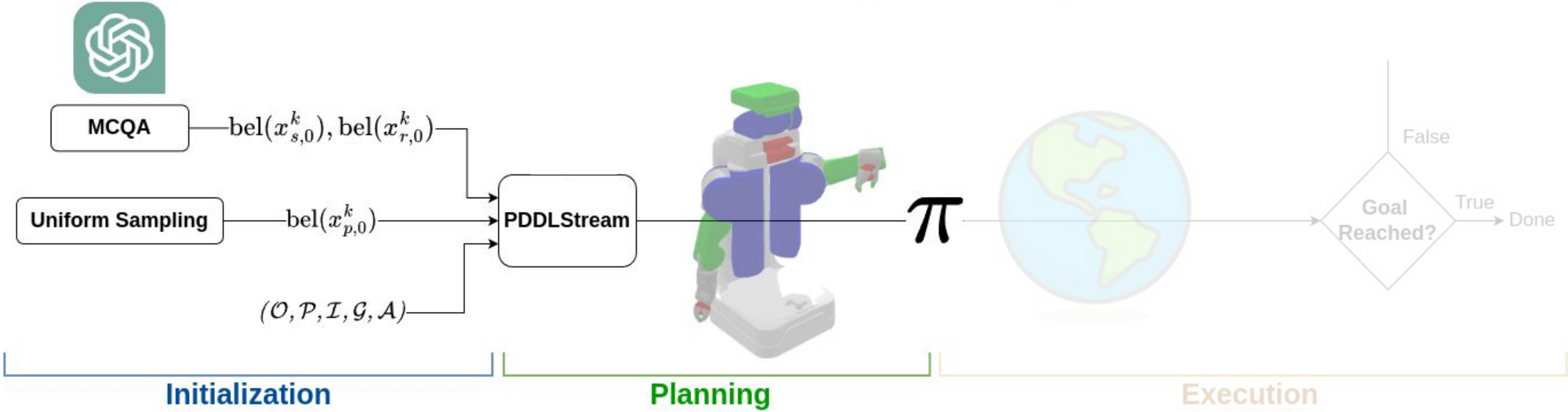


Method

Planning: Off-the-shelf TAMP planner solves a $\boxed{\text{determinized}}$ partially observable TAMP problem.

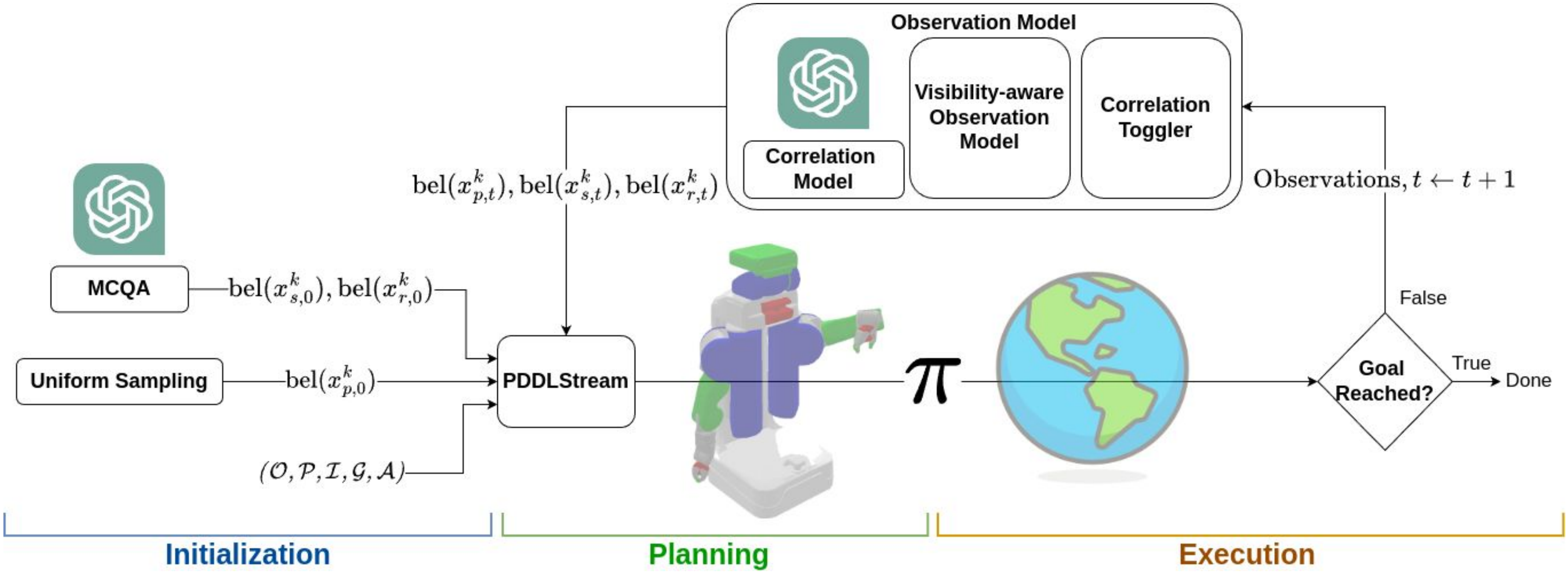
Self-loop determinization heuristic

$$
\begin{aligned}
V^*(s) &= min_{a \in A(s)} \left[Q^*(s,a) \right] \\
&= min_{a \in A(s)} \left[\frac{cost(a)}{p(s'|s,a)} + V^*(s') \right]
\end{aligned}
$$



