Symbolic Search and Abstraction Heuristics for Cost-Optimal Planning

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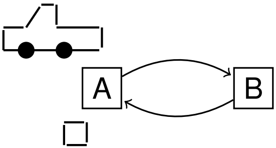
Outline

1. Introduction
   - Cost-Optimal Planning
2. Symbolic Search
   - (Background) Symbolic Search
   - Image Computation
   - State Invariants
3. Abstraction Heuristics
   - (Background) Abstractions
   - Merge-and-Shrink for Symbolic Search
   - Symbolic Perimeter Merge-and-Shrink
4. Symbolic Bidirectional Heuristic Search
5. Conclusions
   - Final Results: IPC14
   - Conclusions

Automated Planning

Given a planning task:

- A *logical description* of the initial situation, goal condition and a set of possible actions



$$\mathcal{V} = \{\text{at-T}= \{A, B\}, \text{at-P}= \{A, B, T\}\ \}$$
$$s_0 = \{\text{at-T } A, \text{at-P } A\}$$
$$s_\star = \{\text{at-P } B\}$$
$$\mathcal{O} = \{\text{move-T } (A, B), \text{move-T } (B, A), \text{load-P}(A), \dots\ \}$$

$\rightarrow$ Find a plan (sequence of actions)

$\rightarrow$ Cost-optimal: plan of minimum cost (prove it)

Empirical Evaluation Methods

SAS+ task $\longrightarrow$ $\boxed{\text{Planner}}$ $\longrightarrow$ Optimal plan

$\rightarrow$ Domain independent!! a planner can deal with any task

Empirical Evaluation Methods

SAS+ task → Planner → Optimal plan

→ Domain independent!! a planner can deal with any task

- Empirical evaluation methods:
  - International Planning Competition: 1998, 2000, 2002, 2004, 2006, 2008, 2011, 2014, . . .
  - Standard set of benchmark domains: 1998-2011
  - Time limit: 30 minutes
  - Memory limit: 4GB RAM
  - Coverage: number of problems solved
  - Time: solve problems faster

Motivation of this Thesis

- Improve state-of-the-art optimal planning

→ Efficiently solve optimal planning problems

- Techniques considered
    - Bidirectional search
    - Symbolic search
    - Abstraction heuristics

- Understand strengths/weaknesses
- Understand relation between techniques

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- Techniques considered
  - Bidirectional search
  - Symbolic search $\Rightarrow$ GAMER: winner of IPC 2008
  - Abstraction heuristics

    $\Rightarrow$ Merge-and-shrink: runner-up and part of the winner of IPC 2011
- Understand strengths/weaknesses
- Understand relation between techniques

State of the Art in Cost-Optimal Planning

Explicit search | Symbolic search

Algorithms

- A*
- Uniform-Cost

- forward
- backward
- bidirectional

Heuristics

- Delete-relaxation: h^{max}, h^{+}
- Landmarks: h^{LA}, LM-cut
- Abstractions: PDBs, M&S
- Critical paths: h^{m}
- Flow
  - max
  - add
  - LP

Pruning techniques

- State invariants
- Symmetries
- Partial-order pruning

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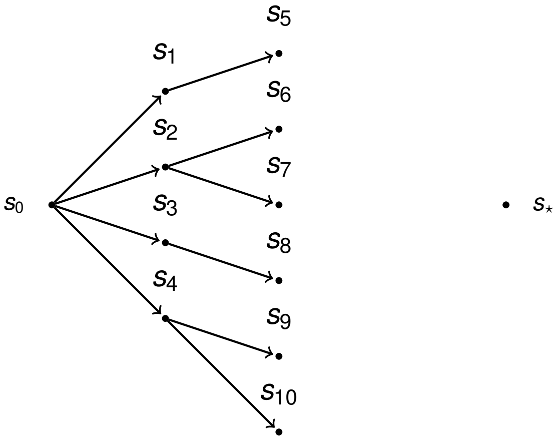
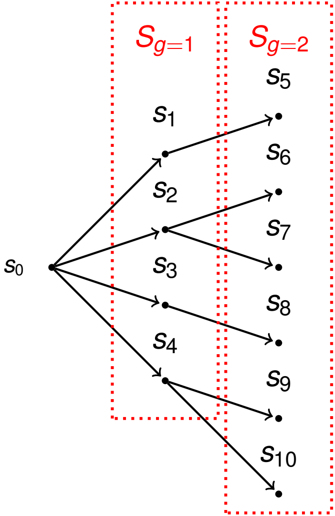
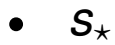


From Explicit to Symbolic Search



Reason with sets of states!



Binary Decision Diagrams (BDDs)

- Sets of states represented with Binary Decision Diagrams
  - Variable ordering
  - Reduction rules
- Possible exponential gain in memory/time
- Efficient operations (polynomial in BDD size)

1. (at Truck A) (at Package A)
2. (at Truck A) (in Package Truck)
3. (at Truck B) (at Package A)

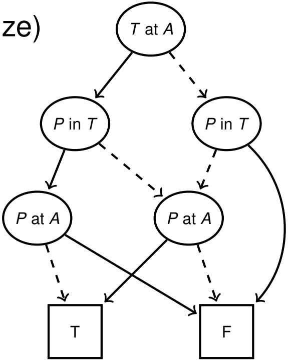
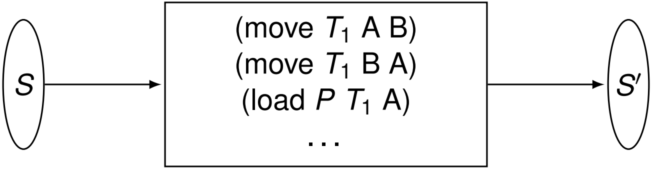


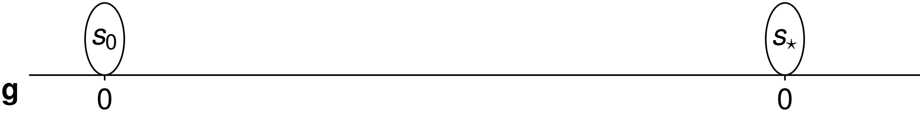
Image Computation

- Expand a set of states and generate the successor states
- Transition Relation: BDD that represents one or more planning actions with the same cost



$$S' \leftarrow image(S, T) = \exists x \,.\, S(x) \wedge T(x, x')[x' \leftrightarrow x]$$

Symbolic Bidirectional Breadth-First Search



Symbolic Bidirectional Breadth-First Search

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- Decide forward or backward direction at each step

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Optimizing Image Computation

- Image computation is the main bottleneck in symbolic search
- How to represent the Transition Relation?
  - Monolithic relation ⇒ may use exponential memory
  - Solution in GAMER ⇒ One TR for each action

move-T (A, B)
load-P (A)
move-T (B, A)
...

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- Idea 1: Separate preconditions and effects

  → avoid using auxiliary variables!

move-T (A, B)	pre: at-T A	eff: at-T B
load-P (A)	pre: at-T A, at-P A	eff: at-P T
move-T (B, A)	pre: at-T B	eff: at-T A

...

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  → avoid using auxiliary variables!
- Idea 2: Conjunction Tree
  → check preconditions of all operators simultaneously

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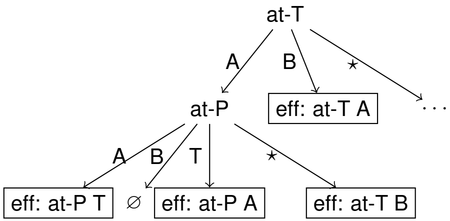
load-P (A)

move-T (B, A)

...



