ICAPS 2006

The English Lake District, Cumbria, UK

Tutorial on Planning Graph Based Reachability Heuristics

Daniel Bryce
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TU6

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Preface

The primary revolution in automated planning in the last decade has been the very impressive scale-up in planner performance. A large part of the credit for this can be attributed squarely to the invention and deployment of powerful reachability heuristics. Most, if not all, modern reachability heuristics are based on a remarkably extensible datastructure called the planning graph–which made its debut as a bit player in the success of Graphplan, but quickly grew in prominence to occupy the center-stage.

In this tutorial, we will start with a discussion of the foundations of reachability analysis with planning graphs. We will then discuss the many ways of applying this analysis to develop scalable planners. Starting with classical planning, we will discuss heuristics for cost-based planning, over-subscription planning, planning with resources, temporal planning, non-deterministic planning as well as stochastic planning.

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Planning Graph Based Reachability Heuristics

Daniel Bryce & Subbarao Kambhampati

ICAPS'06 Tutorial 6

June 7, 2006

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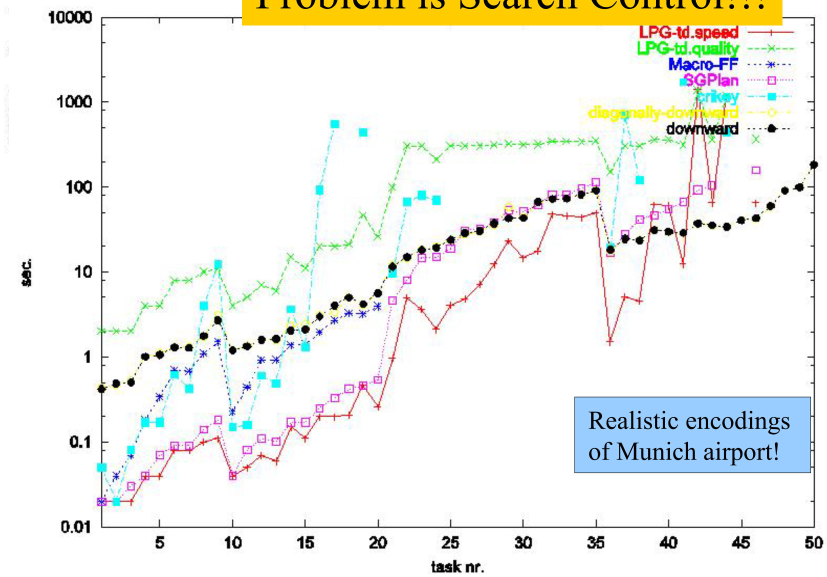
Motivation

- Ways to improve Planner Scalability
  - Problem Formulation
  - Search Space
  - Reachability Heuristics
    - Domain (Formulation) Independent
    - Work for many search spaces
    - Flexible – work with most domain features
    - Overall compliment other scalability techniques
    - Effective!!

Scalability of Planning

Problem is Search Control!!!

- Before, planning algorithms could synthesize about 6 – 10 action plans in minutes
- Significant scale-up in the last 6-7 years
  - Now, we can synthesize 100 action plans in seconds.



The primary revolution in planning in the recent years has been **domain-independent heuristics** to scale up plan synthesis

Topics

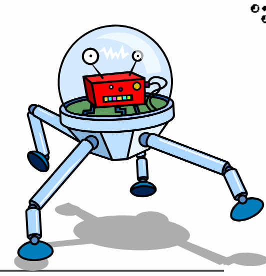
- Classical Planning } Rao
- Cost Based Planning
- Partial Satisfaction Planning } Dan
- Resources (Continuous Quantities)
- Temporal Planning } Rao
- Non-Deterministic/Probabilistic Planning
- Hybrid Models } Dan

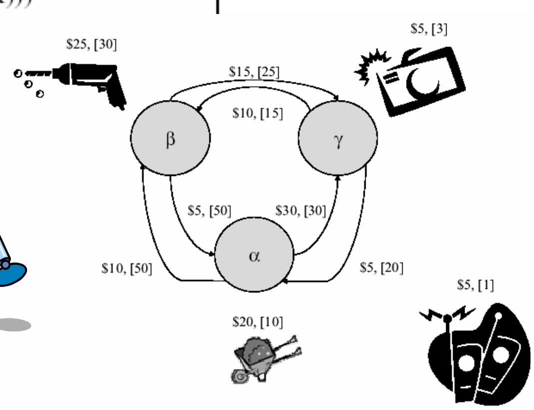
Classical Planning

Rover Domain

```
(define (domain rovers_classical)
  (:requirements :strips :typing)
  (:types waypoint data)
  (:predicates
          (at ?x - waypoint)
          (avail ?d - data ?x - waypoint)
          (comm ?d - data)
          (have ?d - data))
  (:action drive
   :parameters (?x ?y - waypoint)
   :precondition (at ?x)
   :effect (and (at ?y) (not (at ?x))))
  (:action commun
   :parameters (?d - data)
   :precondition (have ?d)
   :effect (comm ?d))
  (:action sample
   :parameters (?d - data ?x - waypoint)
   :precondition (and (at ?x) (avail ?d ?x))
   :effect (have ?d))
)
```

```
(define (problem rovers_classical1)
  (:domain rovers_classical)
  (:objects
     soil image rock - data
     alpha beta gamma - waypoint)
  (:init (at alpha)
        (avail soil alpha)
        (avail rock beta)
        (avail image gamma))
  (:goal (and (comm soil)
              (comm image)
              (comm rock)))
)
```

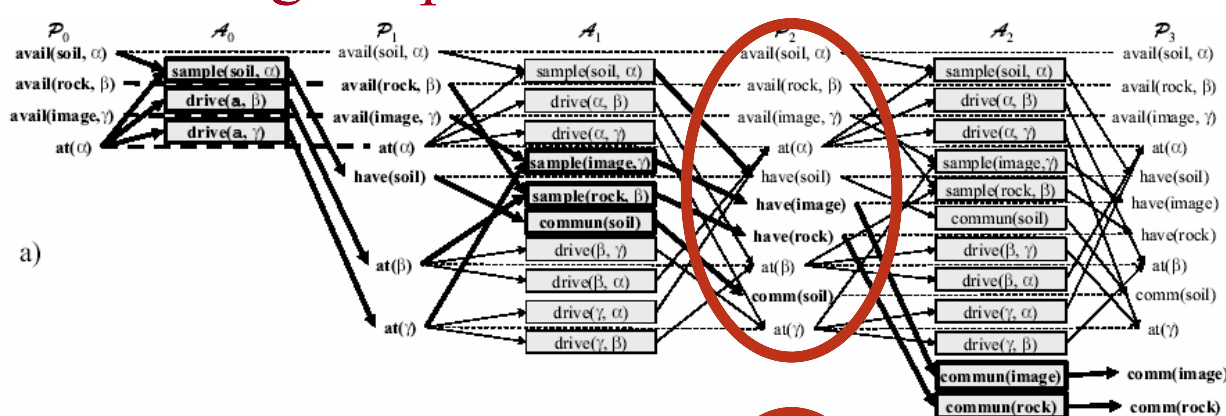




Classical Planning

- Relaxed Reachability Analysis
- Types of Heuristics
  - Level-based
  - Relaxed Plans
- Mutexes
- Heuristic Search
  - Progression
  - Regression
  - Plan Space
- Exploiting Heuristics

Planning Graph and Search Tree



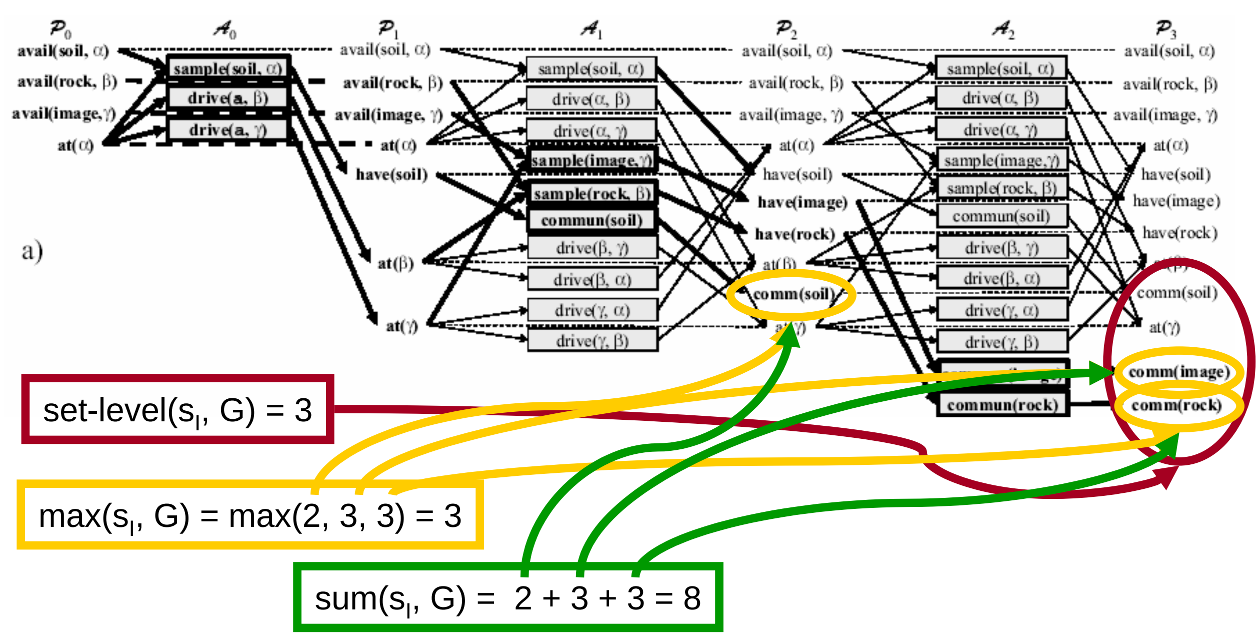
a)

- Envelope of Progression Tree (Relaxed Progression)
  - Proposition lists: Union of states at k^{th} level
- Lowerbound reachability information

Level Based Heuristics

- The distance of a proposition is the index of the first proposition layer in which it appears
  - Proposition distance changes when we propagate cost functions – described later
- What is the distance of a Set of propositions??
  - Set-Level: Index of first proposition layer where all goal propositions appear
    - Admissible
    - Gets better with mutexes, otherwise same as max
  - Max: Maximum distance proposition
  - Sum: Summation of proposition distances

Example of Level Based Heuristics



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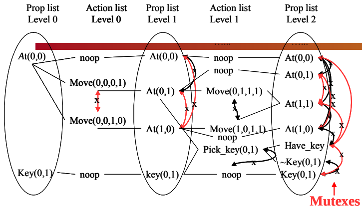
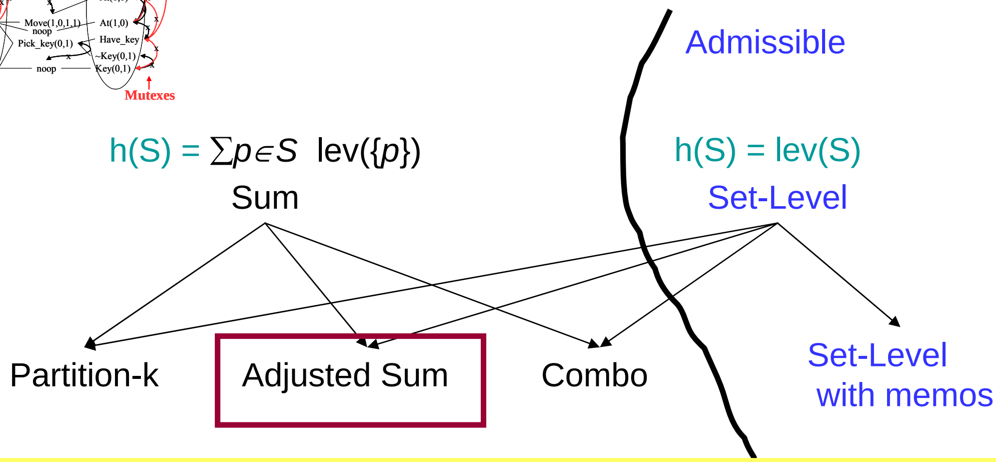
Distance of a Set of Literals





- lev(p) : index of the first level at which p comes into the planning graph
- lev(S): index of the first level where all props in S appear non-mutexed.
  - If there is no such level, then

    If the graph is grown to level off, then ∞

    Else k+1 (k is the current length of the graph)

