Random Walk Planning: Theory, Practice, and Application

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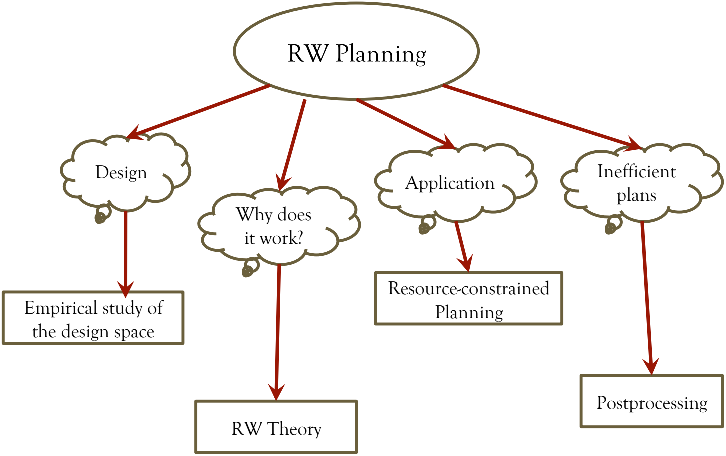
Outline


RW Planning
Design
Why does it work?
Application
Inefficient plans
Empirical study of the design space
RW Theory
Resource-constrained Planning
Postprocessing

Automated Planning

Given a model of the world, generate a plan to achieve predefined goals

Applications

- Autonomous agents
- General solvers

Classical Representations (STRIPS)

State

Each state is a set of propositions

{On(B, A), Ontable(A), Clear(B)}

Action

Each action has preconditions, positive and negative effects

{OnTable(A), Holding(B)}

Plan

A sequence of actions that starts from the initial state and ends in $s \supseteq G$

Planning Methods

Heuristic Search

Common standard systematic search algorithms such as Greedy Best First Search (GBFS) and WA*

Contribution

A new search paradigm for satisficing planning: random walk (RW) search

Why Random Walks?

Random Walk

A sequence of randomly selected actions

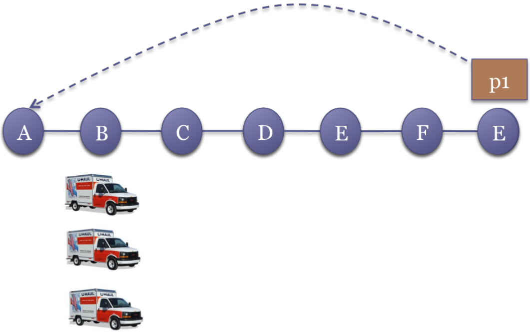
High level and Intuitive Explanations

- Escaping faster from plateaus
- More exploration
- Not wasting time in dead-ends

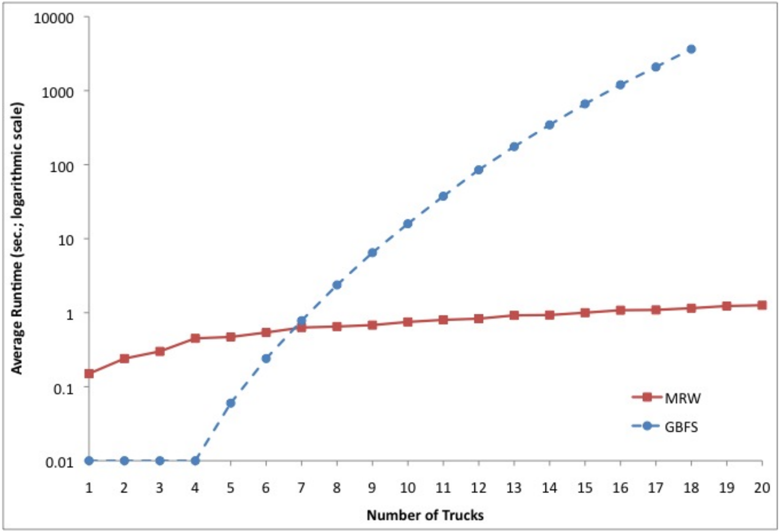
A theoretical model can explain ...

- What are the key features affecting the performance
- How we can improve the algorithms

A Motivating Example: Transportation Domain



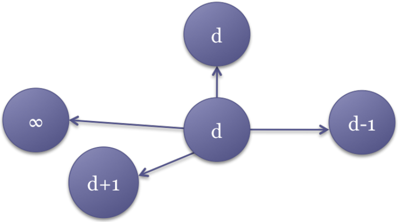
Random Walks vs. Systematic Search



Theoretical Analysis of RW Planning

Graph properties affecting RW performance

- Progress Chance(PC)
- Regress Chance(RC)
- Regress Factor(RF)



$$PC = \frac{1}{4}, RC = \frac{1}{2}, RF = \frac{RC}{PC} = 2$$

Definitions: Fairness and Hitting Time

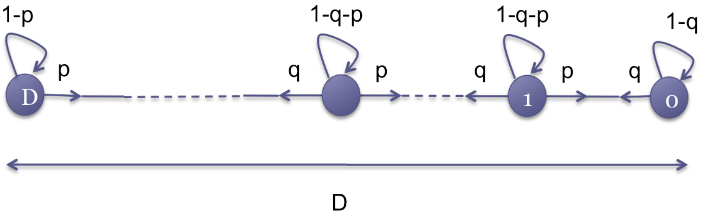
Fairness

A single state transition in the graph cannot change the goal distance by more than one unit.
Every undirected graph is a fair graph.