Optimizing Image Computation

- Image computation is the main bottleneck in symbolic search
- How to represent the Transition Relation?
  - Monolithic relation $\Rightarrow$ may use exponential memory
  - Solution in GAMER $\Rightarrow$ One TR for each action
- Idea 1: Separate preconditions and effects
  $\rightarrow$ avoid using auxiliary variables!
- Idea 2: Conjunction Tree
  $\rightarrow$ check preconditions of all operators simultaneously
- Idea 3: Aggregate TRs
  $\rightarrow$ different strategies to group the actions

move-T (A, B)
load-P (A)
move-T (B, A)
...

move-T (A, B) load-P (A)
move-T (B, A)

Empirical Results

- Compare image computation methods:
  1. TR^1: baseline approach
  2. TR^{1+}: avoid using x' variables
  3. CT^{L}_{20}: conjunction tree
  4. T^{DT}_{100k}: aggregate TRs

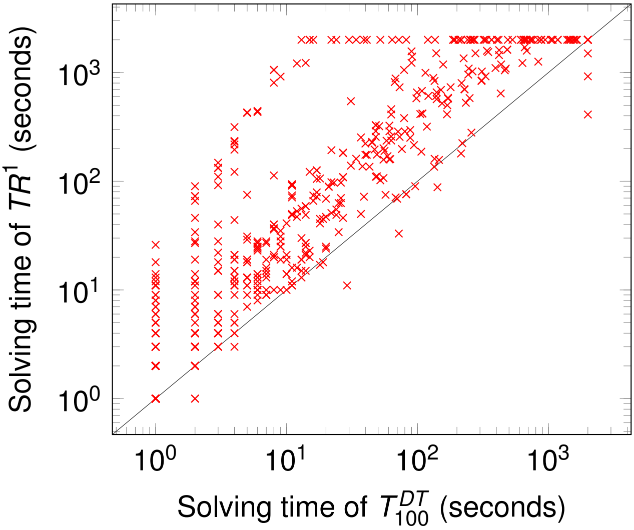
Total coverage of symbolic search algorithms over 1375 instances:

	TR^1	TR^{1+}	CT^{L}_{20}	T^{DT}_{100k}
Forward uniform-cost search	699	676	724	**742**
Backward uniform-cost search	444	525	529	**532**
Bidirectional uniform-cost search	729	763	769	**793**
BDDA* with SPDBs	705	717	724	**764**

$$TR^1 \leq TR^{1+} \leq CT^{L}_{20} \leq T^{DT}_{100k}$$

(across all domains)

Time of Bidirectional Search



Outline

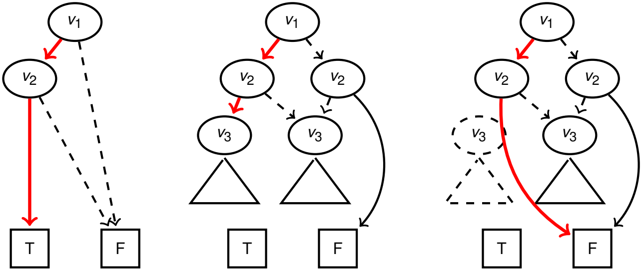
Motivation: State Invariants in Symbolic Search

- Invariant: holds in all states that may belong to a solution path
  1. Mutex: pair of facts that cannot be true in the same state
     $\rightarrow$ a truck cannot be simultaneously at two locations
  2. Invariant group: Set of facts such that exactly one is true
     $\rightarrow$ a truck must be somewhere

- Generated computing h^2 in both directions
- Useful for:
  1. Removing operators from the planning task
  2. Pruning invalid states during the search

Encoding Constraints with *cBDD*

- *cBDD*: BDD that describes invalid states
  1. Mutex: $f_i \wedge f_j$
  2. "At-least-1" invariant: $\neg(f_1 \vee f_2 \vee \ldots \vee f_n)$
- Remove invalid states from S_g: $S_g \setminus cBDD$



(c) *cBDD* (d) S_g (e) $S_g \setminus cBDD$

e-deletion: encode invariants in the TRs

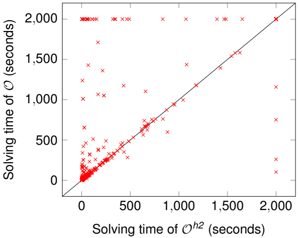
$\rightarrow$ no invalid states are generated

Experimental Results

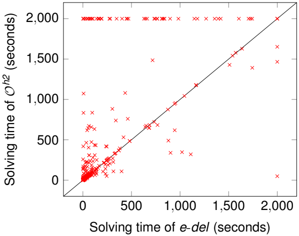
- Constraints found in 35 out of 43 domains
- 10%-74% invalid operators found in 17 out of 43 domains
- Mutex types:
  - Baseline (B)
  - Not pruning invalid states: $\mathcal{M}_\emptyset$
  - Pruning invalid states: *cBDD* or *e-deletion* (*e-del*)

		Remove invalid ops		
	B	$\mathcal{M}_\emptyset$	*cBDD*	*e-del*
Forward uniform-cost search	699	742	745	750
Backward uniform-cost search	509	532	677	696
Bidirectional uniform-cost search	765	793	836	**841**
BDDA* with SPDBs	736	764	777	781

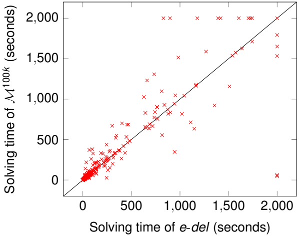
Time of Bidirectional Uniform-Cost Search



(f) remove operators

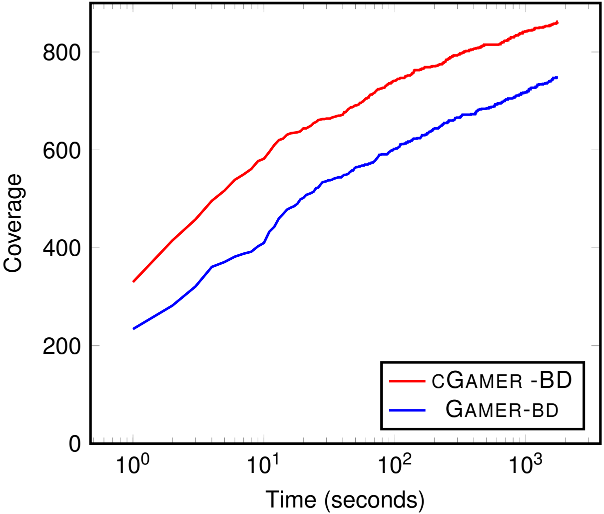


(g) prune invalid states



(h) e-deletion vs cBDD

Comparison with State-of-the-Art Planners



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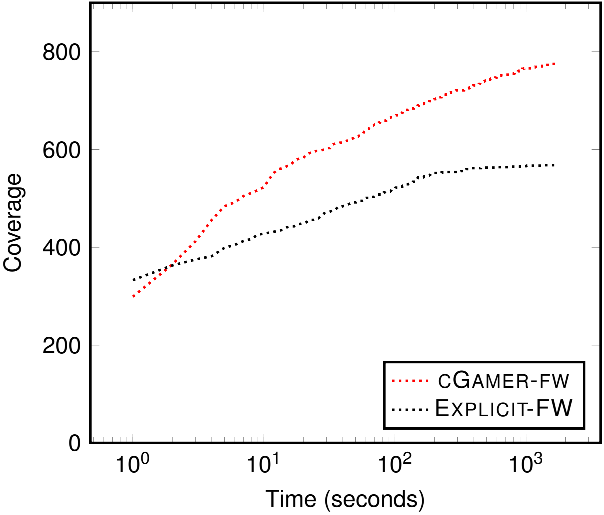

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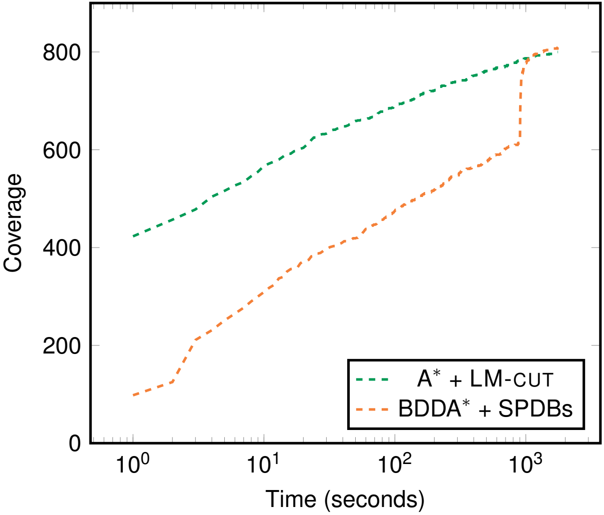