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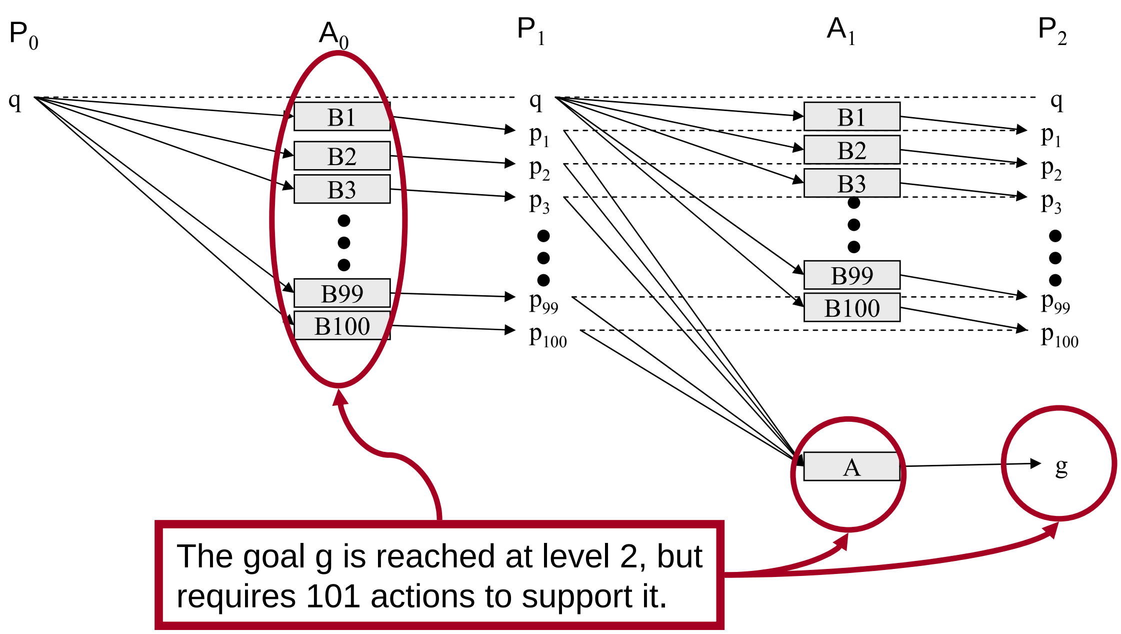
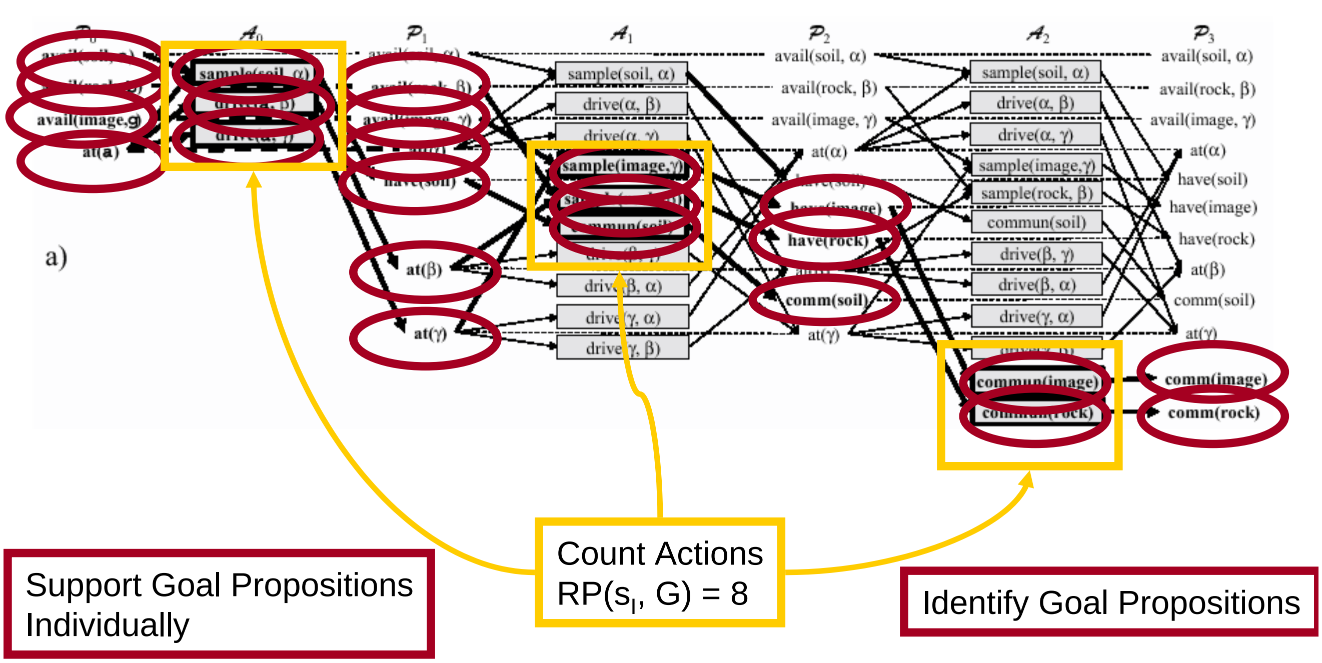
How do Level-Based Heuristics Break?



Relaxed Plan Heuristics

- When Level does not reflect distance well, we can find a relaxed plan.
- A relaxed plan is subgraph of the planning graph, where:
  - Every goal proposition is in the relaxed plan at the level where it first appears
  - Every proposition in the relaxed plan has a supporting action in the relaxed plan
  - Every action in the relaxed plan has its preconditions supported.
- Relaxed Plans are not admissible, but are generally effective.
- Finding the optimal relaxed plan is NP-hard, but finding a greedy one is easy. Later we will see how "greedy" can change.

Example of Relaxed Plan Heuristic



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Results

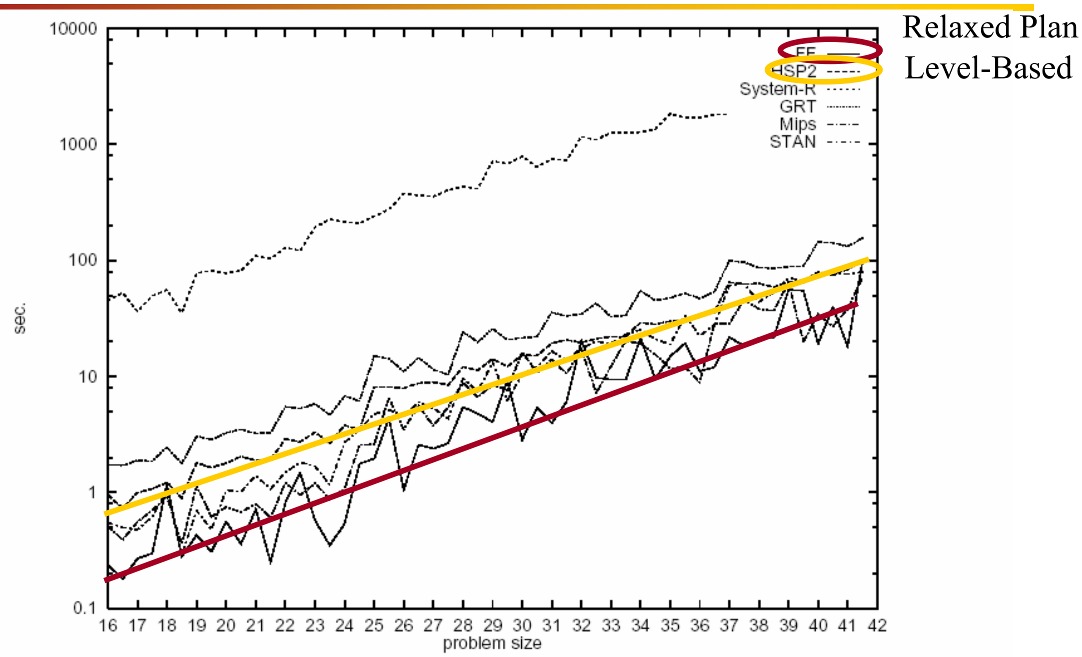

Figure 4: Runtime curves on large *Logistics* instances for those six planners that could scale up to them. Time is shown on a logarithmic scale.

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Results (cont'd)

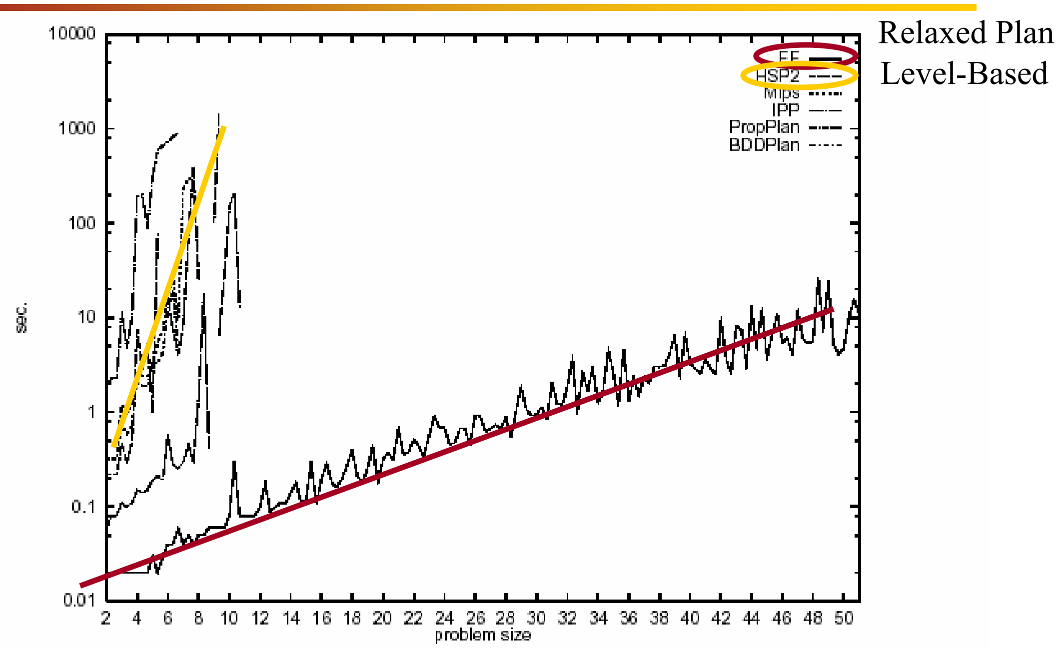
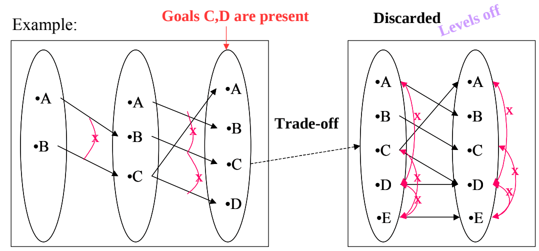
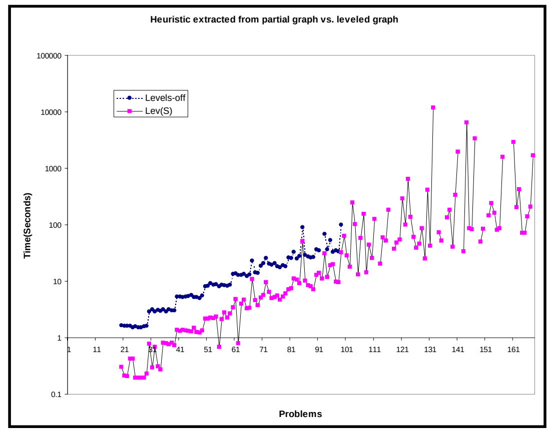


Figure 6: Runtime curves on *Schedule* instances for those planners that could handle conditional effects. Time is shown on a logarithmic scale.

