Compiling Probabilistic Conformant Planning into Mixed Dynamic Bayesian Network June 5th

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Overview

- Goal
	- Solve Probabilistic Conformant Planning by the marginal MAP inference
- Contribution

Contents

- Introduction
- Compiling PCP into Mixed DBN
- Empirical Evaluation
- Conclusion

Introduction

- What is Planning?
- What is Probabilistic Conformant Planning?
- How to formulate PCP as the Marginal MAP inferernce?
- Review the definition of Mixed Network

Planning

- Planning
	- a process of selecting and organizing actions to achieve desried goal
	- $-$ <S, T, A>
		- S : set of world states
		- A : set of actions
		- T : state transition function
			- Deterministic Transition T: S X A \rightarrow S
			- Probabilistic Transition T: S X A X S \rightarrow [0,1]
	- Flat vs. Factored state/action representation
		- Single variable vs. Multiple variables

Probabilistic Conformant Planning

- Probabilistic Planning
	- the effect of an action is random
	- the initial state is uncertain
- State Observability
	- $-$ Fully Observable \rightarrow FOMDP
	- $-$ Partially Observable \rightarrow POMDP
	- $-$ Non Observable \rightarrow NOMDP

Probabilistic Conformant Planning

- $P = \langle S, \mathbf{b_i}, \mathbf{s_G}, A, T \rangle$
	- S : a set of states,
	- $-$ b_i: initial belief state, Pr(S_I)
	- S_G : a set of goal states
	- A : a set of actions
	- $-$ T : S X A X S \rightarrow [0, 1]

$$
S = \{s^0, s^1, \cdots, s^L\} \qquad s^t = \{s_0^t, \cdots, s_n^t\}
$$

- $A = \{a^0, a^1, \dots, a^{L-1}\}\$ $a^t = \{a_0^t, \dots, a_m^t\}$ $T(\mathbf{s}^{\mathbf{t}}, \mathbf{s}^{\mathbf{t}+1}, \mathbf{a}^{\mathbf{t}})$ $Pr(\mathbf{s}^{\mathbf{t}+1} | \mathbf{s}^{\mathbf{t}}, \mathbf{a}^{\mathbf{t}})$
- Finite Horizon PCP <P, L>
	- L : time horizon
- PCP with threshold $\langle P, \theta \rangle$
	- θ : thrshold for probability of success
- Optimal Probabilistic Conformant Plan
	- a plan that achieves the maximum probability of success given fixed time horizon

Probabilistic Conformant Planning

• The joint conditional prob. distribution over all states from time 0 to L time horizon is

$$
Pr(s^{0}...s^{L}|a^{0}...a^{L-1}) = \prod_{i=0...L} Pr(s^{i}|s^{0}...s^{i-1},a^{0}...a^{L-1})
$$

=
$$
\prod_{i=0...L} Pr(s^{i}|s^{i-1},a^{i-1})
$$

=
$$
Pr(s^{0})Pr(s^{L}|s^{L-1},a^{L-1}) \prod_{i=1...L-1} Pr(s^{i}|s^{i-1},a^{i-1})
$$

• Initial belief state and goal are given in advance,

$$
Pr(\mathbf{s}^0 \cdot \mathbf{s}^L | \mathbf{s}^0 = \mathbf{s}_I, \mathbf{s}^L = \mathbf{s}_G, \mathbf{a}^0 \cdot \mathbf{a}^{L-1})
$$

=
$$
Pr(\mathbf{s}^0 = \mathbf{s}_I) Pr(\mathbf{s}^L | \mathbf{s}^L = \mathbf{s}_G, \mathbf{s}^{L-1}, \mathbf{a}^{L-1}) \prod_{i=1...L-1} Pr(\mathbf{s}^i | \mathbf{s}^{i-1}, \mathbf{a}^{i-1})
$$

• PCP as Marginal MAP

$$
(a^0..a^{L-1}) = \arg\max_{(a^0..a^{L-1})}\sum_{s^i \in S}Pr(s^1..s^{L-1}|s^0 = s_I,s^L = s_G,a^0..a^{L-1})
$$

Mixed Network

- Mixed network
	- Belief network + Constraint network
	- The joint probability distribution of Mixed network

$$
Pr_{\mathcal{M}}(\bar{x}) = \begin{cases} Pr_{\mathcal{B}}(\bar{x}), & \text{if } \bar{x} \in \rho(X_{\mathcal{C}}) \\ 0, & \text{otherwise.} \end{cases}
$$

