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Applying Search Based Probabilistic Inference Algorithms to Probabilistic Conformant Planning: Preliminary Results

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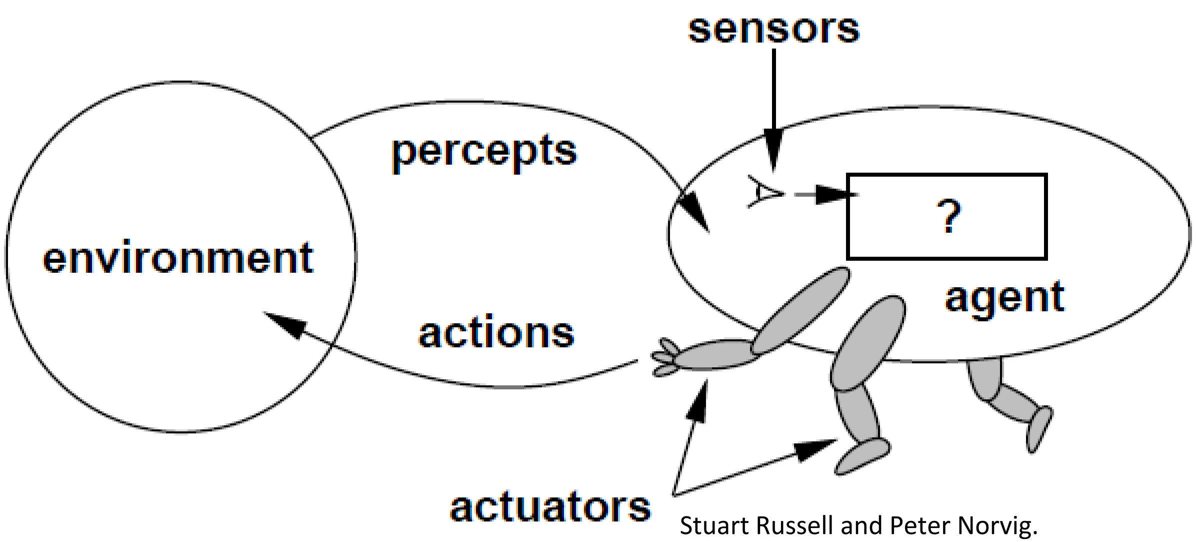
Overview

- Probabilistic Conformant Planning
  - Agent, Example, Problem, and Task
- Graphical Model and Probabilistic Inference
  - Probabilistic Conformant Planning as Marginal MAP Inference
  - AND/OR Search Algorithms for Marginal MAP Inference
- Compiling Graphical Models from Planning Problems
  - Example Domain: Blocks World
  - Compiling Probabilistic PDDL into 2 stage DBN
  - Compiling Finite Domain Representation (SAS+) into 2 stage DBN
- Experiment Results (Blocks World Domain)

Probabilistic Conformant Planning - Agent

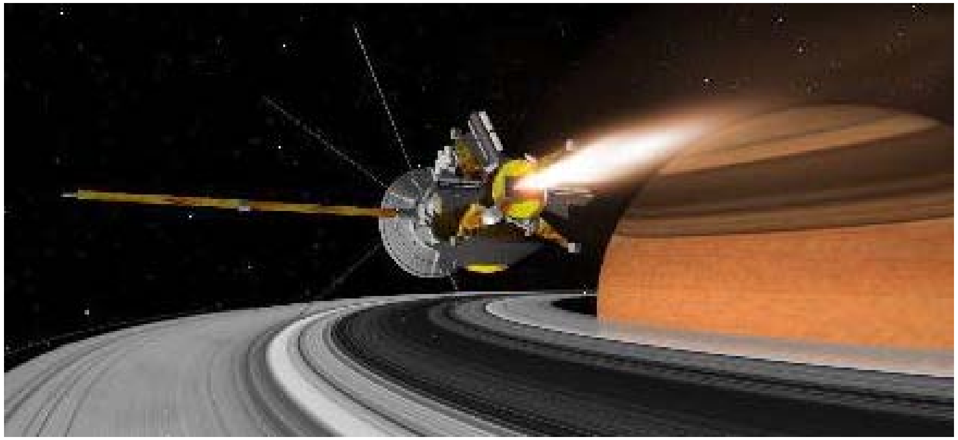


Stuart Russell and Peter Norvig.
Artificial Intelligence: A Modern Approach (3rd Ed.)

- No observation
- Uncertain environment
  - Uncertain initial states: Probability distribution over possible states
  - Uncertain action effects: Probability distribution over possible effects
- Find a sequence of actions that reach goal with desired criteria
  - given plan length, maximize the probability of reaching goal, etc

Probabilistic Conformant Planning - Example

- Spacecraft Recovery*
  - Complex systems could fail
  - Observation is sometimes limited
  - Diagnosis yields plausible states with scores (probability)
  - Generate a fail-safe recovery plan that can be applied to all plausible states.



*Fragment-based Conformant Planning, J. Kurien, P. Nayak, and D. Smith *AIPS 2002*

Probabilistic Conformant Planning - Problem and Task

- Probabilistic Conformant Planning Problem

  P = <S, A, I, G, T>

  - S : a set of possible states
  - A : a set of actions
  - I : initial belief state (probability distribution over initial states)
  - G: a set of goal states
  - T: Markovian state transition function (T: S x A x S → [0, 1])

- Probabilistic Conformant Planning Task

  <P, L>: Maximize probability of reaching goal given fixed plan length L

  <P, θ>: A plan of arbitrary length reaching goal with a probability higher than θ

Graphical Models

- A graphical model (**X, D, F**)
  - $X = \{X_1, \dots, X_n\}$ variables
  - $D = \{D_1, \dots, D_n\}$ domains
  - $F = \{f_1, \dots, f_m\}$ functions
    - Constraints, CPTs, CNFs, …
- Operators
  - Combination (product)
  - Elimination (max/sum)
- Tasks
  - Probability of Evidence (PR)

$$Pr(e) = \sum_{X_s} \prod_j f_j(X_s, e)$$

  - Most Probable Explanation (MPE)

$$\mathbf{x}_{MPE} = argmax_{\mathbf{x}} \prod_j f_j(\mathbf{x})$$

  - Marginal MAP (Maximum A Posteriori)

