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An Analysis of the Deliberation and Task Performance of an Active Logic Based Agent (Student Abstract)

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Abstract

Active logic is a time-situated reasoner that can track the history of inferences, detect contradictions, and make parallel inferences in time. In this paper, we explore the behavior of an active-logic based agent on different sets of action selection axioms for a time-constrained target search task. We compare the performance of a baseline set of axioms that does not avoid redundant actions with five other axiom sets that avoid repeated actions but vary in their knowledge content. The results of these experiments show the importance of balancing boldness and caution for target search.

Introduction

Time is not at a standstill during deliberation, and agents need to be cognizant of this passage of time while considering what to do next. Active logic (AL) (Perlis et al. 1999) is a first-order logic based inference engine that tracks the passage of time while inferences occur and can be used as the internal reasoner (Perlis et al. 2017) of an agent situated in time. AL's concept of *now* evolves from one time step to the next as reasoning proceeds step by step.

In AL, if formulas P, Q, $P \rightarrow X$, $Q \rightarrow Y$ and $Y \rightarrow Z$ are true at time step *t*, then at *t+1*, the logic derives X and Y simultaneously and at *t+2*, it derives Z. This simultaneous derivations of multiple facts at a step has consequences for AL based agents. For instance, if X and Y are actions that the agent can perform and if the agent can cognitively attend to only one action, it has to choose amongst those actions. In this paper, we discuss an AL based agent (Brody, Cox, and Perlis 2014) that can reason in parallel but initiates only one high level action at a time. When an action is initiated, the agent notes that it is doing that action and hence will not initiate another action until that action is done or abandoned.

Methodology

In order to analyze how the parallel deliberation and sequential action execution affect an AL based agent's action selection and behavior, we tested an AL based agent with six different axiom sets for a target search task. The first axiom set serves as a simple baseline for action selection while the remaining sets emphasize avoiding unnecessary repetitions, each set incrementally inferring and utilizing more knowledge for action selection. More inferential knowledge can result in an increase in deliberation time for action selection, pushing an agent from being bold to being cautious. The six sets of action selection axioms are listed below.

- **2 Steps Naive** method randomly chooses one of the actions whose preconditions are met. This axiom describes a bold agent that utilizes minimum knowledge to make an action selection decision and hence may keep checking the same location again and again during the search.
- **2 Steps Redundancy Avoidance** selects an action whose preconditions are met and the post-conditions (the agent has been at the location) are not met. This bold agent that avoids previously visited locations may get stuck when it has already been to all its neighboring locations even when there are unvisited locations further away.
- **2-3 Step Redundancy Avoidance** selects an action whose preconditions are met and post-conditions are not met if such an action exists. It also marks actions whose preconditions are met as *feasible* and selects, at the next time step, one of the feasible actions. However, when an action is chosen, the inferred knowledge about feasible actions are removed. Therefore, a feasible action whose post-conditions are already met will get executed only if there does not exist an action whose preconditions are met while post-conditions are not met, thereby, dispreferring redundant actions.
- **2-4 Step Redundancy Avoidance** selects one of the actions whose preconditions are met and post conditions are not met and marks *feasible* actions as in *2-3 Step*. The difference lies in additionally inferring those *feasible* actions whose preconditions and post-conditions are met as *repeatable* actions, and then choosing one of those *repeatable* actions to be executed. This method uses an extra deliberation step to select an action when previously unchosen actions are absent — *feasible* to *repeatable* to action selection — causing the worst case situation to take 4 steps instead of 3 steps as in the previous case.
- **3-4 Step Redundancy Avoidance** allows agents to execute only actions that have been already inferred as *feasible* (when preconditions are met), and thus requires an extra step (3 total) before an action can be executed even in the best case. Feasible actions that have not been done

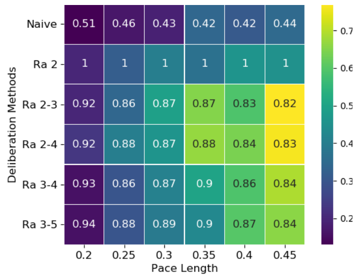

Figure 1: New location visits (number) and accuracy (color)

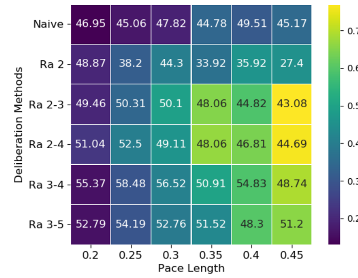

Figure 2: Task finish times (number) and accuracy (color)

before (post conditions are not met) are noted as *new* actions and one of them is chosen for execution, while other feasible actions are marked as *repeatable* actions. If the agent has not derived another action to execute, then it can do one of the feasible actions that is marked as *repeatable*. Hence, the worst case scenario takes 4 steps.

- **3-5 Step Redundancy Avoidance** behaves exactly like the previous one and takes 3 steps for action selection in the best case scenario when there are untried actions. However, it differs from the previous one on when a *repeatable* action is chosen. *Repeatable* actions whose preconditions and post-conditions continue to hold become *contingent* actions. If there are no *new* actions, one of the *contingent* actions then gets executed at the next time step. Thus, this method's worst case scenario is 5 steps.

It should be noted in all the above scenarios, once the agent starts executing an action, the inferred *feasible*, *new*, *repeatable*, and *contingent* action knowledge gets removed.

Experiment

In this research, an AL based agent is tasked with locating a unique object within the AI2-THOR environment. The agent reasons with the axioms associated with any of the six methods above for completing the task. The distance covered by the agent while executing one move action, denoted by pace length, ranges from .2 to .45. The agent has a deadline of 100 AL reasoning time steps to complete the task. When the agent sees the target, it infers and notes in the KB that it has completed its task. A trial starts with the agent and target located in different cells. A trial succeeds if the agent infers that the task is completed within the given deadline. The starting locations of the agent or target were varied between trials. Each trial was repeated 15 times and the average success rates were noted for each method while keeping the pace length constant. The pace length parameter was then changed in increments of .5 pace length and the experiment was repeated for each pace length. Thus, the entire experiment consisted of 20 trials (with 20 different starting locations for the agent or target) repeated 15 times for 6 different pace lengths for a total of 1,800 trials for each method.

Results

The colors within the heatmaps represent the accuracy while the numbers represent the average new locations visited (Figure 1) and average time steps to find targets (Figure 2). The bold agents that result from reasoning using the first two methods make rash decisions and do not find the target as often as seen by the darker colors in the heatmaps. The Naive method only has a 24.7% chance of finding the target. Since, RA 2 always chooses new locations to move to, it either finds the target quickly or fails to find the target. The likelihood of RA 2 finding the target is only 36.7% compared to 50.7% for RA 2-3, 52.7% for RA 2-4, 44.2% for RA 3-4, and 42.3% for RA 3-5. RA 2-3 and RA 2-4 have a good balance between using extra knowledge for deliberation and not using too much, thus finding targets more often quickly. Overall, both excessive and limited knowledge during reasoning resulted in poor performance. RA 3-4 and RA 3-5 use more knowledge, take more time to find the target, and has less success rates compared to RA 2-3 and RA 2-4. The results indicate that changes in best case reasoning time influence performance more than the worst case reasoning time. For all methods, the results also show that the agents perform better at finding targets when they take bigger strides.

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Conclusion

We discussed six sets of action selection axioms and compared the performance of an AL agent on a time-constrained search task while using these methods. Future work will extend this work to a cooperative search task and within a physical agent for applications such as search and rescue.

References

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