The Joy of Forgetting: Faster Anytime Search via Restarting

Silvia Richter
Griffith University & NICTA, Australia

Jordan T. Thayer & Wheeler Ruml
University of New Hampshire, US

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Origin: developing a planner for IPC-2008

IPC-2008 requirement: find best possible plan within 30 minutes.
This suggested an anytime approach:

- Find a solution as quickly as possible (any solution is better than none).
  $\rightsquigarrow$ greedy best-first search
- While there is still time, try to improve the solution.
  $\rightsquigarrow$ weighted A* with decreasing weights

Interesting finding:

A series of independent runs of weighted A* seemed to perform better than one continued search.

Continued WA*

Basic algorithm:

1. Set weight and bound
   bound = cost of best known solution, initially ∞
2. Update open list w. r. t. weight if necessary
3. Conduct WA* search, using bound for pruning
4. Upon new best solution: report solution, goto 1.

Variants used in literature:

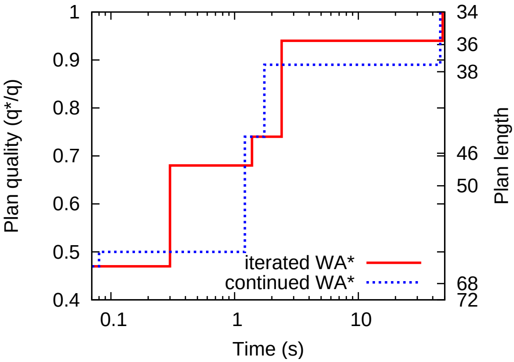
- Anytime A* (Zhou & Hansen 2001, 2004)
- ARA* (Likhachev et al. 2003)

Example: Blocksworld task 11-2

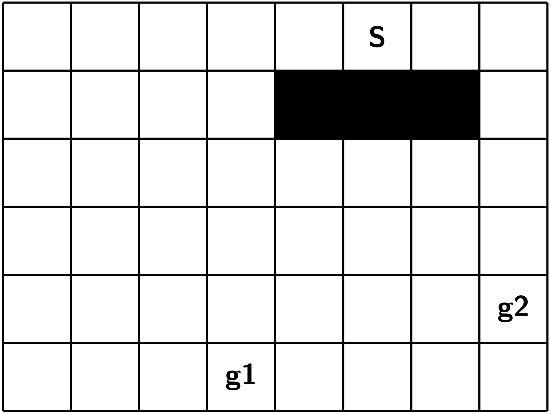
Plan lengths found over time:

GBFS + iterated WA*:	72	50	46	36	34
GBFS + continued WA*:	72	68	46	38	34

Plan qualities (best length / current length):



The problem: low-h bias



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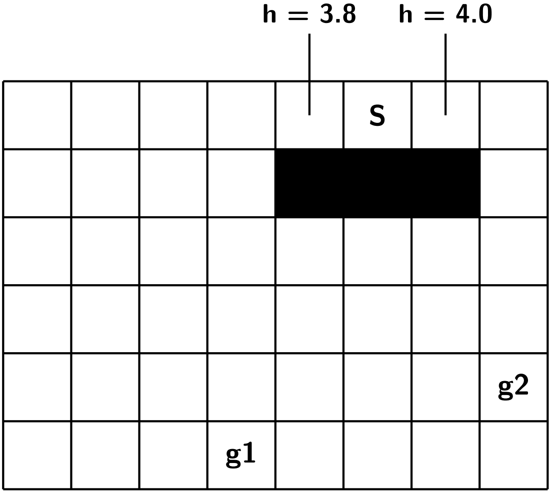