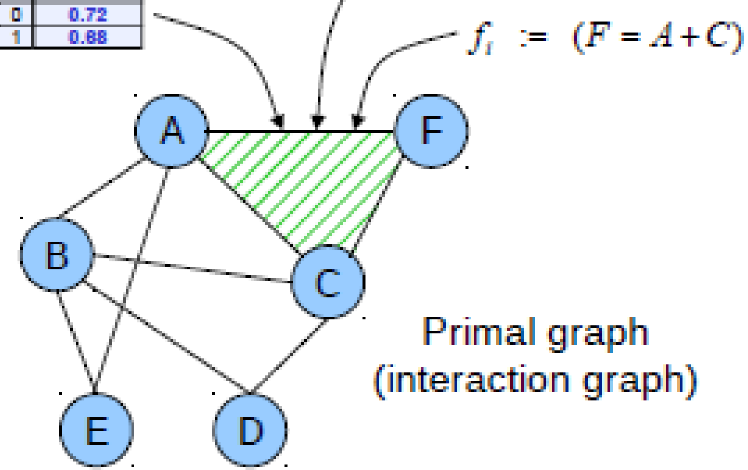
$$\mathbf{x}_{MMAP} = argmax_{\mathbf{x}_m \in X_M} \sum_{\mathbf{x}_s \in X_s} \prod_j f_j(\mathbf{x_m}, \mathbf{x_s})$$

CPT

A	C	F	P(F|A,C)
0	0	0	0.14
0	0	1	0.86
0	1	0	0.40
0	1	1	0.60
1	0	0	0.35
1	0	1	0.65
1	1	0	0.72
1	1	1	0.28

Relation

A	C	F
red	green	blue
blue	red	red
blue	blue	green
green	red	blue



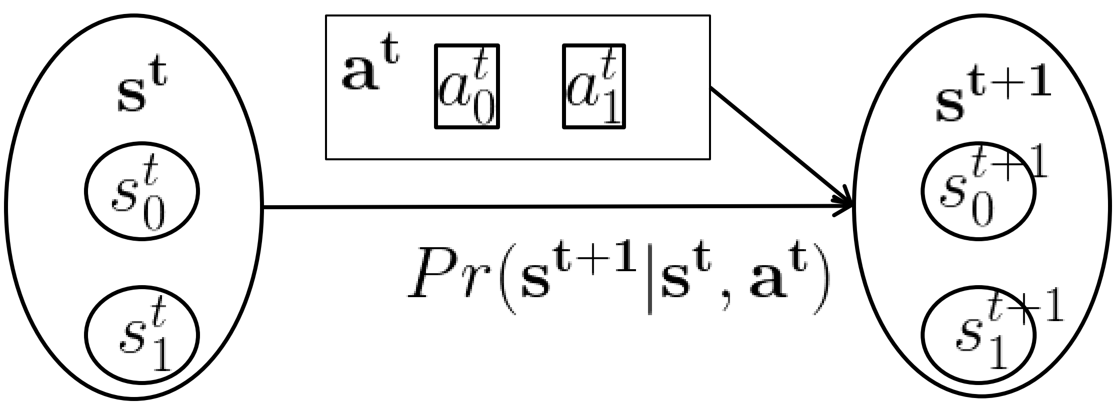
Primal graph (interaction graph)

All these tasks are NP-hard
Exploit problem structure (primal graph)

Conformant Planning as Marginal MAP

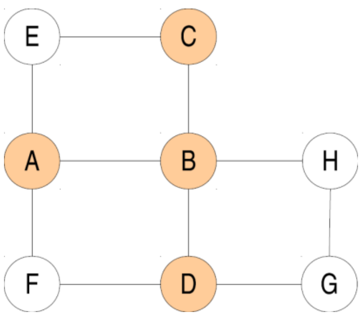
- Finite Horizon Probabilistic Conformant Planning <S, A, I, G, T, L>
  - Random variables
    $$S = \{\mathbf{s^0}, \mathbf{s^1}, \cdots, \mathbf{s^L}\} \quad \mathbf{s^t} = \{s^t_0, s^t_1, \cdots, s^t_N\}$$
    $$A = \{\mathbf{a^0}, \mathbf{a^1}, \cdots, \mathbf{a^L}\} \quad \mathbf{a^t} = \{a^t_0, a^t_1, \cdots a^t_M\}$$
  - State transition function
    $$Pr(\mathbf{s^{t+1}}|\mathbf{s^t}, \mathbf{a^t}) = T(\mathbf{s^t}, \mathbf{a^t}, \mathbf{s^{t+1}})$$
  - Joint probability distribution given a plan that satisfying the goal
    $$P(\mathbf{s^0}, \mathbf{s^1}, \cdots, \mathbf{s^L}|\mathbf{s^L} \in G, \mathbf{a^0}, \mathbf{a^1}, \cdots, \mathbf{a^{L-1}}) = P(\mathbf{s^0})[\textstyle\prod_{t=0..L-1} P(\mathbf{s^{t+1}}|\mathbf{s^t}, \mathbf{a^t})]P(\mathbf{s^L}|\mathbf{s^L} \in G, \mathbf{s^{L-1}}, \mathbf{a^{L-1}})$$
  - Optimal Plan as MMAP

$$argmax_{\{\mathbf{a^0},\mathbf{a^1},\cdots,\mathbf{a^{L-1}}\}} \sum_{\{\mathbf{s^0},\mathbf{s^1},\cdots,\mathbf{s^L}\}} P(\mathbf{s^0}, \mathbf{s^1}, \cdots, \mathbf{s^L}|\mathbf{s^L} \in G, \mathbf{a^0}, \mathbf{a^1}, \cdots, \mathbf{a^{L-1}})$$



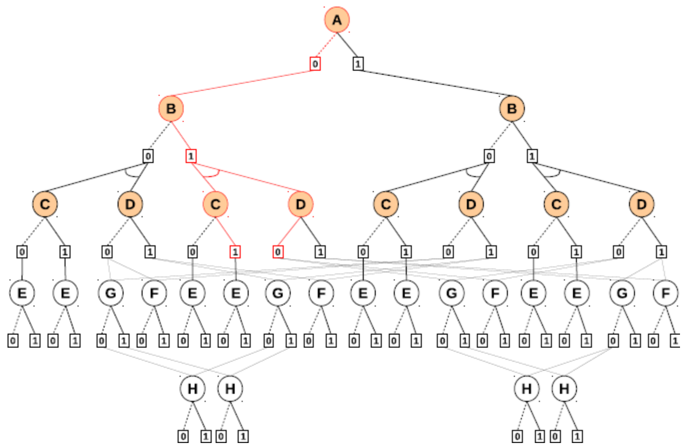
AND/OR Search Algorithm for MMAP

Graphical Model



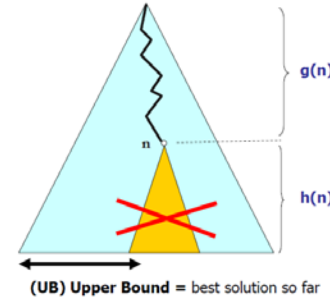
AND/OR Search Graph

[Decther and Mateescue 2006]



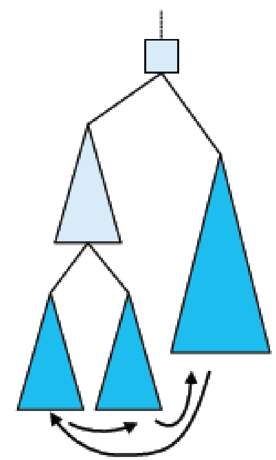
AND/OR Branch and Bound Search

[Kask, Dechter 2001]
[Marinescue, Dechter 2005-2009]