Hitting Time

The expected number of steps in a random walk starting from the initial state and ending in the goal for the first time.

Fair Strongly Homogenous Graph (FSHG)



p = progress chance
q = regress chance
D = largest goal distance

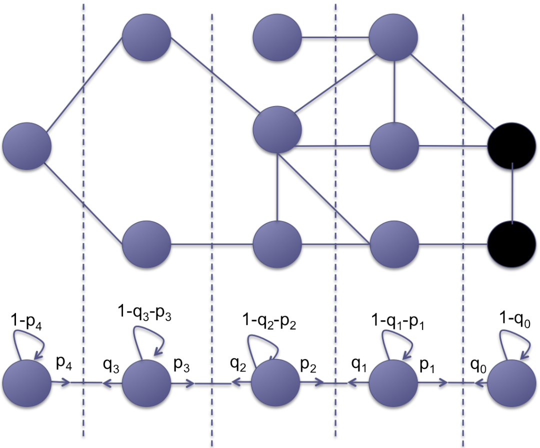
Theorem: Hitting time in FSHG

$$h_x = \begin{cases} \Theta\left(\beta_0 \lambda^D + \beta_1 d_x\right) & \text{if } q \neq p \\ \Theta\left(\alpha_1 D d_x\right) & \text{if } q = p \end{cases}$$

where

$$\lambda = \frac{q}{p}, \beta_0 = \frac{q}{(p-q)^2}, \beta_1 = \frac{1}{p-q}, \alpha_0 = \frac{1}{2p}, \alpha_1 = \frac{1}{p}$$

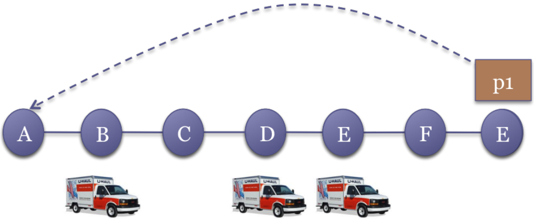
Bounds for more general graphs



q_i = maximum regress chance at the goal distance i

p_i = minimum progress chance at the goal distance i

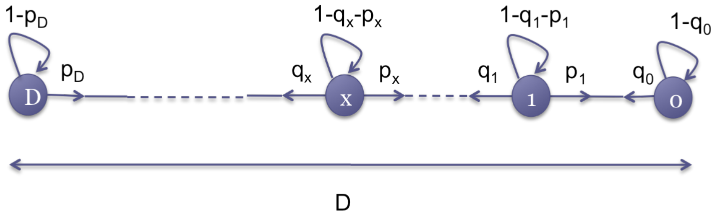
Analysis of the Transport Example



$$RC_{max} = PC_{min} = \frac{1}{2 \times |\text{trucks}|}$$

$$h_x = \frac{Dd_x}{p}$$

Fair Homogenous Graph (FHG)



p_i = progress chance at goal distance i
q_i = regress chance at goal distance i
D = largest goal distance

Hitting time in FHG

$$h_x = \sum_{d=1}^{d_x} \left(\beta_D \prod_{i=d}^{D-1} \lambda_i + \sum_{j=d}^{D-1} \left(\beta_j \prod_{i=d}^{j-1} \lambda_i \right) \right)$$

where for all $1 \leq d \leq D$,

$$\lambda_d = \frac{q_d}{p_d}, \beta_d = \frac{1}{p_d}$$

Theory for Random Walks with Restart

Restarting Random Walks

At each step with probability r restart from the initial state

Hitting Time

$$h_x \in O\left(\beta\lambda^{d_x - 1}\right)$$

where

$$\lambda = \left(\frac{q}{p} + \frac{r}{p(1-r)} + 1\right), \beta = \frac{q+r}{pr}$$

Findings

- Determined the key features of the search space affecting RW
  - Regress factor RF
  - Largest goal distance D
  - Initial goal distance d
- Provides valuable insights to design RW planners
  - Biasing action selection
  - Restarting frequency r

RW Search

The General Framework

- Use forward chaining Local Search
- In each step, run random walks to find the next state
- Use restarts to recover from unpromising search regions