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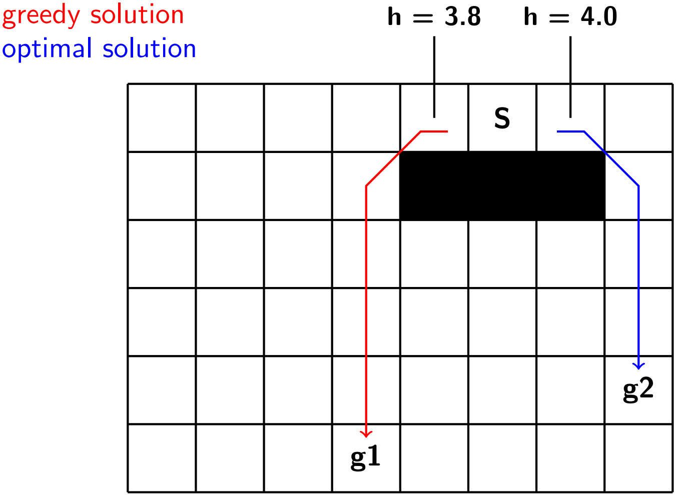

The problem: low-*h* bias

h-values

less accurate the further from goal

less accurate on the left

		3.8	3.8	3.8	**S**	4.0	4.0
		3.4	3.4				3.0
	2.6	2.6	2.6	2.6	1.9	2.0	2.0
2.6	1.8	1.8	1.8	1.8	1.9	1.0	1.0
2.6	1.8	1.0	1.0	1.0	1.9	1.0	**g2**
	1.8	1.0	**g1**	1.0	1.9	1.0	1.0

The problem: low-h bias

f'-values, $w = 2$

		10.6	9.6	8.6	S	9.0	
		9.8	8.8				12.0
	9.2	8.2	8.2	8.2	7.8	9.0	10.0
10.2	7.6	7.6	7.6	7.6	7.8	7.0	8.0
10.2	8.6	7.0	7.0	7.0	8.8	7.0	g2
	9.6	8.0	g1	8.0	9.8	8.0	8.0

The problem: low-*h* bias

f'-values, w = 2
x expanded states

		10.6	9.6	8.6 x	S x	9.0	
		9.8	8.8 x				12.0
	9.2	8.2	8.2 x	8.2	7.8	9.0	10.0
10.2	7.6	7.6	7.6 x	7.6	7.8	7.0	8.0
10.2	8.6	7.0	7.0 x	7.0	8.8	7.0	g2
	9.6	8.0	g1 x	8.0	9.8	8.0	8.0

The problem: low-h bias

f'-values, $w = 2$

x expanded states

states in open list

		10.6	9.6	8.6 x	S x	9.0	
		9.8	8.8 x				12.0
	9.2	8.2	8.2 x	8.2	7.8	9.0	10.0
10.2	7.6	7.6	7.6 x	7.6	7.8	7.0	8.0
10.2	8.6	7.0	7.0 x	7.0	8.8	7.0	g2
	9.6	8.0	g1 x	8.0	9.8	8.0	8.0

The problem: low-h bias

f'-values, $w = 2$

x expanded states

states in open list

must expand for optimal path

		10.6	9.6	8.6 x	S x	9.0	
		9.8	8.8 x				12.0
	9.2	8.2	8.2 x	8.2	7.8	9.0	10.0
10.2	7.6	7.6	7.6 x	7.6	7.8	7.0	8.0
10.2	8.6	7.0	7.0 x	7.0	8.8	7.0	g2
	9.6	8.0	g1 x	8.0	9.8	8.0	8.0

The problem: low-h bias

f'-values, $w = 2$

must expand for optimal path

but many open states have lower f'-value

		10.6	9.6	8.6	S	9.0	
		9.8	8.8				12.0
	9.2	8.2	8.2	8.2	7.8	9.0	10.0
10.2	7.6	7.6	7.6	7.6	7.8	7.0	8.0
10.2	8.6	7.0	7.0	7.0	8.8	7.0	g2
	9.6	8.0	g1	8.0	9.8	8.0	8.0

The problem: low-h bias

f'-values, w = 1.5 (reduced weight)
$\rightsquigarrow$ search less greedy

		8.7	7.7	6.7	S	7.0	
		8.1	7.1				10.5
	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

f'-values, $w = 1.5$ (reduced weight)
$\rightsquigarrow$ search less greedy
but effect still persists

		8.7	7.7	6.7	S	7.0	
		8.1	7.1				10.5
	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

The problem: low-h bias

f'-values, $w = 1.5$ (reduced weight)