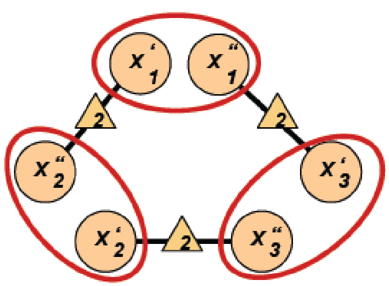
Breadth Rotate Search

[Otten, Dechter 2011]



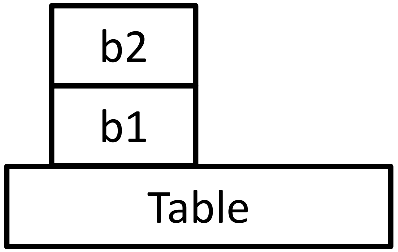
Mini-bucket Elimination with Moment Matching

[Dechter and Rish 1997, 2003]
[Flerova, Ihler 2011]



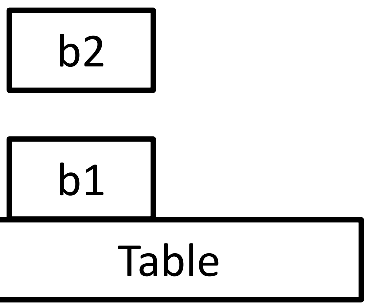
$min_{\lambda} \sum_{(ij)} max_{X}(f_{ij}(X_i, X_j) + \lambda_{ij}(X_i), \lambda_{ji}(X_j))$

Example Domain: Blocks World



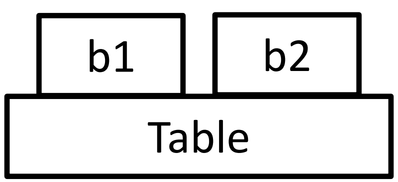
State: OnTable (b1) and On(b2, b1) and Clear(b2) and EmptyHand

action: pick-up-from-block(b2, b1)



State: OnTable (b1) and Clear(b1) and Holding(b2)

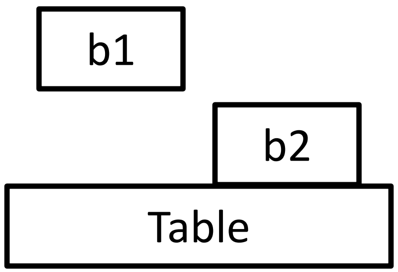
action: put-down-to-table(b2)



State: OnTable (b1) and OnTable(b2) and Clear(b1) and Clear (b2) and EmptyHand

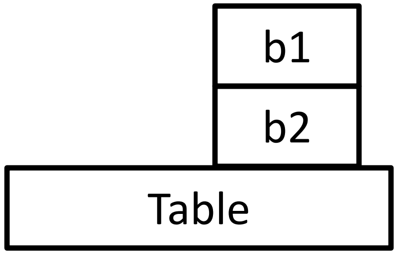
Example Domain: Blocks World

action: pick-up-from-table(b1)



State: OnTable (b2) and Clear(b2) and Holding(b1)

action: put-on-block(b1, b2)



State: OnTable (b2) and On(b1, b2) and Clear(b1) and EmptyHand

Blocks World in PDDL (deterministic)

- Predicates for describing states
  - Clear(?b block), OnTable(?b block),
  - On(?b1, ?b2 block), Holding(?b block), EmptyHand
- Initial State
  - On(b2, b1) and OnTable(b1) and Clear(b2) and EmptyHand
- Goal State
  - On(b1, b2) and OnTable(b2) and Clear(b1) and EmptyHand
- Action Schema for describing actions
  - Pick-up-from-block (?b1 ?b2 - block)
  - Pick-up-from-Table (?b – block)
  - Put-on-block(?b1 ?b2 – block)
  - Put-down-to-table(?b – block)

Blocks World in PDDL (deterministic)

- Action schema for describing deterministic state transitions
  - Pick-up-from-block(?b1, ?b2 - block)
    - Precondition: EmptyHand and Clear(?b1) and On(?b1, ?b2)
    - Effect: Holding(?b1) and Clear(?b2) and
      (Not EmptyHand) and (Not Clear(?b1)) and (Not On(?b1, ?b2))
  - Pick-up-from-table(?b - block)
    - Precondition: EmptyHand and Clear(?b) and OnTable(?b)
    - Effect: Holding(?b) and
      (Not EmptyHand) and (Not OnTable(?b)) and (Not Clear(?b))

Compiling Graphical Models from Planning Domains

IPC-1998, 2000
McDermott et al 1998

Planning Domain Definition Language

-standard language for "classical planning problems"
- influenced by STRIPS and ADL formalism

IPC- 2004
Younes and Littman 2004

Probabilistic Planning Domain Definition Language

Extension of PDDL 2.1 to support "Probabilistic Actions"

Two Encoding Schemes

2 Stage DBN

&

Replicate it over L finite horizon

[Helmert 2006, 2009]

Finite Domain Representation (SAS+)

- Multi-valued state variables
- Simplified Action Structure+ (SAS+) (Backstrom 1995)

