

Generic-to-Specific Reasoning and Learning for Ad Hoc Teamwork

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Abstract

Embodied AI agents deployed in assistive roles often have to collaborate with humans or other agents without prior coordination, quickly adapting to new situations and the behavior of others. State of the art methods for such ad hoc teamwork often pursue a data-driven approach that needs a large labeled dataset of prior observations, lacks transparency, and makes it difficult to rapidly revise existing knowledge in response to changes. This paper advocates the combination of knowledge-based reasoning and data-driven learning for ad hoc teamwork. In the context of collaborating with a human, our architecture enables an ad hoc agent to use a Large Language Model to anticipate abstract future tasks and goals of the human. The agent then computes a plan of concrete actions to achieve these goal(s) based on non-monotonic logical reasoning with the predicted future task(s), prior commonsense domain knowledge, and models that are rapidly learned and revised from limited examples to predict the human’s concrete action choices. The architecture capabilities are illustrated and evaluated in *VirtualHome*, a realistic 3D simulation environment.

1 Introduction

Consider an *embodied* AI agent completing daily living tasks in collaboration with a human it has not worked with before. Figure 1 shows the agent and human working to prepare breakfast and set up a workstation. The human and the agent have a limited view of the environment at each step and do not communicate directly with each other¹. While the human is aware of the upcoming tasks in the domain, the agent is not; it has to reason with different descriptions of domain knowledge and uncertainty, adapting its actions to changes in the domain and the human’s behavior to collaborate efficiently. These characteristics represent Ad Hoc Teamwork (AHT), where an agent must cooperate with others without prior coordination (Stone et al. 2010).

The state of the art in AHT has moved from using pre-determined policies for selecting actions in specific states to methods with a key *data-driven* component that uses a long history of prior experiences to build probabilistic or deep



Figure 1: Screenshots from *VirtualHome* (Puig et al. 2018) showing a human (female in green top) and an embodied AI agent (male in blue shirt) collaborating.

network methods that model the behavior of other agents (or agent types) and optimize the behavior of the ad hoc agent (Mirsky et al. 2022). However, it is difficult to gather large training datasets of different situations in practical domains. Also, these methods lack transparency, and make it difficult to revise existing knowledge over time.

In a departure from existing work, we advocate the design of architectures for AHT that bridge knowledge-based and data-driven reasoning and learning methods. Specifically, we build on our recent work on AHT in structured domains (Dodampegama and Sridharan 2023a,b) to explore human-agent collaboration in more complex domains. An ad hoc agent equipped with our architecture:

1. Leverages the strengths of Large Language Models (LLMs) to anticipate future tasks and goals of the human collaborator using partial sequence of tasks for efficient collaboration in dynamic settings; and
2. Considers current and anticipated tasks as joint goals, and performs non-monotonic logical reasoning with relevant commonsense domain knowledge and a rapidly-learned predictive model of the human’s behavior to determine its actions toward achieving the goals.

We use Answer Set Prolog (Gelfond and Kahl 2014) for non-monotonic logical reasoning and GPT4o mini for high-level task anticipation. We evaluate our architecture’s capabilities in household scenarios in *VirtualHome*, a realistic physics-based 3D simulation environment for multiagent collaboration (Puig et al. 2018).

2 Related Work

Research in AHT evolved from the use of specific protocols defining the agents’ behavior in specific scenarios (Bowl-

¹Our architecture can support communication between agents, but we do not include it here for simplicity.

ing and McCracken 2005), to the use of probabilistic and sampling-based methods (Barrett et al. 2013) over a period of time (Mirsky et al. 2022). Methods currently considered to be state of the art include a data-driven component, using probabilistic, deep-network and/or reinforcement learning (RL) methods to learn *policies* that determine action choices based on a long history of prior observations of different types of agents or situations. For example, RL methods have been used to select a policy for a new teammate from the policies learned for different teammate types (Barrett et al. 2017), and model-based RL has been used to learn environment models and behavior of teammates (Ribeiro et al. 2023). Researchers have used attention-based deep neural networks to jointly learn policies for different agent types (Chen et al. 2020) and different team compositions (Rahman et al. 2021); hierarchical variational auto-encoders and meta-learning to model and infer beliefs over other agents (Zintgraf et al. 2021); Convolutional Neural Networks to detect and adapt to changing teammate types (Ravula, Alkoby, and Stone 2019); sampling strategies combined with learning methods to optimize performance (Zand, Parker-Holder, and Roberts 2022); and meta-RL methods with self-play and perturbed rewards to respond to unknown teammates (Fang et al. 2024). Researchers have also explored communication strategies for AHT, e.g., broadcast messages at a cost or use heuristic methods (Macke, Mirsky, and Stone 2021). Such data-driven methods are resource-hungry, build opaque models, and make it difficult to adapt to changes.