RWS Framework: an Illustration

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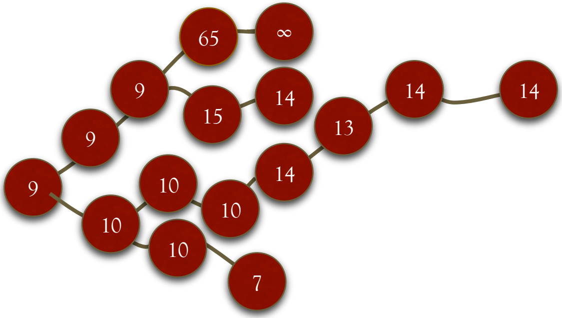
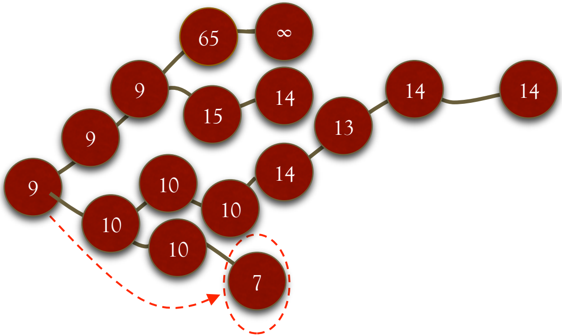
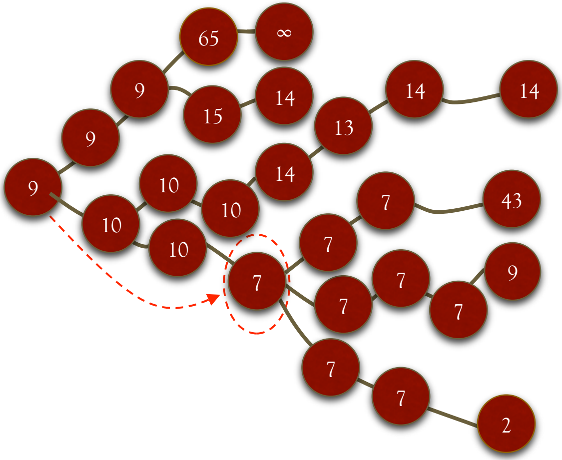


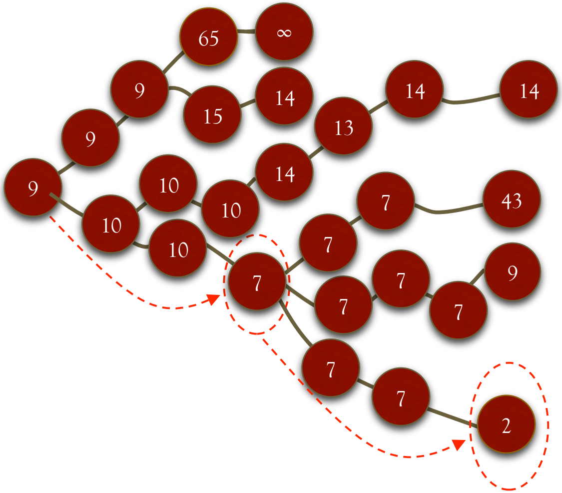
RWS Framework: an Illustration



RWS Framework: an Illustration



RWS Framework: an Illustration



A Basic RW planner

Walk Length

Use a local restarting rate r_l: at each step terminate the walk with probability r_l

Restarting

Use a restarting threshold t_g: restart the search when the last t_g walks have not reached lower heuristic