Optimizations in Heuristic Computation

- Taming Space/Time costs
  - Bi-level Planning Graph representation
  - Partial expansion of the PG (stop *before* level-off)
    - It is FINE to cut corners when using PG for heuristics (instead of search)!!
- Branching factor can still be quite high
  - Use actions appearing in the PG (complete)
    - Select actions in lev(S) vs Levels-off (incomplete)
    - Consider action appearing in RP (incomplete)

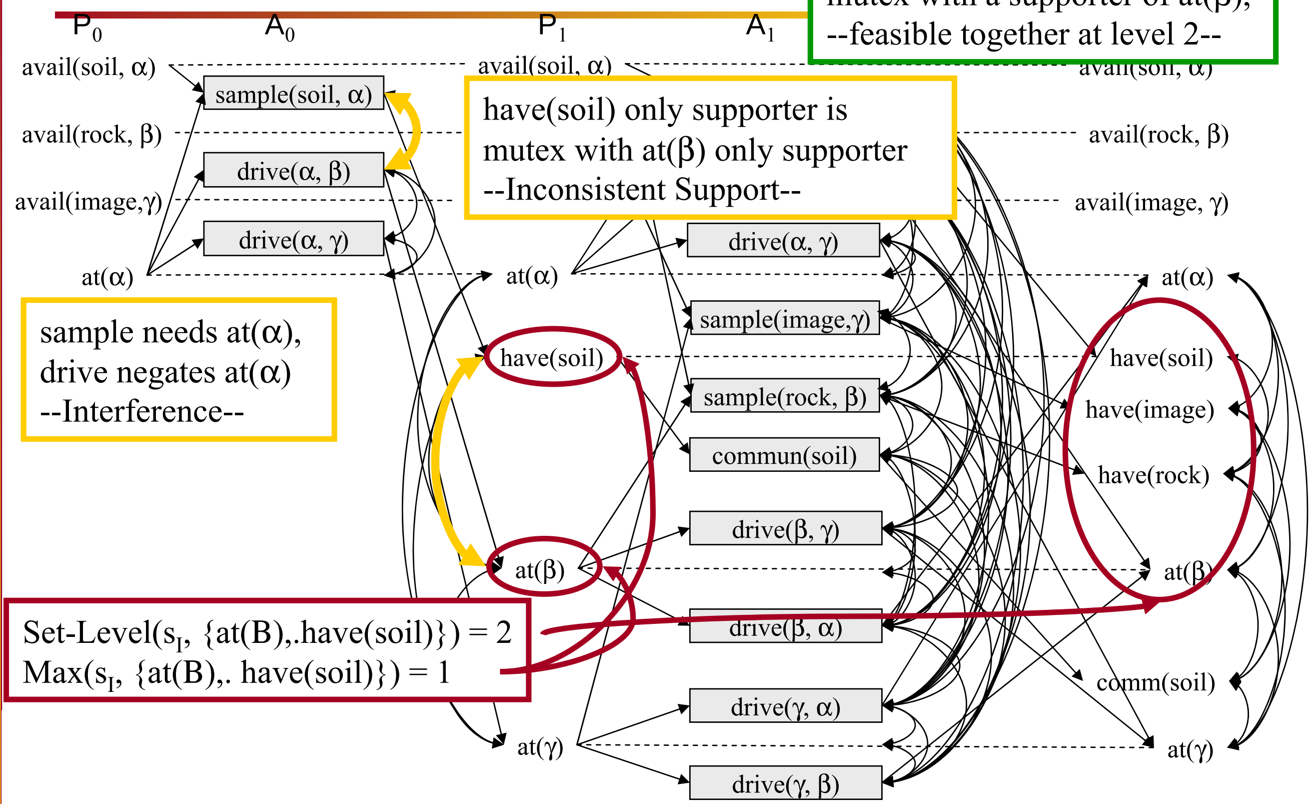




Adjusting for Negative Interactions

- Until now we assume actions only positively interact, but they often conflict
- Mutexes help us capture some negative interactions
  - Types
    - Actions: Interference/Competing Needs
    - Propositions: Inconsistent Support
  - Binary are the most common and practical
  - |A| + 2|P|-ary will allow us to solve the planning problem with a backtrack-free GraphPlan search
    - An action layer may have |A| actions and 2|P| noops
  - Serial Planning Graph assumes all non-noop actions are mutex

Binary Mutexes



Adjusting the Relaxed Plans

- Start with RP heuristic and adjust it to take subgoal interactions into account
  - Negative interactions in terms of "degree of interaction"
  - Positive interactions in terms of co-achievement links
    - Ignore negative interactions when accounting for positive interactions (and *vice versa*)

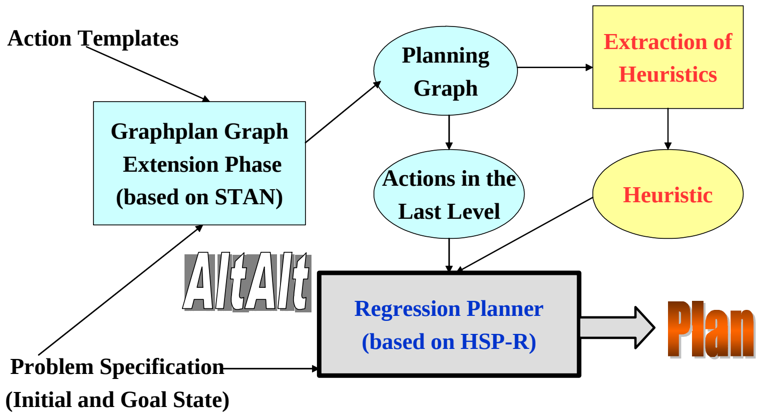
PROBLEM	Level	Sum	AdjSum2M
Gripper-25	-	69/0.98	67/1.57
Gripper-30	-	81/1.63	77/2.83
Tower-7	127/1.28	127/0.95	127/1.37
Tower-9	511/47.91	511/16.04	511/48.45
8-Puzzle1	31/6.25	39/0.35	31/0.69
8-Puzzle2	30/0.74	34/0.47	30/0.74
Mystery-6	-	-	16/62.5
Mistery-9	8/0.53	8/0.66	8/0.49
Mprime-3	4/1.87	4/1.88	4/1.67
Mprime-4	8/1.83	8/2.34	10/1.49
Aips-grid1	14/1.07	14/1.12	14/0.88
Aips-grid2	-	-	34/95.98

HAdjSum2M(*S*) = *length*(*RelaxedPlan*(*S*)) + *max p,q*∈*S* **δ(p,q)**

Where δ(p,q) = lev({p,q}) - max{lev(p), lev(q)} /*Degree of –ve Interaction */

 [AAAI 2000]

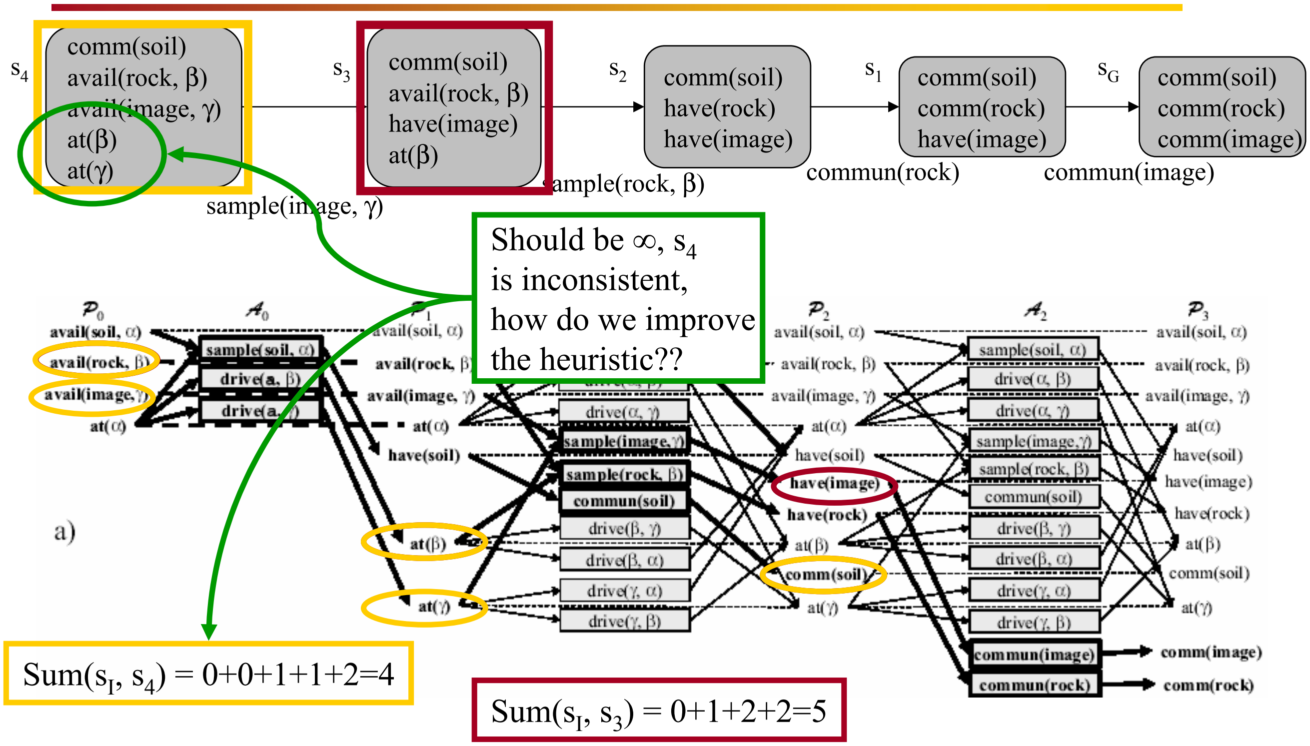
Anatomy of a State-space Regression planner



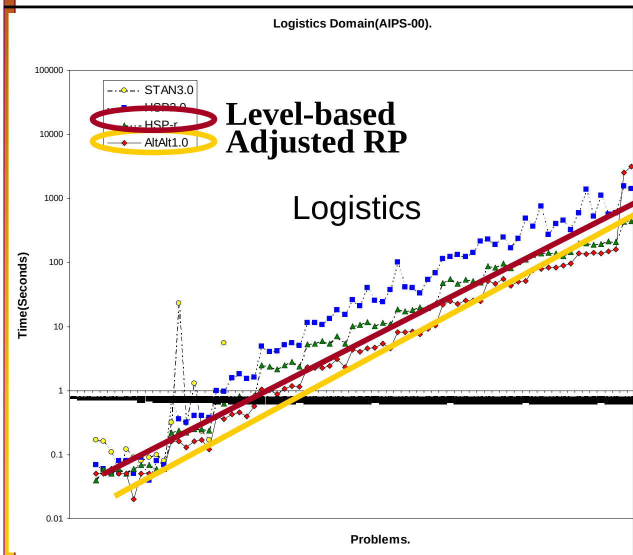
Problem: Given a set of subgoals (regressed state) estimate how far they are from the initial state

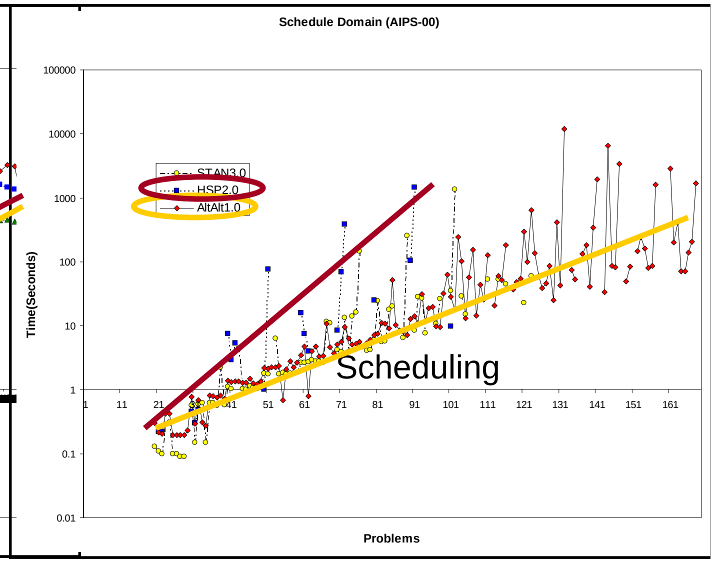
[AAAI 2000; AIPS 2000; AIJ 2002; JAIR 2003]

Rover Example in Regression



AltAlt Performance





Problem sets from IPC 2000

Plan Space Search

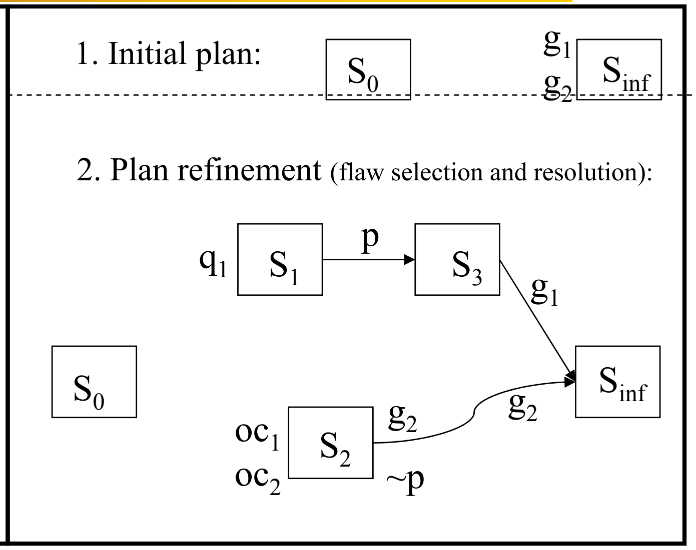
Then it was cruelly UnPOPped

The good times return with Re(vived)POP

In the beginning it was all POP.