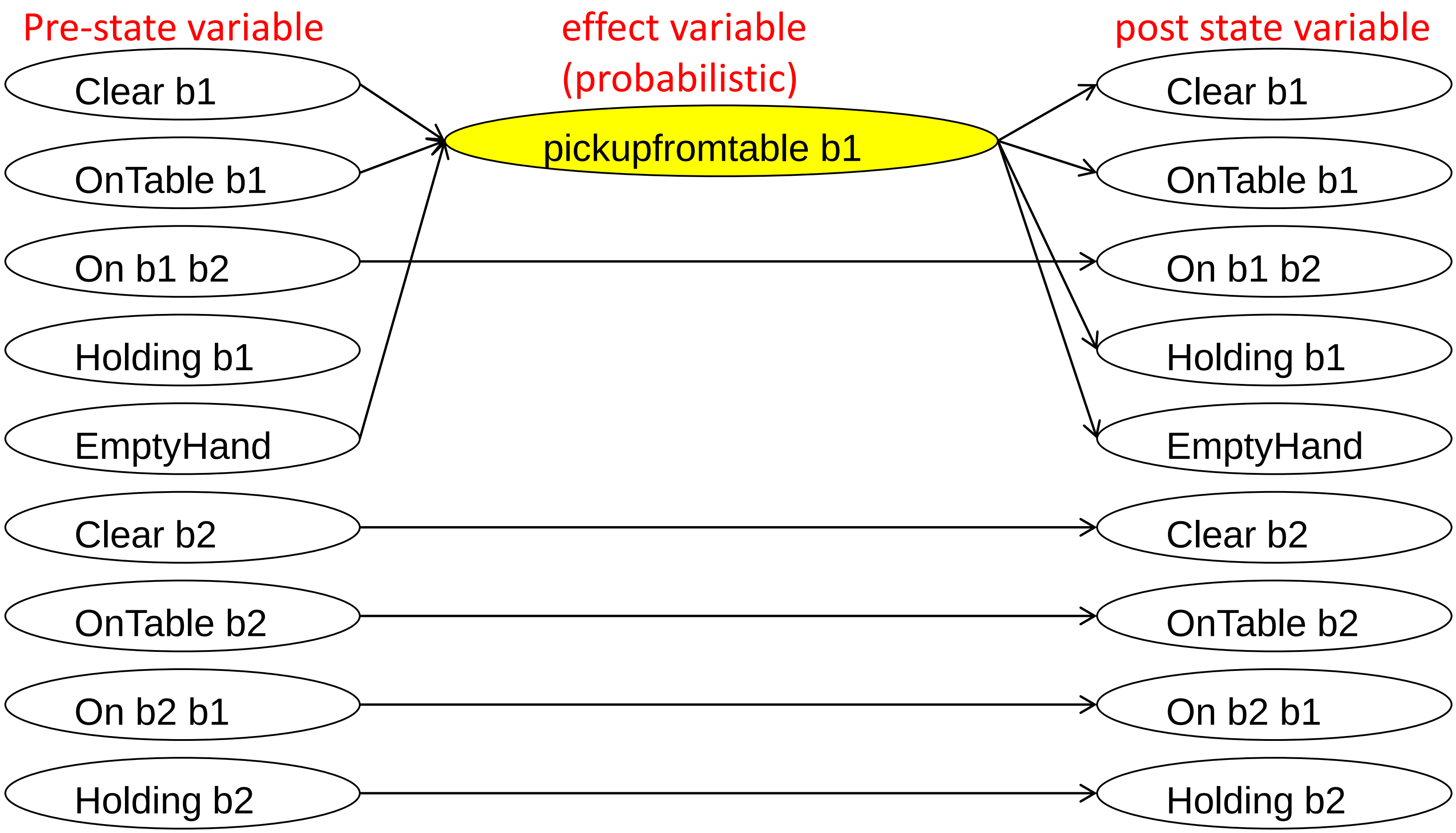
Finite Domain Representation (SAS+) with Probabilistic Effects

Blocks World in PPDDL (Probabilistic)

- Action schema for describing probabilistic state transitions
  - Pick-up-from-block(?b1, ?b2 - block)
    - Precondition: EmptyHand and Clear(?b1) and On(?b1, ?b2)
    - Effect1: **0.75** Holding(?b1) and Clear(?b2) and
      (Not EmptyHand) and (Not Clear(?b1)) and (Not On(?b1, ?b2))
    - Effect2: **0.25** Clear(?b2) and OnTable(?b1) and (Not (On(?b1, ?b2))
  - Pick-up-from-table(?b - block)
    - Precondition: EmptyHand and Clear(?b) and OnTable(?b)
    - Effect1: **0.75** Holding(?b) and (Not EmptyHand) and (Not OnTable(?b)) and (Not Clear(?b))

Compiling PPDDL into 2 stage DBN

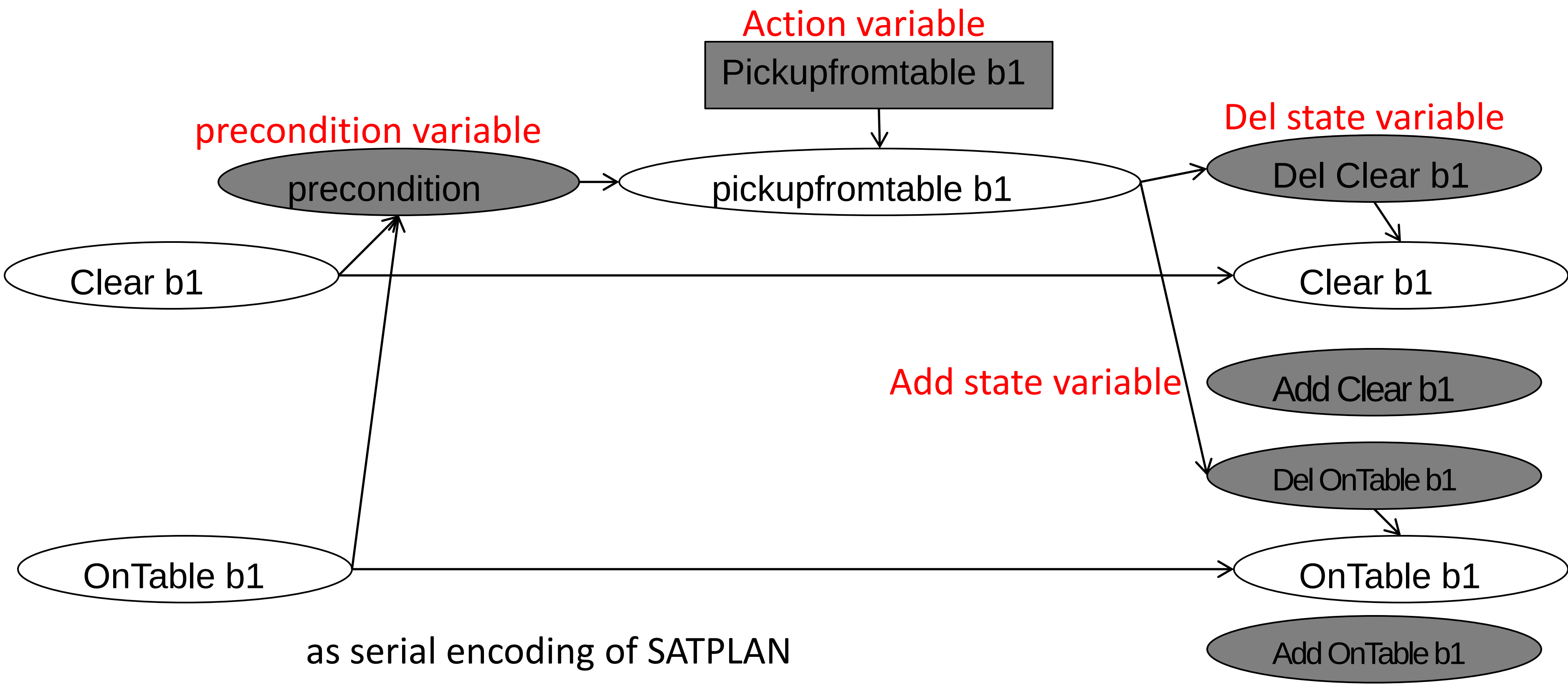
- Convert each ground action schema into 2TDBN