Recent work in AHT has leveraged Large Language Models (LLMs), e.g., an LLM-based hierarchical planner (IRoT) has been used to generate an ad hoc agent’s policy to support zero-shot collaboration (Liu et al. 2024), and memory retrieval and code-driven reasoning have been used for AHT in the AvalonPlay benchmark (Shi et al. 2023). In parallel, there has been increased use such data-driven methods for embodied AI systems in physically realistic simulation environments such as Habitat (Savva et al. 2019) and Virtual-Home (Puig et al. 2018) that support the generation of complex scenarios for evaluating AI systems.

Our architecture combines knowledge-based and data-driven methods for reasoning and learning, allowing an ad hoc agent to adapt to the behavior of its teammate in a complex, realistic household environment. We demonstrate that the interplay between reasoning and learning enables the ad hoc agent to utilize prior knowledge, learn and revise predictive models of human behavior with limited data, and accurately anticipate future tasks with minimal feedback.

3 Architecture

In our architecture for human-embodied AI ad hoc collaboration (Figure 2), the ad hoc agent is an assistive embodied AI agent that utilizes non-monotonic logical reasoning with prior commonsense domain knowledge and an incrementally learned behavior model of its human teammate. At each step, both the human and the ad hoc agent receive state observations from the environment, which they independently use to determine and perform their actions. The tasks to be carried out each day are determined by the task

generator. The ad hoc agent is only aware of the current task of the human. To anticipate the human’s future goals, the ad hoc agent utilizes a LLM. The prompt to the LLM is created following different prompt-engineering techniques (Section 3.3) and the LLM’s output is validated to ensure the feasibility and correctness of the predictions. Any available previous knowledge of tasks in the domain is used in the prompts and the external validation. Each component of the architecture is described using the following example.

Example Domain 1 [Embodied AI Agent]

Consider an AI agent and a human collaborating to complete household tasks; Figure 1 shows snapshots of preparing breakfast and setting up the work-station (Puig et al. 2018). The agent and the human can interact with the environment through actions that involve moving to places, picking up or placing objects, switching appliances on or off, and opening or closing appliances. Completing a task requires a sequence of such actions to be computed and executed by the embodied AI agent and/or the human without direct communication between them. The agent assumes that the human has access to the same information about domain state, predicts the actions that the human will execute over the next few steps, and makes its plan of actions accordingly. The agent’s prior commonsense knowledge includes relational descriptions of some attributes of the domain, objects, and human. It also includes axioms governing actions and changes, such as the agent not being able to hold more than two objects at a time or that it is impossible to pick up objects that are not in the same location as the agent.

3.1 Knowledge Representation and Reasoning

In our architecture, any given domain’s transition diagram is described using an extension of action language \mathcal{AL}_d (Gelfond and Inlezan 2013). Action languages are formal models of parts of natural language for describing transition diagrams of dynamic systems. The domain representation comprises a system description \mathcal{D} , a collection of statements of \mathcal{AL}_d , and a history \mathcal{H} . \mathcal{D} has a sorted signature Σ with basic sorts and describes the domain attributes (statics, fluents) and actions in terms of the sorts of their arguments. *Virtual-Home* domain include basic sorts such as *object*, *appliance*, *ad_hoc_agent*, *human*, and *step* (for temporal reasoning). These sorts are arranged hierarchically, e.g., *apple* is a sub-sort of *food* that is a sub-sort of *graspable*, a sub-sort of *object*. Actions can be *agent_actions*, performed by the ad hoc agent, e.g., *grab(ad_hoc_agent, object)* and *switch_on(ad_hoc_agent, appliance)*, or *exo_actions*, performed by the human, e.g., *exo_grab(human, object)* and *exo_switch_on(human, appliance)*. Statics are domain attributes whose values cannot be changed and fluents are attributes whose values can be changed. Fluents can be *inertial*, which obey inertia laws and are changed by actions, e.g., *at(ad_hoc_agent, location)* is the ad hoc agent’s location; and *defined*, which do not obey inertia laws and are not directly changed by ad hoc agent’s actions, e.g., *agent_at(human, location)* denotes the human’s location.