POP Algorithm

1. *Plan Selection*: *Select a plan P from the search queue*
2. *Flaw Selection*: Choose a flaw f (open cond or unsafe link)
3. *Flaw resolution*:
   If f is an open condition,
   choose an action *S* that achieves *f*
   If f is an unsafe link,
   choose promotion or demotion
   Update P
   Return NULL if no resolution exist
4. *If* there is no flaw left, *return* P

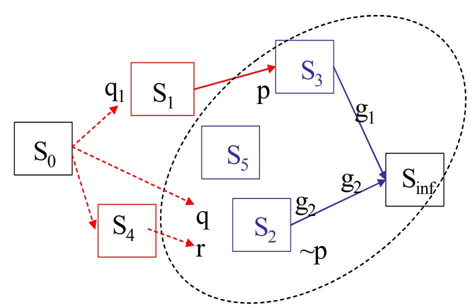


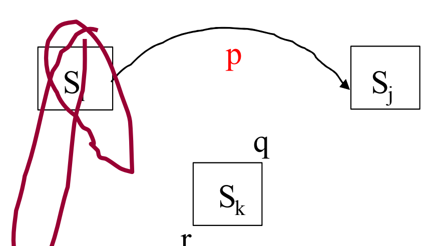
Choice points

- Flaw selection *(open condition? unsafe link? Non-backtrack choice)*
- Flaw resolution/Plan Selection *(how to select (rank) partial plan?)*

PG Heuristics for Partial Order Planning

- Distance heuristics to estimate cost of partially ordered plans (and to select flaws)
  - If we ignore negative interactions, then the set of open conditions can be seen as a regression state
- Mutexes used to detect indirect conflicts in partial plans
  - A step threatens a link if there is a mutex between the link condition and the steps' effect or precondition
  - Post disjunctive precedences and use propagation to simplify





$$\text{if } mutex(p,q) \text{ or } mutex(p,r)$$
$$S_k \prec S_i \vee S_j \prec S_k$$

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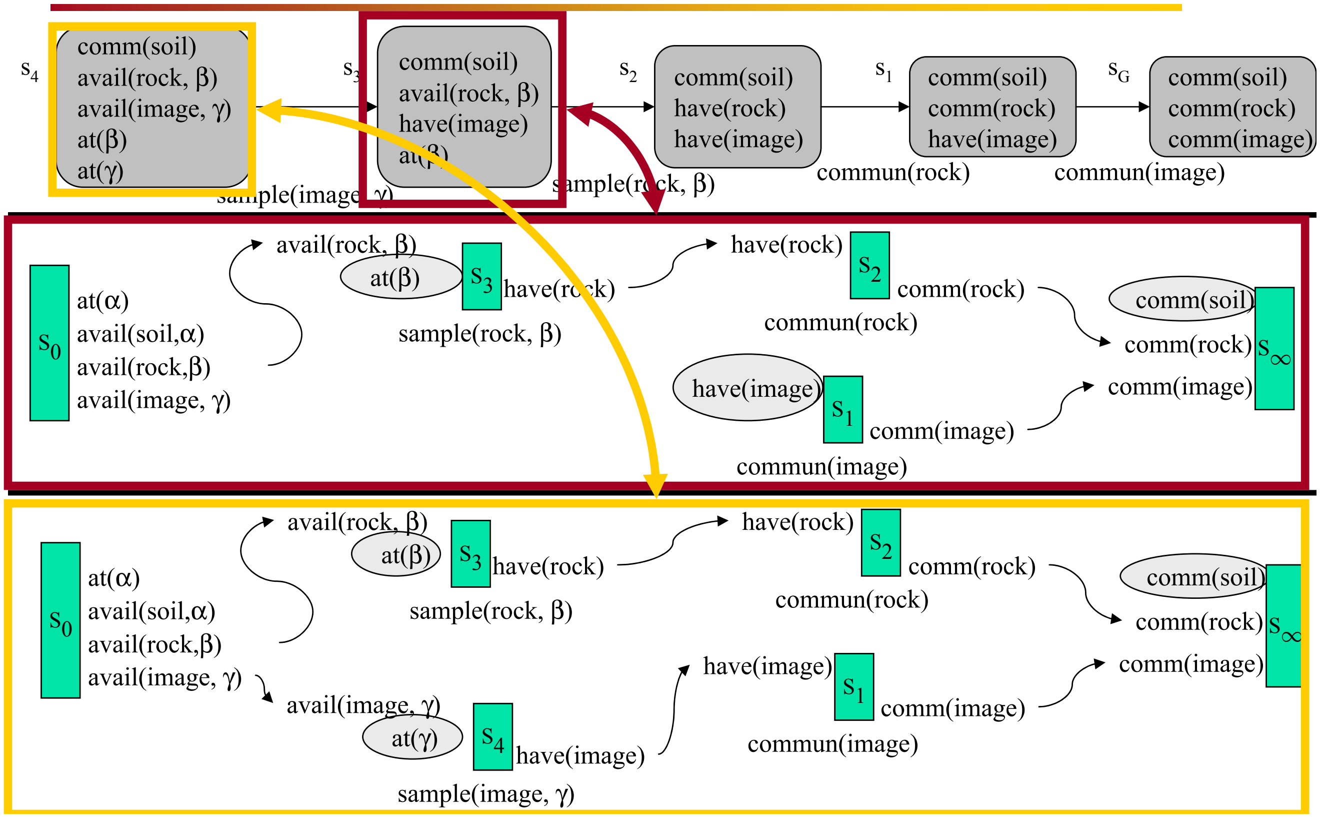
Regression and Plan Space



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RePOP's Performance

- RePOP implemented on top of UCPOP
  - Dramatically better than any other partial order planner before it
  - Competitive with Graphplan and AltAlt
  - VHPOP carried the torch at ICP 2002

Problem	UCPOP	RePOP	Graphplan	AltAlt
Gripper-8	-	1.01	66.82	.43
Gripper-10	-	2.72	47min	1.15
Gripper-20	**-**	**81.86**	**-**	**15.42**
Rocket-a	-	8.36	75.12	1.02
Rocket-b	**-**	**8.17**	**77.48**	**1.29**
Logistics-a	-	3.16	306.12	1.59
Logistics-b	-	2.31	262.64	1.18
Logistics-c	-	22.54	-	4.52
Logistics-d	**-**	**91.53**	**-**	**20.62**
Bw-large-a	45.78	(5.23) -	14.67	4.12
Bw-large-b	-	(18.86) -	122.56	14.14
Bw-large-c	**-**	**(137.84) -**	**-**	**116.34**

Written in Lisp, runs on Linux, 500MHz, 250MB

You see, pop, it *is* possible to Re-use all the old POP work!

[IJCAI, 2001]

Exploiting Planning Graphs

- Restricting Action Choice
  - Use actions from:
    - Last level before level off (complete)
    - Last level before goals (incomplete)
    - First Level of Relaxed Plan (incomplete) – FF's helpful actions
    - Only action sequences in the relaxed plan (incomplete) – YAHSP
- Reducing State Representation
  - Remove static propositions. A static proposition is only ever true or false in the last proposition layer.

Classical Planning Conclusions

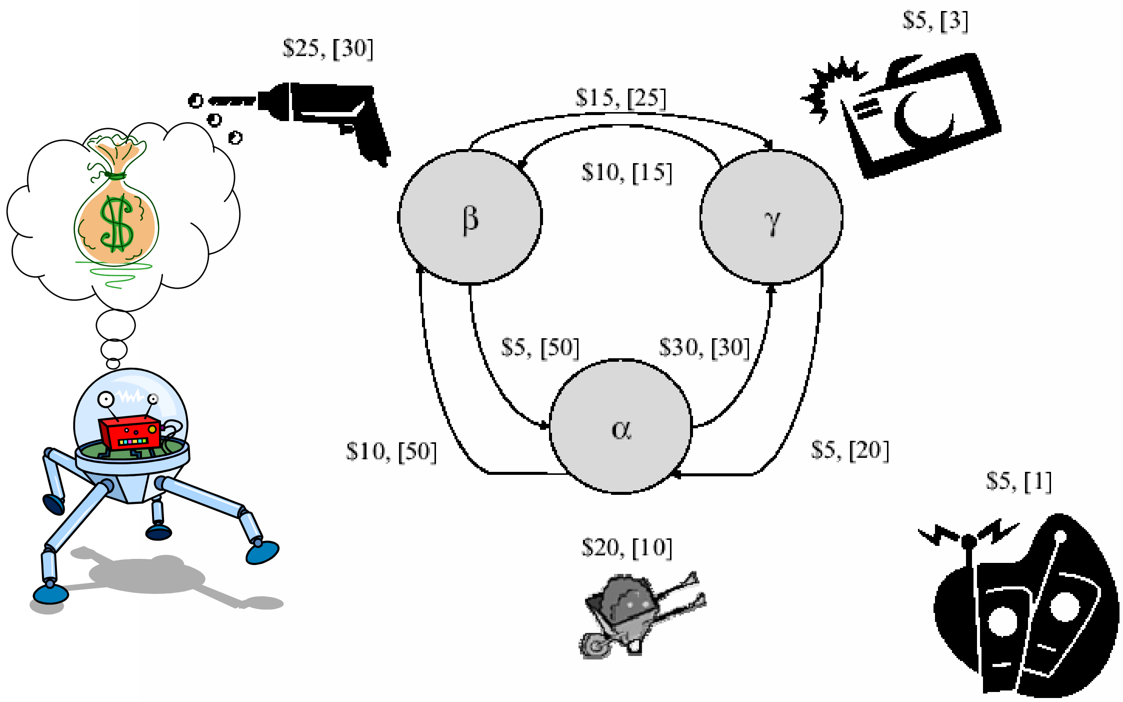
- Many Heuristics
  - Set-Level, Max, Sum, Relaxed Plans
- Heuristics can be improved by adjustments
  - Mutexes
- Useful for many types of search
  - Progresssion, Regression, POCL

Cost-Based Planning

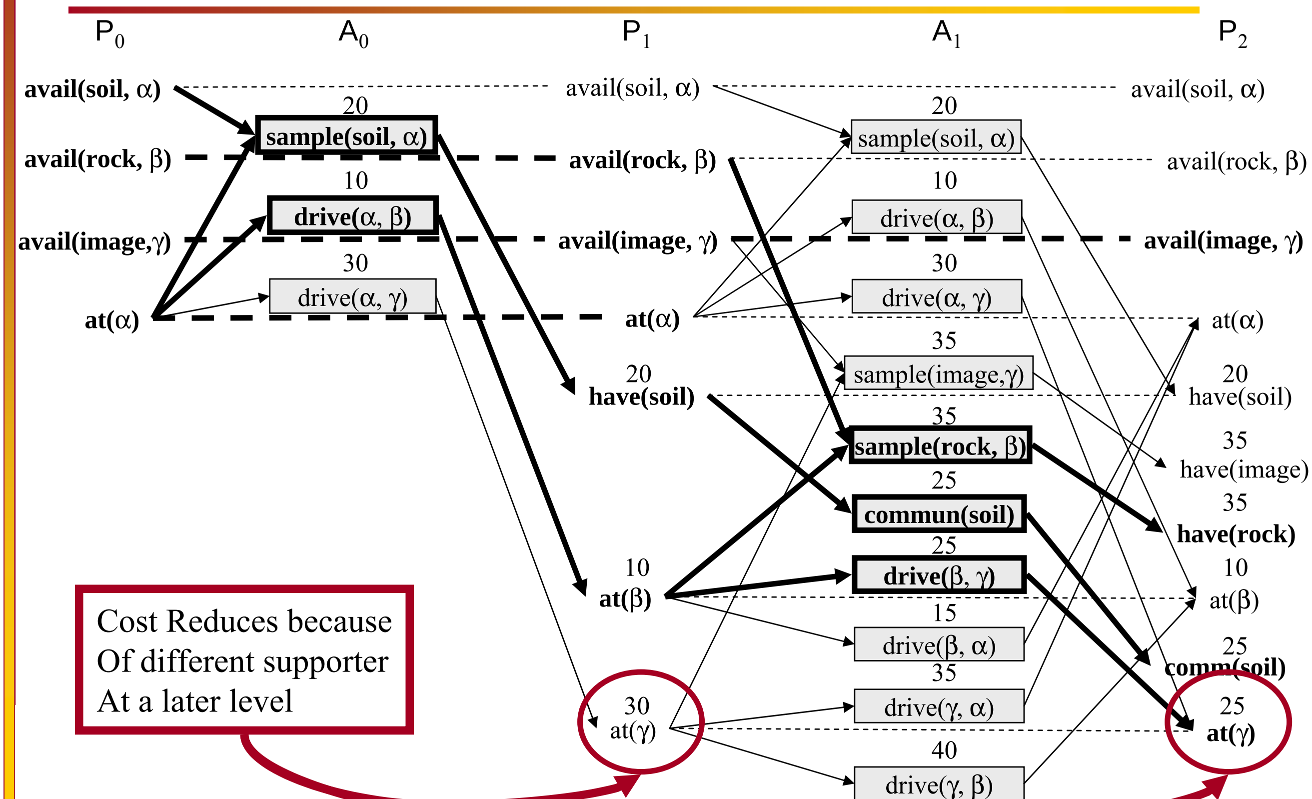
Cost-based Planning

- Propagating Cost Functions
- Cost-based Heuristics
  - Generalized Level-based heuristics
  - Relaxed Plan heuristics

