Anticipate & Act: Integrating LLMs and Classical Planning for Efficient Task Execution in Household Environments

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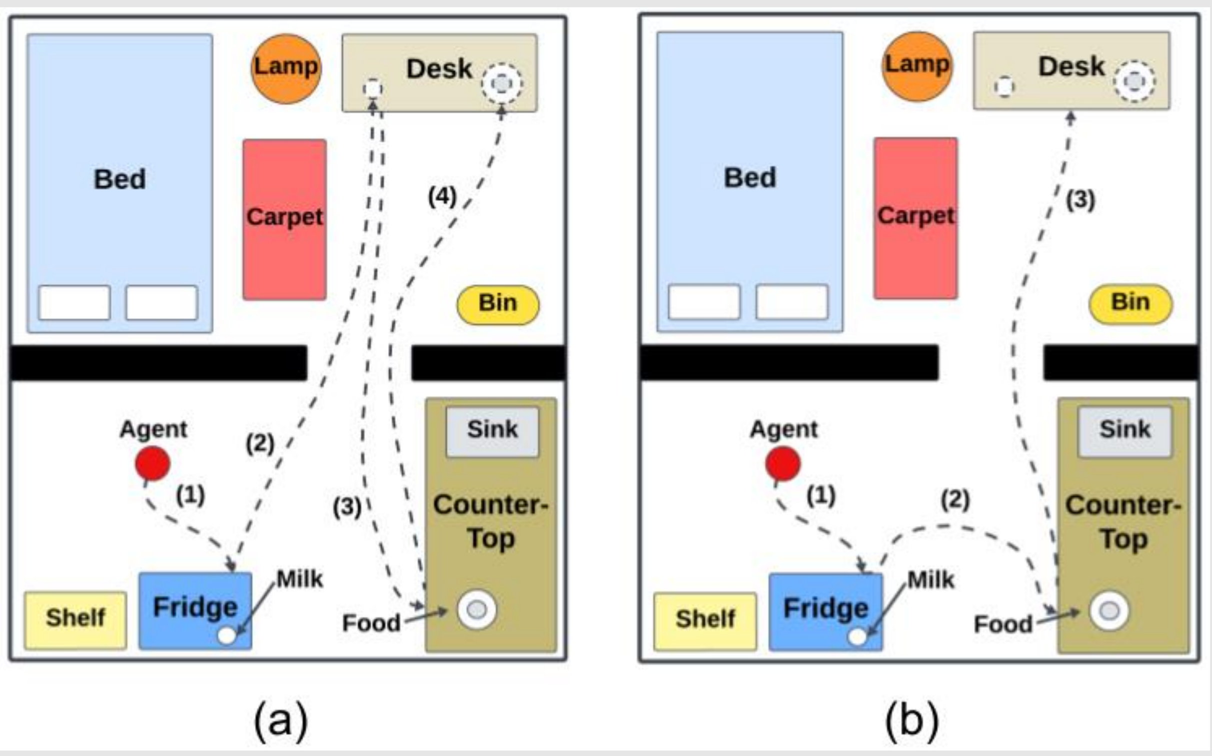
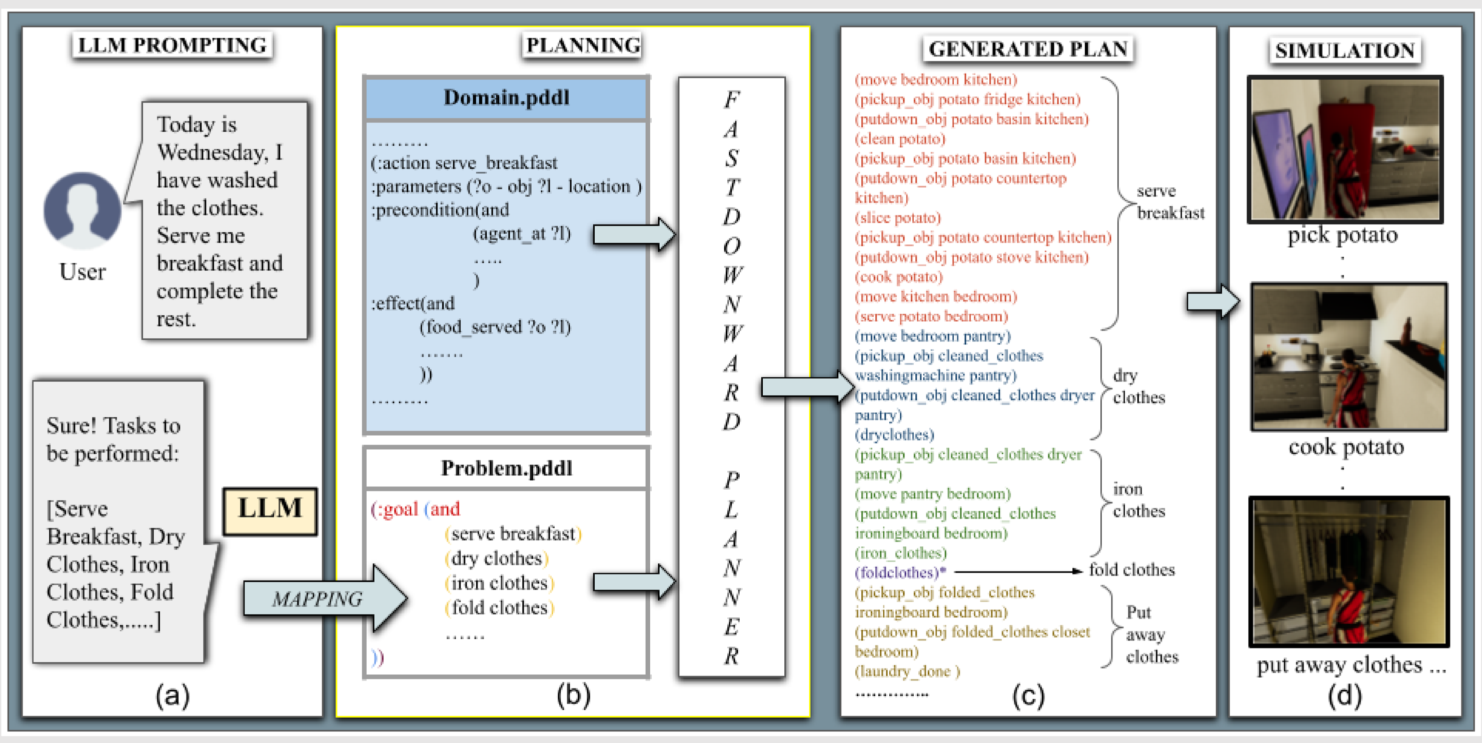
Introduction

