for completing the task. The first action in the plan indicates where the robot should focus its assistance. Based on the action type and how much assistance the user needs, the Hint Engine uses the assistance model to determine the appropriate assistive action for the robot to perform.

To generate a plan, the Hint Engine uses its domain model, which is represented with a hierarchical task network (HTN) (**?**). The HTN used for medication sorting is shown in Figure 3. At the top level, the user is working toward sorting the pills for all of the medications. To complete the task, the user needs to go through each medication, sorting the pills for each. For a given medication, a user may go through the days of the week, adding and removing pills as they go. If no mistakes have been made, the user is just missing pills (leading to `addPill` actions). If a pill has been placed at the wrong time of the day, then the action pair `removePill` and `addPill` are included in the plan to indicate the moving of a pill.

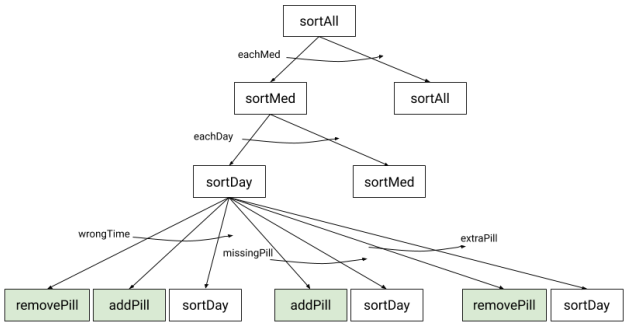

Figure 3: Hierarchical task network representing a medication sorting task. It assumes task is done by sorting all pills of one medication before doing the next one. White boxes are tasks, and shaded boxes are operators.

To determine whether there is a missing pill, an extra pill, or a pill placed at a wrong time, the planner checks the preconditions of the method, which includes the constraints defined for the given medication. For example, each medication defines the maximum number to be taken in a day. If the number of pills for that medication exceed the maximum, allowed, then the `extraPill` condition is satisfied.

We extend the precondition checks to also consider user preferences. For example, a vitamin could be taken at any time, but a user may prefer to take it in the morning. Similarly, a medication like Levodopa might be taken before physical activity, and the user may have preferences regarding how long before the activity. In this case, there is a constraint of the form `(beforeActivity pill row col activity)` that can be inferred with a rule like the following:

```
(beforeActivity pill row col activity) <-
(activityAt activity rowX col)
(isa pill med)
(medicationBeforeActivityBy med
distance)
(difference rowX row distance)
```

In this example, the HTN represents blocks of time as they relate to the sorting grid (i.e., morning, noon, etc.) and not specific times in the day.

Explanation

The explanations are generated from an existing system (**?**; **?**) that incorporates commonsense knowledge, rules, and constraint checking towards an explanation of intended behavior. The Explanation Synthesizer proceeds in 3 steps:

1. Parsing and aggregation: The input query is parsed for key *concepts*. Those concepts are used as search terms in the commonsense knowledge base. A list of facts (symbolic triples) is returned.
2. Constraint Checking: Commonsense rules are triggered to generate new facts and evidence.
3. Synthesizing: Once all the facts are aggregated, an explanation synthesizer constructs the most plausible chain of reasoning towards an explanation.

For example, consider the query `(pill onDate Friday)` which justifies that the user can take the pill on Friday. The query is parsed and the key concepts are `pill` and `Friday`, which are search terms for the commonsense knowledge base (KB). The KB returns facts like `(Friday IsA 'business day')`. The relation `onDate` is used as a constraint in the system.

The constraints are a combination of commonsense rules and user preferences. These constraints are application dependent. In the medication sorting domain, they are rules related to the requirements for each type of pill, as well as user preferences. For example, the user may prefer to take pills in the morning, or users may be *instructed* to ingest pills with meals or food. The facts are forward chained against these rules to generate new facts and evidence.

After this process, there may be more than one plausible explanation supporting the query. The explanation synthesizer starts from the query and constructs a goal tree to satisfy the query (**?**). For this paper, we only examine one explanation. Choosing the best explanation may be explored in future work.

Proof of Concept

To demonstrate our components adapting to and explaining with user preferences, we consider the scenario in which the user has already correctly placed all of their Vitamin D and is now working to sort their Levodopa, which is to be taken before activity. The user has two activities planned for the week, Wednesday at 1pm and Friday at 8pm. The user just placed one Levodopa pill in the space for Monday midday.

We assume that the user has a previously stated preference to take Levodopa during time slot prior to an activity. When the user misplaces the Levodopa, the Adaptive Assistance component recognizes that the user needs assistance and generates a plan to move the Monday pill to an earlier time slot:

```
(planFor state8
((preference beforeActivity 1))
((removePill Levodopa 3 1)
(addPill Levodopa 3 0)
(addPill Levodopa 5 2)))
```

The first action, `(removePill Levodopa 3 1)`, is used along with an inference of a level of assistance to determine that the robot should provide direct assistance, which has the robot clearly stating what should be done next. In this case, the pill needs to be removed and the robot would say "Try removing a Levodopa from Wednesday".