		8.7	7.7	6.7	S	7.0	
		8.1	7.1				10.5
	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

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	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

The problem: low-h bias

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		8.7	7.7	6.7	S	7.0	
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	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

The problem: low-*h* bias

f'-values, w = 1.5 (reduced weight)

		8.7	7.7	6.7	S	7.0	
		8.1	7.1				10.5
	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

The problem: low-*h* bias

f'-values, w = 1.5 (reduced weight)

		8.7	7.7	6.7	S	7.0	
		8.1	7.1				10.5
	7.9	6.9	6.9	6.9	6.85	8.0	9.0
8.9	6.7	6.7	6.7	6.7	6.85	6.5	7.5
8.9	7.7	6.5	6.5	6.5	7.85	6.5	g2
	8.7	7.5	g1	7.5	8.85	7.5	7.5

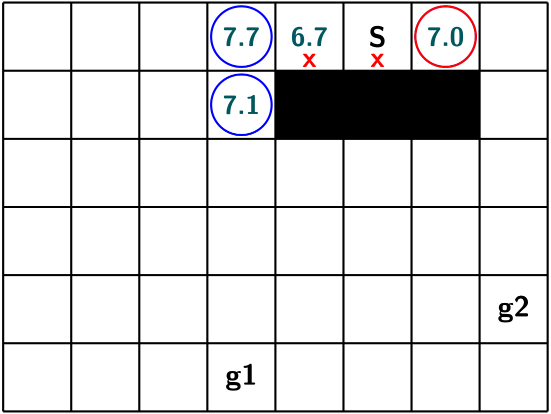
The problem: low-*h* bias

10 expanded states
29 generated states
between finding g1 and expanding right of S

		8.7	7.7	6.7 x	S x	7.0	
		8.1	7.1 x				10.5
	7.9	6.9 x	6.9 x	6.9 x	6.85 x	8.0	9.0
8.9	6.7 x	6.7 x	6.7 x	6.7 x	6.85 x	6.5 x	7.5
8.9	7.7	6.5 x	6.5 x	6.5 x	7.85	6.5 x	g2
	8.7	7.5	g1 x	7.5	8.85	7.5	7.5

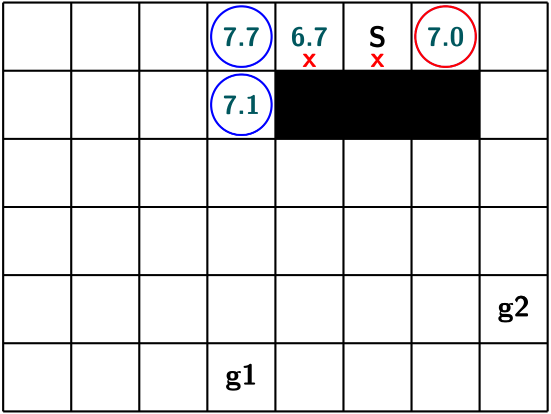
Restarted search

starting from scratch
$w = 1.5$



Restarted search

2 expanded state
5 generated states
before expanding right of S to find optimal path



Insight

Continued search may be biased due to early mistakes:

- Greedy search: suboptimal area of search space
- Open list: many open states around previous goal
- Low h-value makes them look attractive
  $\Rightarrow$ Biased search explores suboptimal area in depth

Restarts overcome early mistakes of greedy search

Related Work

Restarts used with randomization in CSPs:

- Local search (Selman et al. 1992)
- Systematic search (Gomes et al. 1998)
- Purpose: undo bad random decisions (parameter choices)
  $\rightsquigarrow$ escape barren areas of search space

We propose restarts for a deterministic, A*-type algorithm

- Purpose: undo bad greedy decisions (low-h bias)
- Motivation similar to that of limited-discrepancy search (Harvey & Ginsberg 1995)

Restarting weighted A^* (RWA^*)

RWA^*: forget open list between iterations:

1. Set weight and bound
2. Clear open list, (re-)start from initial state
3. Conduct WA^* search, using bound for pruning
4. Upon new best solution: report solution, goto 1.

