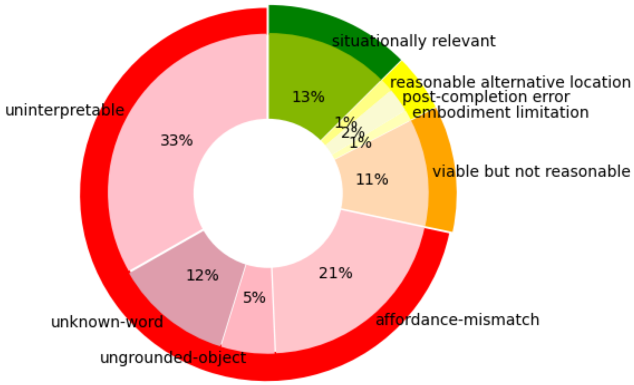

Figure 4: Categorization of responses retrieved from the LLM during agent experiment.

Further evaluation of responses using other capabilities of cognitive architectures is potentially useful, but not yet explored. A cognitive architecture agent could use episodic memory to see if retrieved knowledge matches actions performed in the past. It could also use planning knowledge to see if retrieved goals are achievable, or retrieved actions are executable. Cognitive architectures also support interfacing with other knowledge sources (e.g., knowledge bases such as WordNet or ConceptNet) which could provide additional information for evaluation (e.g., finding synonyms for unknown words).

Conclusion

Autonomous systems, whether they are realized with cognitive architectures or not, will have to acquire new knowledge to perform tasks and accomplish their goals. However, the lack of reliable, scalable acquisition of new task knowledge, especially online acquisition of knowledge, has limited the operation and impact of cognitive systems. The integration of LLMs with cognitive architectures presents an intriguing opportunity to exploit the breadth of knowledge in LLMs to overcome limits on knowledge acquisition.

In this paper, we presented various ways one might approach this problem and highlighted the potential of direct extraction from LLMs as an integration path. We summarized the challenges and requirements for exploring this integration and a high-level, step-wise process for pursuing this goal. We outlined some of the ways we are attempting to pursue this research vision, highlighting the use of template-based prompting and knowledge-driven evaluation that enables more reliable and useful responses from the LLM.

A more complete realization of the entire task-learning pipeline (as envisioned in Figure 2), as well as an evaluation of the pipeline in terms of scaling for knowledge acquisition, remain as future work. One notable result in terms of scaling, however, has been to observe the synergistic interactions between different sources of knowledge within task learning. The extended ITL Agent uses look-ahead planning, human oversight, and the LLM to attempt to acquire new knowledge. Early results (**?**) suggest that planning can virtually eliminate the need for an agent to ask for actions (at least in the task domains we have explored) when the agent acquires a correct (i.e., verified) goal description. Similarly, using LLMs to elicit goals in conjunction with the verification process requires significantly less human oversight. In summary, this integrated-knowledge approach realized within and enabled by a cognitive architecture, is suggestive of a potential breakthrough in knowledge acquisition and task learning for cognitive agents.

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