Based on Σ , the domain dynamics are described in \mathcal{D} using three types of axioms: *causal law*, *state constraint*, and

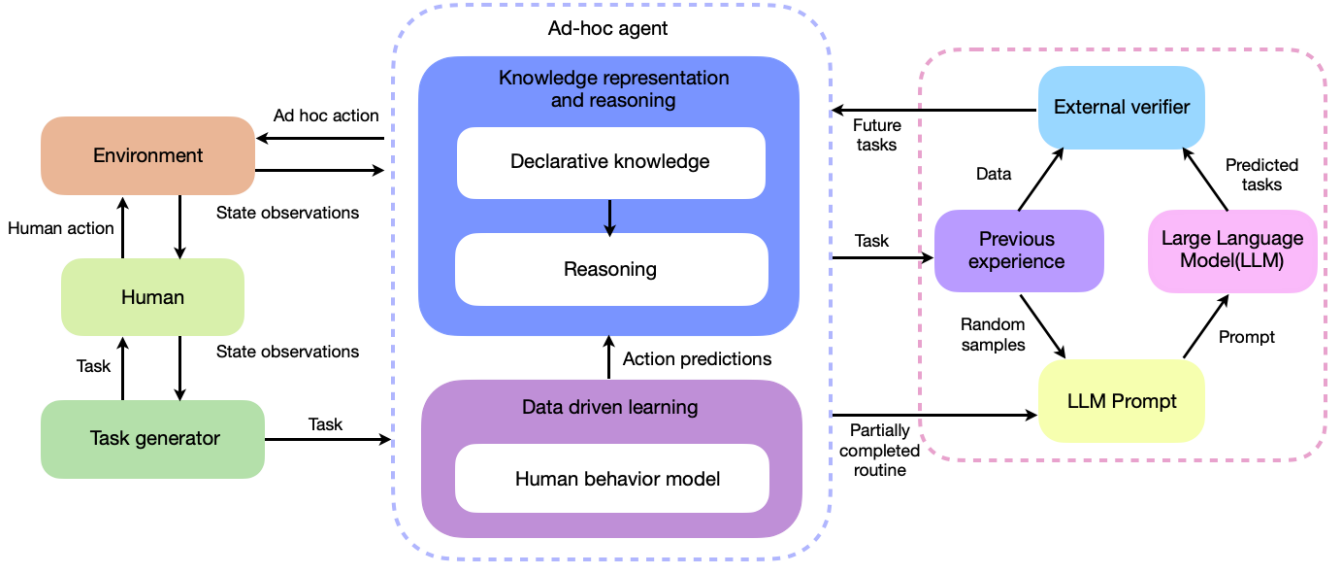


Figure 2: Our architecture combines the complementary strengths of knowledge-based and data-driven reasoning and learning, along with the anticipation capabilities of Large Language Models.

executability condition such as:

$$\text{open}(A, E) \text{ causes } \text{opened}(E) \quad (1a)$$

$$\neg(\text{at}(A, L1), I) \text{ if } \text{at}(A, L2), I, L1 \neq L2 \quad (1b)$$

$$\text{impossible } \text{grab}(A, O) \text{ if } \text{on}(O, E), \quad (1c)$$

$$\text{not opened}(E)$$

where Statement 1(a), a causal law, implies that an agent(A) opening an appliances(E) causes it to be opened; Statement 1(b), a state constraint, implies that an agent(A) cannot be in two places($L1, L2$) at the same time; and Statement 1(c), an executability condition, prevents the ad hoc agent(A) from trying to grab an object(O) from an appliance(E) with a closed door.

History \mathcal{H} is a record of statements of the form $\text{obs}(\text{fluent}, \text{boolean}, \text{step})$, which represent observations, and statements of the form $\text{hpd}(\text{action}, \text{step})$, which represent action execution, at specific time steps. It also includes default statements that are true in the initial state.