Re-use previous search effort by

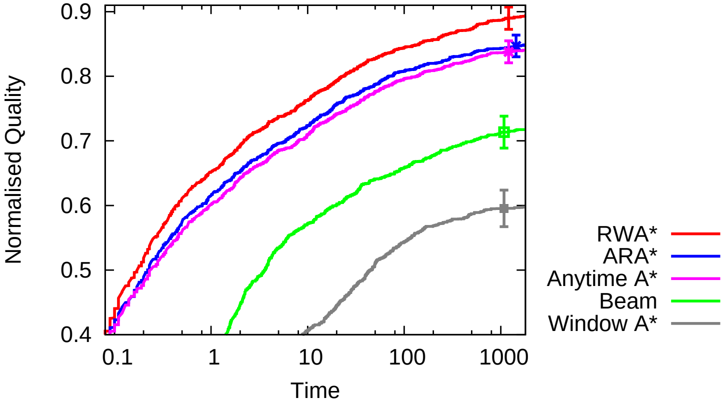
- Not re-calculating h-values of states seen previously
- Remembering best known paths to states

Extra cost: re-expansions. But expansions often cheap compared to evaluations (planning: 20% vs. 80%)

Empirical Evaluation

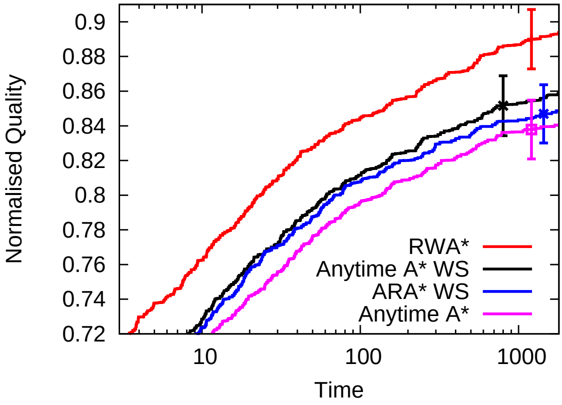
- Implemented in Fast Downward (Helmert 2006)
- Replaced greedy BFS with anytime algorithms:
  - RWA*
  - Anytime A*
  - ARA*
  - Beam-stack search
  - Window A*
- Planner-specific search enhancements used
- All 1612 classical tasks, 31 domains of previous IPCs
- Also: 3 other search benchmark domains

Planning



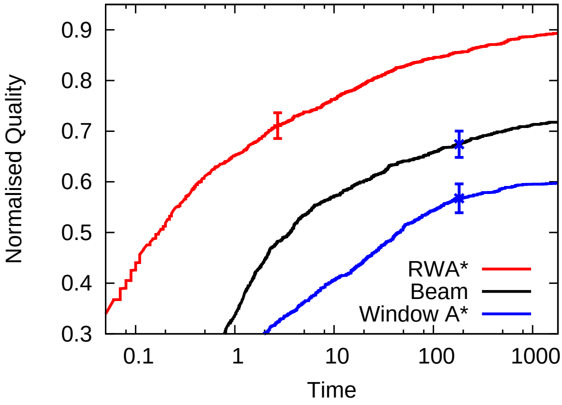
WA* methods much better than others; RWA* best

Planning

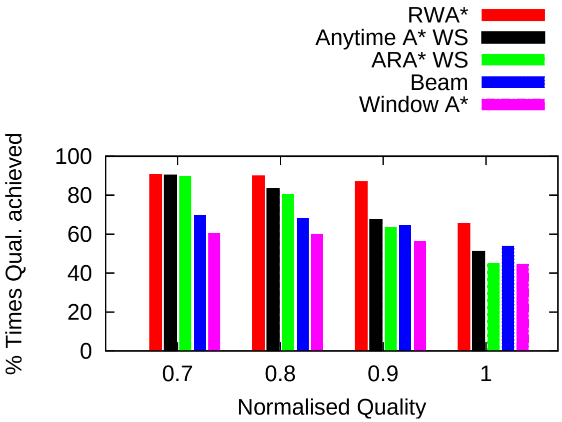


RWA* $>$ other WA* methods in 40% of domains, rest on par

Planning

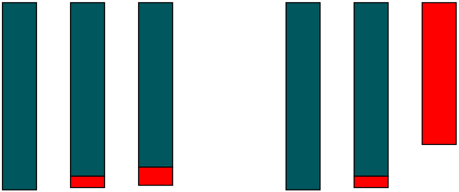


Beam-stack search, Window A* $>$ WA* in some domains,
but much worse in many other domains