as shown in PPDDL 1.0 Specification

Compiling PPDDL into 2 stage DBN

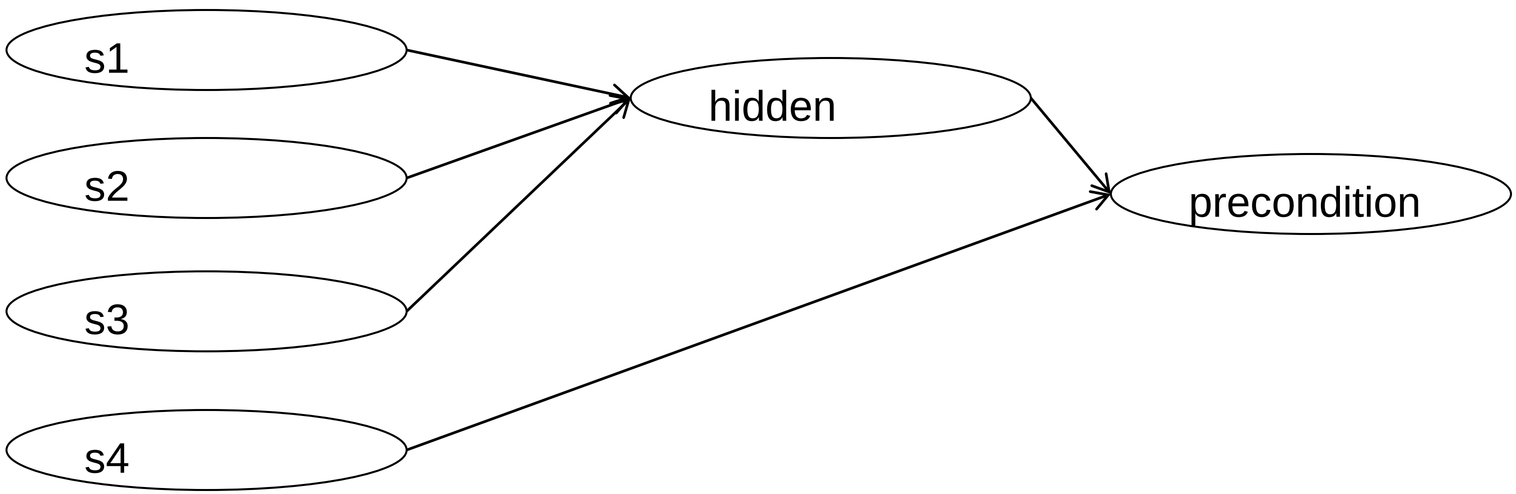
- Introduce additional variables to bound scope
  - Precondition, Add effect, Del effect, Action



as serial encoding of SATPLAN

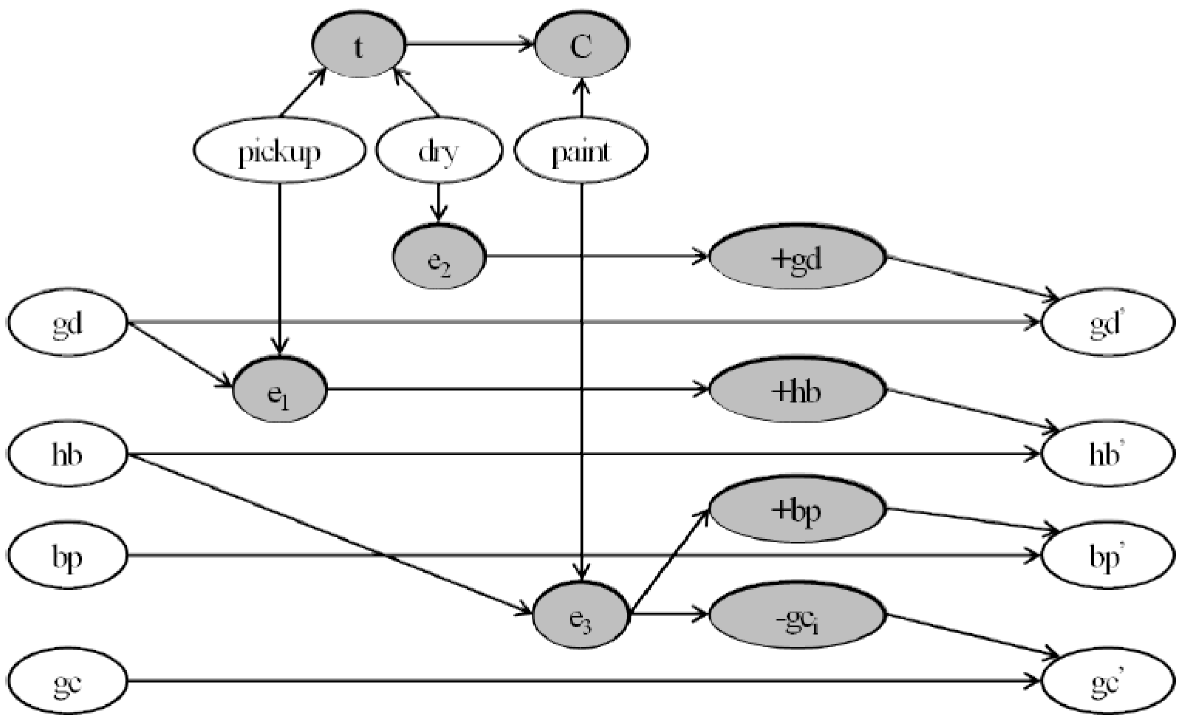
Compiling PPDDL into 2 stage DBN

- Combine all 2TDBNs into Single 2TDBN
  - If scope size needs to be bounded, introduce hidden variables



Compiling PPDDL into 2TDBN

- Slippery Gripper Domain Example



Complexity of Translation from PPDDL

- Input PPDDL parameters
  - Number of ground objects = $|Obj|$
  - Number of action schemata = $|AS|$
    - Maximum number of object parameters = $|P|$
    - Maximum number of probabilistic effects = $|Eff|$
  - Number of predicates = $|Pred|$

- Number of Variables at each time
  - Number of action variables $\leq 2 \cdot |AS| \cdot |Obj|^{|P|}$
  - Number of state variables $= |Pred| \cdot |Obj|^{|P|}$
  - Number of effect variables $= |AS| \cdot |Obj|^{|P|}$
  - Number of Add/Del state variables $\leq 2 \cdot |Pred| \cdot |Obj|^{|P|} \cdot |Eff|$
  - $O(3 \cdot |AS| \cdot |Obj|^{|P|} + (3 + |Eff|) \cdot |Pred| \cdot |Obj|^{|P|})$

Compiling Graphical Models from Planning Domains

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Planning Domain Definition Language

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Younes and Littman 2004

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Extension of PDDL 2.1 to support "Probabilistic Actions"

[Helmert 2006, 2009]

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Finite Domain Representation (SAS+) with Probabilistic Effects

Two Encoding Schemes

2 Stage DBN

&

Replicate it over L finite horizon

Blocks World in FDR (SAS+)

- Simplified Action Structure+ (Backstrom 1995)
  - Multi-valued state variables
    - State variable is an aggregate of mutually exclusive ground predicates
  - Operators (collection of changes of values in state variables)
    - Prevail condition: Value of a variable remains same
    - Pre-condition: Value of a variable before state transition
    - Post-condition: Value of a variable after state transition
- Translate PDDL → FDR (Helmert 2009)
  - Generalize SAS+ with conditional effects and derived predicates
  - Automated translator from PDDL 2.2 to SAS+