To reason with knowledge, we automatically construct program $\Pi(\mathcal{D}, \mathcal{H})$ in CR-Prolog (Balduccini and Gelfond 2003), an extension to ASP that supports consistency restoring (CR) rules. $\Pi(\mathcal{D}, \mathcal{H})$ includes statements from \mathcal{D} and \mathcal{H} , inertia axioms, reality check axioms, closed world assumptions for defined fluents and actions, helper relations, e.g., $\text{holds}(\text{fluent}, \text{step})$ and $\text{occurs}(\text{action}, \text{step})$ to imply that a fluent is true and an action is part of a plan at a time step, and helper axioms that define goals and guide planning and diagnosis. ASP is based on stable model semantics, and encodes *default negation* and *epistemic disjunction*, i.e., unlike “ $\neg a$ ” that states a is believed to be false, “ $\text{not } a$ ” only implies a is not believed to be true, and unlike “ $p \vee \neg p$ ”, “ $p \text{ or } \neg p$ ” is not tautologous. Each literal is true, false, or unknown, and the agent only believes what it is forced to believe. ASP supports non-monotonic reasoning, i.e., the

ability to revise previously held conclusions, which is essential for agents reasoning and acting in practical domains based on incomplete knowledge and noisy observations. The CR rules allow the agent to make assumptions (e.g., that a default statement does not hold) under exceptional circumstances to recover from inconsistencies. All reasoning tasks, i.e., planning, diagnostics, and inference are reduced to computing *answer sets* of Π . We use the SPARC system (Balai, Gelfond, and Zhang 2013) to solve CR-Prolog programs.

The *VirtualHome* scenario is complex, with many objects scattered in different compartments. Achieving goals often requires a computationally expensive process to compute plans with multiple steps. To ensure scalability, we build on prior work in our group on a refinement-based architecture (Sridharan et al. 2019). The ad hoc agent represents and reasons at two resolutions, with the fine-resolution transition diagram defined as a *refinement* of the coarse-resolution one, automatically selecting and using the resolution and the part of the description relevant to the task at hand.

Knowledge-based reasoning and learning methods are often criticized for their need for comprehensive domain knowledge, but existing methods can leverage incomplete knowledge and revise it over time (Sridharan and Meadows 2018). Also, the effort to encode this knowledge is much less than the effort needed to train purely data-driven systems.

3.2 Agent Behavior Models

Practical human-agent collaboration domains change over time, e.g., due to the human’s actions. In addition to prior knowledge, our architecture enables the ad hoc agent to reason with models that predict the human’s behavior. We use the Ecological Rationality (ER) principle (Gigerenzer 2020), based on Herb Simon’s definition of Bounded Rationality and the algorithmic theory of heuristics, to quickly

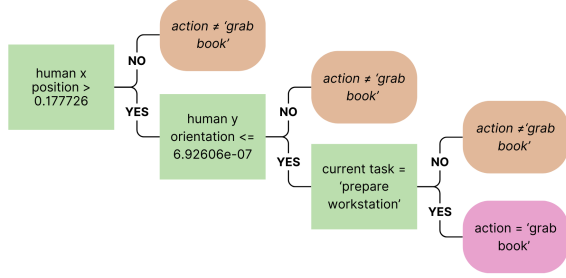


Figure 3: FF tree model of human behavior for the grab_book action in the *VirtualHome* domain.

learn and update predictive behavior models of the human (i.e., the other agent). ER explores decision making “in the wild”, i.e., under open world uncertainty with the space of possibilities not fully known, and characterizes behavior as a function of internal cognitive processes and the environment. It prioritizes *adaptive satisficing* because in the absence of comprehensive knowledge, optimal decisions may be unknowable and not just hard to compute. Also, heuristics are used to ignore part of the information to make decisions more quickly, frugally, and/or accurately than complex methods (Gigerenzer and Gaissmaier 2011). This approach has provided better performance than more sophisticated ones in practical applications (Gigerenzer 2016).

Our architecture enables the ad hoc agent to select relevant attributes and learn a model of the human behavior incrementally and from limited data. Specifically, the agent learns an ensemble of *Fast and Frugal* (FF) trees to predict the human’s behavior. Each FF tree provides a binary choice for a particular action, and the number of leaves in a tree is limited by the number of attributes (Katsikopoulos et al. 2021). Each level of the tree contains an exit allowing the agent to make quick decisions based on available data. Unlike many current methods for AHT, these predictive models can be learned and revised incrementally and rapidly, which is a useful capability for AHT.

Figure 3 shows one such FF tree learned for the human. Our trees are built while minimizing false positives. The initial version of these trees were built using only 1000 traces of human action choices and domain state from the *VirtualHome* domain, with the corresponding attributes listed in Table 1. Since each FF tree provides a binary choice we build an ensemble of trees with a simple decision tree considering the output from the FF trees. Furthermore, consistent agreement (or disagreement) between observations and model predictions can trigger model selection or revision of the existing models, allowing the ad hoc agent to quickly adapt to changes in the domain or the human’s behavior.