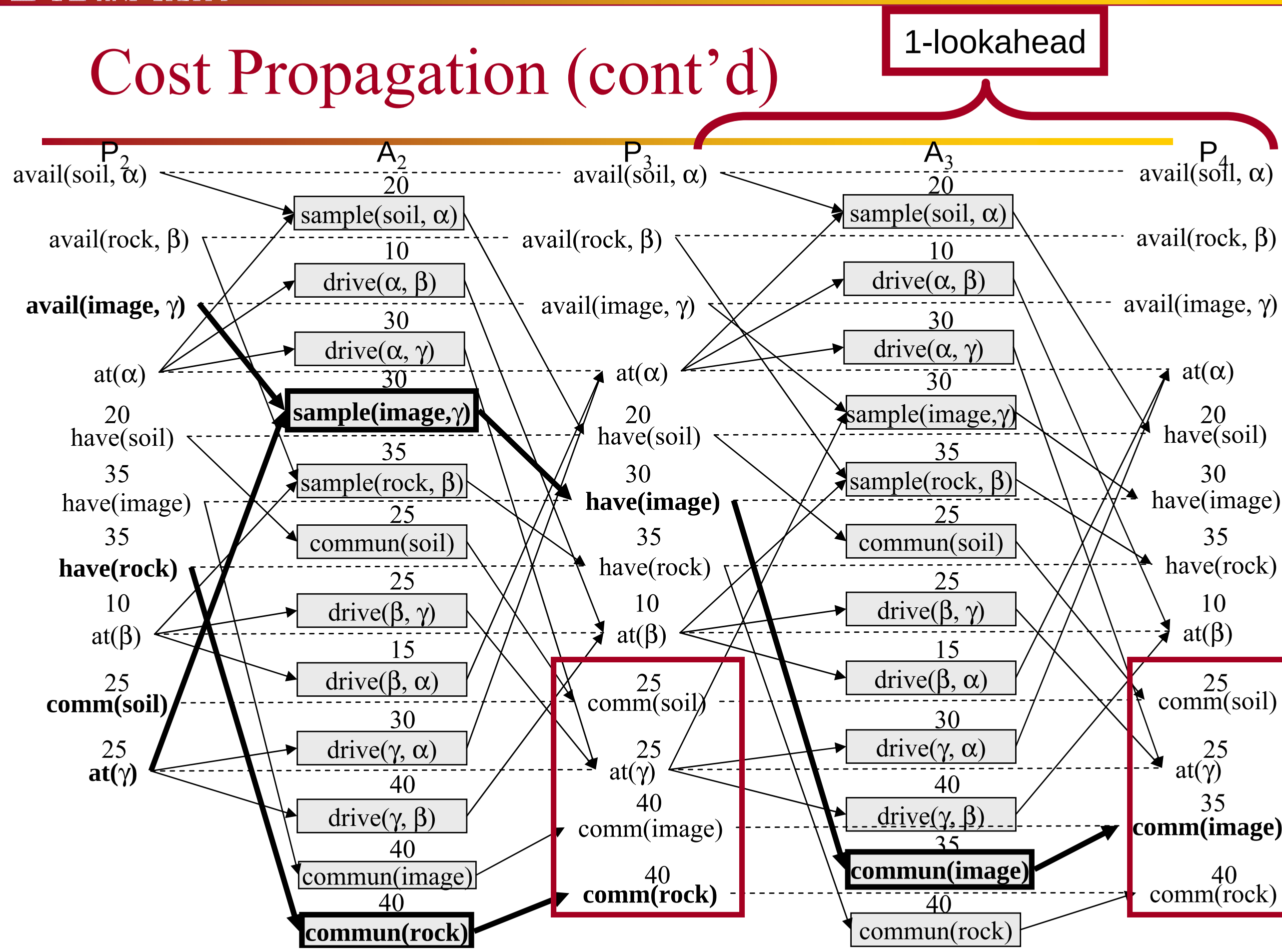
Rover Cost Model



Cost Propagation



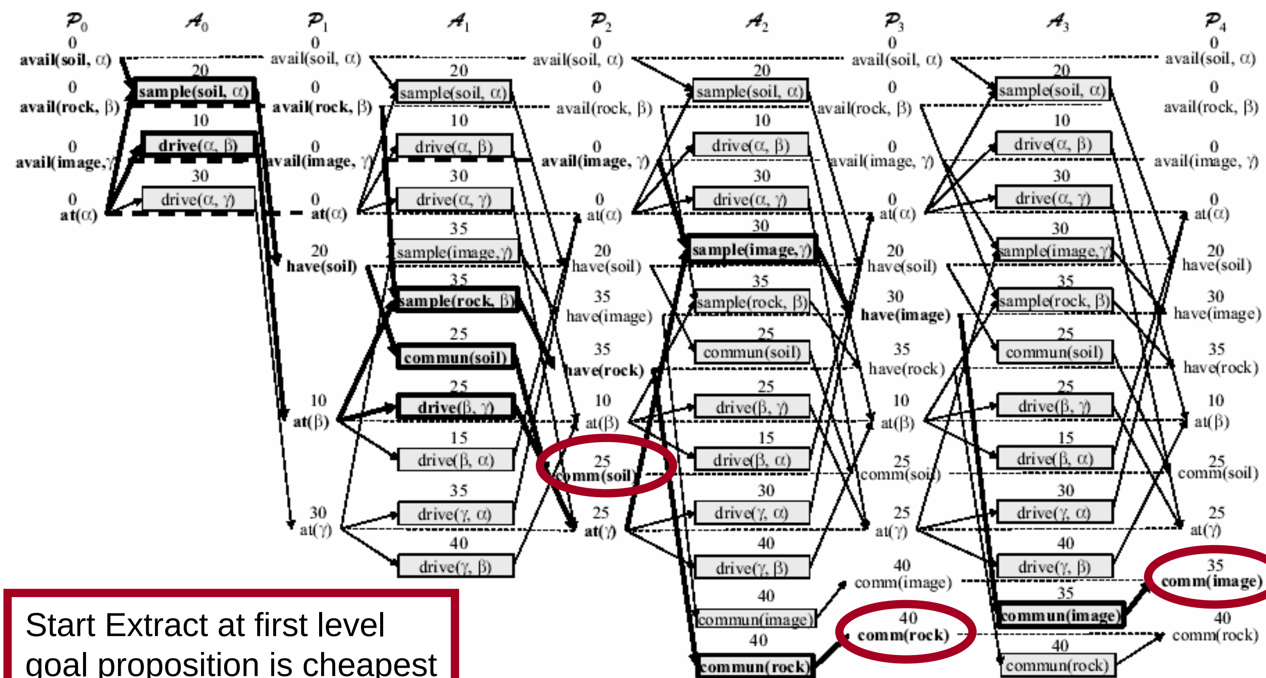
Cost Propagation (cont'd)



Terminating Cost Propagation

- Stop when:
  - goals are reached (no-lookahead)
  - costs stop changing (∞-lookahead)
  - k levels after goals are reached (k-lookahead)

Guiding Relaxed Plans with Costs



Start Extract at first level goal proposition is cheapest

Cost-Based Planning Conclusions

- Cost-Functions:
  - Remove false assumption that level is correlated with cost
  - Improve planning with non-uniform cost actions
  - Are cheap to compute (constant overhead)

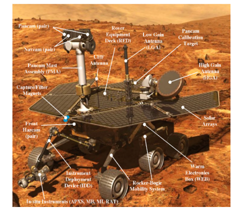
Partial Satisfaction (Over-Subscription) Planning

Partial Satisfaction Planning

- Selecting Goal Sets
  - Estimating goal benefit
- Anytime goal set selection
- Adjusting for negative interactions between goals

Partial Satisfaction (Oversubscription) Planning

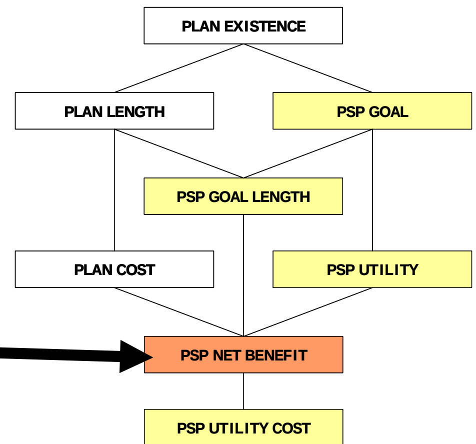
In many real world planning tasks, the agent often has more goals than it has resources to accomplish.



Example: Rover Mission Planning (MER)

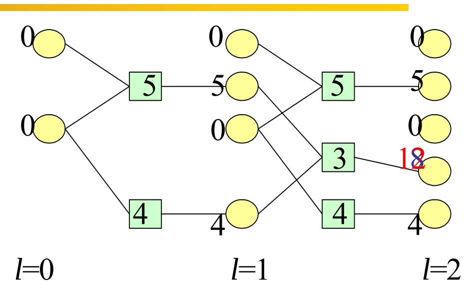
Need automated support for Over-subscription/Partial Satisfaction Planning

Actions have execution costs, goals have utilities, and the objective is to find the plan that has the highest net benefit.

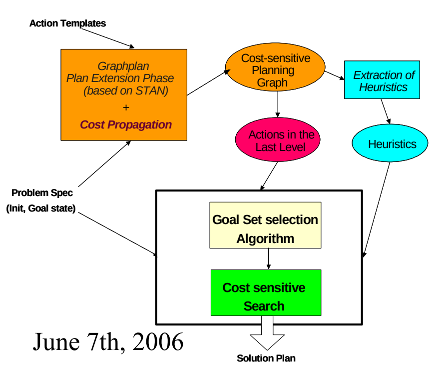


Adapting PG heuristics for PSP

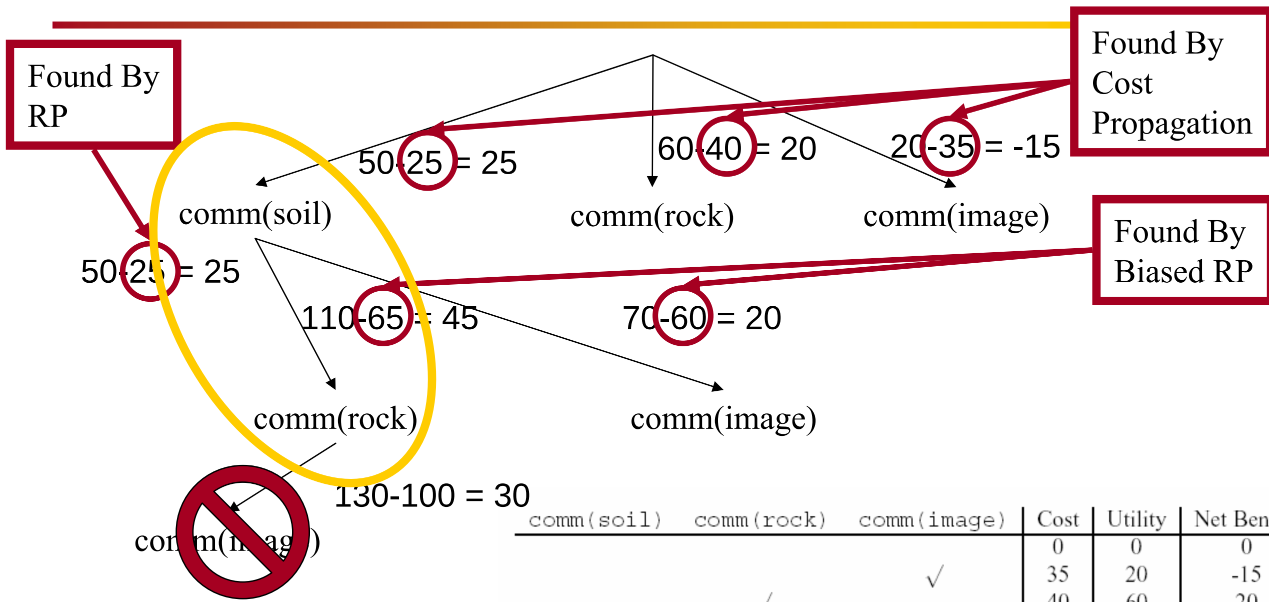
- **Challenges:**
  - **Need to propagate costs on the planning graph**
  - The exact set of goals are not clear
    - Interactions between goals
    - Obvious approach of considering all 2^n goal subsets is *infeasible*



