Probabilistic Temporal Logic for Reasoning about Bounded Policies

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Yet another temporal logic...

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Reasoning about such intentions requires an appropriate probabilistic temporal logic, allowing us to explicitly reason about the execution and executability of the agent's **actions**

But well-known (**infinite-trace**) ones like PCTL, pCTL*, PATL/PATL* or Probabilistic Strategy Logic do not have this! Plus: they have high complexity (sometimes undecidable) **model checking**, and the decidability of **satisfiability** is still open

PBLP

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The logic is interpreted w.r.t. **finite traces** and **bounded policies** - a policy/strategy that holds for a certain number of steps.

PBLP is expressive enough for our needs (and can in fact express properties important for other AI applications), and it has good computational properties.

Markov Decision Processes and bounded policies

Fix a finite set A of actions, and for every $a \in A$ a precondition pre_a and finite set of postconditions Post_a - these are conjunctions of literals.

Definition

An **MDP** is a tuple $\mathbb{M} = \langle S, P, V \rangle$, where S is a set of *states*, $P : S \times \mathcal{A} \rightsquigarrow \Delta(S)$ is the *partial probabilistic transition function*, and $V : S \rightarrow 2^{\mathsf{Prop}}$ is the *valuation*.

(+ coherence conditions ensuring that pre- and postconditions are meaningful)

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Definition

For $n \ge 1$, an *n*-step policy from a state *s* is a function $\pi : S_s^{\le n} \to \mathcal{A}$ (where $S_s^{\le n}$ is the set of all length $\le n$ sequences from *s*) such that $s_k \models \operatorname{pre}_{\pi(s_1 \cdots s_k)}$.

Syntax & semantics

n-step path formulas (defined inductively w.r.t. *n*):

$$\Phi^{0} ::= \varphi \quad \Phi^{n+1} ::= \varphi \mid \mathsf{do}_{\mathbf{a}}(\mathbf{a} \in A) \mid \Phi^{n+1} \land \Phi^{n+1} \mid \neg \Phi^{n+1} \mid \mathsf{X} \Phi^{n}$$

Interpreted over state-action paths $\mathbf{w} = s_1 a_1 \cdots s_n a_n s_{n+1}$, with $\mathbf{w} \models do_a$ iff $a_1 = a$, and $\mathbf{w} \models X\Phi$ iff $s_2 a_2 \cdots s_{n+1} \models \Phi$

State formulas:

$$\varphi ::= \mathbf{x} (\in \mathsf{Prop}) \mid \varphi \land \varphi \mid \neg \varphi \mid \Diamond_{\bowtie r}^{\mathbf{n}} \Phi^{\mathbf{n}}$$

here, $n \ge 1$, $r \in [0, 1]$ and $\bowtie \in \{<, =, >\}$

For states: $s \models \Diamond_{\bowtie r}^n \Phi$ iff there is an *n*-step policy π from *s* such that under the policy, the probability that the next *n* steps of states and actions satisfies Φ is $\bowtie r$

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- We can reason about specific policies: consider a 2-step policy saying to do a now, and afterwards b₁ if we got the first postcondition of a, otherwise b₂. The formula ◊²_{=0.6}(do_a ∧ Λ_{i=1,2} X(post_{a,i} → do_{b_i}) ∧ XXφ) states that under this policy, φ holds with probability 60% in two steps.

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- Following Shoham (2009) in considering basic intentions to be pairs (a, t) denoting 'the agent intends to do a at time t', coherence of a set I of such intentions with respect to a set Γ of formulas representing the agent's beliefs is stating that

$$\Gamma \cup \{ \diamondsuit_{>0}^{t_{\max}} \bigwedge_{(a,t) \in I} \mathsf{X}^t \mathsf{do}_a \} \quad (\text{where } t_{\max} = \max_{(a,t) \in I} t)$$

is satisfiable - the agent does not believe that their intentions are not realizable

Computational properties

Model checking is **PSPACE-complete**: membership is shown using an NPSPACE-algorithm that traverses the MDP by guessing actions to take; hardness is shown by a reduction from QSAT inspired by Bulling & Jamroga (2010)

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More excitingly: satisfiability is decidable in **2-EXPSPACE**: PBLP has the bounded model property, so the algorithm iterates over S and V up to the bound, and for each determines whether there is P and s satisfying the formula by checking whether a certain existential first-order logic sentence is valid in the theory of real closed fields

Wrapping up

Summing up:

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Thank you!