Blocks World in FDR (SAS+)

- Multi-Valued State Variables
  - 9 binary state variables
    - clear b1, OnTable b1, On b1, b2, Holdig b1, Emptyhand, clear b2, OnTable b2, Onb2 b1, Holding b2

translated as

  - 5 multi-valued state variables
    - Var0 = {Clear(b1), Not Clear(b1)}
    - Var1 = {Clear(b2), Not Clear(b2)}
    - Var2 = {EmptyHand, Not EmptyHand}
    - Var3 = {Holding(b1), On(b1, b2), OnTable(b1)}
    - Var4 = {Holding(b2), On(b2, b1), OnTable(b2)}

Blocks World in FDR (SAS+)

- Operators for describing **deterministic** state transitions
  - Translate each ground action schema as a collection of transitions of state variables

  - Pick-up-from-block(?b1, ?b2 - block)
    - Precondition: EmptyHand and Clear(?b1) and On(?b1, ?b2)
    - Effect: Holding(?b1) and Clear(?b2) and
      (Not EmptyHand) and (Not Clear(?b1)) and (Not On(?b1, ?b2))

translated as

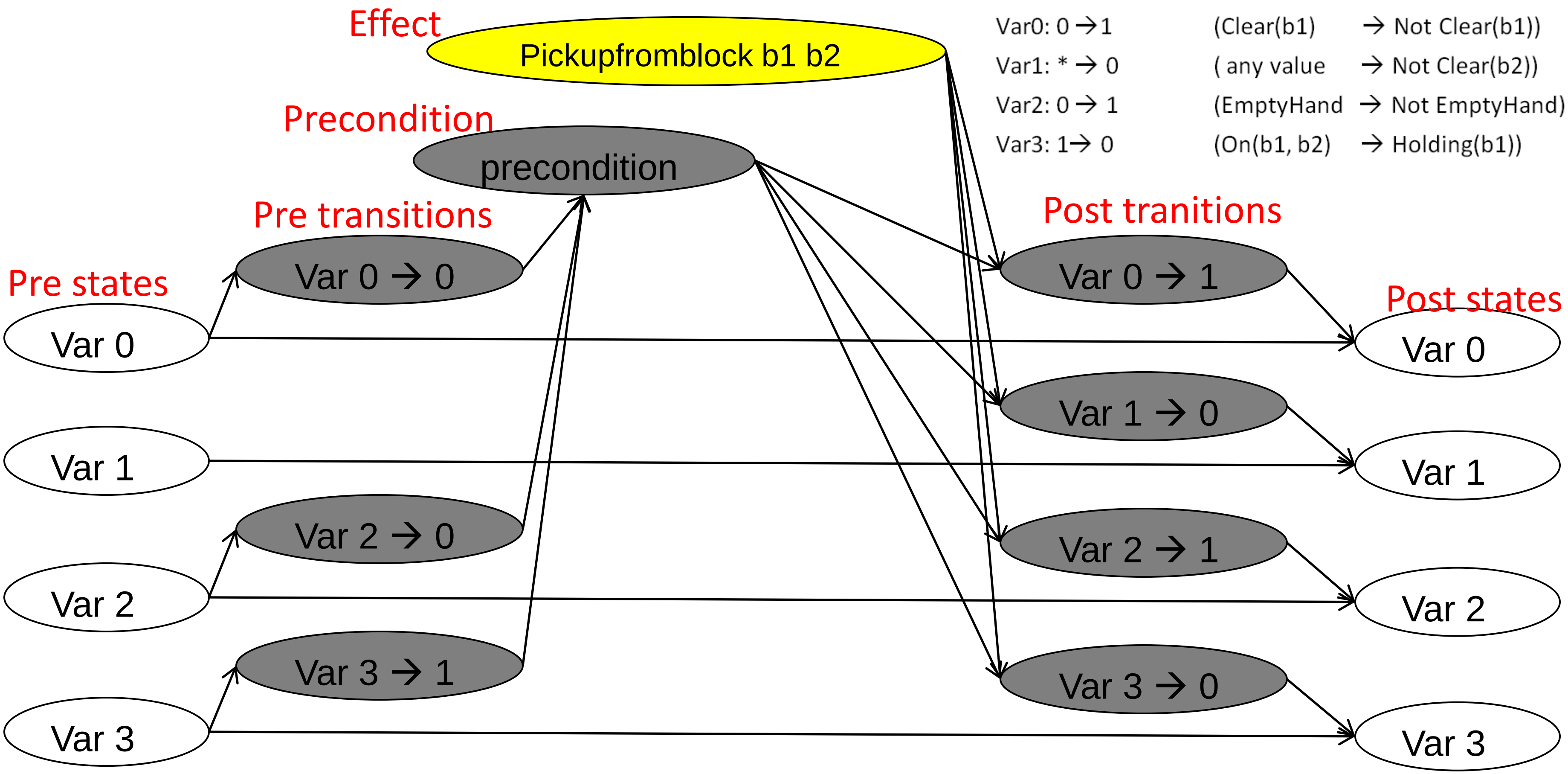
- Pick-up-from-block(?b1, ?b2 - block)
  - Var0: 0 → 1 (Clear(b1) → Not Clear(b1))
  - Var1: * → 0 (any value → Not Clear(b2))
  - Var2: 0 → 1 (EmptyHand → Not EmptyHand)
  - Var3: 1 → 0 (On(b1, b2) → Holding(b1))

Blocks World in FDR (SAS+)

- Operators for describing **probabilistic** state transitions
  - Original FDR(SAS+) does not translate probabilistic actions
  - Determinization of PPDDL action schema
    - FF-Replan (Yoon, Fern, and Giva 2007)
    - make each of the probabilistic effects as a single action schema and drop the probability value
  - Translate determinized PPDDL as FDR(SAS+)
  - Combine probabilistic effects

Compiling FDR(SAS+) into 2 stage DBN

- Convert each ground action into 2TDBN



Compiling FDR(SAS+) into 2 stage DBN

- Combine all 2TDBNs into Single 2TDBN
  - If scope size is too big, introduce hidden variables

- Optimize translation (in progress)
  - Minimize number of
    - Precondition, pre/post transition variables
    - Hidden variables
  - Minimization turns into finding maximal bi-cliques
    - action effects are expressed as conjunction of state value assignments (equality predicates)

Complexity of Translation from FDR(SAS+)

- Input PDDL/FDR parameters for action variables
  - Number of ground objects = $|Obj|$
  - Number of action schemata = $|AS|$
    - Maximum number of object parameters = $|P|$
    - Maximum number of probabilistic effects = $|Eff|$
  - Number of multi-valued state variables =$|S|$