Experimental Study of the Design Space

Local Exploration

- Length of Walks
- Evaluation Rate
- Action Selection Bias

Global Exploration

- Jumping Strategies
- Restarting Strategies

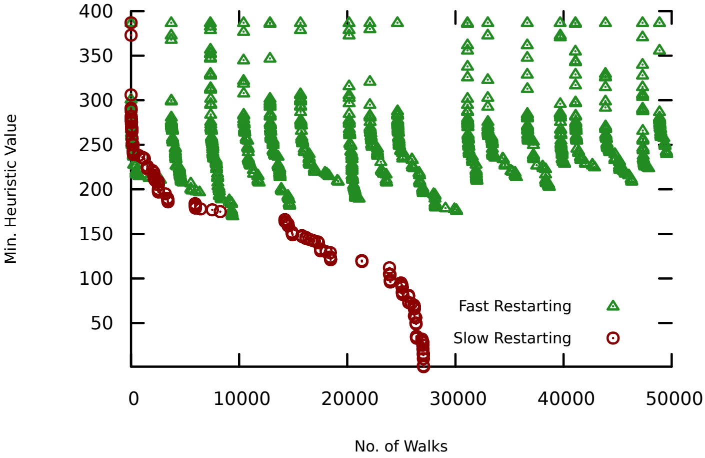
Heuristic function

- Type of the heuristic function
- The accuracy of the heuristic function

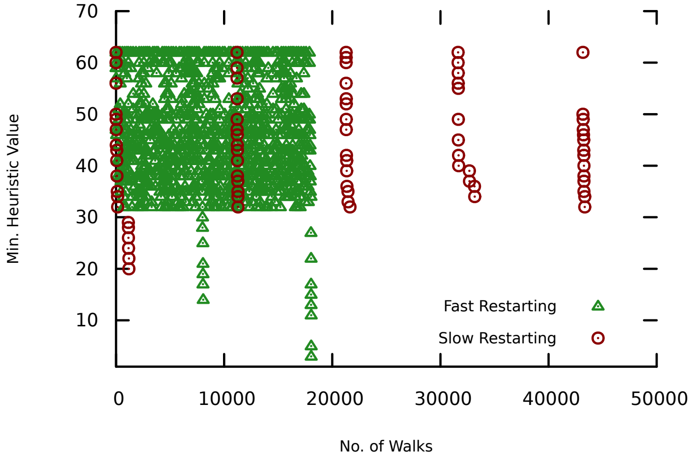
Two Practical Outcomes

- Learning systems that adapt parameters to the input problem
- Effective Biasing techniques

The Effect of Restarting Threshold: Elevators 03

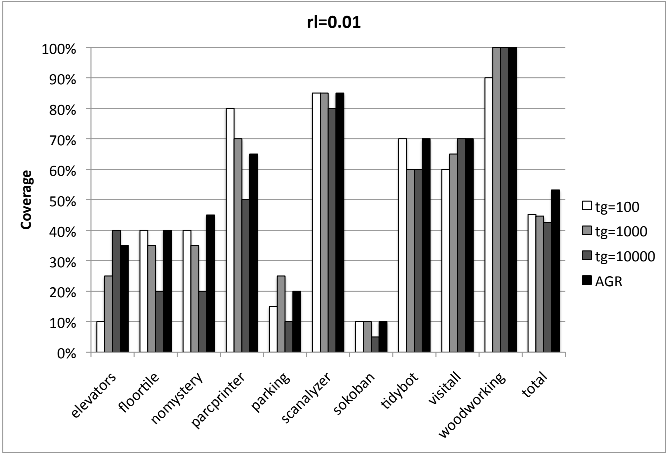


The Effect of Restarting Threshold: Floortile 01

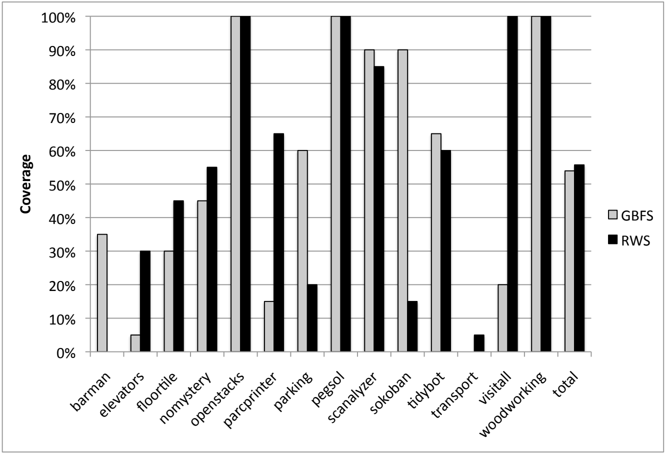


Adaptive Global Restarting (AGR)

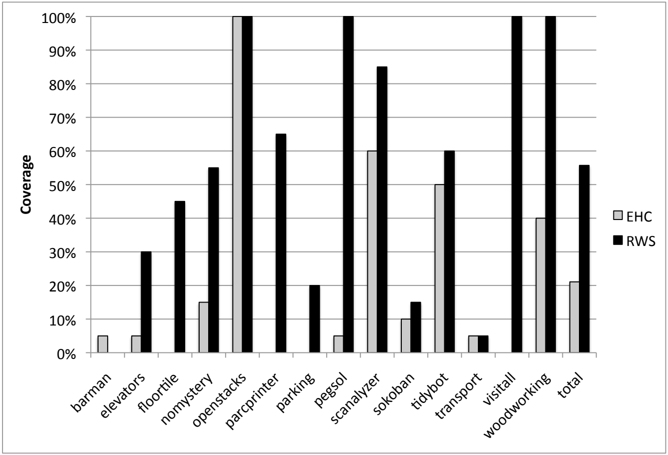
- Let V_w be the average heuristic improvement per walk
- AGR continually estimates V_w and sets $t_g = \frac{h_0}{V_w}$



Comparison with GBFS



Comparison with EHC



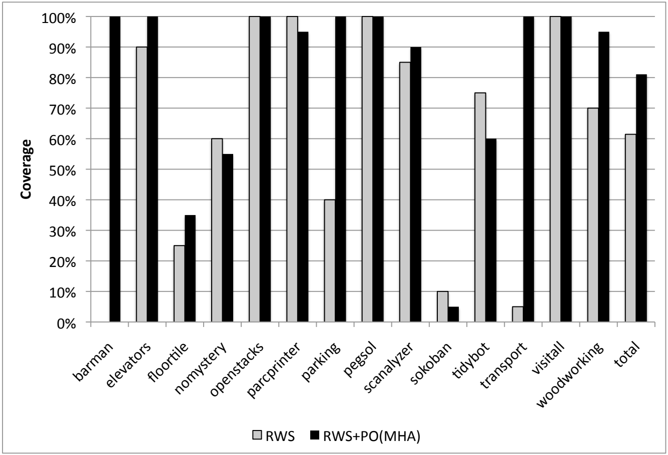
Biasing Action Selections

Monte Carlo Helpful Actions (MHA)

