high, though, the user made enough progress that they found the agent's late response less useful.

(Un)Intentional Communication When the autonomous agent in human-robot interactions has its own personal goals, it can communicate its intentions towards these goals to the human via legible planning with low-level motions (**?**) or high-level actions (**?**). However, our assistive agent's personal goal is more abstract: "to help the user with their own goal." So the agent does not have a personal goal until an intermediate one is recognized and computed. **?** (**?**) account for communicating the agent's newfound goals during the negotiation step, but their assistive agent pipelines the interaction process so that no further recognition is performed after negotiating its goals. We assumed that the *cognitive load of frequent negotiations would not be ideal* as PRETCIL loops indefinitely.

However, our implementation's planner assumes what the user will do, which is sometimes reordered or extraneous enough to confuse the user instead. In one instance, the user looked at the debug data to read the assumed actions and mentioned that providing this expectation would have been a useful explanation for the unexpected behavior. Providing explanations for decision making systems (**?**) has been growing in popularity recently, but we need to be careful that these explanations do not constrain the user's freedom to act in accordance to what the machine does (**?**).

Some users at the demonstration already succumbed to such constraints when selecting their own actions to ensure legibility to the recognition algorithm, viewing the demonstration as a puzzle rather than an open-ended interactive experience. Does this *defeat the purpose of closed-loop interaction* if people adjust their own behaviors *to satisfy the algorithms around them rather than act naturally*? Though we mentioned that **?**'s (**?**) assistive agents have more restricted interactions using a library of precomputed plans, this library often contains multiple plans that allow flexibility to the interactive partner (this is the purpose behind their *choice nodes* where the human can take one of several actions). This leads to a research challenge for finding the balance in a hybrid of closed-loop interaction frameworks. If a joint-agent planner finds multiple plans to the intermediate goal, then which plans' action should be used when there are multiple matches to the next observation? That is, when monitoring the execution, which plans are "going according to plan"?

What Information Actually Matters? While most of the challenges discussed so far involve general issues that relate specifically to the interactive experience, it is also important to consider some algorithmic challenges. The most critical ones we identified during the demonstration relate to *using all the available information*. Some plan recognition algorithms already address noisy sensing (**?**) and irrelevant experimental actions while exploring the environment (**?**), but these methods still assume that the observed agent is the only actor in the world. Planning algorithms can address various forms of uncertainty, but we are unaware of any that consider the uncertainty of the goal's validity.

The assistive agent's actions also change the world, and these need to be acknowledged during recognition. We simply encoded them as observations because recognition as planning handles missing observations by assuming actions that can connect two consecutive observations were performed. However, the potential for poorly chosen intermediate goals threw off the recognition algorithms due to the agent's sometimes incorrect actions and state modifications. Accounting for them as noise or experimentation might work pragmatically, but they are conceptually different because these actions have purpose and influence the interactive partner's later actions toward their goal. Furthermore, for long-term interactive systems that cannot be reset like our demonstration, how should observation sequences be modified over time for relevancy to the current interaction only?

When our demonstration's assistive agent computes a joint plan with its intermediate goal, it currently uses the same search heuristics; the state space and set of actions change to address turn-taking. However, the above issues with useless goals present two things to consider. First, when the goal contains contradicting conditions, is there a way to find a plan that satisfies some largest possible subset of conditions so that the agent can do something? Second, if the agent is unable to find a plan, should the agent perform a default action or replan for some default goal? We programmed our assistive agent to perform a no-op, but this led to a few failed demonstrations where the user needed a block that the agent was holding before it failed to find a plan. Even if these users intended to confuse the assistive agent with noisy observations, a default goal of not holding any blocks would at least allow the user to complete the task on their own.

4 Conclusion

For less structured interactions between users and intelligent systems, closed-loop interaction that perceives what people do and decides how to appropriately respond is necessary. We introduced the PRETCIL framework as a cognitive architecture for such interaction and implemented it as an assistive agent for a game. A recent demonstration revealed new research challenges for artificial intelligence methods involved in closed-loop interaction. Future research will explore these challenges, but we encourage the artificial intelligence for human-robot interaction community to consider their own solutions and identify additional problems. *Many novel situations from interactive experiences and integrated frameworks take these traditional algorithms out of their original context*, and we need to address them as we continue to study and create intelligent interactive systems.

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