- **Idea:** Select a subset of the top level goals upfront
- Challenge: Goal interactions
  - Approach: Estimate the net benefit of each goal in terms of its utility minus the cost of its relaxed plan
    - Bias the relaxed plan extraction to (re)use the actions already chosen for other goals



Goal Set Selection In Rover Problem

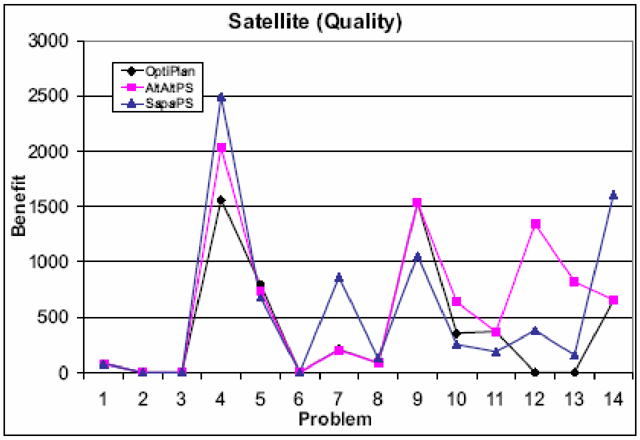


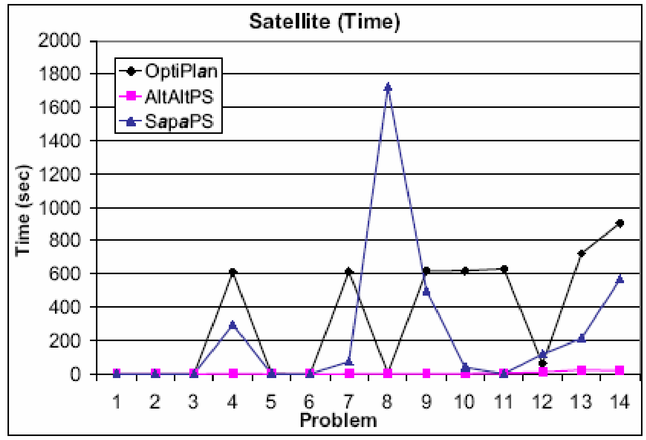
comm(soil)	comm(rock)	comm(image)	Cost	Utility	Net Benefit
			0	0	0
		√	35	20	-15
	√		40	60	20
	√	√	65	80	15
√			25	50	25
√		√	60	70	10
√	√		**65**	**110**	**45**
√	√	√	90	130	40

SAPA^{PS} (anytime goal selection)

- A* Progression search
  - g-value: net-benefit of plan so far
  - h-value: relaxed plan estimate of best goal set
    - Relaxed plan found for all goals
    - Iterative goal removal, until net benefit does not increase
  - Returns plans with increasing g-values.

Some Empirical Results for AltAlt^{ps}





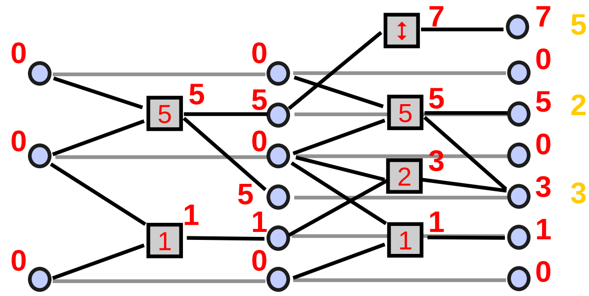
Exact algorithms based on MDPs don't scale at all

[AAAI 2004]

Adjusting for Negative Interactions (AltWlt)

- Problem:
  - What if the apriori goal set is not achievable because of negative interactions?
  - What if greedy algorithm gets bad local optimum?
- Solution:
  - Do not consider mutex goals
  - Add penalty for goals whose relaxed plan has mutexes.
    - Use interaction factor to adjust cost, similar to adjusted sum heuristic
      - $\max_{g1, g2 \in G} \{lev(g1, g2) – max(lev(g1), lev(g2)) \}$
  - Find Best Goal set for each goal

The Problem with Plangraphs [Smith, ICAPS 04]



Assume independence between objectives

For rover: all estimates from starting location

Approach

- Construct *orienteering* problem
- Solve it
- Use as search guidance

Orienteering Problem

TSP variant

– Given:

network of cities

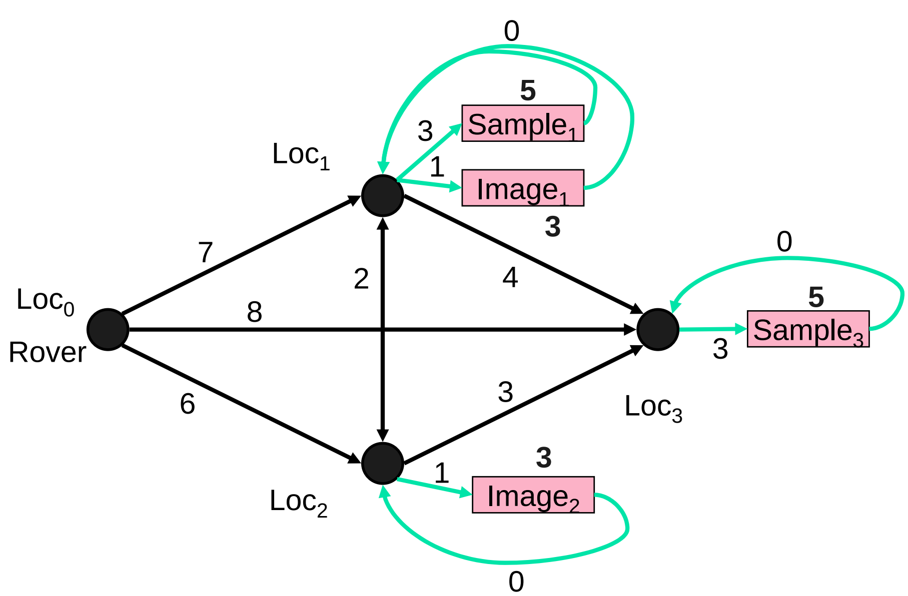
rewards in various cities

finite amount of gas

– Objective:

collect as much reward as possible before running out of gas

Orienteering Graph



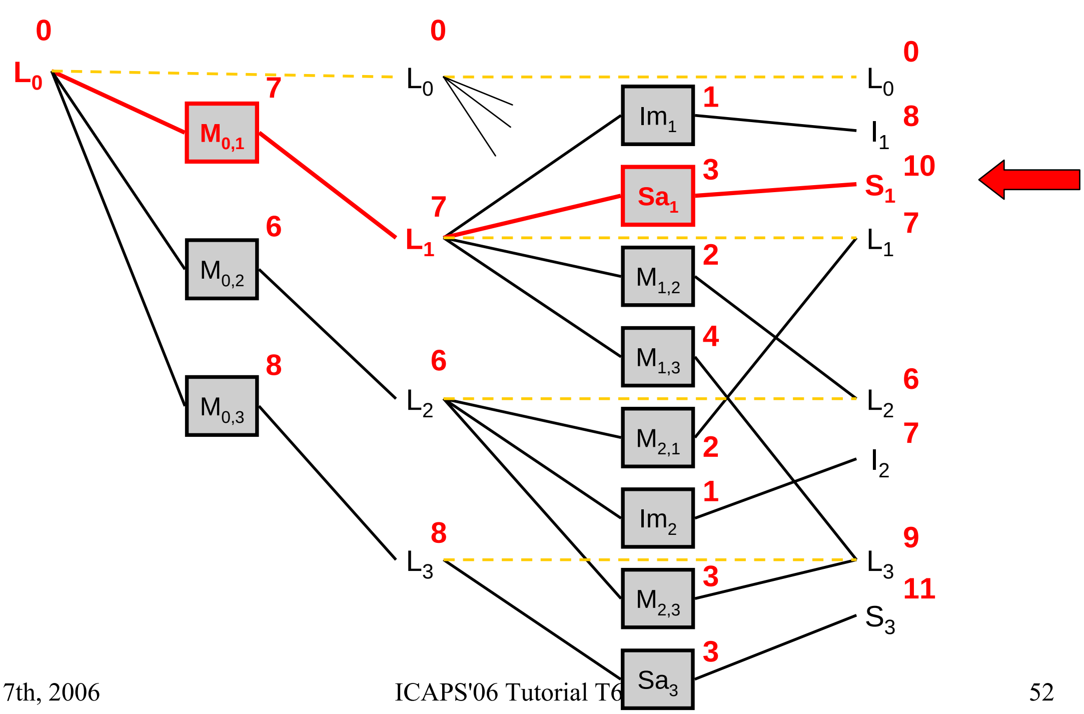
The Big Question:

How do we determine which propositions go in the orienteering graph?

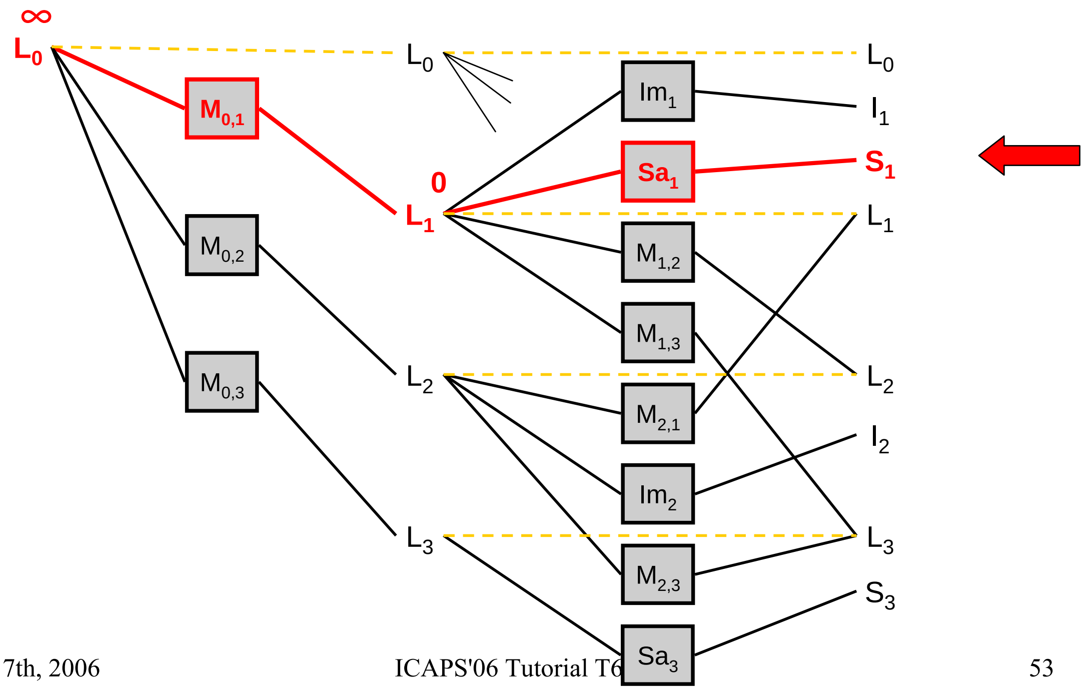
Propositions that:
- are changed in achieving one goal
- impact the cost of another goal

Sensitivity analysis

Recall: Plan Graph



Sensitivity Analysis



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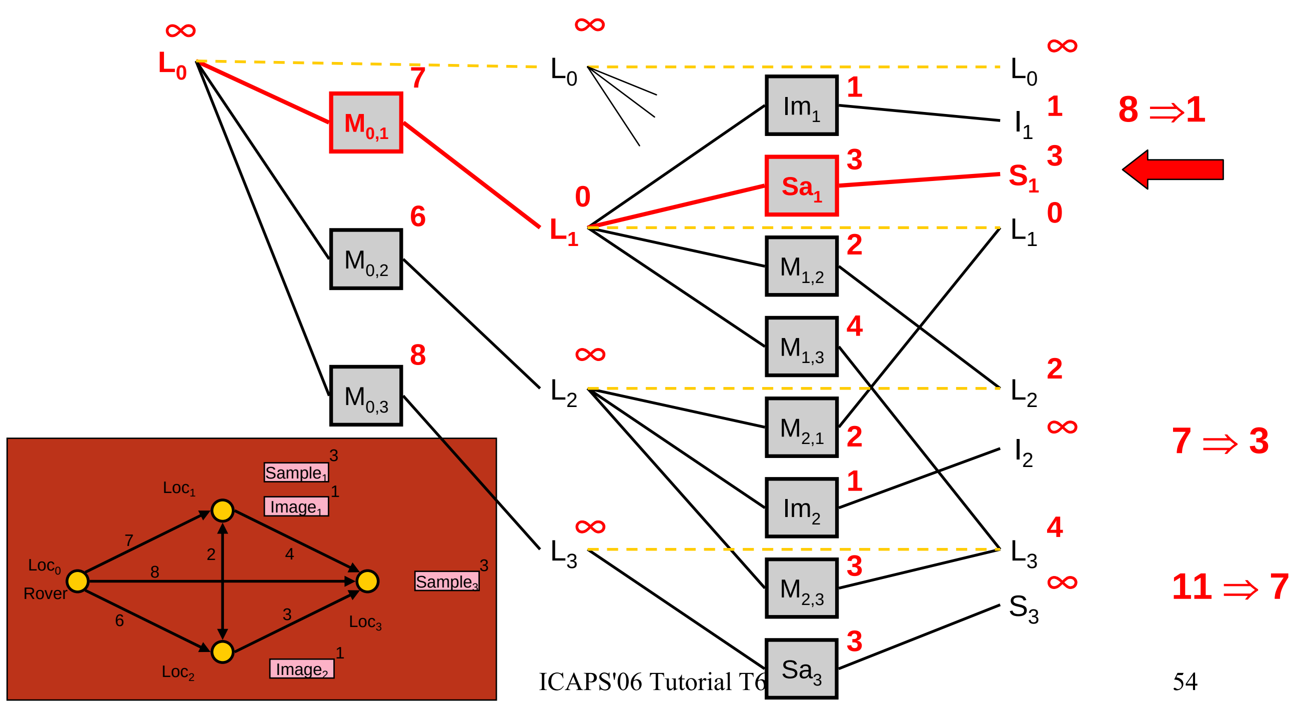
Sensitivity Analysis