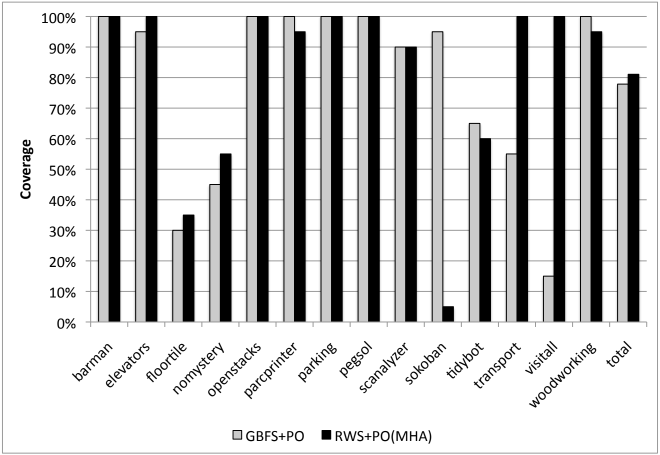
MHA gives a higher priority to *preferred operators*.

$$P(a, s) = \frac{e^{Q(a)/T}}{\sum_{b \in A(s)}^{n} e^{Q(b)/T}}$$

MHA vs. Uniform Action Selection



MHA vs. GBFS+PO



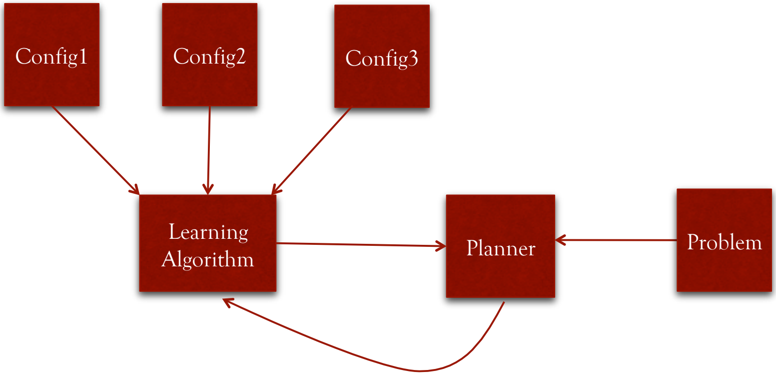
Building a Planning System

- Combine several techniques that complement each other

Examples

- Multiple heuristics in LAMA and Fast Downward
- Multiple search strategies in Fast Forward and FD Stone Soup

Learning the Best Configuration



Comparing Arvand-2013 with Top Satisficing Planners

Table: IPC problems without Derived Predicates

No. of Problems	Arvand-2013	LAMA-2011	FDFSS2	Probe	Roamer
1661	**1552**	1540	1533	1422	1507

Table: All IPC problems

No. of Problems	Arvand-2013	LAMA-2011	FDFSS2	Probe	Roamer
1857	1666	1659	**1668**	–	1635

The Gap Between RW and Systematic Planning

Domains	Arvand-2013	LAMA-2011
Airport (50)	**44**	31
Notankage (50)	**50**	44
Sokoban (20)	1	**19**
Storage (30)	**30**	19
Tankage (50)	**44**	41
Woodworking (30)	14	**20**
Philosophers (48)	**44**	34
PSR Large (50)	19	**31**
PSR Middle (50)	43	**50**

Reasoning about Resources

Examples of limited resources

Fuel, energy, money, time

Model: not replenishable resources

- Initial supply
- Some actions consume resources

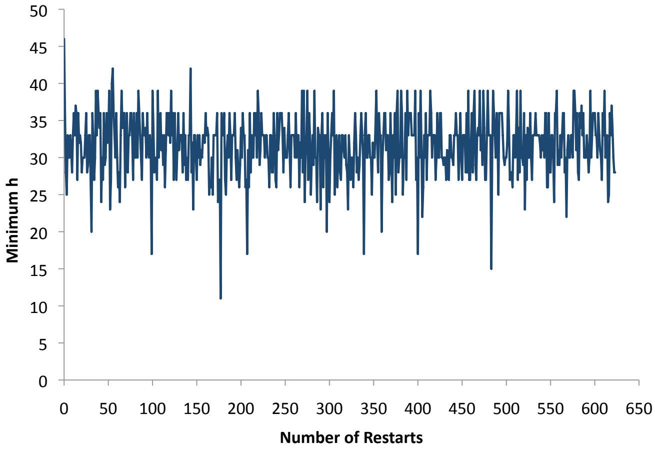
Limitation of the Current Methods

- Relaxation heuristics do not model resource consumption at all
- Greedy search algorithms add more problems