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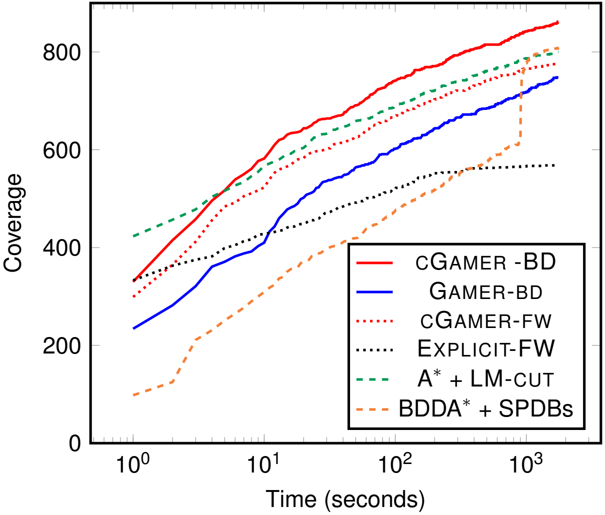

Summary

1. Image computation
   - Analyzed different methods for image computation
   - Best method: aggregate TRs
2. State invariants
   - Pruning invalid states (specially useful in bw search)
   - Best encoding for symbolic search: e-edeletion

These significantly improved performance of symbolic planning

$\rightarrow$ Symbolic bidirectional blind search is the current state-of-the-art for cost-optimal planning

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Motivation: Heuristics in Symbolic Search

Heuristics

- Delete-relaxation: h^{max}, h^{+}
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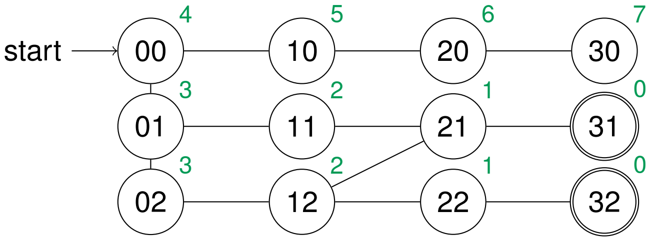
- Abstraction: Mapping from states to abstract states
  - Smaller abstract state space → easier to search
  - Use optimal distances in abstract state space as heuristic
  - Preserve transitions → admissible estimation



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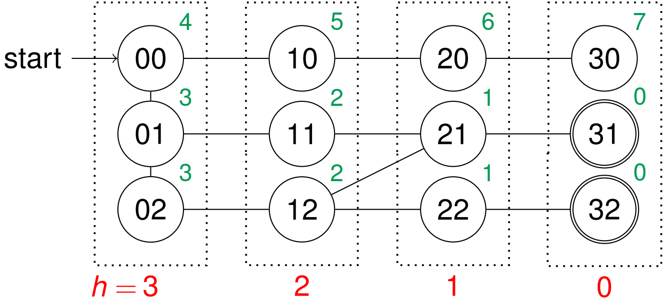

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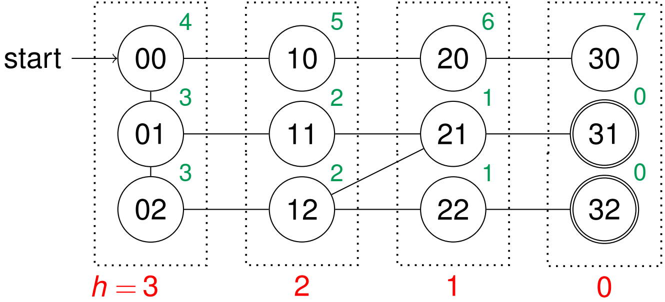

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  - Limitation: ignoring a single variable may relax too much

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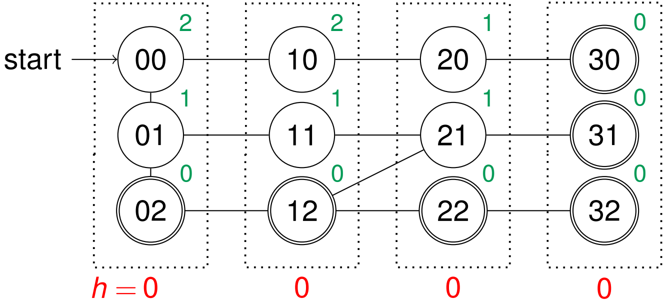

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Merge-and-Shrink Algorithm (M&S)

Algorithm 1: M&S

$\alpha_1 \leftarrow \Pi_{v_1}$
foreach $v \in \{v_2 \dots v_n\}$**:**
  if $|\alpha| > N$**:**
    $\texttt{shrink}(\alpha_{i-1}) \otimes \Pi_i$
  $\alpha_i \leftarrow \alpha_{i-1} \otimes \Pi_i$
return α

- Merge strategy: **Linear**
  $\rightarrow$ variable ordering
- Shrink strategy
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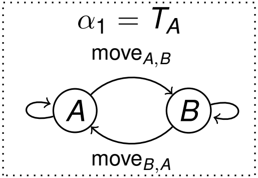

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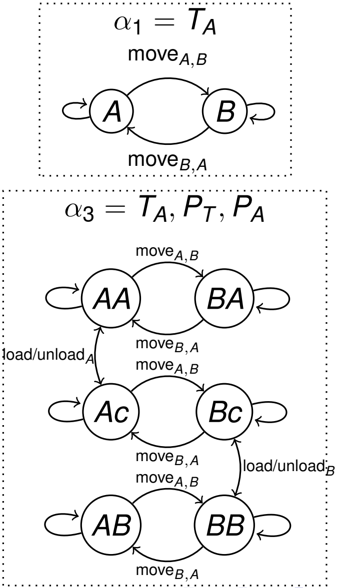

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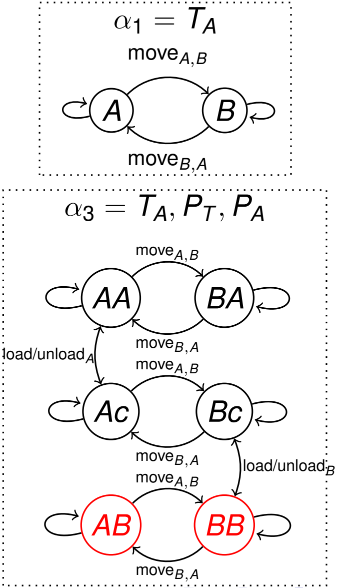
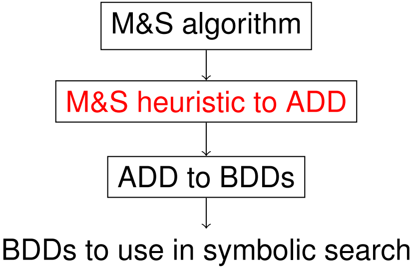


Outline

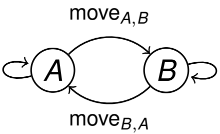
Merge-and-Shrink for Symbolic Search

- Hypothesis: BDDA* lacks good heuristics
  $\rightarrow$ BDDA* + M&S can improve results
- How to use M&S in symbolic search:

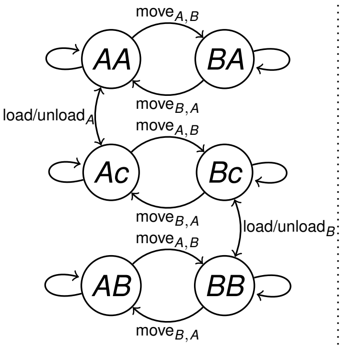


Merge-and-Shrink as ADDs

$\alpha_1 = T_A$



$\alpha_3 = T_A, P_T, P_A$



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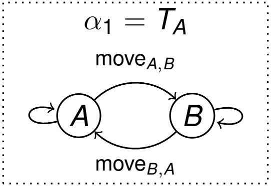