RWA*
Anytime A* WS
ARA* WS
Beam
Window A*
% Times Qual. achieved
100
80
60
40
20
0
0.7
0.8
0.9
1
Normalised Quality

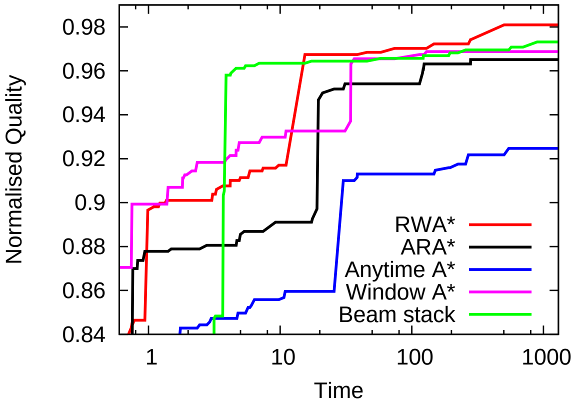
Restarts change beginning of plan rather than end (Gripper #20):

ARA*, Anytime A* | RWA*



	ARA*, Anytime A*			RWA*		
Plan length	165	163	161	165	165	125
Change index	—	153	145	—	153	1

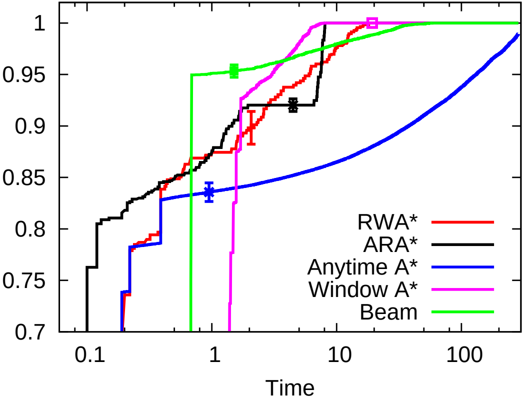
Robotic arm



RWA* $>$ other WA* methods.

Beam-stack search and Window A* very good here.

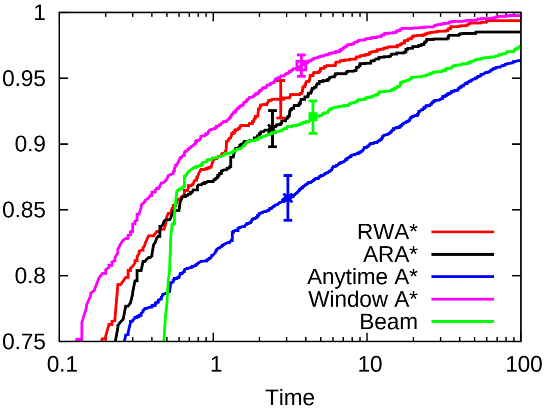
Gridworld



RWA* $\approx$ other weight-decreasing WA* methods.

Beam-stack search, Window A*: worse anytime performance.

Sliding-tile puzzle



RWA* $\approx$ other weight-decreasing WA* methods.

Window A* very good here.

Summary

RWA* dominates other methods in planning

- Restarts useful if greedy search is highly suboptimal
- E. g. if heuristics vary strongly locally

On par in other domains

- RWA* always $\geq$ other WA* methods
  $\rightsquigarrow$ even if restarts do not help, they do not hurt
- RWA* always performs fairly well $\rightsquigarrow$ robust,
  while beam-stack search, Window A* vary strongly

Undoing search effort can be worthwhile in anytime algorithms

Thank you!

Questions?