HumemAI: A Machine With Human-Like Memory Systems

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Abstract. HumemAI is a framework of an AI agent that has human-like memory systems. Its memory systems are modeled with knowledge graphs, which are both human and machine-readable. Combined with machine learning to learn the agent's core functions, e.g., memory management, navigation, question answering, etc., HumemAI allows one to design an agent that can both learn and reason. **The code is open-sourced at https://github.com/humemai/.**

Keywords: Human-like memory · Knowledge graphs · Machine learning.

Fig. 1. The HumemAI symbol represents a machine with human-like memory. Its memory is modeled with a knowledge graph, which allows for both symbolic and sub-symbolic learning and reasoning.

1 Symbolic AI of HumemAI

A knowledge graph [1] is a graph enriched with knowledge and constrained by logic, e.g., FOL. It allows a machine to perform logical reasoning. For example, if a machine has knowledge `[Kitchen, north, Bathroom]` and `south` is an inverse relationship of `north`, then it also knows that `[Bathroom, south, Kitchen]`. Various organizations and companies have built both open and closed knowledge graphs, e.g., Wikidata, Google Knowledge Graph, etc., to store and retrieve their data.

Although knowledge (memory) can be retrieved by various algorithms, e.g., embedding-based, BM25, etc., current AI models, e.g., LLMs, mostly have their memory encoded in their weights. This makes it hard to update their outdated knowledge without catastrophic forgetting. In addition, coupling memory and reasoning has resulted in a huge monolithic architecture of an AI system that is not easily deployable.

That is why HumemAI separates the memory from reasoning in an external database, e.g., RDF storage, to overcome the problems. Also, it includes a unique ontology inspired by cognitive science theories to learn and reason like humans.

2 Sub-symbolic AI of HumemAI

The HumemAI agent can perform various tasks. In our experiments, we started with some specific tasks in a controlled environment. For example, in our Gymnasium environments [2,3,4], it was tasked with memory management, navigation, question answering. Although these tasks can be tackled with symbolic reasoning, e.g., $\texttt{At}(\texttt{Kitchen}) \land \texttt{North}(\texttt{Kitchen}, \texttt{Bathroom}) \land \neg\, \texttt{BeenTo}(\texttt{Bathroom}) \Rightarrow \texttt{Go}(\texttt{Bathroom})$, there is a limit to which we can make rules. Also, this kind of symbolic approach is often not generalizable.

Therefore, we let machine learning, specifically deep reinforcement learning, learn the functions (policies) to solve its tasks. In our experiments, we formulated the functions (memory management, navigation, and question answering) as policies that the agent should optimize to maximize its return, i.e., cumulative discounted rewards. To be specific, we used value-based model-free methods, e.g., DQN [5] to obtain the optimal policies. We observed that indeed, our deep RL agent utilizes its knowledge graph based human-like memory to solve the tasks.

We tried different neural network function approximators for the deep Q networks. The best performing one was message passing based GNN. It is no surprise that the GNN performed the best, since our data were mostly based on knowledge graphs, and GNNs are known to be good at learning good node and relation representations.

3 Future Work

Our successful results gave us confidence that we can scale up HumemAI to solve more complex tasks. For example, different modalities, e.g., text, image, etc., and different benchmarks, e.g., natural language QA, visual QA, etc., can be considered to further test our methodology.

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