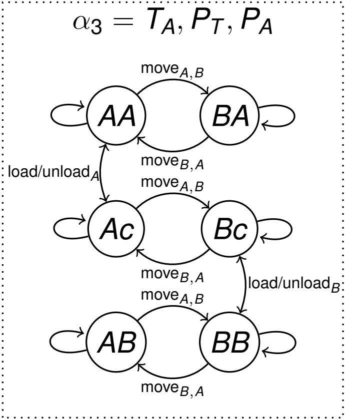

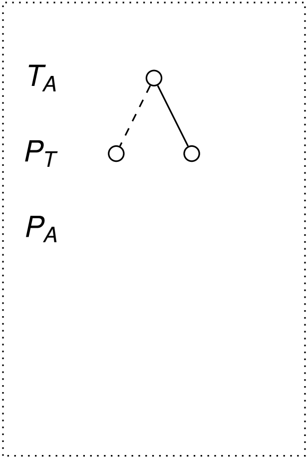

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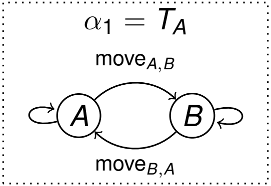

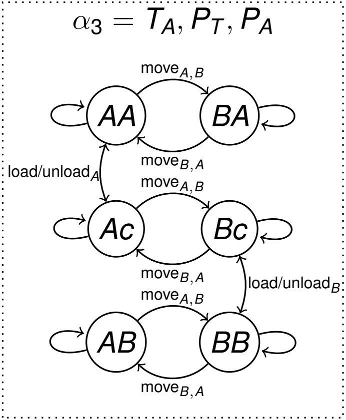

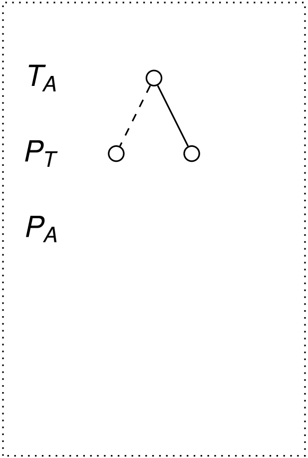

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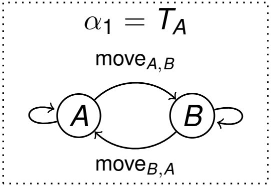

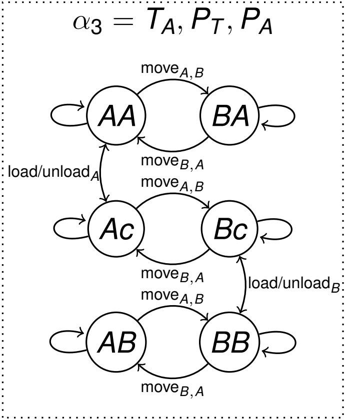

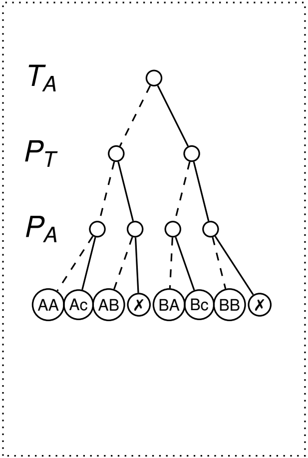

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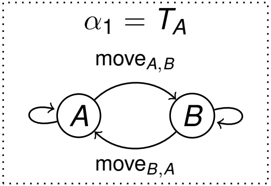

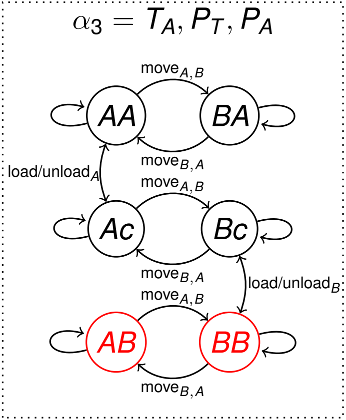

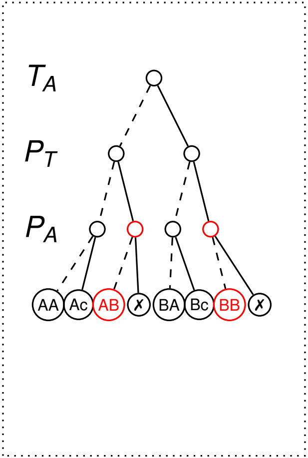

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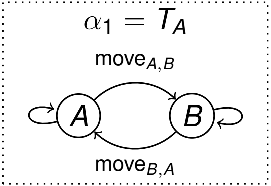
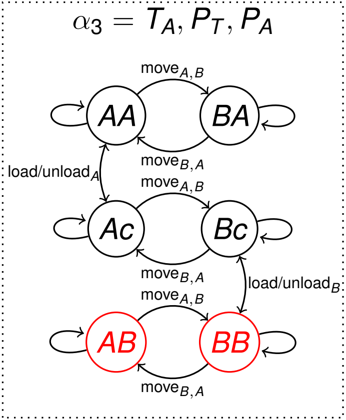
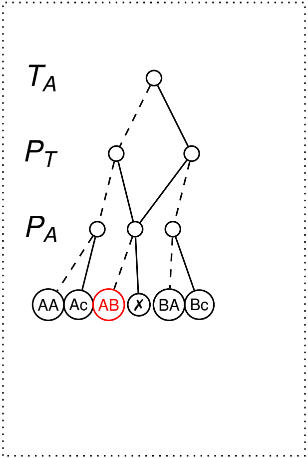






Theoretical Results

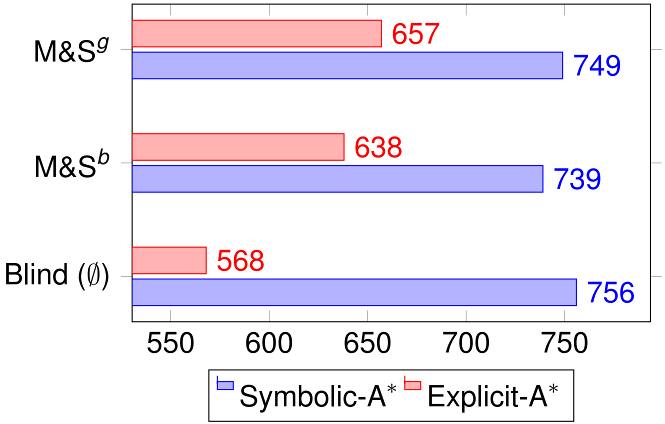
- M&S to ADDs/BDDs in polynomial time
- Related empirical results:
  - ADD representation of heuristics reduces memory
  - Variable ordering has a huge impact

- ADD/BDD reduction rules may achieve exponential gain in memory with respect to shrinking perfect strategies

  $\rightarrow$ shows potential of improvement for M&S strategies

Empirical Results

- Used M&S in symbolic search → Worse than symbolic PDBs



  - Contradicts our hypothesis

Outline

Motivation: Combine Symbolic Search and M&S

1. Symbolic PDBs: larger abstract state spaces
2. M&S: flexible abstractions

Can we get the best of both worlds?

Motivation: Combine Symbolic Search and M&S

1. Symbolic PDBs: larger abstract state spaces
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Can we get the best of both worlds?

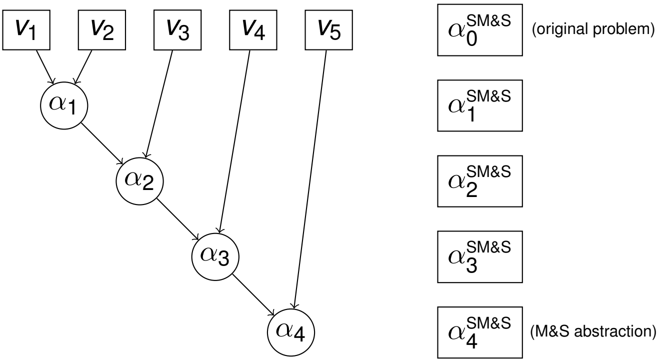
$\rightarrow$Use symbolic search to search M&S abstractions!