Basis Set Algorithm

For each goal:

Construct a relaxed plan

For each net effect of relaxed plan:

Reset costs in PG

Set cost of net effect to 0

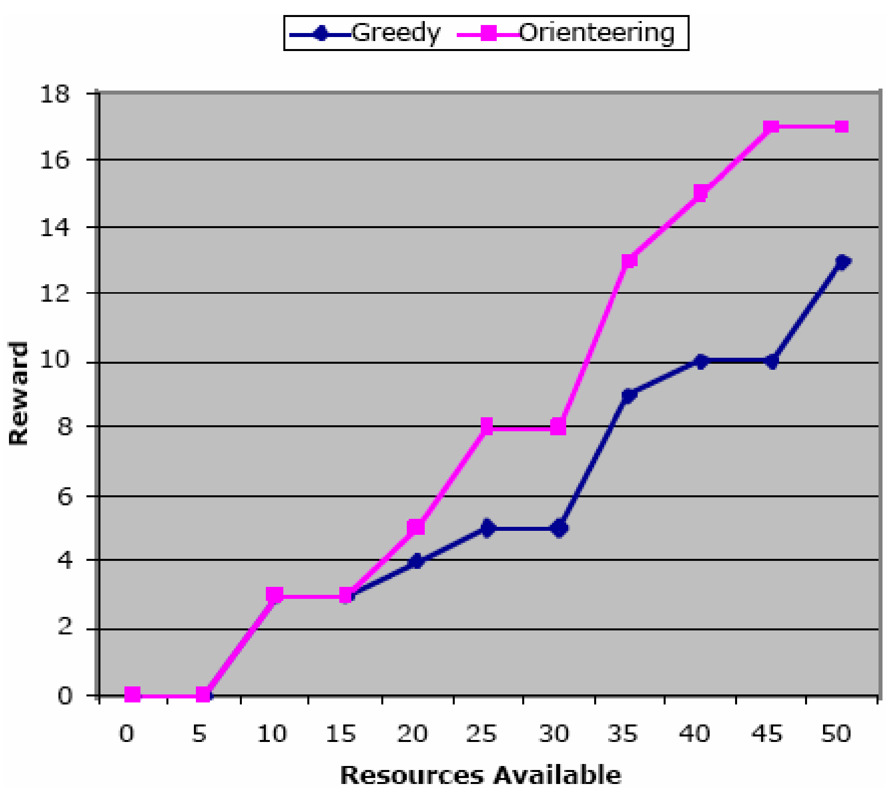
Set cost of mutex initial conditions to ∞

Compute revised cost estimates

If significantly different,

add net effect to basis set

25 Rocks



PSP Conclusions

- Goal Set Selection
  - Apriori for Regression Search
  - Anytime for Progression Search
  - Both types of search use greedy goal insertion/removal to optimize net-benefit of relaxed plans
- Orienteering Problem
  - Interactions between goals apparent in OP
  - Use solution to OP as heuristic
  - Planning Graphs help define OP

Planning with Resources

Planning with Resources

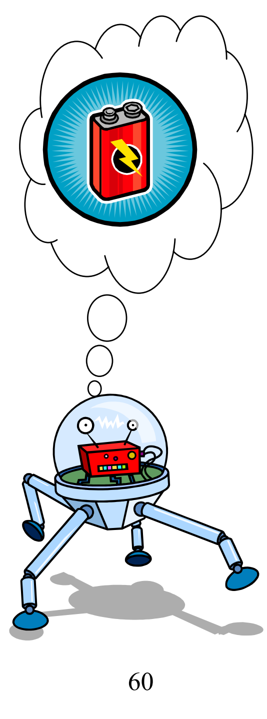
- Propagating Resource Intervals
- Relaxed Plans
  - Handling resource subgoals

Rover with power Resource

```
(define (domain rovers_resource)
  (:requirements :strips :typing)
  (:types waypoint data)
  (:predicates (comm ?d - data)
               (have ?d - data)
               (at ?x - waypoint)
               (avail ?d - data ?x - waypoint))
  (:functions (power)
              (effort ?x ?y - waypoint)
              (effort ?d - data))
  (:action drive
   :parameters (?x ?y - waypoint)
   :precondition (and (at ?x) (>= (power) (effort ?x ?y)))
   :effect (and (at ?y) (not (at ?x))
           (decrease (power) (effort ?x ?y))))
  (:action commun
   :parameters (?d - data)
   :precondition (and (have ?d)(>= (power) 5))
   :effect (and (comm ?d) (decrease (power) 5)))
  (:action sample
   :parameters (?d - data ?x - waypoint)
   :precondition (and (at ?x) (avail ?d ?x)
                 (>= (power) (effort ?d)))
   :effect (and (have ?d) (decrease (power) (effort ?d)))
  (:action recharge
   :parameters ()
   :precondition (and (at ?x) (avail ?d ?x) (<= (power) 75))
   :effect (and (have ?d) (increase (power) 25)))
)
```

```
(define (problem rovers_resource1)
  (:domain rovers_resource)
  (:objects
     soil image rock - data
     alpha beta gamma - waypoint)
  (:init (at alpha)
       (avail soil alpha)
       (avail rock beta)
       (avail image gamma)
       (= (effort alpha beta) 10)
       (= (effort beta alpha) 5)
       (= (effort alpha gamma) 30)
       (= (effort gamma alpha) 5)
       (= (effort beta gamma) 15)
       (= (effort gamma beta) 10)
       (= (effort soil) 20)
       (= (effort rock) 25)
       (= (effort image) 5)
       (= (power) 25))
  (:goal (and (comm soil)
              (comm image)
              (comm rock)))
)
```

Resource Usage, Same as costs for This example



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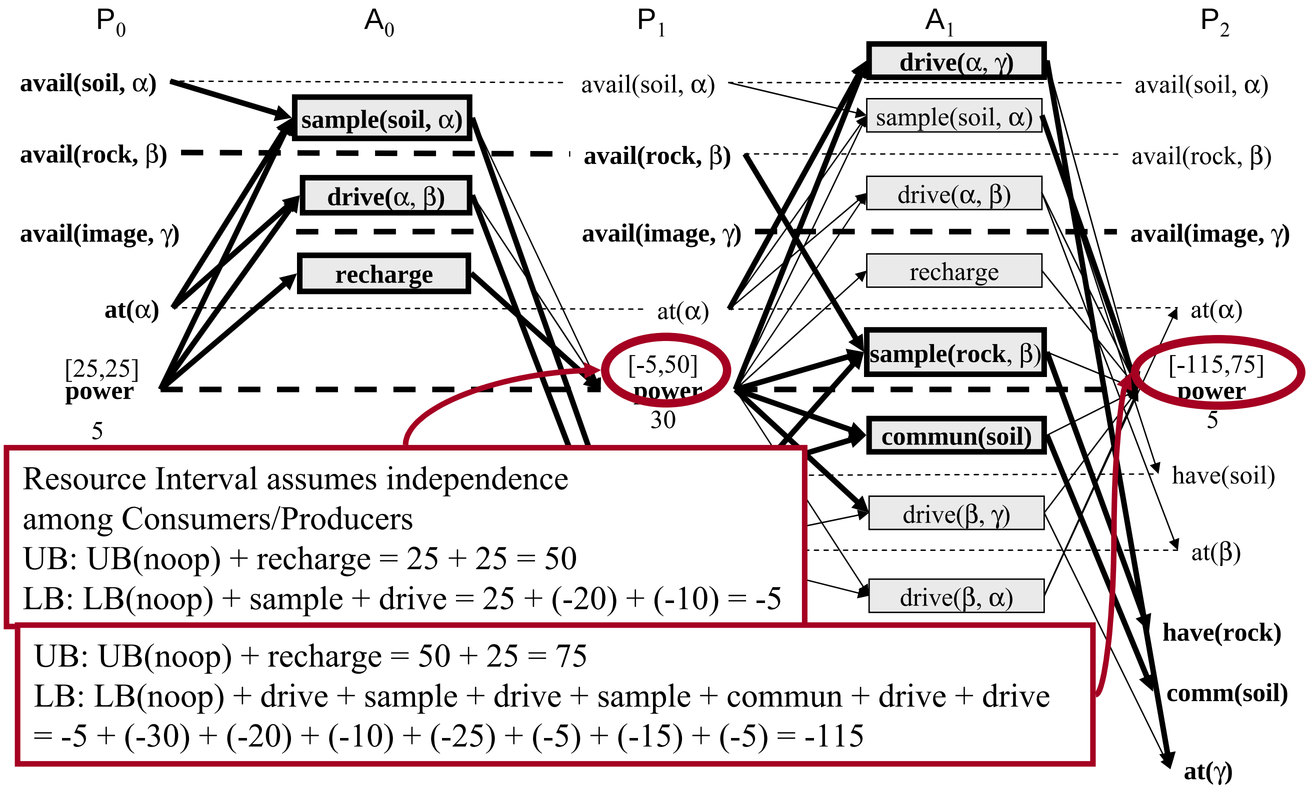
Resource Intervals



Resource Interval assumes independence among Consumers/Producers

UB: UB(noop) + recharge = 25 + 25 = 50

LB: LB(noop) + sample + drive = 25 + (-20) + (-10) = -5

UB: UB(noop) + recharge = 50 + 25 = 75

LB: LB(noop) + drive + sample + drive + sample + commun + drive + drive = -5 + (-30) + (-20) + (-10) + (-25) + (-5) + (-15) + (-5) = -115