- Assistive agents performing household tasks often compute and execute actions that accomplish one task at a time.
- Efficiency can be improved by anticipating upcoming tasks and computing an action sequence that jointly achieves these tasks.
- We use:
  - world knowledge of LLMs for high-level task anticipation
  - classical planning system to compute a sequence of finer granularity actions
  - realistic scenarios in the *VirtualHome* environment for task execution and grounding.



Framework



Routine: $\mathcal{R} = \{\tau_1, \tau_2, \dots, \tau_n\}$

$\forall\, \tau_j \in \mathcal{T}$ (known tasks)

LLM objective: predicting tasks τ_i for a routine $\mathcal{R}$

Each task τ_j requires a sequence $\{a_1^j, a_2^j, \dots, a_k^j\}$ to be executed

Every action a_k^j has a cost c_k^j

$$\text{Plan} : \pi = (a_1, \dots, a_K)$$

$$\text{Planner objective} : \pi^* = (argmin)_{\pi^j} \mathcal{C}(\pi^j),$$

$$\text{where } \mathcal{C}(\pi^j) = \textstyle\sum_{k=0}^{K} c_k^j$$

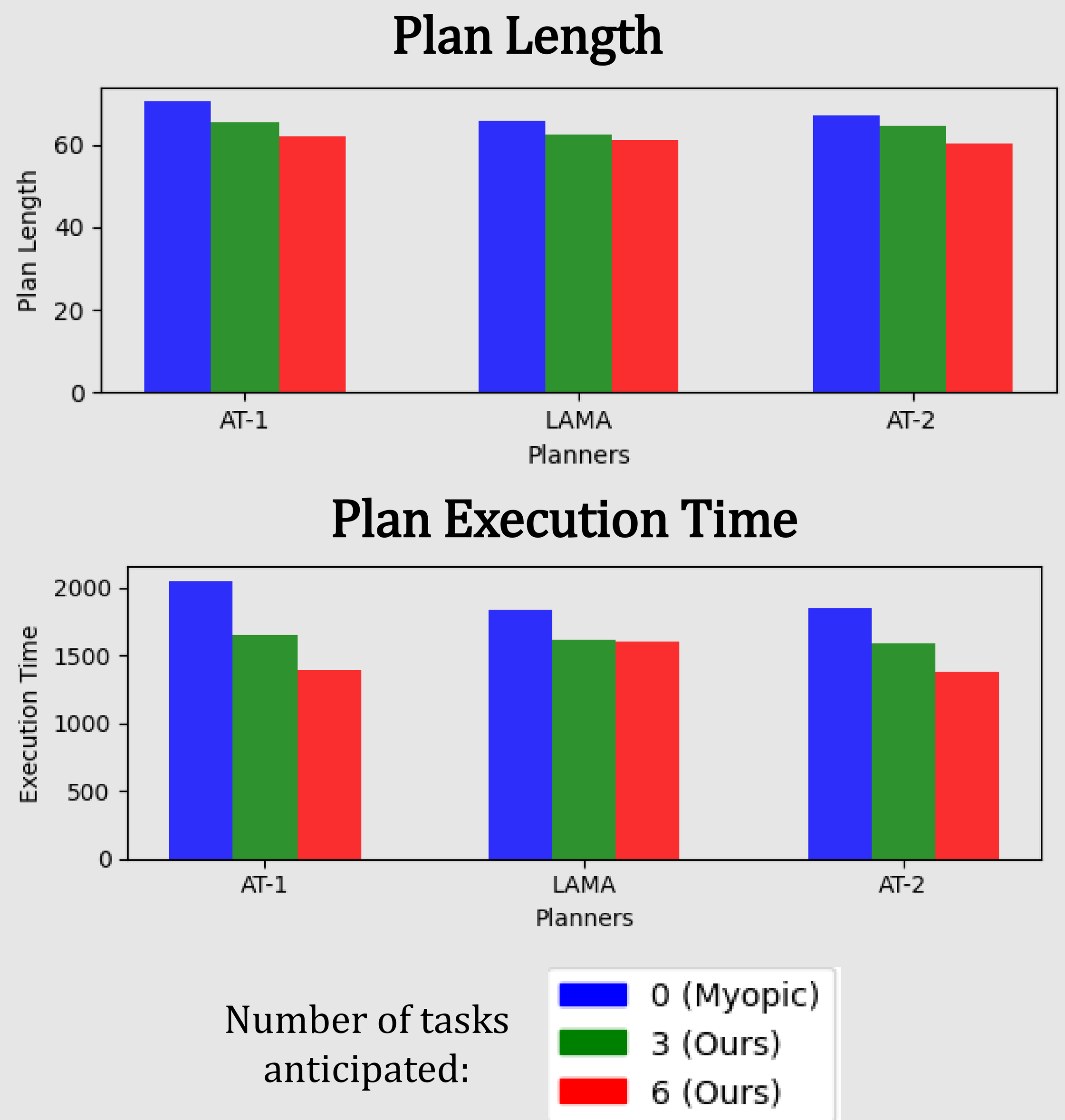
Cost c_k^j represents the time taken by the agent for execution.

