Learning Context Conditions for BDI Plan Selection

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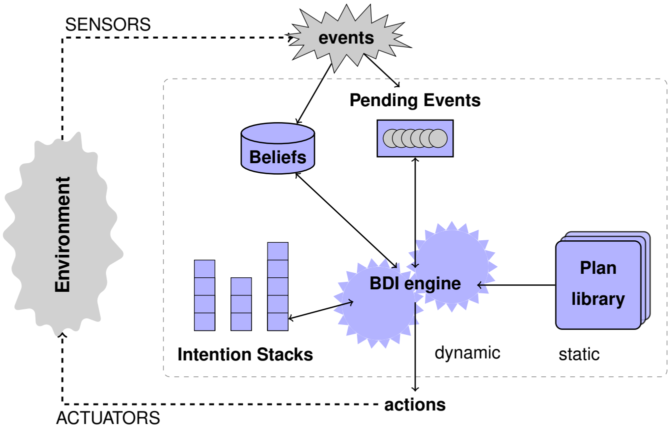

Plan δ is a strategy to resolve event *e* whenever context ψ holds.
Our focus is the plan selection problem i.e. to learn ψ.

Motivation for Learning

The Belief-Desire-Intention (BDI) model of agency

- Is robust and well suited for dynamic environments.
- Has inspired several development platforms (PRS, AgentSpeak(L), JACK, JASON, SPARK, 3APL and others).
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Nonetheless

- Behaviours (plans) and the situations where they apply (context) are fixed at design time.
- For complex domain, it is difficult to specify complete context conditions upfront.
- Once deployed, the agent has no means to adapt to changes in the initial environment.

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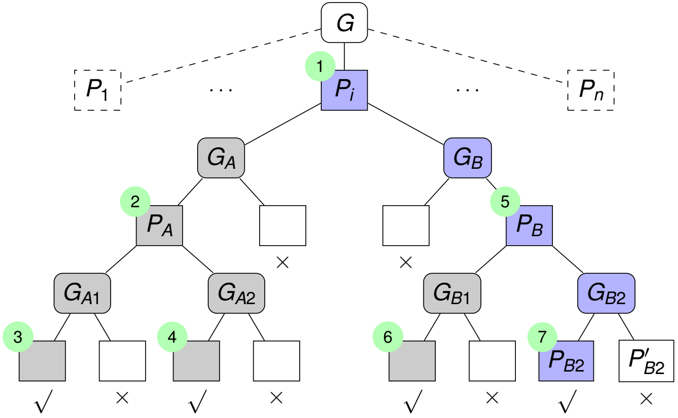
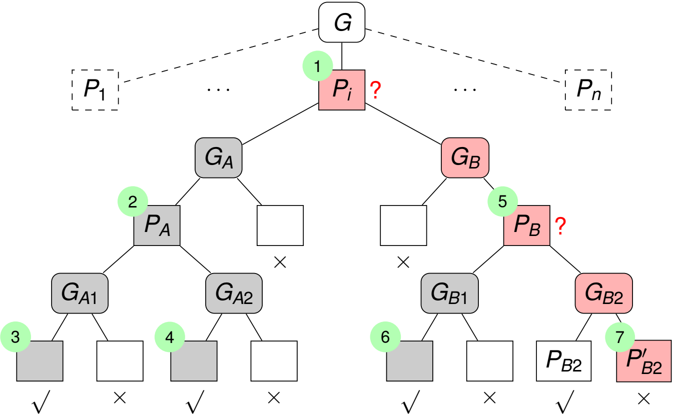
Learning From Plan Choices



Execution trace for successful resolution of goal G given world state w.
Success means that all correct choices were made.

Learning From Plan Choices



Possible execution trace where goal G is not resolved for w.
Should non-leaf plans consider this failure meaningful?

Learning Considerations

1. Collecting training data for learning

- ACL: Aggressive approach that considers all failures as meaningful.
- BUL: Conservative approach that records failures only when choices below are considered to be well-informed.
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- Obtain a numeric measure of confidence in the ongoing learning output (i.e. a plan's likelihood of success in the situation).
- Use the confidence measure to adjust selection weights during probabilistic plan selection.

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BDI Learning Framework

Previous work (Airiau et al. 2009)

- Augment static logical context conditions of plans with dynamic decision trees.
- Select plans probabilistically based on their ongoing expectation of success.
- Learn context conditions over time by training decision trees using success/failure outcomes under various situations.

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Contributions of this paper

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- Learning with applicability filtering (using thresholds to filter plans that do not apply in a given situation).