Improvements to Arvand for RCP

- Smart Restarting (SR)
- On-path Search Continuation (OPSC)

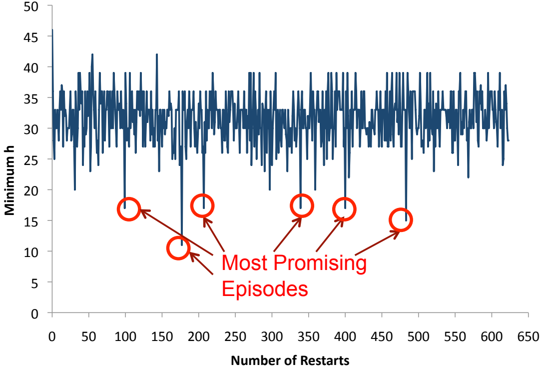
Basic Restarting in an Example



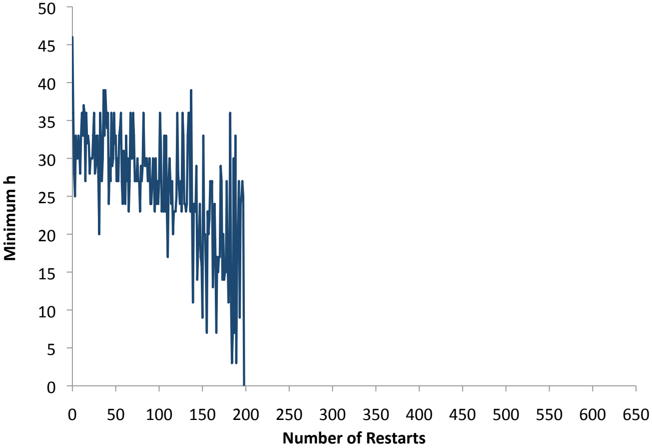
Smart Restarting

Algorithm

- Maintain a pool of most promising episodes performed
- When an episode gets stuck restart from a state visited in an episode in the pool



Smart Restarting in an Example



How to test RCP planners?

Performance as a function of constrainedness

Resource constrainedness C (Hoffmann et. al. IJCAI-2007)

$$C = \frac{\textit{initial supply}}{\textit{minimum need}}$$

The closer C is to 1, the more constrained is the problem.

My Contributions

- Extended the definition of C to multiple resources
- Developed two new benchmarks for RCP