Method

Execution: Upon executing the observation action, the beliefs are updated to reflect the detection of both similar and dissimilar objects while accounting for occlusions. The planner replans with the updated beliefs.



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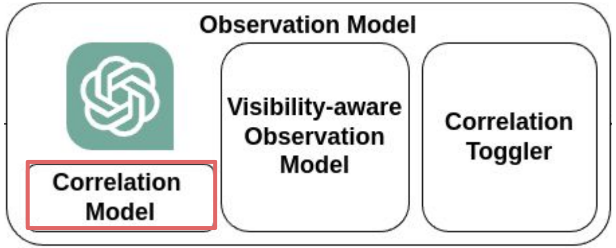
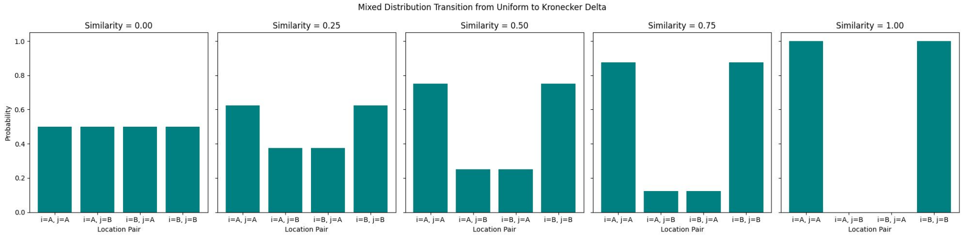
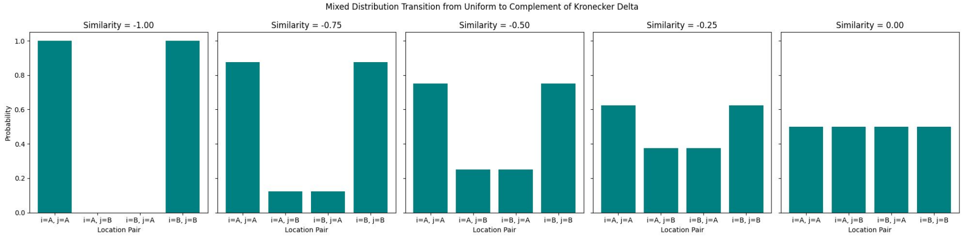


$$P(x^{j}_{r,t} | x^{k}_{r,t}) = \begin{cases} \mathrm{sim}(j,k)\, \delta_{jk} + (1 - \mathrm{sim}(j,k))\, u_{jk}, & \mathrm{sim}(j,k) \geq 0, \\ \mathrm{abs}(\mathrm{sim}(j,k)) \bar{\delta}_{jk} + (1 + \mathrm{sim}(j,k))\, u_{jk}, & \mathrm{sim}(j,k) \leq 0. \end{cases}$$





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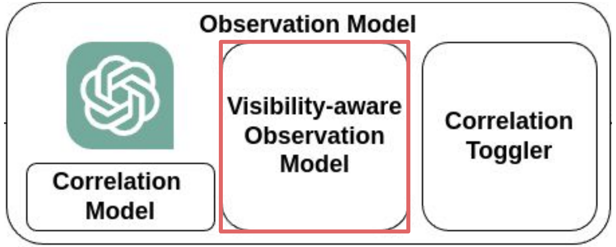
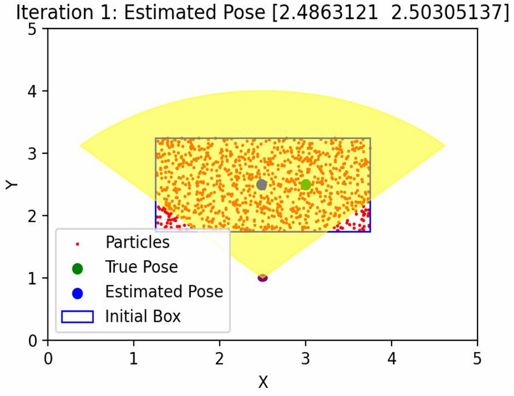
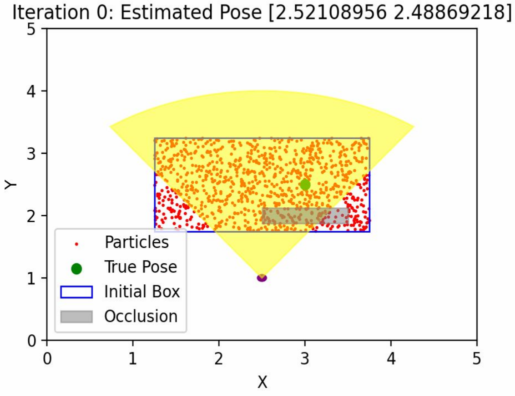