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Assumptions

Aim is to understand the nuances of learning under different goal-plan hierarchies using a simplified setting:

- Recursive/parameterised events or relational beliefsets not addressed.
- BDI failure recovery mechanism disabled during learning.
- Synthetic plan library with empty initial context conditions used.
- Simple account of non-determinism: successful actions have a 10% probability of failure.

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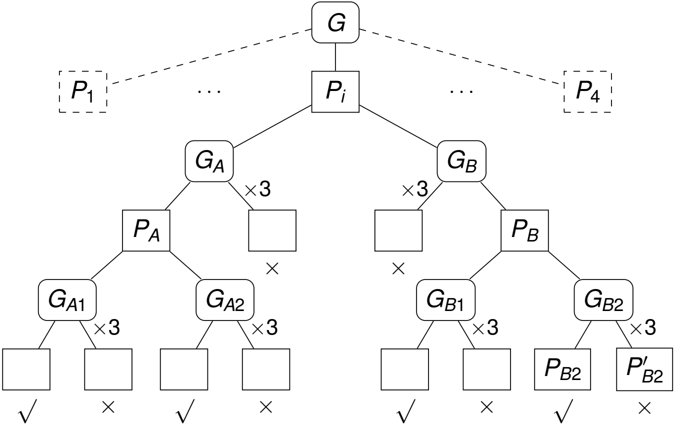
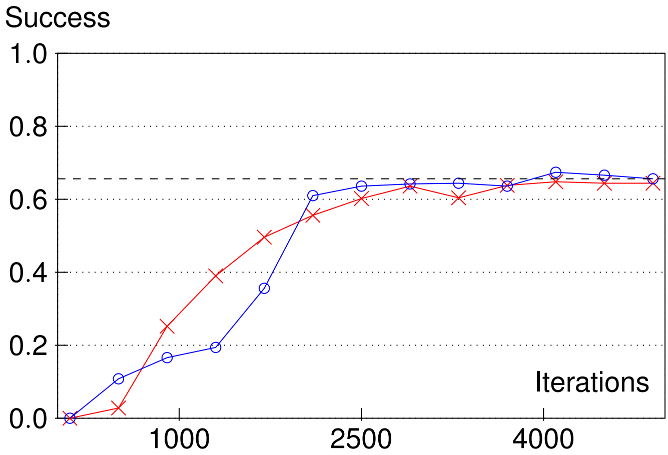
Ongoing work aims to relax these constraints towards a more practical system.

Results: Does Selective Recording Matter?



Structure where both schemes show comparable performance.

Results: Does Selective Recording Matter? (cont.)



Performance of ACL (crosses) vs. BUL (circles).
Dashed line shows optimal performance.

Results: Learning with Applicability Filtering

Plan execution is generally not cost-free, so agent may fail a goal without even trying if it is unlikely to succeed.

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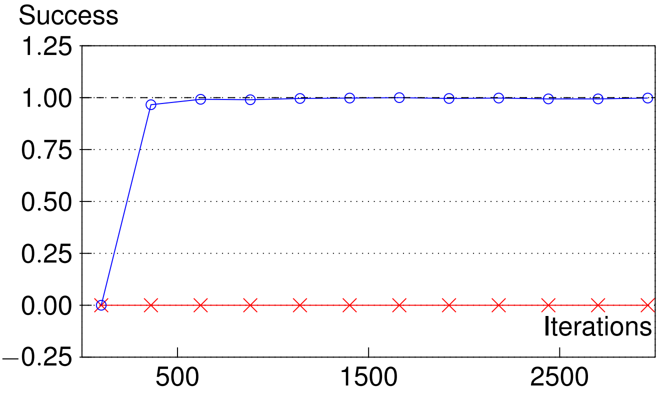

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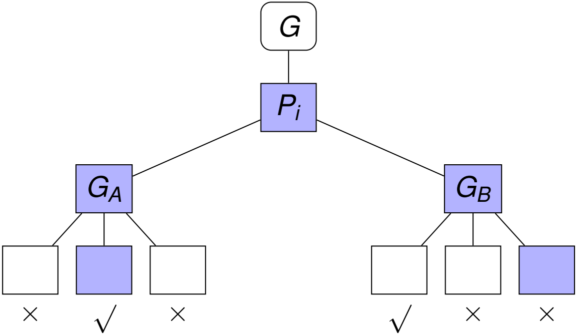
Improving Plan Selection

Coverage-based confidence measure

Idea is that confidence in a plan's decision tree increases as more choices below the plan are covered.



Highlighted path shows $1/9$ possible choices under P_i.