3.3 Task Anticipation with LLMs

While LLMs have demonstrated impressive statistical prediction capabilities, they (by themselves) are not capable of effective planning or self-validation (Kambhampati et al. 2024). They have been shown to be much more effective when they are used to generate generic (high-level) plans

Description of the attribute

Immediate two previous actions of the human
Position of the human (x,y,z)
Orientation of the human (x,y,z)
Any objects in the hand of the agent
Current and previous tasks
Flags (day of the week, going to office, guests expected)

Table 1: Attributes used to create the behavior models of the human in the *VirtualHome* domain.

that are then validated externally to ensure correctness and feasibility before using suitable subroutines to implement each plan step (Kambhampati et al. 2024). LLMs can thus also be viewed as good translators between natural language and domain-specific languages that help refine and correct planning models (Guan et al. 2023).

Motivated by the above findings, we use LLMs in our architecture to anticipate high-level future tasks to be executed. In the absence of the LLM, the ad hoc agent and the human come to know of tasks (to be completed in *VirtualHome*) one at a time. When the LLM is included in the architecture, the ad hoc agent obtains the anticipated next task/goal that is likely to be assigned once the current task is done. By jointly considering the current and next tasks, the ad hoc agent can come up with a better plan of actions that can enhance the overall team performance.

Figure 4 shows an example input prompt for the LLM in *VirtualHome* by the ad hoc agent. We employ three prompt engineering strategies for refining LLM performance.

1. **Adopting a persona:** Assign a specific role or character to the LLM model to guide its responses. This helps the model generate responses that are consistent with the assigned role and contextually appropriate.
2. **Few-shot prompting:** The model is provided some examples within the prompt, guiding the use of pretrained knowledge to perform any given task with limited data.
3. **Chain-of-thought (CoT):** Step-by-step reasoning process that could be followed when arriving at an answer. This helps the model generate intermediate reasoning steps leading to more accurate and relevant responses.

More specifically, we asked the LLM to adopt the persona of an intelligent household assistant for more accurate and contextually appropriate responses. Then we utilized ‘few-shot’ prompting by including two example task routines from previous days in the prompt. These examples were dynamically selected from a list of past tasks, randomly chosen from two different days to provide as examples to the LLM. These example routines can be at various stages of completion: one with no completed task for the LLM to predict, and another partially completed routine for the LLM to continue. Finally we utilized the CoT method to describe the reasoning behind each of the selected tasks of the examples in a day. This provided the LLM with additional context and guidance allowing for rapid adaptation, which is critical in AHT settings. We provided the LLM with a list of possible high-level tasks