Compiling PCP into Mixed DBN

- Overview of Process
- What is PPDDL?
- SAT Encoding of PPDDL
- Converting SAT Encoding into Mixed DBN.
- Example

Compiling PCP into Mixed DBN

Planning Formalisms

- $\langle P, O, I, G \rangle$ • Classical Propositional STRIPS
	- P: a set of propositional atoms
	- O: a set of operators
	- I: a list of positive atoms at init.
	- G: a list of atoms that must be true at goal
	- operator o $\langle pre(o), add(o), del(o) \rangle$
		- Precondition list
		- Add list
		- Delete list

– Closed world assumption

Action Description Language

• ADL

– more expressive than STRIPS

Planning Domain Definition Language

PPDDL

• Probabilistic Effect

PPDDL Example

```
(define (domain ext-slippery-gripper)
 (:requirements :negative-preconditions :conditional-effects
                :probabilistic-effects)
 (:predicates (qripper-dry) (holding-block) (block-painted)
              (gripper-clean))
 (:action pickup
     :effect (and (when (gripper-dry)
                         (probabilistic 0.95 (holding-block)))
                   (when (not (gripper-dry))
                         (probabilistic 0.5 (holding-block)))))
(:action dry
     :effect (probabilistic 0.8 (gripper-dry)))
(:action paint
     :effect (and (block-painted)
                   (when (not (holding-block))
                         (probabilistic 0.1 (not (gripper-clean))))
                   (when (holding-block)
                         (not (gripper-clean)))))(define (problem ext-slippery-gripper)
 (:domain ext-slippery-gripper)
(:init (gripper-clean)
        (probabilistic 0.7 (gripper-dry)))
(:goal (and (gripper-clean) (holding-block) (block-painted))))
```
SAT Encoding for PPDDL

SAT Variables

- For each ground predicate/action, introduce a boolean state/action variable s_i/a_i .
- For each action a_i , introduce a multi-valued effect variable e_{a_i} which has $n+1$ values if the effect had *n* outcomes. The first value of an effect variable e_{a_i} is *no-op*, which means that the result of the effect will be null effect, and the rest of the values refer to conditional effects c_i defined earlier.
- For each state variable s_i , we introduce two auxiliary boolean variables for state transition, $+s_i$ and $-s_i$. The $+s_i$ is true if execution of any action could add the state variable s_i at the next time stage. Similary the $-s_i$ is true if execution of any action could delete the state variable s_i at the next time stage.

SAT Encoding for PPDDL

SAT Clause for Qualifying Precondition

• For each ground action a_i , let ϕ_i be a CNF clause for a action precondition, then

 $a_i \wedge \phi_i \Leftrightarrow (e_{a_i} \neq \text{no-op})$, where the $(e_{a_i} = v)$ is an equality predicate that is true if

the value of the multi-valued variable e_{a_i} equals v.

SAT Clause for State Transition the auxiliary value +s is TRUE iff one of the effect that contains positive literal s happens

 $\forall (e_{a_i} = v) \Leftrightarrow +s_i$, if $+s_i \in add(e_{a_i} = v)$

SAT Clause for mutual exclusivity

only 1 action per time stage, and only single effect can happen

$$
\forall_j \vee a_j, \forall_{j \neq k} a_j \rightarrow \neg a_k \qquad \forall_{a_i, a_j} (e_{a_i} = v_i) \wedge (e_{a_j} = v_j) \rightarrow \neg \texttt{+} \texttt{I-s}_i
$$

SAT Clause for the frame axiom

$$
s_i^{'}, \neg {+} s_i \wedge \neg s_i \rightarrow (s_i \wedge s_i^{'}) \vee (\neg s_i \wedge \neg s_i^{'})
$$

- : action
- : precondition (φ_1)
-

(a) conditional effects inside probabilistic effect

 $: action$: precondition (φ_1)

: effect $(p_1 \varphi_2 \triangleright v_1)$, $(p_2 \varphi_3 \triangleright v_2)$: effect $(\varphi_2 \triangleright v) \wedge ((p_1 \vee_1), (p_2 \vee_2))$

