Bayesian Inference of Temporal Task Specifications from Demonstrations

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Specifications for setting a dining table:

- Necessity of object placements
- Correct object positions
- No collisions
- Placement orders

Not Markovian in object poses

Expressible in Linear temporal logic (LTL), a flexible specification language used:

- Synthesis of verifiable controllers[3]
- Reinforcement learning[2]
- Goal description in symbolic planning[2]

Aim:
- Infer task specifications from demonstrations

Approach:
- Bayesian specification inference for task specifications as LTL formula

Bayesian Formulation

\[ P(\phi|d) = \frac{P(d|\phi)P(\phi)}{\sum_{\phi'} P(d|\phi')P(\phi')} \]

- \( P(\phi) \) must have positive support over all relevant formulas.
- \( P(d|\phi) \) is the likelihood distribution that honors the size principle:
  - Large likelihood for complex formula.
  - Small likelihood for simple formula.
- Number of conjunctions a measure of formula complexity
- Probabilistic programming languages for sampling based inference[3]

Global satisfaction:

\[ \psi_{\text{global}} = \bigwedge_{i \in G} \tau_i \subseteq T \]
\[ P(\psi_{\text{global}}) = P(\tau) \]
\[ \text{Supp}(P(\tau)) = \rho(\tau) \]

Eventual Conjunction:

\[ \psi_{\text{eventual}} = \bigwedge_{i \in \omega} (\tau_i \rightarrow F \omega_i) \]
\[ W_2 \subseteq \Omega \]
\[ P(\psi_{\text{eventual}}) = P(\omega_i) \]
\[ \text{Supp}(P(\omega_i)) = \beta(\Omega) \]

Ordering:

\[ \psi_{\text{order}} = \bigwedge_{i \in \omega} \pi_i \rightarrow (\neg w_{\omega_i} \cup w_{\omega_i}) \]
\[ W_2 = \{(w_1, w_2); w_1 \in \Omega, w_2 \in \text{desc}(w_1)\} \]
\[ \text{Supp}(P(\psi_{\text{order}})) = \text{supp}(P(W_2)) = \text{all directed acyclic graphs (DAG) over } \Omega \]

We consider these restrictions

- Linear Chains
- Set of linear chains
- Forest of subtasks

References


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Motivation

Formula Template

Priors

\[ P(\phi) = P(\phi_{\text{global}})P(\phi_{\text{eventual}})P(\phi_{\text{order}}) \]

<table>
<thead>
<tr>
<th>Prior</th>
<th>( \psi_{\text{global}} )</th>
<th>( \psi_{\text{eventual}} )</th>
<th>( \psi_{\text{order}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>deterministic</td>
<td>deterministic</td>
<td>deterministic</td>
</tr>
<tr>
<td>2</td>
<td>Random Formation</td>
<td>Random Formation</td>
<td>Random Formation</td>
</tr>
<tr>
<td>3</td>
<td>Forest Formation</td>
<td>Forest Formation</td>
<td>Forest Formation</td>
</tr>
</tbody>
</table>

Prior distributions induced by probabilistic program

1. Scenario Formation
2. CB vs CI: Effect of Size principle

Scenario 1 (fully ordered) using Prior 1 (Linear Chains)

- CB performs better with more training examples
- CB posterior has greater confidence in predictions

Synthetic Domain

Efficacy across scenarios

Scenario 1: Priors 2 and 3

Scenario 2: Priors 2 and 3

- >90% similarity to ground truth with more than 10 demonstrations

Dinner Table Domain

- 6 Demonstrators with 4 configurations
- 8 Dinner table objects
- >90% similarity to ground truth

Prior 3 shows inductive bias towards longer task chains