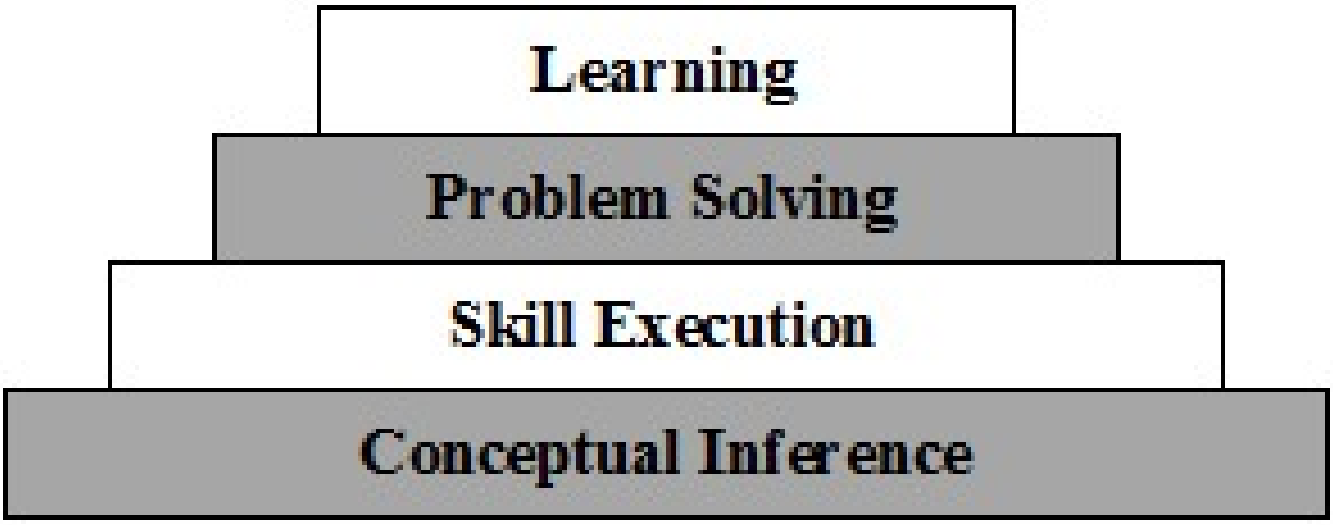

Figure 4: Graphs showing performance of DQN-static/adaptive and planning-static/repairing agents. Episodes in a trial are on the x-axis and reward earned is shown on the y-axis. The results are averaged over 5 trials. Red line indicates the episode where environment parameters were changed.

responds to the changes in the environment.

Resilience of model-based agents The novelty-induced performance drop is more significant in learning agents. For both types of novelties, the performance of the DQN agents drops below 30% of its value in the canonical setup. In contrast, the performance of the planning agents drop to $\approx 50\%$. This difference can be explained by the agents' design. The planning agents' PDDL+ model defines the system dynamics in a general manner. Thus, it can still be sufficiently accurate in some conditions. In contrast, the DQN agent's learned policy is not general and is only applicable for much reduced subset of cases after novelty.

Quick adaptation via model-space search As expected, after novelty is introduced, the static versions of the DQN and planning agents continue performing poorly, while the adaptive agents improve their performance over time. However, the time taken to improve differs greatly between the DQN-adaptive and planning-adaptive agents. Learning in DQN-adaptive is slow, requiring multiple interactions with the environment. In our experiments, DQN-adaptive took $\approx$ 75 episodes to reach 90% of optimal performance as shown in Appendix **??**, Fig. **??**. In contrast, the planning-adaptive agent recovers very quickly in < 20 episodes for both novelties (Fig. 4). This observation supports our central thesis: model-space search enables quick adaptation in dynamic environments because it can localize changes in the explicit model. Repair-based adaptation is scalable and can handle very impactful novelty changes in system dynamics from the canonical setup (shown in Appendix **??**, Fig. **??**).

Explainable by design The model repair mechanism proposes concrete changes to the agent's explicit PDDL+ model. Thus, adaptation in the planning-adaptive agent is *explainable*. A model designer can inspect the proposed repair to understand why and how the novelty affected the agent's behavior. In contrast, learning in model-free systems such as DQN-adaptive cannot be interpreted directly.

The following text shows the distinct repairs that were found by the planning-repairing agent using the method proposed in this paper. Note that the reported values are changes from the nominal values used in the model.

