Together is Better! Integrating BDI and RL Agents for Safe Learning and Effective Collaboration

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Introduction and Motivation

Innovative combination of symbolic – i.e., Belief-Desire-Intention (BDI) – and sub-symbolic – i.e., Reinforcement Learning (RL) – agents.

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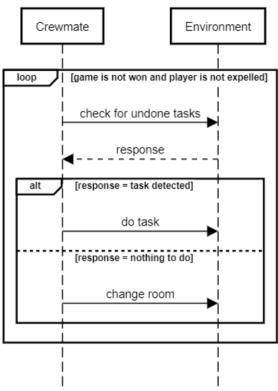


Case study

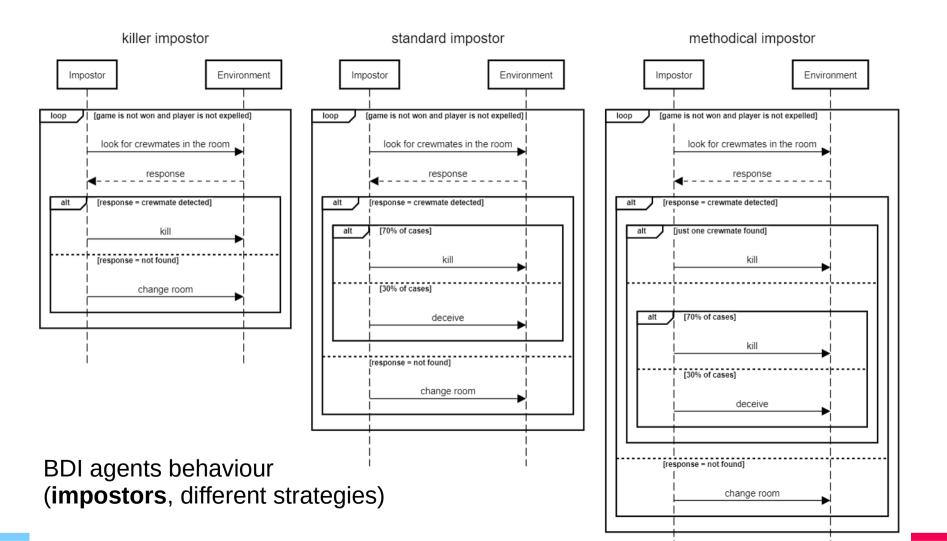




BDI agents



BDI agents behaviour (crewmates, single strategy; crewmates have a skill level between 0 and 1)



BDI agents implementation

First batch of experiments aimed at understanding which impostor strategy and which crewmate skill level would make the game as balanced as possible.

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We wanted to find balanced behaviours, for the **second** batch of experiments: *having fixed (balanced) BDI crewmates, does the impostor team benefit from mixing BDI and RL agents?*

RL agents

RL agents implementation

```
learning rate(0.2).
discount factor(0.1).
epsilon(0.3).
@startPlan[atomic]
+start <-
          .print("starting");
          +myState(standing, noSubState).
@myStatePlan[atomic]
+myState(S1,S2) : epsilon(EPSILON) <-
          .findall(action_value(V,A), state_action(S1,S2,A,V),L);
          .random(R);
          if (R < EPSILON) {
                     .max(L,action value(Value,Action));
          } else {
                     .shuffle(L,L1);
                     .nth(0,L1,action_value(Value,Action));
          +myAction(Action);
          executeAction(Action, S1, S2).
```

Standard Q-Learning algorithm implemented in Jason

Integration of BDI and RL - Agent level

Integration of symbolic and sub-symbolic techniques at agent level

The implementation of the safe RL approach based on the teacher [García J. and Fernández F., 2015 A comprehensive survey on safe reinforcement learning. J. Mach. Learn. Res., 16:1437–1480] in our RL agents only requires the addition of a few lines of code to the RL agent implemented in Jason and gives the advantage of full transparency of the process, explainability, and traceability of the information learnt from the teacher.

Integration of symbolic and sub-symbolic techniques at agent level

Integration of BDI and RL - MAS level

Integration of symbolic and sub-symbolic techniques at MAS level

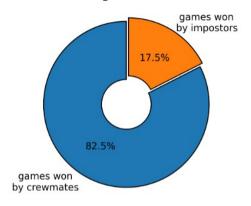


Figure 8: Win ratio when the impostor team consists **solely of RL impostors** and BDI crewmates have skill level **0.52**.

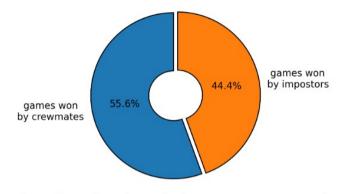


Figure 9: Win ratio when the impostor team consists of **2 RL and 2 BDI methodical impostors** and BDI crewmates have skill level **0.52**.

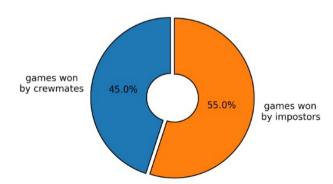


Figure 10: Win ratio when the impostor team consists of **1 RL impostor and 3 BDI methodical impostors** and BDI crewmates have skill level **0.52**.

Integration of symbolic and sub-symbolic techniques at MAS level

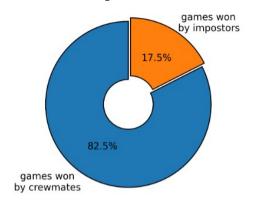


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dynamics.

BDI impostor agents seem to disrupt crewmate clustering, games won prompting RL impostors to by crewmates 45.0% 55.0% games won initiate kills earlier, resulting by impostors in a more effective team

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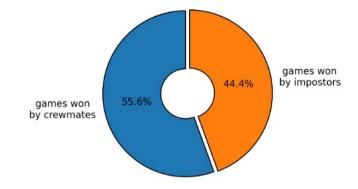


Figure 9: Win ratio when the impostor team consists of 2 **RL** and **2 BDI** methodical impostors and BDI crewmates have skill level 0.52.

Comparison

Table 1: General information on recent proposals for integrating BDI and RL agents.

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→ SafeRLJ	2024	Jason 3.1	SARSA	Jason Plan

Table 2: Features, examples, and licensing of recent proposals for integrating BDI and RL agents.

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