Symbolic Perimeter M&S:

1. Symbolic M&S abstractions: larger M&S abstract state spaces
2. Perimeter abstractions

SM&S Hierarchy

Enlarged M&S abstractions: to perform symbolic search



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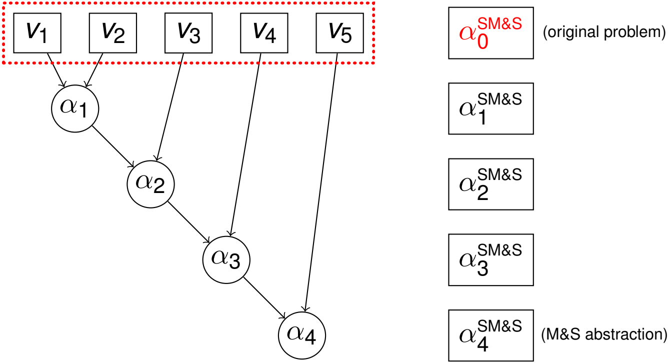

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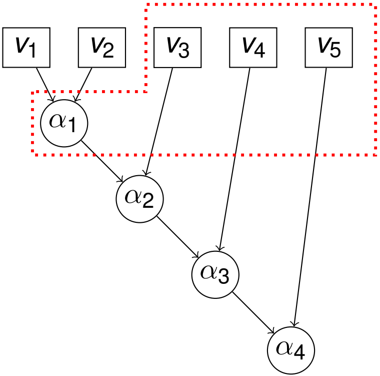


$\alpha_0^{\text{SM\&S}}$ (original problem)

$\alpha_1^{\text{SM\&S}}$

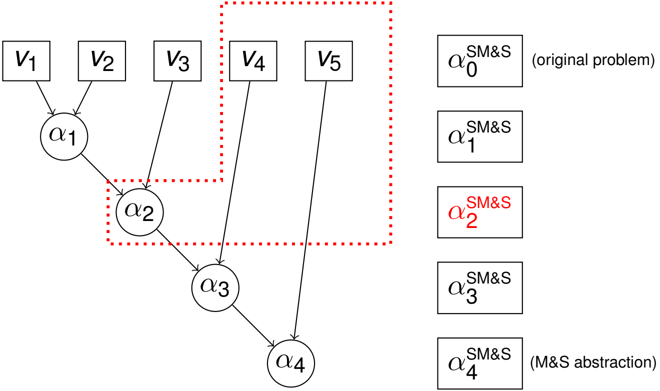
$\alpha_2^{\text{SM\&S}}$

$\alpha_3^{\text{SM\&S}}$

$\alpha_4^{\text{SM\&S}}$ (M&S abstraction)

SM&S Hierarchy

Enlarged M&S abstractions: to perform symbolic search



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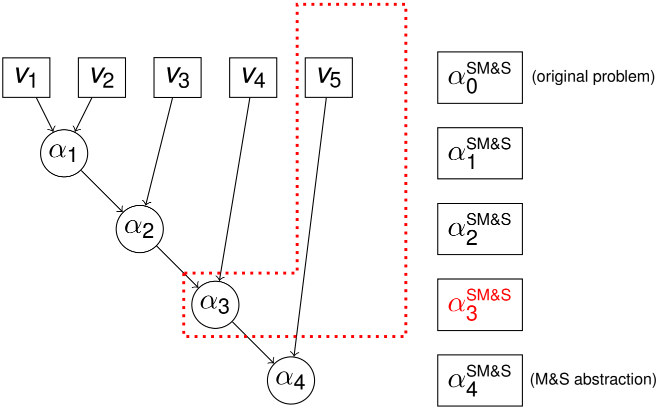

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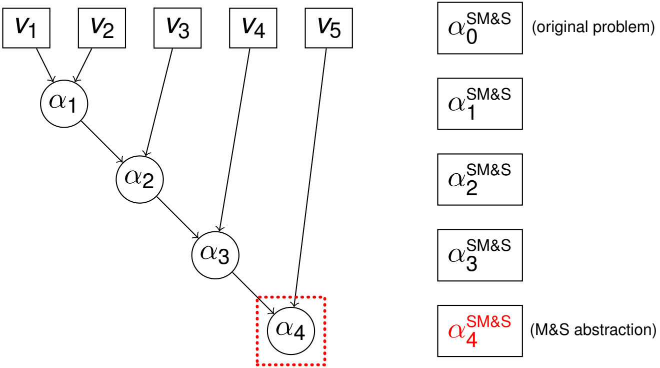
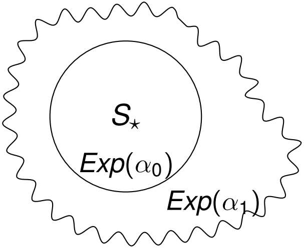


Perimeter Abstractions

- Challenges addressed with symbolic search
  1. Regression
  2. Expensive operations:
     - ★ membership in perimeter
     - ★ frontier mapping
  3. Set perimeter radius
- Contributions
  1. Multiple abstraction levels
  2. Improved initialization of abstract searches



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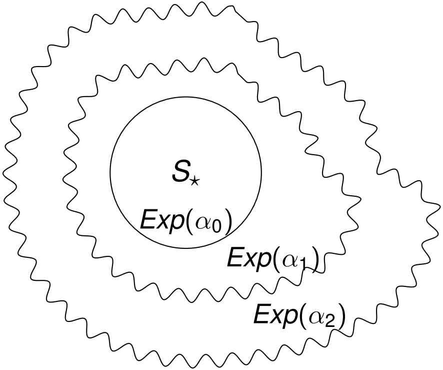
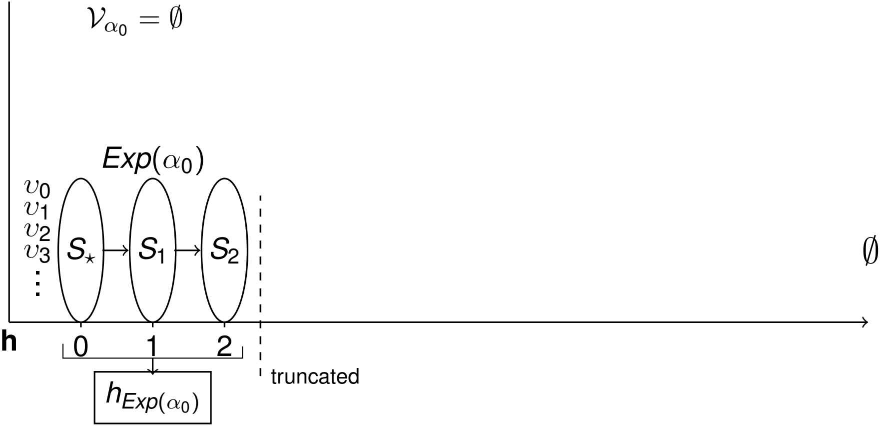


Symbolic Perimeter Merge-and-Shrink



- $h_{\text{SPM\&S}}$ heuristic is admissible and consistent

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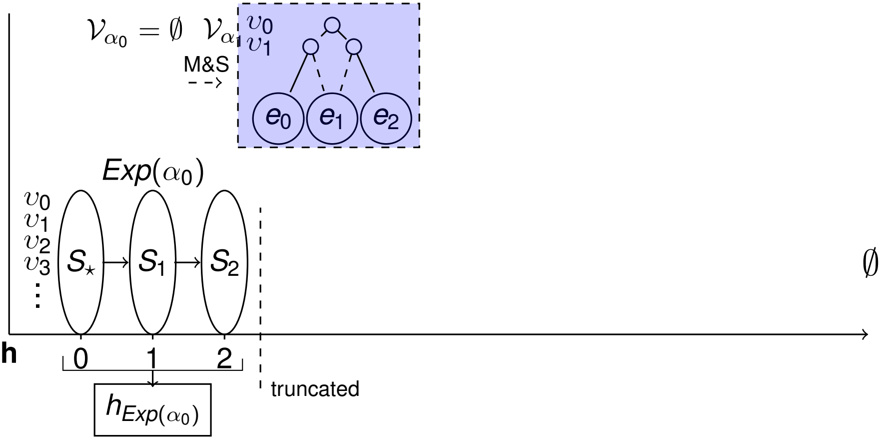