Repair 1: mass_cart: 0, length_pole: 0.3, mass_pole: 0, force_mag: 0, gravity: 0, angle_limit: 0, x_limit: 0
Repair 2: mass_cart: 0, length_pole: 0, mass_pole: 0, f The model-based planning agents worce_mag: 0, gravity: 1.0, angle_limit: 0, x_limit: 0
Repair 3: mass_cart: 0, length_pole: -0.1, mass_pole: -0.1, force_mag: -1.0, gravity: 0, angle_limit: 0, x_limit: 0

Despite these repairs being different from each other, the agent's performance converged to optimal with each one. One potential reason is that there are equivalence classes in the set of environmental parameters and their values. The agent uses only its observations over one episode in the environment to guide its search. It is likely that the observations by themselves do not provide sufficient information to determine the parameter values exactly and only differentiate between equivalence classes.

Experiment 2

Next we evaluate if the proposed method can alleviate inaccuracies in domain modeling by using observed data from execution. This test was done in Angry Birds. The objective in Angry Birds is to destroy pigs by launching birds at them from a sling-shot (shown in Figure 5). The launched birds obey the laws of motion and gravity. It is a difficult problem

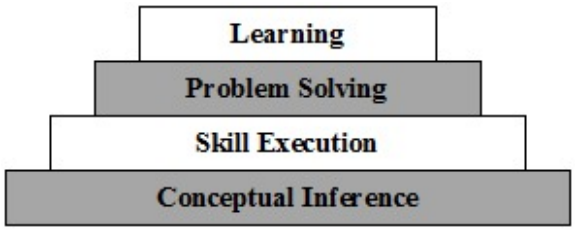

Figure 5: Angry Birds Level used in our experiment

as it requires predicting outcomes of physics-based actions without having complete knowledge of the world, and then selecting an appropriate action out of infinitely many possible options. An Angry Birds level is *passed* when all the pigs have been destroyed.

Our tests were conducted in a specific subset of Angry Birds levels containing a small number of birds, blocks, and pigs (a sample is shown in Figure 5). We implemented a competent *planning-static* agent using PDDL+. The PDDL+ model includes dynamics of launching a bird at maximum velocity at a certain angle, motion of birds and blocks, collisions between various objects, etc. The *planning-adaptive* agent engages repair of the PDDL+ model when its observations become inconsistent with its expectations. We conducted 11 trials of 25 levels each. To simulate inaccuracies in modeling that invariably creep in during model design phase, we deliberately encoded incorrect values for certain parameters in the agents. Specifically, we reduced the maximum bird velocity by 4 from its canonical value of $v_{bird} = 186$. We measured how frequently each agent passes levels in a trial or the *win rate*. We report the mean win rate for each agent and the 95% confidence interval.

The planning-static agent scored $0\%(0\%, 0\%)$ showing that the inaccuracy introduced in the model drastically degraded its performance. The planning-adaptive agent scored $52.36\%(28.72\%, 75.96\%)$ indicating that the proposed repair mechanism can alleviate inaccuracies in the agent's model and improve its performance significantly.

The results from CartPole and Angry Birds demonstrate that our proposed approach is applicable diverse scenarios. They highlight that not only the proposed approach can be used to develop robust planning agents that can handle sudden changes in the environment, it can also be used to improve accuracy of models of environment dynamics starting from rough approximations.

Conclusions and Future Work

Realistic dynamical environments require building planning models without perfect information or full observability of the target environment. Additionally, in such scenarios, unexpected novelty can be introduced, significantly impacting the environment's features and dynamics in unknown ways. Such novelties can render any existing planning models obsolete, resulting in plan execution failures.

In this paper, we presented a domain-independent approach to model repair using heuristic search which enables autonomous agents to reason with novelties and mitigate their impact on the agent's performance. The approach works to correct inaccuracies in the agent's internal PDDL model based by measuring inconsistencies between its own planned expectations and observations from the execution environment. A state-based search algorithm guided by an inconsistency-based heuristic searches through different combinations of model modifications to find a viable repair which accounts for the novelty interference. We demonstrated our approach on complex PDDL+ domains, proving its applicability to realistic applications. Additionally, the presented approach can be used to design more accurate PDDL models by helping to find exact values of environmental parameters starting from rough approximations.

To the best of our knowledge, this is the first attempt at model repair in state-based AI Planning, with previous works relating to plan execution failures choosing to focus largely on plan repair or replanning strategies.

Future work will concentrate on automatically defining the set of repairable fluents and corresponding deltas, and improving the accuracy of the inconsistency metric. In the next stage, we will extend model repair to include modifications to the structure of the PDDL domain by adding, removing, and modifying preconditions, effects, and entire happenings.

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