$$
\begin{aligned}
\mathrm{bel}(x^k_{p,t}) &= P(x^k_{p,t} | x^k_{s,t}, x^k_{r,t} z^k_{p,t}), \\
&= \eta P(z^k_{p,t} | x^k_{p,t}, x^k_{s,t}, x^k_{r,t}) \overline{\mathrm{bel}}(x_p(t)), \text{ or} \\
&= \eta P(\overline{z^k_{p,t}} | x^k_{p,t}, x^k_{s,t}, x^k_{r,t}) \overline{\mathrm{bel}}(x_p(t)).
\end{aligned}
$$

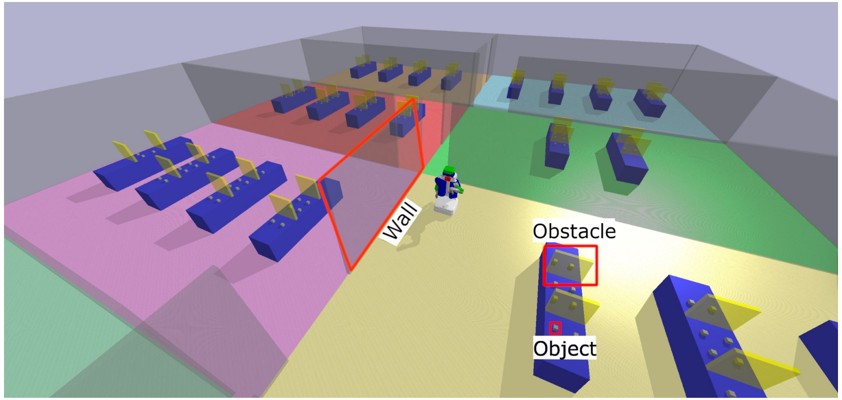


Without Occlusion

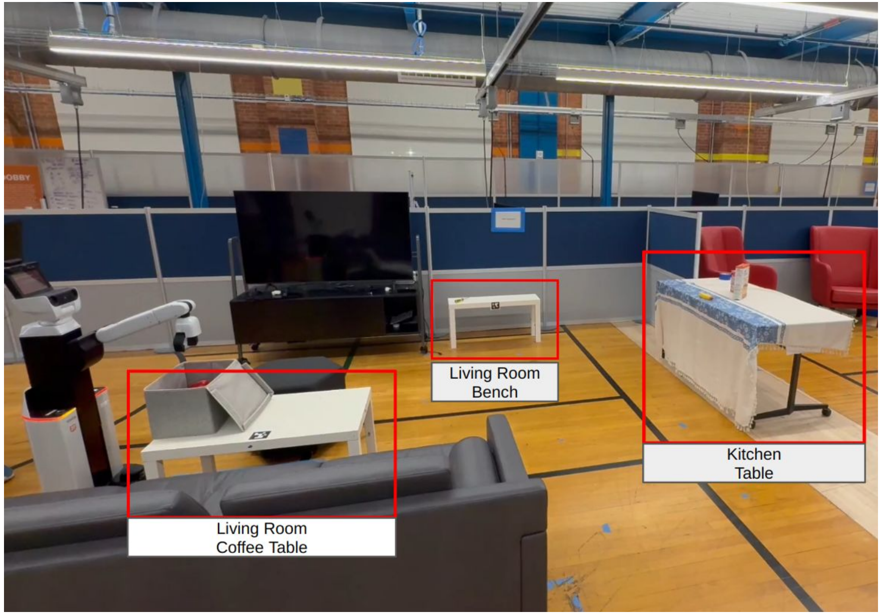


With Occlusion

Experiments



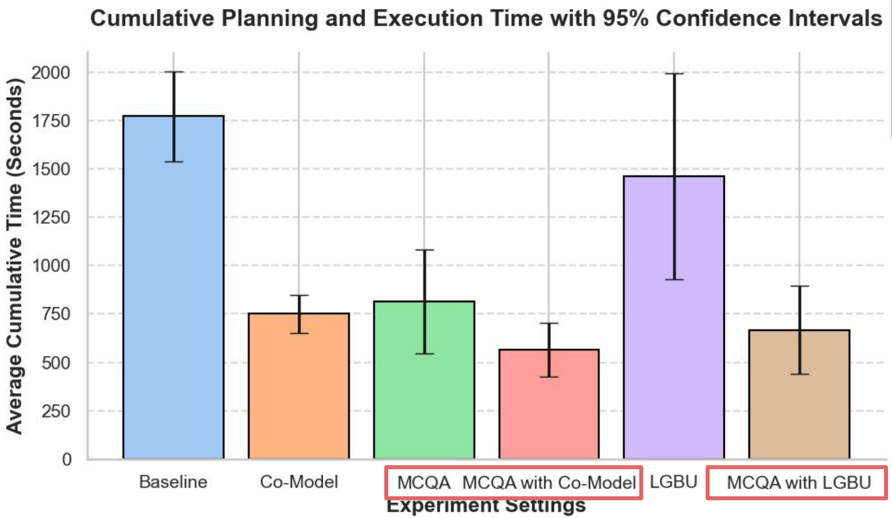
Large scale simulation experiment through sampling household environments from human annotated dataset.



Real world experiment.

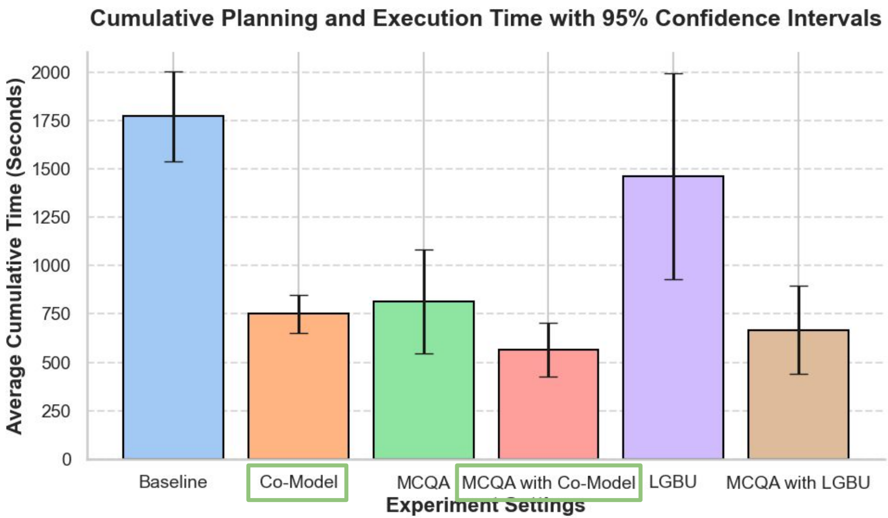
Housekeep: Tidying Virtual Households using Commonsense Reasoning by Kaht et al.