Additionally, the Adaptive Assistance component considers alternative plans, a counterfactual reasoning over different preferences. The alternative plans do not affect how the robot assists but would be sent to the Explanation component. An alternative plan

for taking Levodopa at the same time as the activity is shown below. The plan indicates that the Monday pill is in the correct location and the only action remaining is to place the Friday pill:

```
(alternativePlanFor state8
((preference beforeActivity 0))
((addPill Levodopa 5 3)))
```

Finally, the user can inquire about the robot's actions. For example, the user can ask why the robot said to "Try removing a Levodopa from Wednesday." This question is parsed into an intermediate representation: `(onDate Levodopa Wednesday)`, which is passed to the Explanation Synthesizer along with the associated *preference*; the user prefers to take the medication before an activity. The following is a trace of the reasoning of the Explanation Synthesizer

```
[(IsA Levodopa pill), 'Given']
[(AtLocation pill cabinet), 'ConceptNet']
...
[(IsA Wednesday weekday), 'ConceptNet']
[(IsA Wednesday day), 'ConceptNet']
...
[(prefers user (before pill activity)),
'Given preference']
[(IsA appt activity), 'Given knowledge']
[(atTime appt '1pm'), 'calendar']
[(onDay appt Wednesday), 'calendar']
[(atTime appt afternoon), 'Rule fired']
```

The justification is that `(onDay pill Wednesday) (beforeTime pill afternoon)`. And the final explanation reads in a series of symbolic triples: `(prefers user (before pill activity)) (IsA user activity) (atTime appt '1pm') (onDay appt Wednesday) (IsA '1pm' afternoon)`.

Future Work

The work we describe here sets the foundation for a whole line of work in designing social robots to adapt to users, adhere to user preferences, and provide explanations. The most immediate next step is to build upon the proof of concept we have demonstrated here by integrating the individual parts and evaluating the system on more complex scenarios. Once we have a fully integrated system, the critical next step is to incorporate feedback from the user. One of the greatest advantages of taking a knowledge-driven approach is that the entire system is inspectable, which will facilitate integrating the user feedback. The user may provide feedback after the robot provides an explanation to the user. An explanation synthesizer extracts key terms from the feedback, interprets the feedback, and determines which component(s) need adjustment. The explanation synthesizer also *validates* its conclusion by verifying with the user. In this ongoing work, if the explanation synthesizer identifies that the feedback is related to the user preferences, the Preference Reasoner will construct a new case that is used by AToM to update the model of the user. Even a single piece of feedback from the user can be sufficient for AToM to learn the user's preferences because analogical learning, which is used by AToM, is data efficient and capable of learning from only a few examples (**?**; **?**).

Related Work

Consideration of *user preferences* is an important aspect of human-robot interaction, as it allows the robot to modify its behaviors according to its understanding of the user. Hiatt, Harrison, and Trafton (**?**) found that people prefer collaborating with robots that adapt their behaviors in this way. However, most approaches to recognizing users' preferences use statistical techniques like reinforcement learning (**?**) and Markov Decision Processes (**?**) to predict preferences. This means that they require large amounts of training data, are not responsive to user feedback, and are not explainable. That is, once trained, such systems predict preferences based on their built-up statistical models; a user cannot state a preference directly or inspect why the robot predicts a particular preference. By incorporating stated user preferences, and moving toward learning preferences by analogy, we attempt to avoid these pitfalls.

There are many forms of *adaptive assistance* in robotics. One approach is shared autonomy, in which the system infers human intentions and adapts how much assistance in provided in controlling a robot (**?**; **?**). This work is focused on assisting people in physically controlling robots, whereas we are working towards an autonomous robot that provides social assistance. Other work has looked at adapting a robot's behavior based on user preferences. For example, a recursive neural network was used to learn weights pertaining to user preferences, which influence the plans for a robot (**?**). While the preferences did affect the plans used by a robot, the plans are used to improve the robot's navigation. Thus, the user preferences do not relate to assistance provided to the user.

A model of Theory of Mind (ToM) has been proposed to adapt the assistance provided by a social robot (**?**). A stochastic model is used to infer what action a person could be executing. Based on this estimate, they generate a plan to determine with which action the robot should help. While they use ToM to estimate a user's intent (via a set of possible actions), they do not represent a user's preference for how the task should be completed. One way to understand complex decision making systems is with *interpretable* or *explainable* parts. Explanations can describe proxy methods (**?**; **?**; **?**), representations (**?**; **?**), or be inherently explanation-producing (**?**). In the context of human-robot interaction, explanations can help to communicate and build trust (**?**), justify the robot's actions (**?**) or motions (**?**), or describe *unreasonable* perceptions (**?**). But most of these explanations are generated *after-the-fact* and cannot be used to improve the completion of tasks moving forward.

We propose to use explanations as *feedback* to augment assistive robots. This has been explored for agents playing games, especially *when* to provide explanations (**?**). This approach builds on Rainbow, a self-adaptive system that can correct itself and reuse the same baseline framework (**?**). To our knowledge, this is the first work to propose a knowledge-driven architecture that could use explanations to *improve* robotic reasoning and inference.

Contributions

In this paper, we motivate a knowledge-driven architecture for adaptive assistance. We demonstrate the functionality of the components of this architecture in a task for socially assistive robots (SARs). In future work, we will expand the architecture to incorporate and process feedback and learn user preferences. This paper opens a new area of research in adaptable and interpretable SARs.

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