Experiments

3 RCP Domains

NoMystery, Rovers, TPP

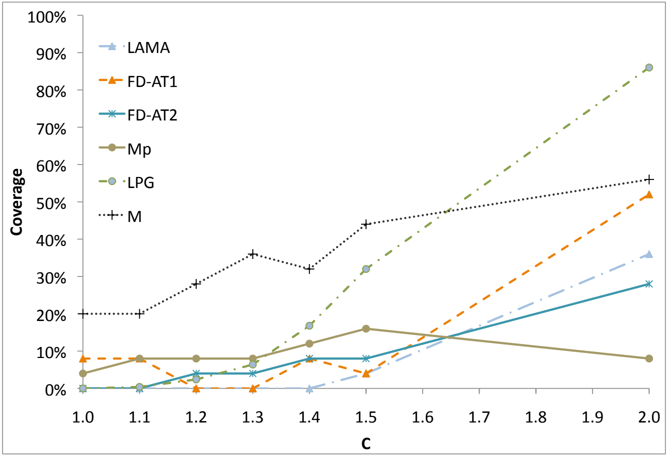
8 Satisficing Planners

Arvand, FD-AT1, FD-AT2, LAMA, FF, LPG, M, Mp, LPRPGP

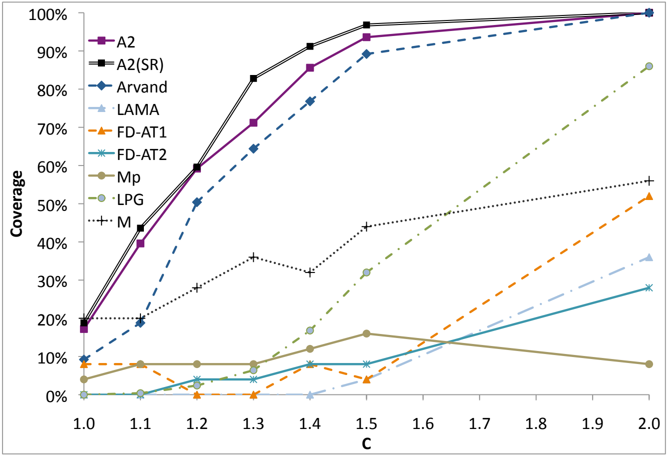
5 Optimal Planners

Num-2-sat, LM-cut, Merge and Shrink, Selmax, FD-AT-OPT

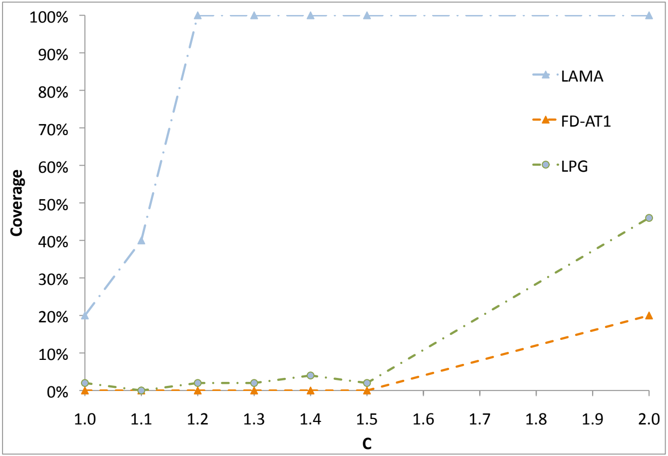
Results: Rovers, small



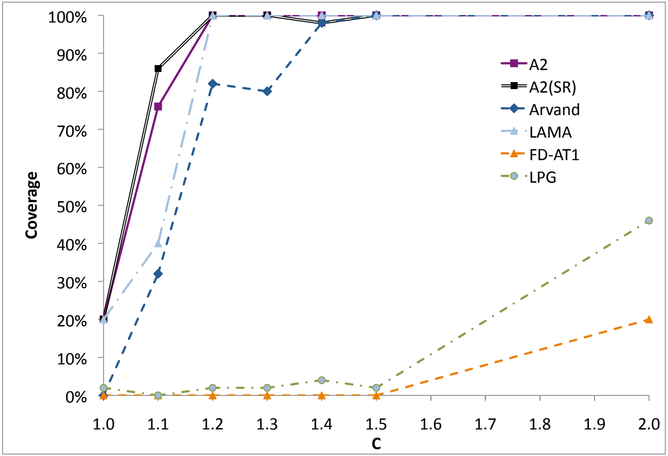
Results: Rovers, small



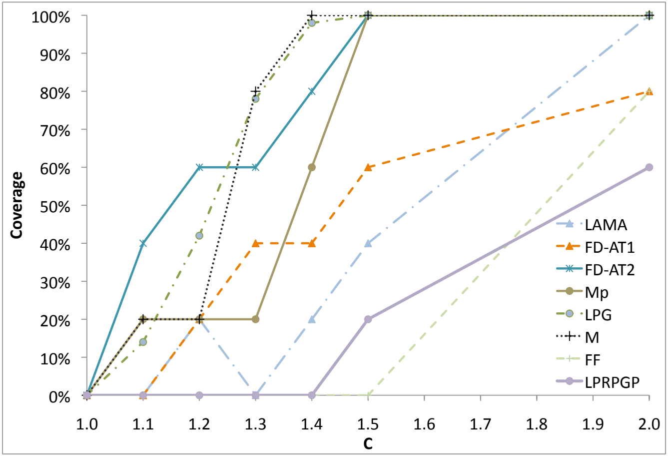
Results: Rovers, large



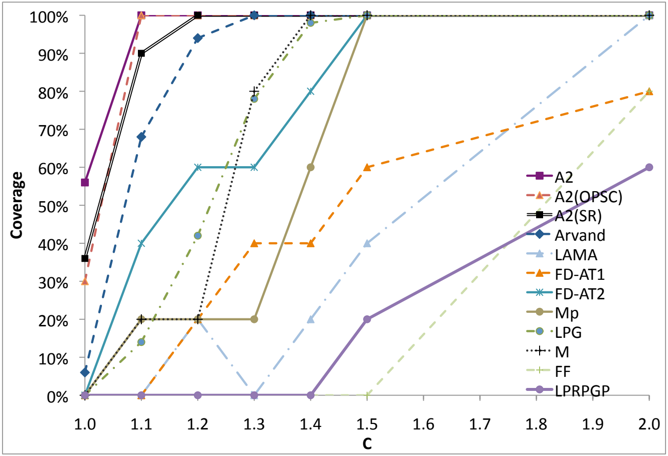
Results: Rovers, large



Results: NoMystery, large



Results: NoMystery, large



Plan Improvement

RW planning can generate bad-quality solutions

Idea

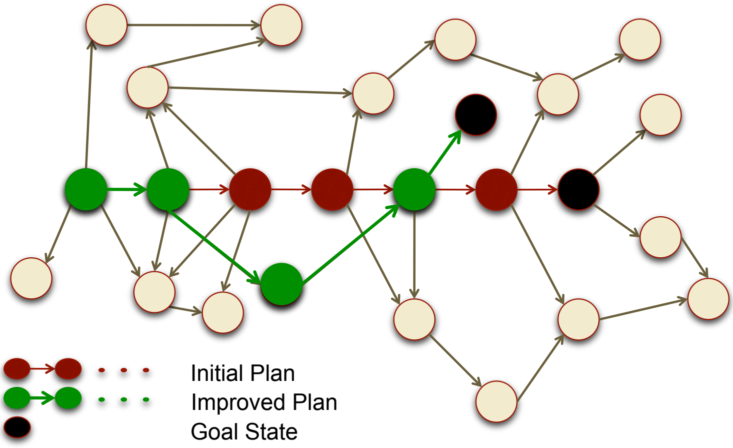
Develop fast post-processing techniques to improve the solutions