    Maximum domain size = k
- Number of Variables at each time stage
  - action variables $= |AS| \cdot |Obj|^{|P|}$
  - state variables $= |S|$
  - Pre-transition variables $= |S| \cdot k$
  - Post-transition variables $\leq 2 \cdot |S| \cdot k$
  - Pre-condition variables $\leq 2 \cdot |AS| \cdot |Obj|^{|P|} \cdot |Eff|$
  - FDR $O((1 + 2 \cdot |Eff|)(|AS| \cdot |Obj|^{|P|}) + (1 + 3k) \cdot |S|)$
  - ppddl $O(3 \cdot |AS| \cdot |Obj|^{|P|} + (3 + |Eff|) \cdot |Pred| \cdot |Obj|^{|P|})$

Experiment Results: Blocks World

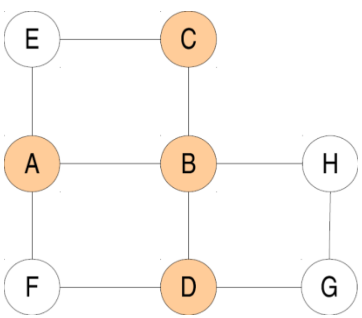
Probabilistic Inference Algorithms

	BRAOBB-MMAP	BRAOBB-MAP + PR	GLS+ PR
Optimality	Optimal	Suboptimal	Suboptimal
Search Space	Marginal MAP/ Constrained	MAP / Unconstrained	MAP / Unconstrained
Heuristic	WMB-MM(i)	MBE-MM(i)	-

- Breath Rotate + AOBB [Otten, Dechter 2011] [Marinescue, Dechter 2005-2009]
  - Branch and Bound Search on AND/OR Graph with Sub-problem rotations
- WMB-MM(i) [Dechter, Rish 1997, 2003] [Liu, Ihler 2011] [flerova, Ihler 2011]
  - Weighted mini-bucket elimination with moment matching
- GLS+ [Hutter et al, 2005]
  - Stochastic local search algorithm for MAP inference
- PR
  - Perform summation in AND/OR search graph

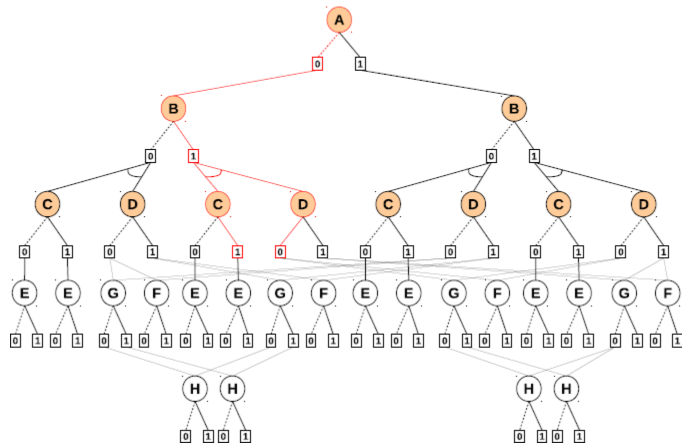
AND/OR Search Algorithm for MMAP

Graphical Model



AND/OR Search Graph

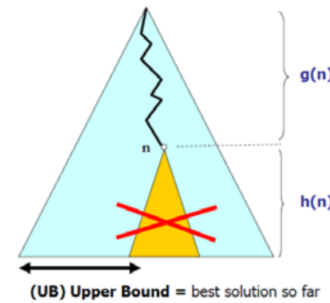
[Decther and Mateescue 2006]



AND/OR Branch and Bound Search

[Kask, Dechter 2001]

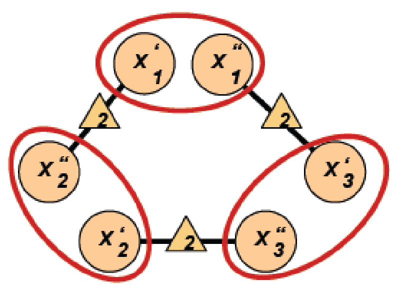
[Marinescue, Dechter 2005-2009]



Mini-bucket Elimination with Moment Matching

[Dechter and Rish 1997, 2003]

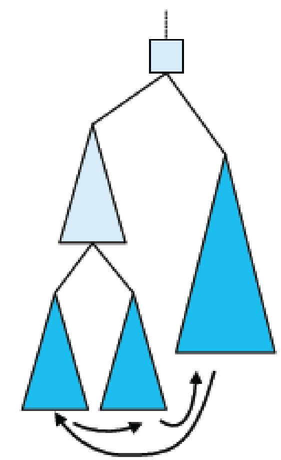
[Flerova, Ihler 2011]



$$min_{\lambda} \sum_{(ij)} max_{X}(f_{ij}(X_i, X_j)+ \lambda_{ij}(X_i), \lambda_{ji}(X_j))$$

Breadth Rotate Search

[Otten, Dechter 2011]



Experiment Results: Blocks World

- Blocks World Domains
  - Taken from International Planning Competition '04
    - The original task was planning with full observation

      Easier problem (MAP inference)
    - Original domain has 7 action schemata (removed 3)
  - Problem Instances
    - Reverse configuration

      Initially all blocks are stacked as a tower.Planning task is reversing the stack
    - Number of Blocks: 2, 3, 4 blocks
    - Length of Time: up to 20 time horizon

PPDDL vs. FDR(SAS+) translation

	Translation From PPDDL				Translation From FDR(SAS+)			
instance	ppddl to dbn		braobb-mmap		sas+ to dbn		braobb-mmap	
blocks, horizon	n, a, w_c, h_c	i_{best}	time (sec)	pr(G)	n, a, w_c, h_c	i_{best}	time (sec)	pr(G)
2, 5	299, 40, 48, 76	10	1.56	0.703125	406, 5, 22, 64	2	1.65	0.703125
2, 8	473, 64, 72, 112	10	2990.73	0.91626	646, 8, 24, 76	14	1857.33	0.91626
2, 11	647, 88, 96, 149	16	oot	0.966007	886, 11, 24, 86	6	oot	0.943176
2, 14	821, 112, 120, 169	2	oot	0.91626	1126, 14, 28, 100	8	oot	0.91626
2, 17	995, 136, 144, 199	10	oot	0.91626	1366, 17, 28, 108	10	oot	0.91626
2, 20	1169, 160, 168, 237	2	oot	0.870117	1606, 20, 26, 103	2	oot	0.870117
3, 5	741, 90, 132, 182	6	2.53	0.079102	833, 5, 44, 85	4	0.96	0.079102
3, 8	1176, 144, 159, 251	6	5767.69	0.494385	1328, 8, 45, 125	4	4382.65	0.494385
3, 11	1611, 198, 213, 328	10	oot	0.494385	1823, 11, 46, 132	2	oot	0.494385
3, 14	2046, 252, 267, 401	10	oot	0.454834	2318, 14, 46, 146	2	oot	0.494385
3, 17	2481, 306, 326, 474	2	oot	0.395508	2813, 17, 44, 183	4	oot	0.494385
3, 20	2916, 360, 380, 545	2	oot	0.395508	3308, 20, 44, 178	6	oot	0.494385
4, 8	2185, 256, 370, 477	10	108.7	0.177979	2266, 8, 67, 164	6	55.04	0.177979
4, 9	2455, 288, 415, 520	12	5717.1	0.222473	2548, 9, 68, 188	2	2291.27	0.222473
4, 10	2725, 320, 397, 556	2	oot	0.222473	2830, 10, 68, 179	2	oot	0.222473
4, 11	2995, 352, 491, 624	2	oot	0.222473	3112, 11, 68, 214	2	oot	0.222473
4, 13	3535, 416, 541, 716	2	oot	0.222473	3676, 13, 68, 222	2	oot	0.222473
4, 15	4075, 480, 672, 841	10	oot	0.222473	4240, 15, 82, 263	2	oot	0.222473