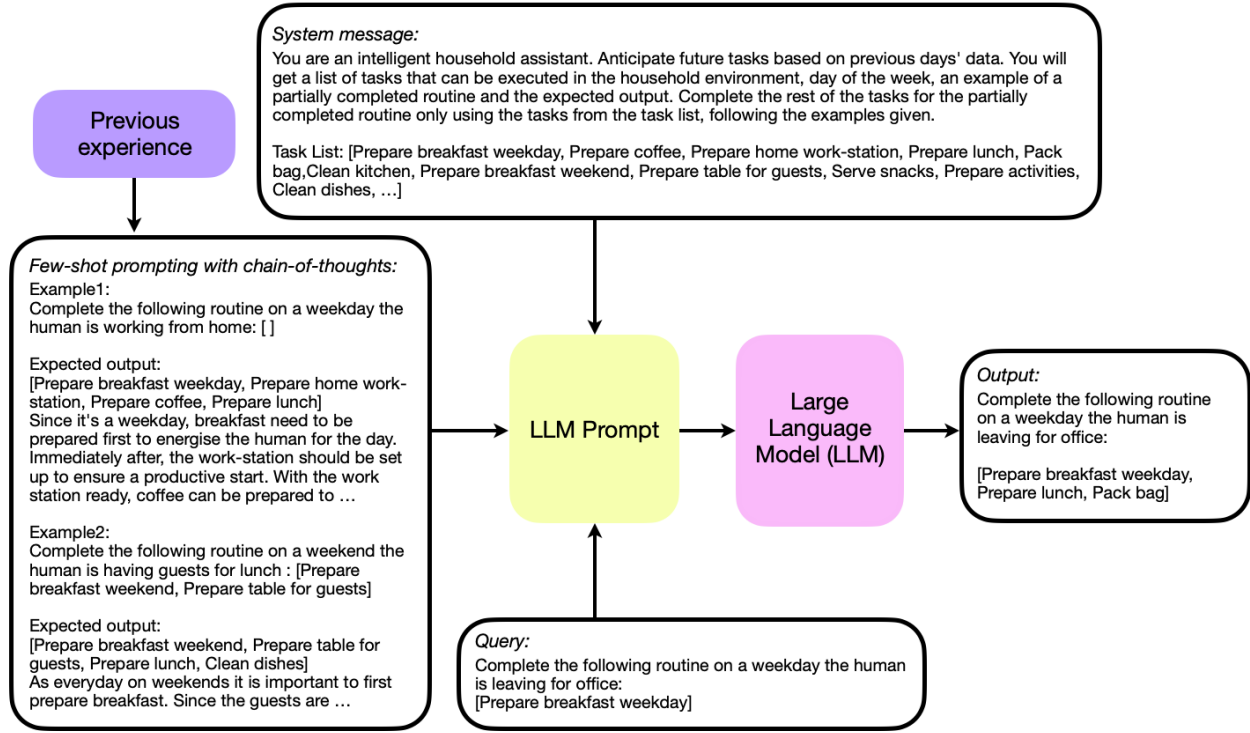


Figure 4: Example prompt sent to the LLM to anticipate the human’s future tasks. Each prompt includes a list of possible tasks, two partially completed example routines, and a partially completed routine for the LLM to complete.

in the *VirtualHome* domain. This enabled the LLM to provide more accurate and contextual responses. We then asked the LLM to complete a routine for a given day.

The tasks predicted by the LLM are parsed by an external validator. Specifically, the future task list from the LLM output is compared with the existing knowledge in the ASP program and previous experience (i.e., observations) to ensure that the tasks are feasible (for the given day) and that the task order is reasonable. Given that the LLM is not trained in the specific domain, there may be a difference between the task order preferred by a human in *VirtualHome* and the order suggested by the LLM. Thus, we re-order the tasks if they are not in a reasonable (or preferred) order. For example, the agent may need to prioritize preparing the workstation for work over packing a bag for shopping when the human is working from home, or the human may prefer breakfast before starting on coffee. This ensures plan feasibility and prioritizes tasks that require more attention.

The validated high-level LLM-based task predictions can be set as joint goals to be achieved. In our architecture, the ad hoc agent considers one anticipated (future) task along with the current task and the predicted human actions toward the current task, planning a sequence of actions that it then executes. We show that team performance is much better with the LLM-based anticipation than without it.

4 Experimental Setup and Results

We experimentally evaluated the following hypotheses regarding the capabilities of our architecture:

- **H1:** Reasoning with prior domain knowledge and predictive behavior models improves team performance;
- **H2:** Considering anticipated tasks from the LLM as joint goals improves team performance compared with pursuing one goal at a time;
- **H3:** Incrementally-updated prompts of recent experiences and external validators lead to better LLM-based task anticipation and improved team performance; and
- **H4:** Using LLMs to predict low-level actions(planning) in complex domains results in poor performance.

We evaluated these hypotheses in *VirtualHome* with the latest GPT-4o-mini LLM. Each episode continued until the human-agent team completed all tasks for the given day. We recorded the number of steps (plan length) and the total time taken by the team (i.e., human and embodied AI agent) to complete the task as the *performance measures*. More details of the experiments and baselines are provided below.

4.1 Experimental Setup

In the *VirtualHome* domain, we modeled the human as a simulated entity that selects its actions based on an ASP program. This program (and thus the human) does not reason about the agent’s capabilities. An external task generator

computes a sequence of tasks, but the human and the ad hoc agent only receive one task (to be completed) at a time. Both the human and the ad hoc agent received the same observations from the domain at each step, which they used to plan their respective actions in the domain.

When the ad hoc agent received a task from the task generator, it prompted the LLM for any future tasks. As described in Section 3.3 (also see Figure 4), these anticipated tasks were validated to check their feasibility and execution order. The validated goals were then mapped to a ASP goal and set as the goal of the ad hoc agent together with the goal received from the task generator. In our implementation, the ad hoc agent planned jointly for the goal from the task generator and the next (anticipated) task from the LLM. During this planning process, the ad hoc agent also used the learned human behavior prediction model to predict the possible future actions of the humans, as described in Section 3.2. Recall that these predictive models were built only using 1000 examples of prior traces of human actions and domain state.