(b) conjunciton of conditional effect and probabilistic effect

 $\mathsf C$ a_1 $a₂$ $a₃$

(a) Auxiliary network for the frame axiaom

(b) Auxiliary network for the mutual exclusivity constraint

Complexity of Translation

• Number of Variables per time

- $-$ n_actions = ground actions, $|A|$
- $-$ n_states = ground states, $|S|$
- $-$ n effects = n action
- n hidden \leq 2n states* $|E|$
	- E : maximum number of effects that affecting a single state; depends on the problem
- n_constraint = n_actions (including hidden variables)
- O (|A| + |S| + |A| + 2|S| + |A| + |S|*|E|) = O(3|A| + (3+ |E|) |S|)
- $|A|$
	- number of action schema * KP
		- K : maximum number of constant objects
		- p: maximum number of parameters for action schema
- $|S|$
	- number of predicates * K^q

Slippery Gripper Problem

Empirical Evaluation

- Benchmark Sets
- AOBB-JG vs. BBBTi vs. Yuan's algorithm
- AOBB-JG vs. Probabilistic-FF

Benchmark Sets

• 3 Benchmark Problems

- 3 Marginal MAP algorithms
	- $-$ AOBB-JG : (i, c, j)

AND/OR branch and bound search algorithm using weighted mini bucket heuristic with join graph cost shifting scheme

 $-$ BBTi : (i, c)

Branch and bound search algorithm using incremental mini cluster tree elimination heuristics

– Yuan's :

Depth first branch and bound search algorithm using incremental joint tree upper bound with unconstrained variable orderings

Slippery Gripper

- 2TDBN
	- 4 state vars
	- 3 action vars
	- 23 vars

Slippery Gripper

- Run time results – Yuan < BBTI < AOBB-JG
- Heuristic Upper bounds – WBM-JG provided the tightest bound – AOBB-JG solved up to 7 horizon w/o search
- Induced width:
	- unconstrainted induced width 6
	- constrained induced width increases with L

Comm

• 2TDBN : 45 state vars, 46 action vars, 349 vars

Comm

- AOBB-JG was the only algorithm that solved up to 9 time horizon.
- The induced width of the constrained ordering is 103 for the length 2 plan problem and 467 for the length 9 plan problem
- The only probabilistic tables in the problem are two state variables at the initial state.
- AOBB-JG could solvethe problem efficently by detecting the zero probability subplans early by constraint processing
- The large induced width of the problem not only makes the heuristic inaccurate but also consumes huge amount of memory.
- i-bound was limited by 2 up to 9 time horizon and solver was terminated due to out of memory from 10 time horizon.

Blocks World

• 2TDBN: 9 state vars, 8 action vars, 73 vars

Comaprison with COMPLAN

- COMPLAN
	- Depth First Branch & Bound Search using approxiamte marignal MAP qeury to DNNF (compiled diagram).
		- similar to Yuan's algorithm
	- Compiles problems as SAT with chance variables \rightarrow compile CNF as DNNF
- Running time comparison?

– NA

Comaprison with Probabilistic-FF

- Probabilistic-FF
	- Sub-optimal planner, returns any plan that acheives a threshold
	- Heuristic Forward Search in a Belief State Space
	- Built on
		- Fast Forward Classical Planner
		- Conformant-FF
	- Internally represent blief states by DBN, and compile it into weighted CNFs \rightarrow weighted model counting

Comparison with Probabilistic-FF

Conclusion

- Converted PPDDL Format to UAI Format
- Empirical Evaluation
	- 3 Problems (Slippery Gripper, Comm, Blocks world)
	- AOBB-JG Performed Best in overall
		- AOBB-JG equipped with constraint processing
		- w/o zero probability detection,
			- Slippery Gripper : Yuan < BBBTi < AOBB-JG
			- Blocks World : AOBB-JG < BBBTi < Yuan
	- AOBB-JG vs. Probabilistic FF
		- Probabilistic-FF generates suboptimal plans really fast
		- For optimal length plan, AOBB-JG was faster
		- In blocks world, Probabilistic FF couldn't find solution if threshold was $>= 0.6$

Conclusion

- Downsides of Current Compilation
	- The number of variables is exponential in the number of ground objects
		- comm domain had 46 actions in 1 step.
		- cannot solve blocks world problem having 4 blocks
	- Large scope sized deterministic constraints
		- Mutually exclusive action constriant
		- The state transition constraint
	- All tables have huge redundancy
		- Decision diagrams

Future Work

- Compact Translation (semi-lifted model)
	- Formulate Problems in SAS+ formalism
		- Actions will be splitted
		- Reduce the coupling between state variables
- Compressed Representation
	- Contraints, CNFs
	- Decision Diagrams
- Lifted Inference
	- Incorported lifted inference algorithms on the relational representation
- Extend the Problem Formulation to
	- Probabilistic Planning with Rewards
	- POMDP