Outcome: Aras

A postprocessor that works well for a wide range of planners

- Even for those like LAMA that are well-designed to generate good-quality solutions

Plan Neighborhood Graph Search (PNGS)



Anytime PNGS

- Iteratively increase the expansion limit
- Each iteration starts with last plan generated in previous iterations

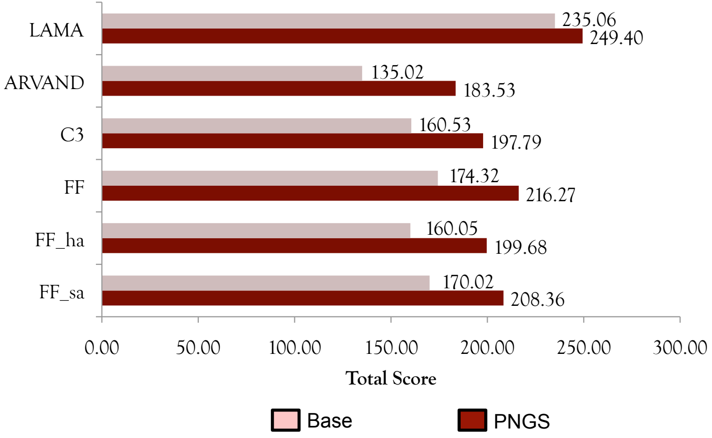
Experiments

- Compare state-of-the-art planners with and without plan improvement on IPC domains
- Scoring function: the cost of the best plan produced by any planner divided by the cost of the generated plan
- Issue: how to divide time between planner and postprocessor

Cutoff Time

- Run the planner until a cutoff time is reached
  - If no solution is found, keep running until the first solution is found
- Use the postprocessor to improve the best generated plan

IPC-2008 PNGS



Integration of Arvand-2013 and Aras

- Repeat until the time limit (30 min.) is reached:
  - Run Arvand-2013 until a solution *s* is found
  - Run Aras to improve *s* until a memory/time limit (2 GB) is reached
- The cost of the best previous plan is used for prunning
- Report the best plan found as the result

Arvand-2013 vs. Top Planner (Solution Quality)

Domain	Arvand-2013	LAMA-2011	FDFSS2	FDFSS1	Roamer
Scanalyzer	16.17	15.63	16.91	**17.70**	15.46
Pegsol	**19.88**	**19.88**	16.02	14.70	18.11
Floortile	5.00	4.46	**6.35**	5.44	1.63
Tidybot	11.22	14.53	11.23	**14.82**	13.03
Nomystery	**13.39**	11.33	10.80	13.33	9.51
Transport	12.10	12.39	9.14	9.46	**14.39**
Parcprinter	**19.00**	18.87	18.95	16.65	5.83
Elevators	8.64	10.62	8.70	**12.41**	11.74
Visitall	11.89	15.84	3.08	2.77	**16.89**
Parking	10.11	**16.96**	12.40	8.72	8.34
Woodworking	12.75	14.23	18.42	**18.56**	11.78
Barman	**19.93**	17.15	10.86	14.31	15.30
Sokoban	1.00	**16.28**	13.90	15.88	13.22
Openstacks	11.83	**18.36**	11.11	12.68	17.57
Total	172.88	**206.52**	167.88	177.43	172.80

Random Walk Planners

- Arvand-2009: Establishing the foundation
- Arvand-RC: Using RW Search for RCP
- Arvand-2011: Learning the Best Configuration and Using Aras
- Arvand-LS: RandomWalks with Memory
- ArvandHerd: Parallel portfolio

Contributions

RW search as an effective framework for satisficing planning

- A theoretical framework for studying RW search
  - Determined key features affecting RW
  - Explained where and why RW exploration is effective
- A detailed experimental study of design space
  - Built effective learning systems that adapt parameters
  - Built efficient biasing techniques
  - Gained valuable insights regarding the effects of different parameters

Contributions

- Application of RW search to RCP
  - Extended the definition of C to multiple resources
  - Developed of new benchmarks
  - Significantly improved the state of the art
- Aras: a very effective postprocessing system
- Several strong planning systems
  - Arvand-2009: Establishing the foundation
  - Arvand-2011: Configuration learner and Aras
  - Arvand-2013: Empirical study of the design space
  - Arvand-RC: Using RW search for RCP
  - Arvand-LS: RW with memory
  - ArvandHerd: Parallel portfolio

Thank you for your attention!