The ASP program of the ad hoc agent included additional axioms for reasoning about these predicted actions (of the human) that are mapped to exogenous actions. As a result, the ad hoc agent’s plan anticipates that the preconditions for some intermediate steps will be created by the human’s actions, even though the human may not always do so. On the other hand, the human cannot predict the ad hoc agent’s actions, and the ASP program governing the human’s action choices (in simulation) does not include axioms for reasoning about these actions, leading to the human’s actions being determined primarily by the current state and goal.

For evaluating **H1** and **H2** in **Exp1**, we randomly selected 100 task routines and measured the ability of the team comprising a human and an embodied AI agent to successfully complete these tasks in *VirtualHome*. The performance measures were the number of steps and time taken to complete the tasks. We used three specific baselines to evaluate the contribution of each component of our architecture.

- **Base1:** used the LLM for anticipating future tasks, but did not use the predictive behavior models to anticipate the future actions of the human.
- **Base2:** did not use the LLM to predict the future tasks, but used the predictive behavior models to anticipate the human’s future actions.
- **Base3:** did not use the LLM for task anticipation or behavior models to predict the human’s future actions.

The agent only planned for current task in **Base2** and **Base3**.

Next, for evaluating **H3** in **Exp2**, we randomly selected 20 task routines from the domain and recorded the team performance (number of steps and task completion time) when the LLM used different prompt-engineering methods (adopting a persona, few-shot prompting, CoT; Section 3.3) and when the LLM did not use the prompt-engineering methods. We used three baselines to evaluate the importance of each prompt-engineering method and the external validator.

- **Base4:** did not use any specific prompt-engineering method or external validator.
- **Base5:** used few-shot prompting (i.e., two examples of

partially completed routines and their expected answers included in the prompt) but no external validator.

- **Base6:** used CoT prompting i.e., each example was accompanied by a step-by-step explanation on arriving at the answer, but no external validator.
- **Base7:** used external validator to filter (and reorder) LLM output but no prompt-engineering methods.

For evaluating **H4**, we conducted a special experiment where we extended our architecture to utilize the LLM for low-level planning (**Base8**). Specifically, we extended our prompt to include information on the low-level actions that can be executed in *VirtualHome* along with their intended purposes, such as: `move(agent, location)`: move the agent to an adjacent location; `grab(agent, object)`: pick up an object. We also supplied the LLM with **Action Feasibility Rules**:

- *Movement Limitation* (critical): you must only move to adjacent locations defined by the `next_to` relationships. Any move to a destination that is not adjacent is prohibited. Always check adjacency before predicting a move.
- *Object Location*: you must be in the same location as an object to perform any action on it (e.g., `grab` or `put`).
- *Carrying Limit*: you cannot hold more than two objects at a time. Also, when holding two objects, actions like `open`, `close`, `switch-on`, or `switch-off` require you to put down at least one object first.
- *Appliance Safety*: for safety, you should not open appliance doors when they are switched on.
- If the human is holding an object, assume they will handle all tasks involving the object. Do not attempt to grab or interact with the object the human is holding. Instead, focus on parts of the goal unrelated to that object.

Then we included information about adjacent places in the domain emphasizing the fact that the agent can only move between the defined adjacent places.

```
next_to(counter_one, kitchen_table)
next_to(livingroom_desk, livingroom_coffee_table)
```

The LLM had access to the current world state, including the location of the human, agent, objects, and appliances, each appliance’s state, and information about the objects held by the agent or human. The problem specification also described the task to be performed; the immediate previous actions of the human and the agent; any specific information to be considered on any given day (e.g., human working from home or the office); whether it is a weekday or the weekend; and whether the human is expecting guests. In addition, the prompt included a detailed example of selecting an action, and asked the LLM to generate a plan for achieving the assigned goal and specify the next action to execute.

The action choice by the LLM was then assigned as the action of the ad hoc agent. As a recovery mechanism, we corrected identified errors in the LLM output up to three times per trial. For example, if the LLM selected an action that was not feasible in its current location, such as attempting to grab an object without moving to the appropriate location or trying to move to a non-adjacent place, we provided

Architecture	Steps	Time(s)
Proposed (With LLM and behavior models)	26.8	361.0
Base1 (With LLM task anticipation)	29.3	385.8
Base2 (With Behavior models)	34.1	443.0
Base3	37.5	487.4

Table 2: Average number of steps and time taken by team (human, ad hoc agent) to complete the task routines.

feedback explaining why the action choice was incorrect. The feedback allowed the LLM to predict another action for that step, and we measured the ability of the human-ad hoc agent team to achieve success in completing the tasks in the previously selected 100 task routines. As before, the performance measures were the number of steps and time taken to complete the set of tasks.