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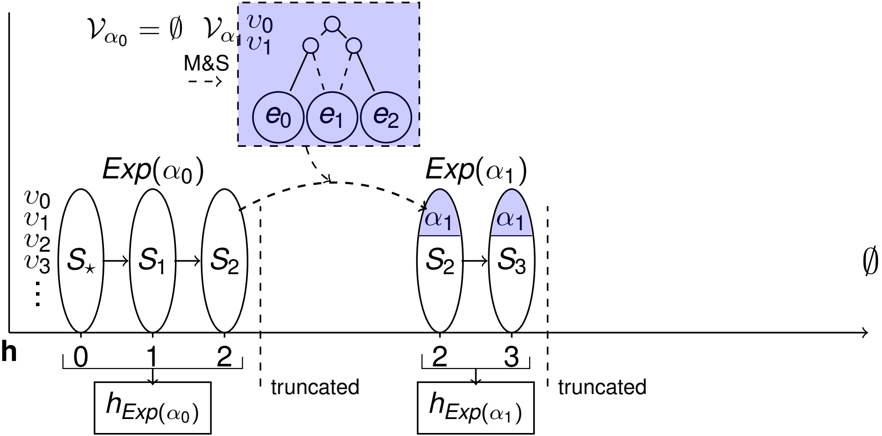

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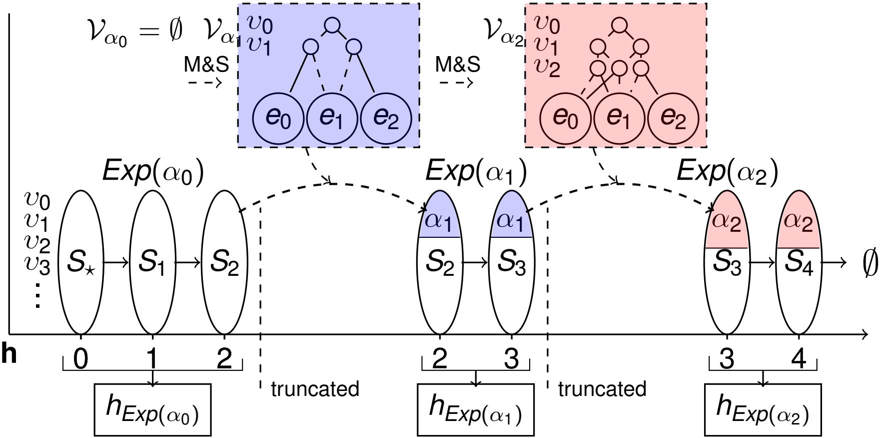

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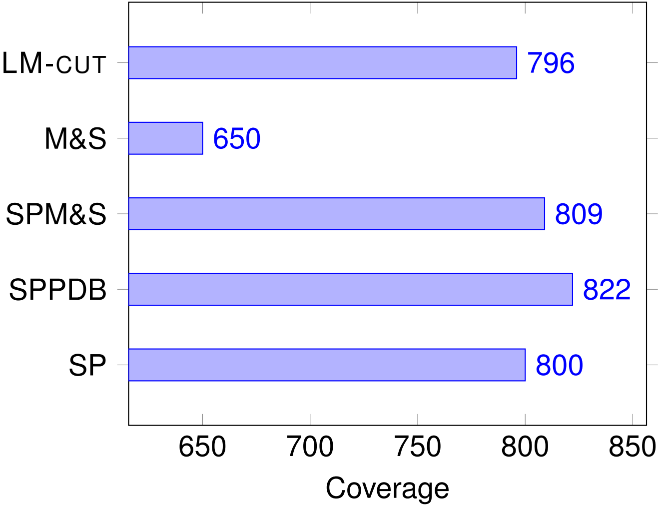
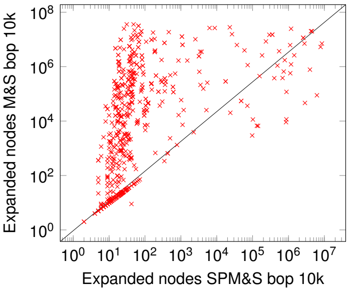
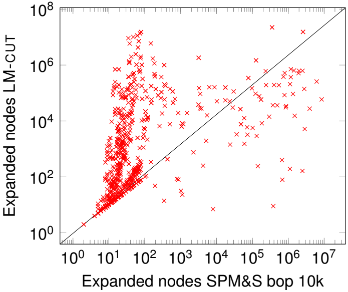
Empirical Results



Empirical Results: Expanded Nodes





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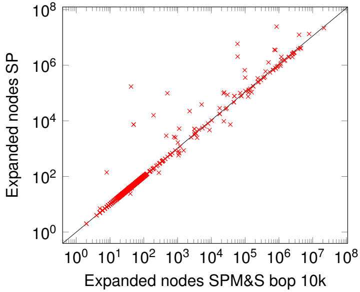

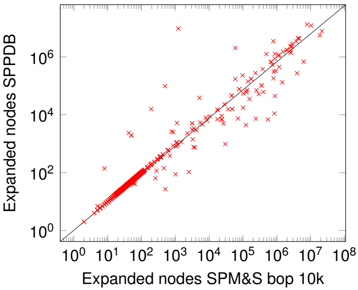

Summary

Symbolic Perimeter M&S

- Combines M&S, perimeter abstractions and symbolic search
- Improvements to perimeter abstractions
- Synergy between symbolic search and perimeter abstractions
- More accurate heuristic than both!

But...

Results still worse than symbolic bidirectional uniform-cost search

Outline

Motivation: Heuristics in Symbolic Bidirectional Search

- Observations
  1. Bidirectional brute-force search is a state-of-the-art technique
  2. Good symbolic abstraction heuristics

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  2. Good symbolic abstraction heuristics

- Use abstraction heuristics in symbolic bidirectional search!

- However, bidirectional heuristic search is not so easy:
  - Very promising since years ago
  - Never really able to outperform A^* or bidirectional uniform-cost search

Algorithm

- Main idea:
  1. Start symbolic bidirectional uniform-cost search
     - ★ If it succeeds → done!
  2. Detect when it is going to fail and activate heuristics
- Abstraction heuristics: Bidirectional, Partial, Perimeter

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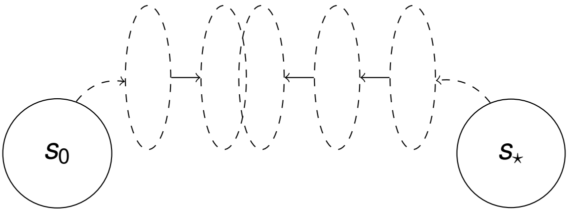

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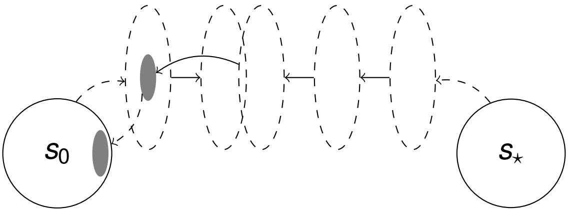