- Translation from FDR(SAS+)
  - 1.3 ~ 2.6 times speed up
  - constrained induced width of problem is much less

MMAP vs. MAP + PR Inference

instance	ppddl to dbn	BRAOBB-MMAP		BRAOBB-MAP		GLS+	
blocks, horizon	n, a, w_c, h_c, w_u, h_u	time (sec)	pr(G)	time (sec)	pr(G)	time (sec)	pr(G)
2, 5	299, 40, 48, 76, 17, 56	1.56	0.703125	4.34	0.5625	0.33	0.5625
2, 8	473, 64, 72, 112, 17, 88	2990.73	0.91626	6.63	0.5625	1.82	0.5625
2, 12	647, 88, 96, 149, 17, 111	oot	0.966007	9.71	0.5625	3.63	0.74707
2, 14	821, 112, 120, 169, 17, 163	oot	0.91626	15.54	0.5625	25.45	0.823975
2, 17	995, 136, 144, 199, 17, 241	oot	0.91626	29.29	0.316406	84.71	0.922302
2, 20	1169, 160, 168, 237, 17, 292	oot	0.870117	35.92	0.624023	25.2	0.886399
3, 5	741, 90, 132, 182, 34, 129	2.53	0.0791016	9.49	0.079102	4.85	0.079102
3, 8	1176, 144, 159, 251, 34, 157	5767.69	0.494385	53.77	0.316406	26.64	0.316406
3, 11	1611, 198, 213, 328, 34, 317	oot	0.494385	128.28	0.316406	69.57	0.454834
3, 14	2046, 252, 267, 401, 34, 382	oot	0.454834	495.64	0.316406	671.34	0.415283
3, 18	2481, 306, 326, 474,36, 350	oot	0.395508	oot	na	1743.19	0.395508
3, 20	2916, 360, 380, 545, 34, 518	oot	0.395508	oot	na	126.36	0.237305
4, 8	2185, 256, 370, 477, 60, 347	108.7	0.177979	106.88	0.177979	257.99	0.177979
4, 9	2455, 288, 415, 520, 61, 321	5717.1	0.222473	556	0.177979	146.52	0.222473
4, 10	2725, 320, 397, 556, 61, 382	oot	0.222473	418.75	0.0444946	413.68	0.222473
4, 11	2995, 352, 491, 624, 61, 497	oot	0.222473	552.66	0.177979	2003.72	0.222473
4, 13	3535, 416, 541, 716, 62, 598	oot	0.222473	oot	na	186.66	0.125141
4, 15	4075, 480, 672, 841, 62, 533	oot	0.222473	oot	na	720.01	0.044495

- MMAP finds optimal solution if it could
- MAP finds suboptimal plan faster than MMAP
- GLS+ can reach longer horizon than MMAP and MAP

MMAP vs. Probabilistic-Fast Forward

BW2	θ	0.1	0.15	0.2	0.35	0.4	0.5	0.7	0.8	0.85
	PFF	**0.06 (4)**	**0.04 (4)**	**0.05 (4)**	**0.05 (4)**	**0.06 (4)**	**0.05 (4)**	err	err	err
	BRAOBB-MMAP	1.55(5)	1.55(5)	1.55(5)	1.55(5)	1.55(5)	1.55(5)	1.55(5)	25.07 (6)	247.08 (7)
	BRAOBB-MAP	4.12 (3)	4.22 (4)	4.22 (4)	4.22 (4)	4.22 (4)	4.22 (4)	8.31 (10)	65.21 (30)	65.26 (30)
	GLS+	0.12 (3)	0.22 (4)	0.22 (4)	0.22 (4)	0.22 (4)	0.22 (4)	**0.71 (7)**	**5.25 (14)**	18.26 (17)
BW3	**θ**	**0.1**	**0.15**	**0.2**	**0.35**	**0.4**	**0.5**	**0.7**	**0.8**	**0.85**
	PFF	**0.07 (6)**	**0.06 (6)**	**0.09 (6)**	**0.12 (7)**	err	err	err	err	err
	BRAOBB-MMAP	65.79 (6)	65.79 (6)	65.79 (6)	212.01 (7)	5647.65 (8)	oot	oot	oot	oot
	BRAOBB-MAP	14.47 (6)	14.47 (6)	14.47 (6)	2069.56 (15)	oot	oot	oot	oot	oot
	GLS+	18.88 (10)	18.88 (10)	18.88 (10)	18.88 (10)	**49.57 (11)**	oot	oot	oot	oot
BW4	**θ**	**0.1**	**0.15**	**0.2**	**0.35**	**0.4**	**0.5**	**0.7**	**0.8**	**0.85**
	PFF	**0.15 (8)**	**0.14 (8)**	err	err	err	err	err	err	err
	BRAOBB-MMAP	90.32 (8)	90.32 (8)	6489.2 (9)	oot	oot	oot	oot	oot	oot
	BRAOBB-MAP	106.88 (8)	106.88 (8)	oot	oot	oot	oot	oot	oot	oot
	GLS+	146.52 (9)	146.52 (9)	**146.52 (9)**	oot	oot	oot	oot	oot	oot

- Finding any plan that exceeds threshold
  - Probabilistic-FF [Domshlak and Hoffmann. 2007] produces plan quickly when threshold is small
  - Search based inference algorithms finds plan at higher threshold

Conclusion

- Applied probabilistic inference to conformant planning
  - MMAP produces optimal plan
  - Specialized solver (PFF) performed well on low probability of success regime but it fails on high probability regime
  - MAP inference algorithm could produce suboptimal plans in a shorter time bounds

Conclusion

- Limitations of grounding & translation
  - Translation from FDR produced better results
  - Size of translation matters!
    - Exponential ($|objects|^{|params|}$)
    - Duplicate the structure over L time horizons
  - Typical size of problems
    - POMDP |A| ~ 10
    - Conformant Planning (uncertainty in initial states)
- State-of-the-art
  - (Taig and Brafman 2015)
  - (Domshlak and Hoffman 2007)