4.2 Experiment Results

Table 4 summarizes the results of **Exp1**. When the ad hoc agent use task anticipations from the LLM and the action predictions for the human using the behavior prediction models we observed the minimum number of steps and time to complete the task routines. When the ad hoc agent used the LLM for future task anticipation but not the output from the predictive behavior model (Base1) this increased both the number of steps and time taken to complete the tasks. This is caused by the lack of the ad hoc agent’s ability to anticipate the human’s future actions. Hence, the agent may select the same actions as the human leading to conflicts and unnecessary actions. This prevents the human-agent team from completing the tasks efficiently and lead to increased number of steps and time. This emphasizes the importance of using the behavior prediction models in planning and support hypotheses **H1**.

When the ad hoc agent does use the behavior prediction models to anticipate the future actions of the human, but do not use the LLM to predict possible future tasks (Base2), the number of steps and time taken to complete the task by the human-agent team is even higher. This is due to the agent only planning for a single goal at each step. This prevents the agent from leveraging the efficiency of planning for multiple goals simultaneously, which could save both time and effort. For example, when the agent visits the bedroom to retrieve a board game to entertain guests, it could have also picked the wine from the bedroom. Instead, making two separate trips for these tasks unnecessarily extends the plan length and increases the time required. These results indicate the benefit of planning for joint goals, significantly enhancing the overall performance. This supports hypotheses **H2**.

Base3 does not use the future task anticipation form the LLM as well as the predictions from the behavior models. This has led to significantly low performance as this increase both number of steps and time taken by the human-agent team to complete the tasks significantly. This further supports both hypotheses **H1** and **H2**.

Table 3 show the results from **Exp2**, where we used the LLM to predict the future tasks in the *VirtualHome* domain with and without the external validators and the

Architecture	Steps	Time(s)
Proposed (all techniques, with validators)	27.5	372.7
Base4 (no techniques, no validators)	33.1	427.7
Base5 (few-shot prompting, no validators)	32.1	441.1
Base6 (chain-of-thoughts, no validators)	31.7	430.8
Base7 (no techniques, with validators)	28.9	387.5

Table 3: Average number of steps and time taken by the human-ad hoc agent team to successfully complete the task routines when using the prompt-engineering techniques together with external validators.

Architecture	Steps	Time
Base8 (LLM predict low-level actions)	39.7	520.0

Table 4: Average number of steps and time taken by the human-ad hoc agent team to successfully complete the task routines when using the LLM to predict low-level actions that can be directly executed in the *VirtualHome* domain.

prompt-engineering techniques such as few-shot examples and chain-of-thoughts as discussed in section 3.3. The improved performance both in terms of lower number of steps and time taken to successfully complete the task routines when utilizing the techniques and validators support **H3**.

Table 4 show the results from **Exp3**, where we used the LLM to directly anticipate the low-level actions for the ad hoc agent in the *VirtualHome* domain. The number of steps and time taken to successfully complete the task routines are significantly higher than our architecture as well as all the baselines (Base1, Base2, Base3). These results support **H4**.

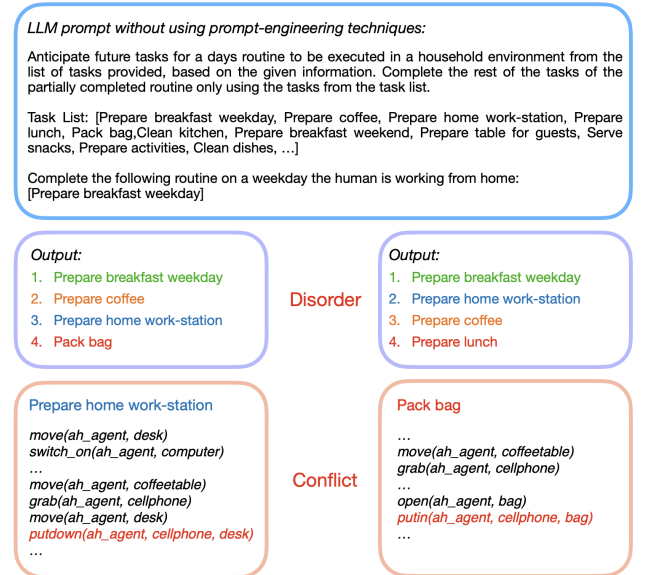


Figure 5: Execution example where using the LLM without prompt-engineering techniques and external validators causes disorder and conflicts in plan execution.

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