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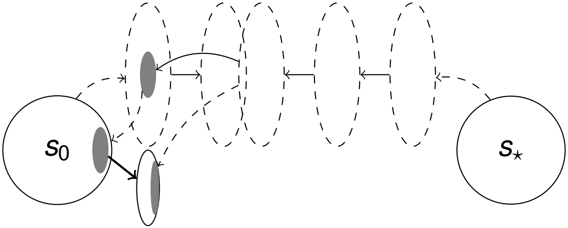
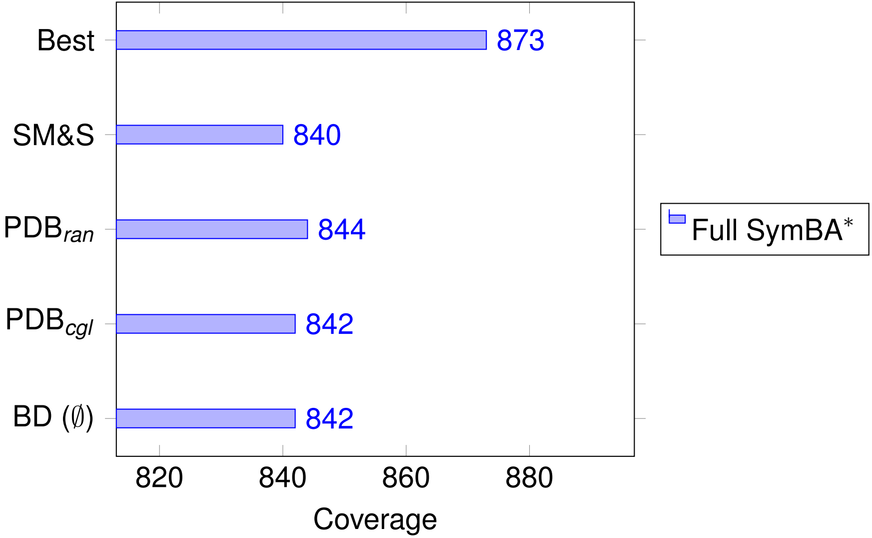


Empirical Results



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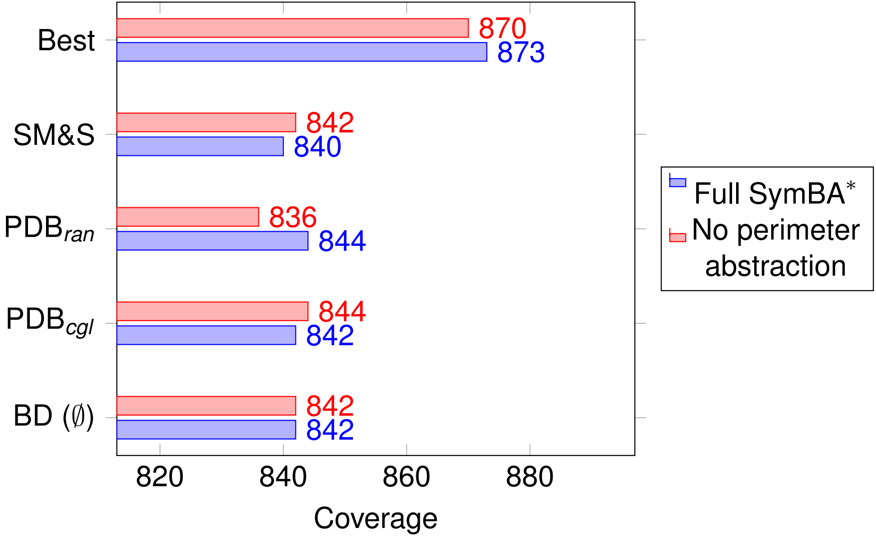

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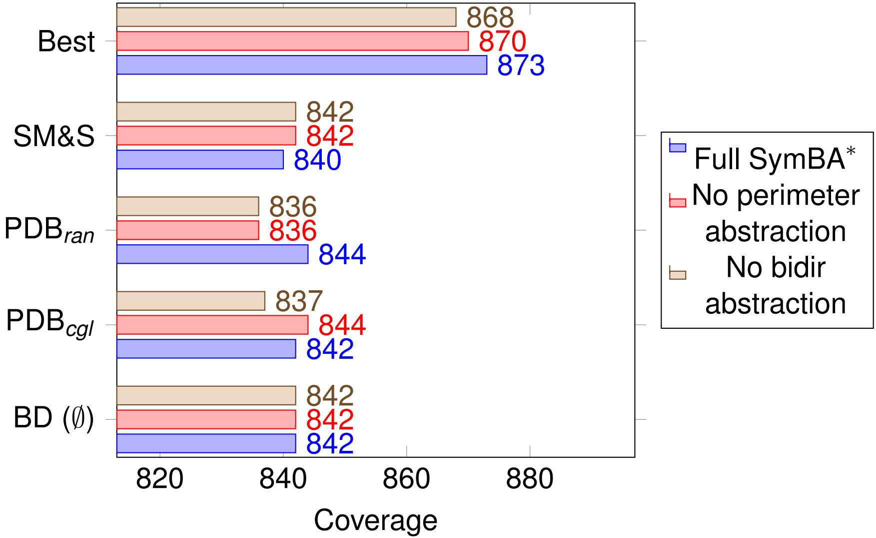


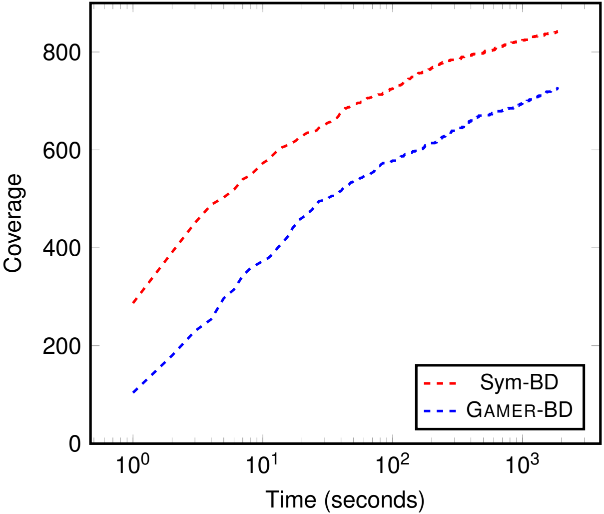
Summary

- Contributions:
  - SymBA*: a symbolic bidirectional heuristic search algorithm
  - Bidirectional search in abstract state spaces
  - Synergy: Symbolic search + Bidirectional search + Perimeter abstractions

- Symbolic Bidirectional A* is possible
  - Future work: domain-independent abstraction strategies (better than a random selection)

Outline

Final Results



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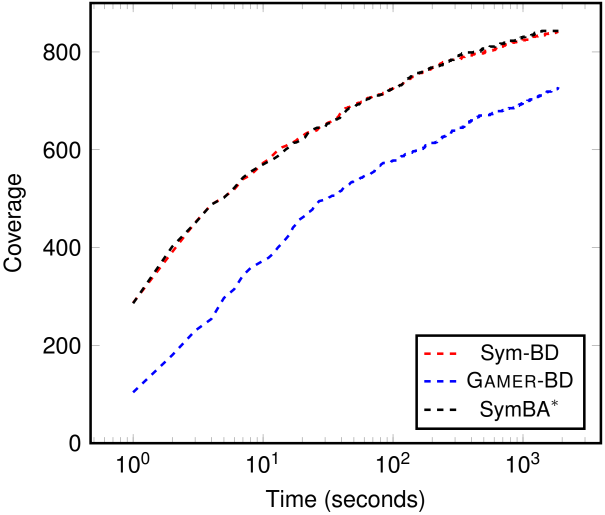

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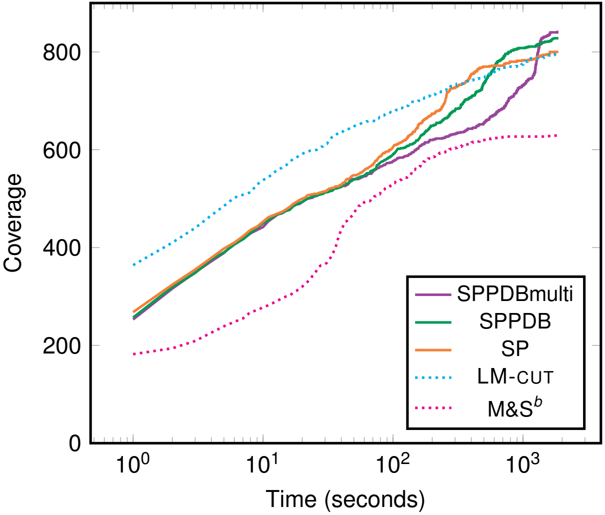