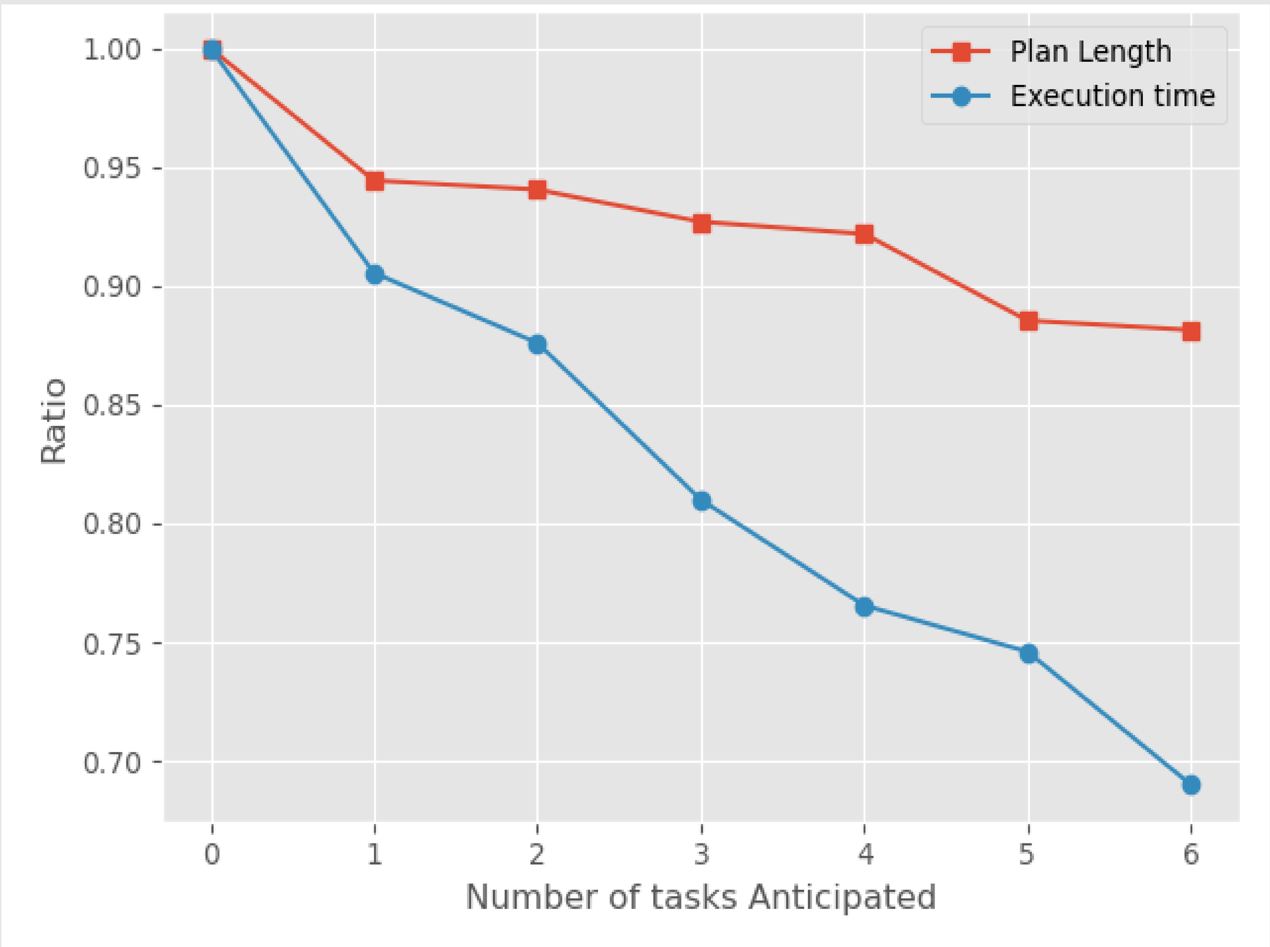
Results

LLMs	Without context			With Context		
	Miss Ratio (Miss.) ⇓	Partial Ordering Count (POC) ⇑	$KRCC$ ⇑	Miss Ratio (Miss.) ⇓	Partial Ordering Count (POC) ⇑	$KRCC$ ⇑
PaLM	0.361	0.974	0.993	0.034	0.994	0.996
GPT-3.5-turbo	0.282	0.676	0.906	0.0698	0.806	0.976
GPT-4	**0.037**	**0.960**	**0.995**	**0.0006**	**1.0**	**1.0**

$$KRCC = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

Performance of LLMs for Task Anticipation. Results over 500 experiments with ≈ 20 tasks per experiment.





Mean execution cost ratio and plan length ratio WRT Myopic Agent

Qualitative evaluation in VirtualHome simulation (Pickup of multiple items for anticipated tasks)

Discussion

We describe a framework: **Anticipate&Act**, for task anticipation and action execution by an agent in complex household environments. We use Planning Domain Definition Language (PDDL) as the action language to create a household domain and use the Fast Downward solver to compute plans for any goal state.

We present a **31% reduction** in execution time and a **12% reduction** in plan length compared to a system that does not anticipate upcoming tasks

References

1. Dhakal, R., Talukder, M. R. H., & Stein, G. J. (2023). Anticipatory Planning: Improving Long-Lived Planning by Estimating Expected Cost of Future Tasks. *IEEE International Conference on Robotics and Automation*, 11538–11545. London, UK.
2. Valmeekam, K., Marquez, M., Olmo, A., Sreedharan, S., & Kambhampati, S. (2023). PlanBench: An Extensible Benchmark for Evaluating Large Language Models on Planning and Reasoning about Change. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, & S. Levine (Eds.), *Advances in Neural Information Processing Systems* (Vol. 36, pp. 38975–38987).
3. Silver, T., Dan, S., Srinivas, K., Tenenbaum, J. B., Kaelbling, L. P., & Katz, M. (2023). Generalized Planning in PDDL Domains with Pretrained Large Language Models. *arXiv [Cs.AI]*. Retrieved from http://arxiv.org/abs/2305.11014
4. Ghallab, M., Knoblock, C., Wilkins, D., Barrett, A., Christianson, D., Friedman, M., … Weld, D. (08 1998). *PDDL - The Planning Domain Definition Language*.