Results



Takeaway 1: Common-sense knowledge about object locations, encoded in LLMs, can improve efficiency.

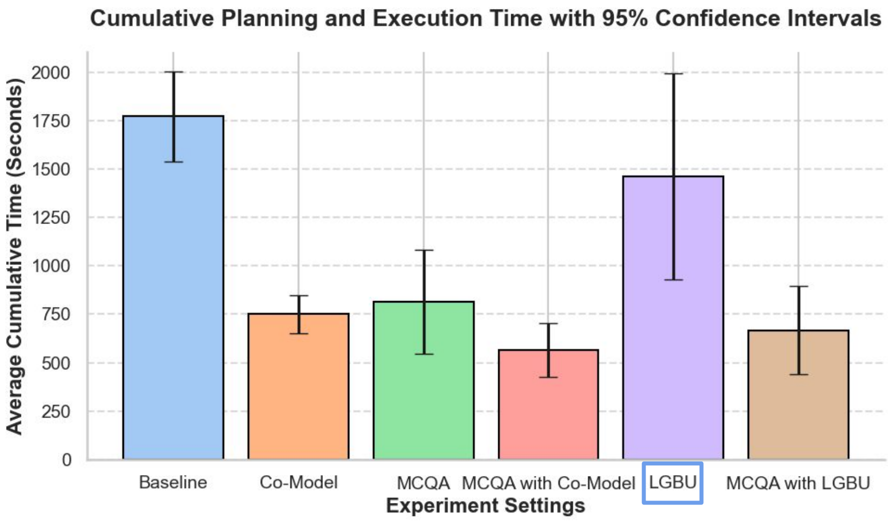
Results



Takeaway 1: Common-sense knowledge about object locations, encoded in LLMs, can improve efficiency.

Takeaway 2: Semantic similarity between objects provides useful inductive bias that can improve efficiency.

Results



Takeaway 1: Common-sense knowledge about object locations, encoded in LLMs, can improve efficiency.

Takeaway 2: Semantic similarity between objects provides useful inductive bias that can improve efficiency.

Takeaway 2: Solely relying on LLMs for belief updates (LGBU) is insufficient for long-horizon planning and execution.