Improving Plan Selection (cont.)

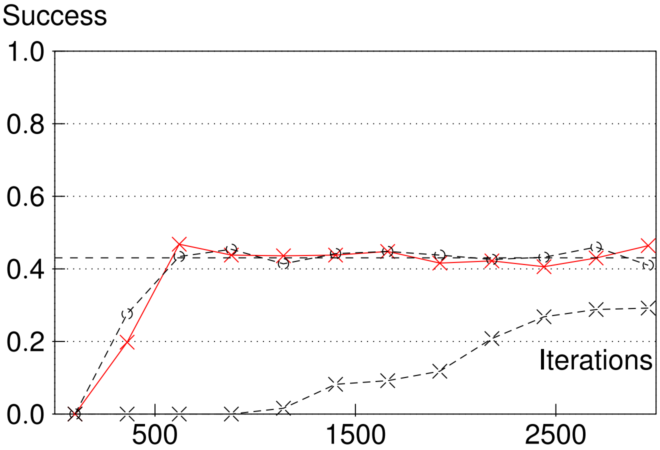
How confidence influences plan selection

- When the plan has not been tried before (zero coverage) we bias towards the default weight of 0.5.
- As more options are tried (approaching full coverage), we progressively bias towards the decision tree probability $p_T(w)$.

Plan selection weight calculation

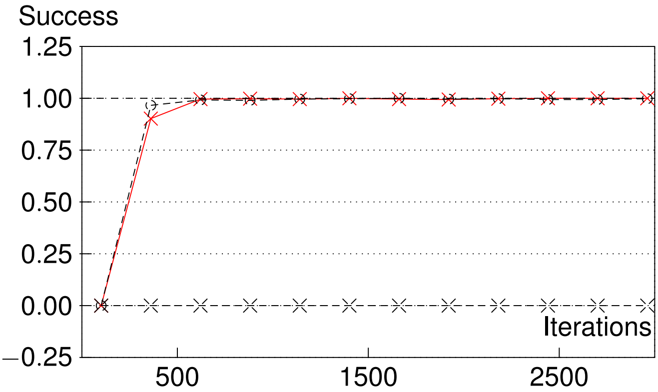
$$\Omega'_T(w) = 0.5 + [c_T(w) * (p_T(w) - 0.5)] \,.$$

Results: Goal-Plan Hierarchy B



Performance of ACL+Ω'_T (red crosses) vs. previous results in structure that suits the conservative BUL approach. Dashed line shows optimal performance.

Results: Learning with Applicability Filtering



Performance of ACL+Ω'_T (red crosses) vs. previous results

Learning Context Conditions for BDI Plan Selection

- Learning BDI plan selection is desirable since designing exact context conditions for practical systems is non-trivial.
- Our approach uses decision trees to learn the context condition of plans.
- We suggest that an aggressive sampling scheme combined with a coverage-based confidence measure is a good candidate approach for the general hierarchical setting.

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References

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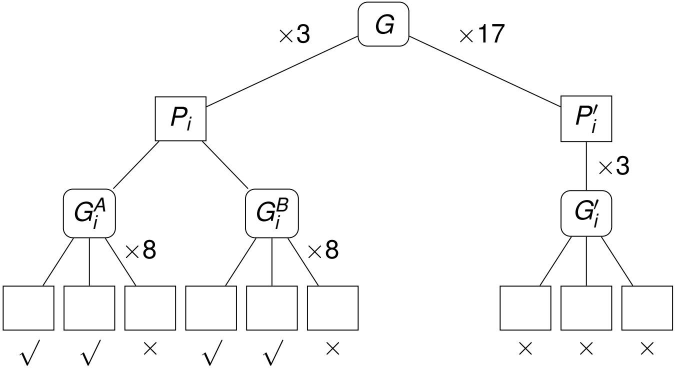
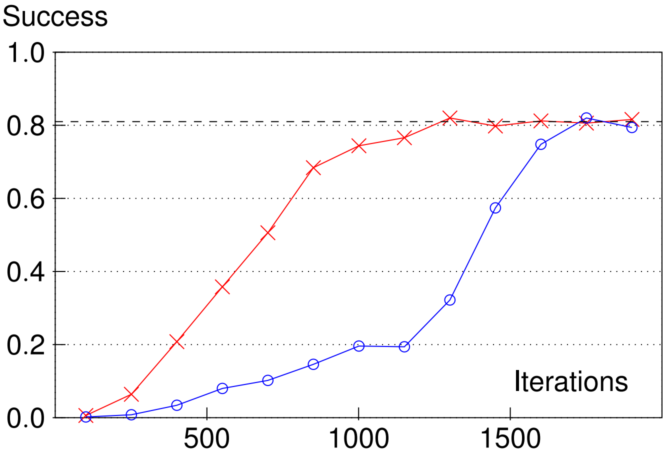
Goal-Plan Structure T1



Structure where one of many complex options has a solution. This configuration suits the aggressive ACL approach.