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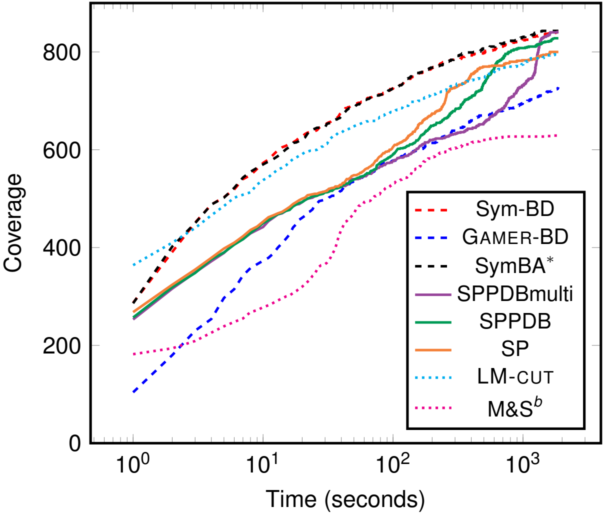

2014 International Planning Competition

- Submitted our planners to the 2014-IPC
    1. cGAMER: Symbolic Bidirectional uniform-cost search with image computation and state-invariant constraints
    2. SPM&S: A^* with symbolic perimeter PDBs and M&S
    3. SymBA*: Symbolic Bidirectional A^* with SPM&S
- Competed against:
    - GAMER: baseline symbolic planner
    - Top explicit-state search planners and portfolios
- Disclaimer: IPC results are not everything
    - Domains/Instances selection, bugs, . . .

2014 International Planning Competition

	Barman	Cave	Childsnack	Citycar	Floortile	GED	Hiking	Maintenan	Openstack	Parking	Tetris	Tidybot	Transport	Visitall	Total
symba-2	**6**	3	4	**18**	**20**	**20**	**20**	4	**20**	0	10	10	**9**	7	**151**
symba-1	**6**	3	4	**18**	**20**	19	**20**	4	**20**	0	10	4	**9**	6	143
cgamer-bd	**6**	0	1	**18**	**20**	0	15	0	19	3	**11**	**13**	8	6	120
spmas	5	3	2	1	**20**	18	12	4	14	4	7	8	**9**	7	114
rida	0	3	0	16	5	19	17	**5**	3	**6**	8	8	8	**15**	113
dynamic-gamer	3	3	**10**	15	14	0	17	3	19	0	2	0	7	6	99
all-paca	0	**7**	0	17	6	15	13	**5**	8	**6**	3	1	5	12	98
cedalion	0	**7**	0	14	5	15	13	**5**	1	2	5	7	6	13	93
metis	3	**7**	6	0	8	15	13	**5**	3	4	8	7	6	6	91
nucelar	0	**7**	0	13	0	15	13	**5**	3	5	9	0	7	13	90
rlazya	0	**7**	0	17	5	15	9	**5**	2	4	6	7	6	5	88
gamer	3	3	2	**18**	13	0	14	0	16	0	3	0	6	5	83
hflow	0	3	0	0	3	7	4	**5**	1	0	10	0	5	**15**	53
miplan	0	**7**	0	11	0	0	10	**5**	0	1	0	0	0	13	47
dpmplan	0	**7**	0	8	0	0	0	**5**	0	5	0	0	6	12	43
hpp-ce	0	0	0	7	0	3	0	**5**	0	0	0	0	0	0	15
hpp	0	0	0	6	0	3	0	**5**	0	0	0	0	0	0	14

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metis	3	**7**	6	0	8	15	13	**5**	3	4	8	7	6	6	91
nucelar	0	**7**	0	13	0	15	13	**5**	3	5	9	0	7	13	90
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hflow	0	3	0	0	3	7	4	**5**	1	0	10	0	5	**15**	53
miplan	0	**7**	0	11	0	0	10	**5**	0	1	0	0	0	13	47
dpmplan	0	**7**	0	8	0	0	0	**5**	0	5	0	0	6	12	43
hpp-ce	0	0	0	7	0	3	0	**5**	0	0	0	0	0	0	15
hpp	0	0	0	6	0	3	0	**5**	0	0	0	0	0	0	14

2014 International Planning Competition

	Barman	Cave	Childsnack	Citycar	Floortile	GED	Hiking	Maintenan	Openstack	Parking	Tetris	Tidybot	Transport	Visitall	Total
symba-2	**6**	3	4	**18**	**20**	**20**	**20**	4	**20**	0	10	10	**9**	7	**151**
symba-1	**6**	3	4	**18**	**20**	19	**20**	4	**20**	0	10	4	**9**	6	143
cgamer-bd	**6**	0	1	**18**	**20**	0	15	0	19	3	**11**	**13**	8	6	120
spmas	5	3	2	1	**20**	18	12	4	14	4	7	8	**9**	7	114
rida	0	3	0	16	5	19	17	**5**	3	**6**	8	8	8	**15**	113
dynamic-gamer	3	3	**10**	15	14	0	17	3	19	0	2	0	7	6	99
all-paca	0	**7**	0	17	6	15	13	**5**	8	**6**	3	1	5	12	98
cedalion	0	**7**	0	14	5	15	13	**5**	1	2	5	7	6	13	93
metis	3	**7**	6	0	8	15	13	**5**	3	4	8	7	6	6	91
nucelar	0	**7**	0	13	0	15	13	**5**	3	5	9	0	7	13	90
rlazya	0	**7**	0	17	5	15	9	**5**	2	4	6	7	6	5	88
gamer	3	3	2	**18**	13	0	14	0	16	0	3	0	6	5	83
hflow	0	3	0	0	3	7	4	**5**	1	0	10	0	5	**15**	53
miplan	0	**7**	0	11	0	0	10	**5**	0	1	0	0	0	13	47
dpmplan	0	**7**	0	8	0	0	0	**5**	0	5	0	0	6	12	43
hpp-ce	0	0	0	7	0	3	0	**5**	0	0	0	0	0	0	15
hpp	0	0	0	6	0	3	0	**5**	0	0	0	0	0	0	14

Outline

Conclusions

- Symbolic search for cost-optimal planning:
  - Analysis of image computation
  - State-invariant pruning
- M&S heuristics in symbolic search planning
- SPM&S: new perimeter abstraction heuristic based in symbolic search and M&S
- Big question: can we use heuristics in symbolic planning?
  1. Used M&S and SPM&S in BDDA*
  2. SymBA*: symbolic bidirectional search + perimeter abstractions

Conclusions

- Symbolic bidirectional blind search
  - $\rightarrow$ Currently, the best method for cost-optimal planning (only beaten by heuristics in domains where the heuristics are very precise).
- SPM&S: state-of-the-art heuristic
- Highlighted the relevance of symbolic search and regression
- Synergy of symbolic bidirectional search and perimeter abstractions

List of Publications

Álvaro Torralba, Stefan Edelkamp, and Peter Kissmann. Transition trees for cost-optimal symbolic planning.
In *ICAPS*, 2013

Álvaro Torralba and Vidal Alcázar. Constrained symbolic search: On mutexes, BDD minimization and more.
In *SoCS*, 2013

Stefan Edelkamp, Peter Kissmann, and Álvaro Torralba. Symbolic A* search with pattern databases and the merge-and-shrink abstraction.
In *ECAI*, 2012

Álvaro Torralba, Carlos Linares López, and Daniel Borrajo. Symbolic merge-and-shrink for cost-optimal planning.
In *IJCAI*, 2013

Thank you for your attention!

Questions?