1. Relational Reinforcement Learning (RRL)

Given:
- set of possible states $S$
- set of possible actions $A$
- unknown transition function $\delta : S \times A \times S$
- unknown reward function $r : S \times A$

Find policy $\pi^*: S \times A$, maximizing $V^*(s_t) = \arg\max_{\pi} V^\pi(s_t)$

2. Model-Assisted Approaches for RRL

- The (full or fully correct) MDP is not always available
  - Learning extra information can be useful
- Learn a model of the world while performing RL
  - Knowing world dynamics and exploiting this knowledge
    - Learning good models might require a policy that reach important places
    - Knowledge of the world may be essential to learn a good policy
- Relational domains
  - Learning a (good) model is more challenging
  - Even impossible how to handle this uncertainty?
- First indirect RRL approach
  - Learn transition and reward probability distributions
  - Improve policy by performing a (small) local search starting in current state

3.1. Learning the transition function

- Represent as a Relational Dynamic Bayesian Network
  - Assume that random variables describing the next state only depend on the current state and the action
  - Only parameter learning
- Conditional probability distribution modeled as a relational probability tree for every state predicate

3.3. Preliminary Experiments

- Convergence results for stack and logistics domains

3.2. Q-Learning with Lookahead

When an action needs to be chosen, instead of using the Q-values for the current state, the agent can look some steps ahead to obtain more informative Q-values.

$$Q(s, a) = \sum_{n=0}^{N} \left( r(s, a) + \gamma^{n} \sum_{s'} \max_{a'} Q(s', a') \right)$$

4. Challenges and Open Problems

- Evaluate different components of the learned model
- Efficient sampling strategies
- Efficient planning techniques

4.1. Challenges

- Evaluate different components of the learned model
- Efficient sampling strategies
- Efficient planning techniques

5. Conclusions

- First model-assisted RRL approach
- Incrementally learn a RDBN to model the transition function
- Improved convergence speed by looking some steps ahead

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