Results: Goal-Plan Structure T1



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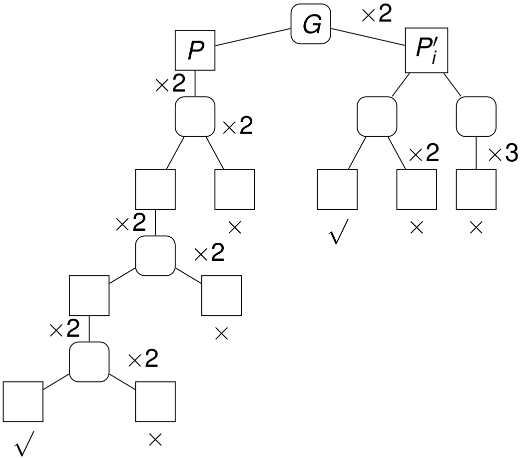
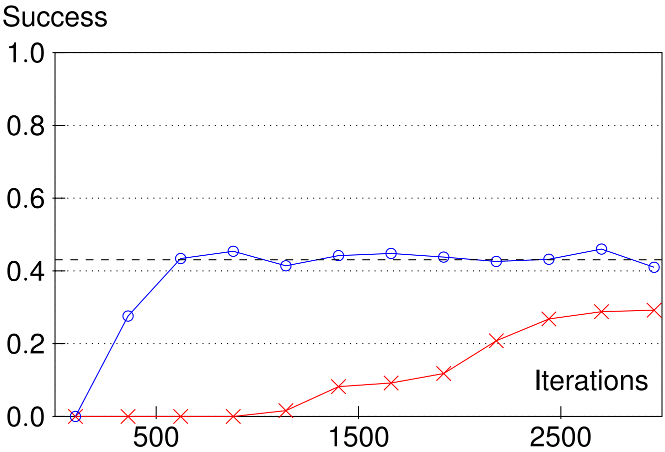
Goal-Plan Structure T2



Structure has solution in one complex option.
This configuration suits the conservative BUL approach.

Results: Goal-Plan Structure T2



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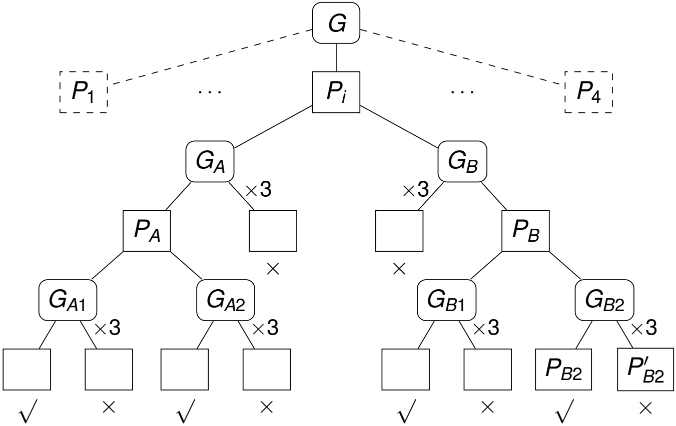
Goal-Plan Structure T3



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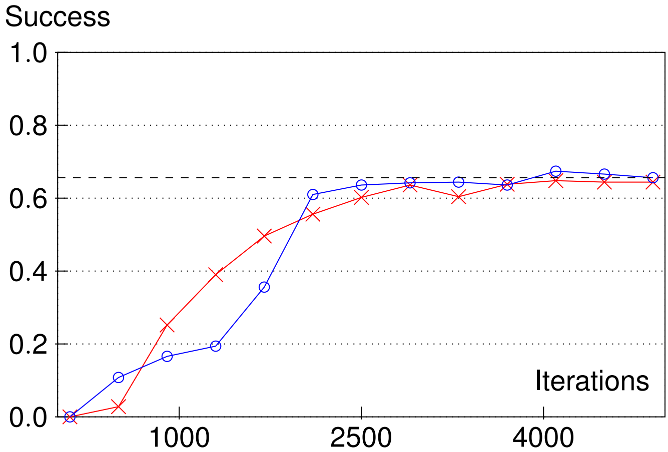
Results: Goal-Plan Structure T3



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