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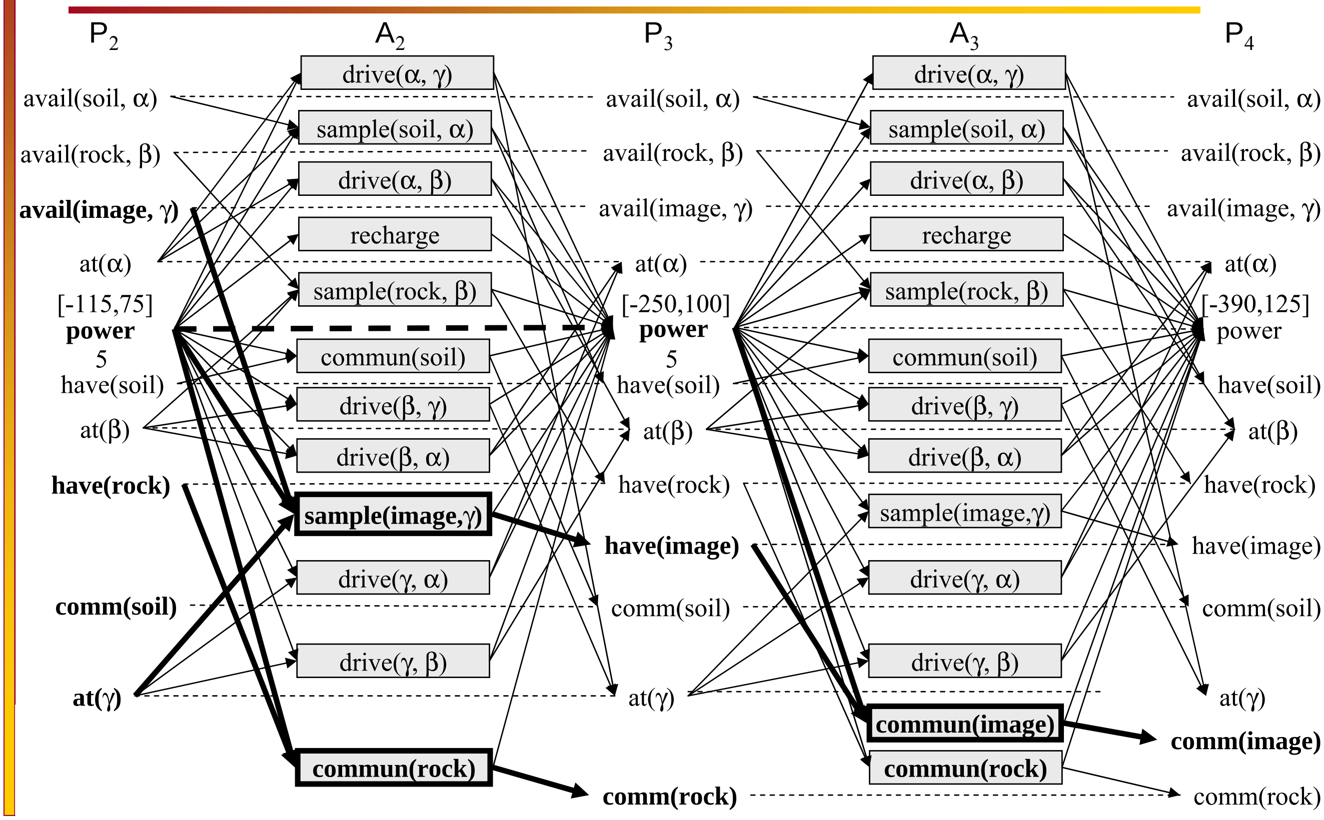
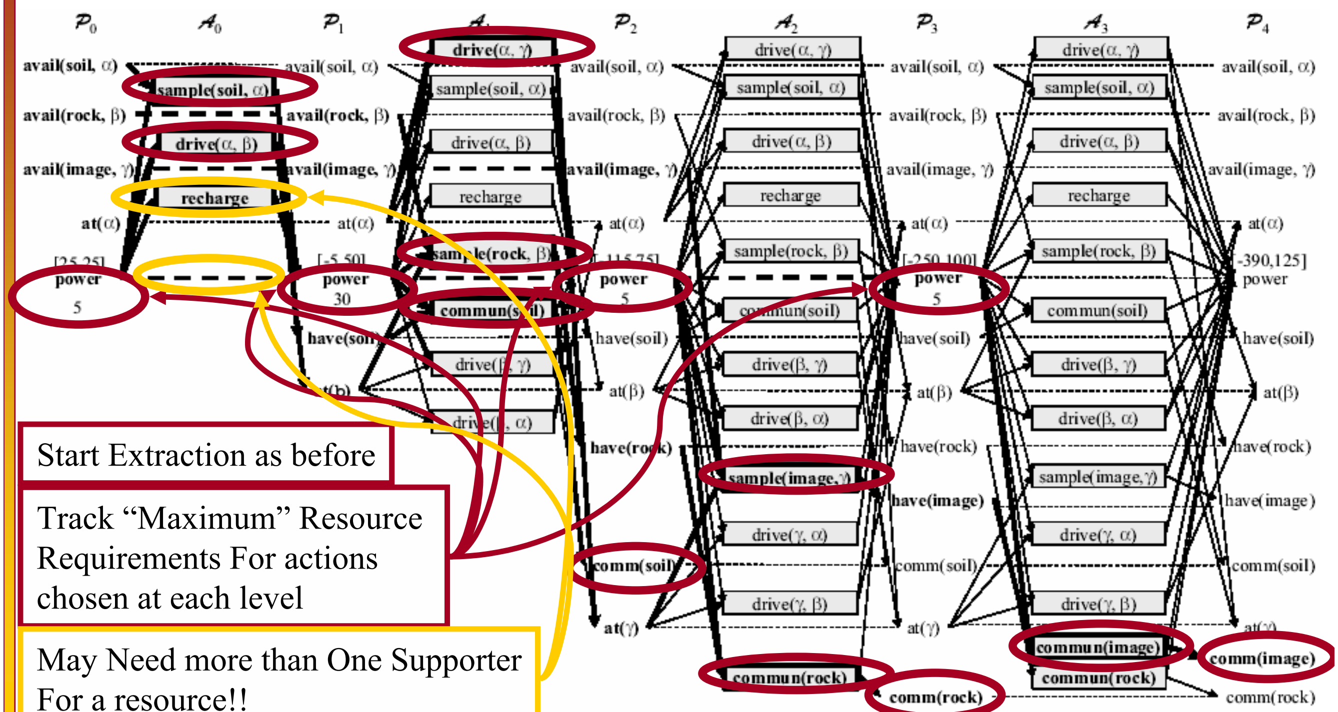
Resource Intervals (cont'd)



Relaxed Plan Extraction with Resources



Start Extraction as before

Track "Maximum" Resource Requirements For actions chosen at each level

May Need more than One Supporter For a resource!!

Results

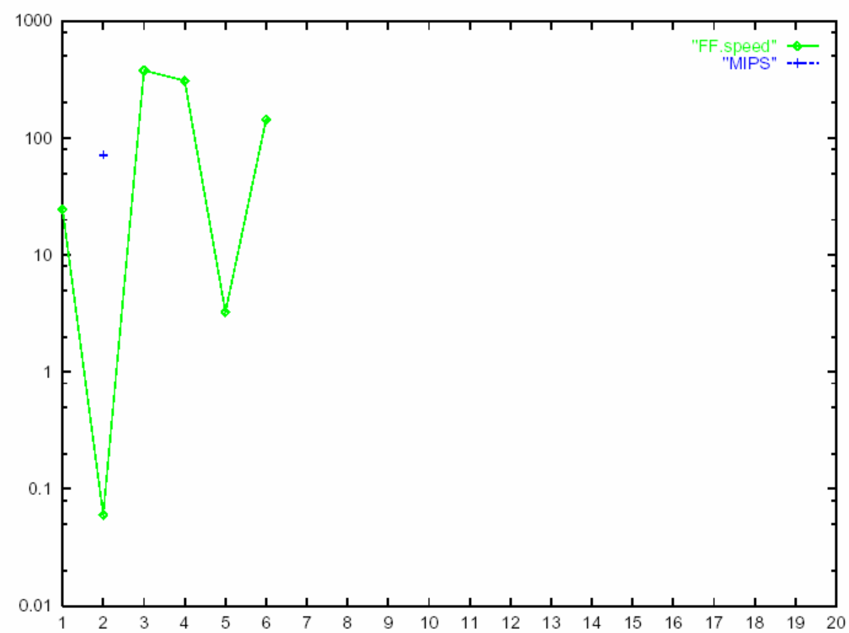


Figure 13: Runtime curves on *Settlers* instances for the planners favoring speed. Time is shown on a logarithmic scale, instance size scales from left to right.

Results (cont'd)

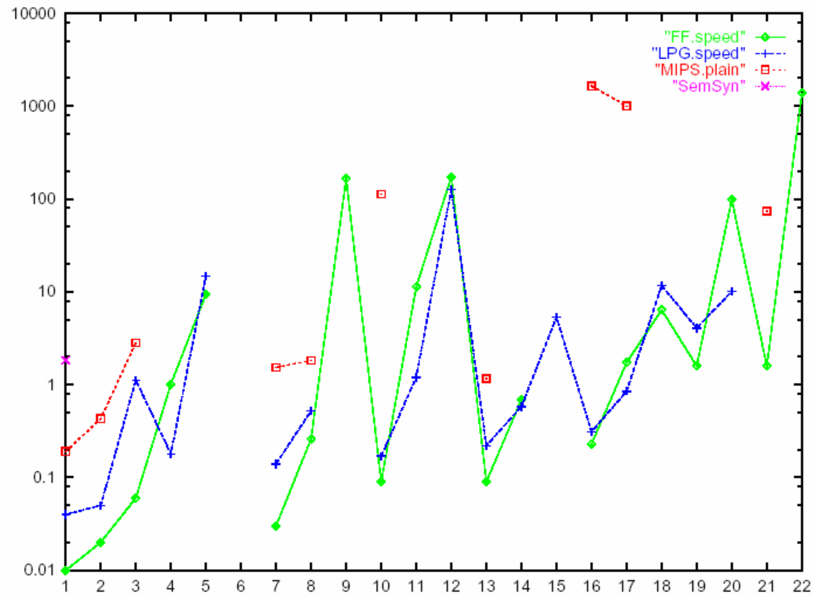


Figure 8: Runtime curves on *Depots* instances for the planners favoring speed. Time is shown on a logarithmic scale, instance size scales from left to right.

Planning With Resources Conclusion

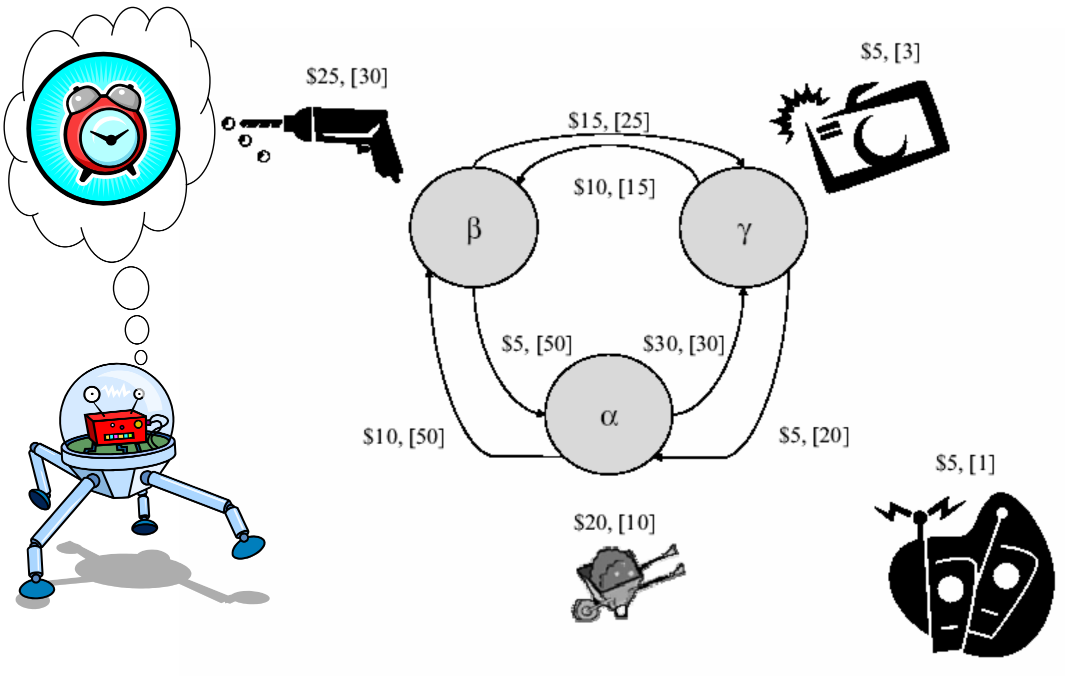
- Resource Intervals allow us to be optimistic about reachable values
  - Upper/Lower bounds can get large
- Relaxed Plans may require multiple supporters for subgoals
- Negative Interactions are much harder to capture

Temporal Planning

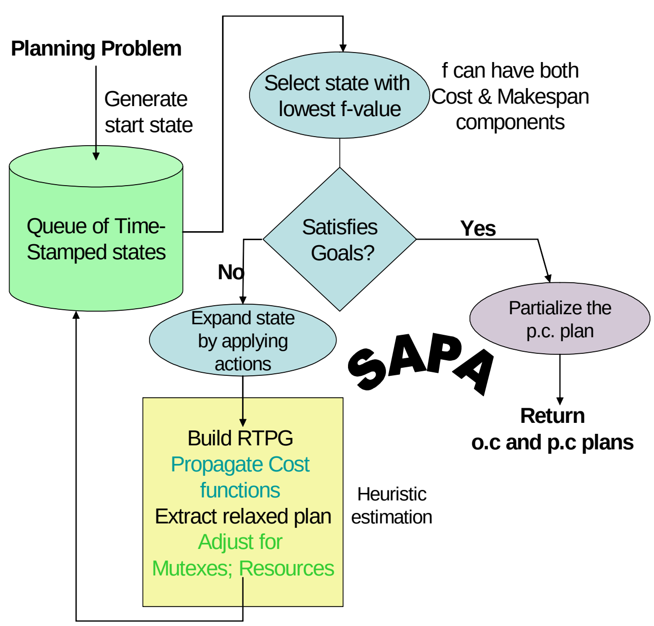
Temporal Planning

- Temporal Planning Graph
  - From Levels to Time Points
  - Delayed Effects
- Estimating Makespan
- Relaxed Plan Extraction

Rover with Durative Actions



SAPA



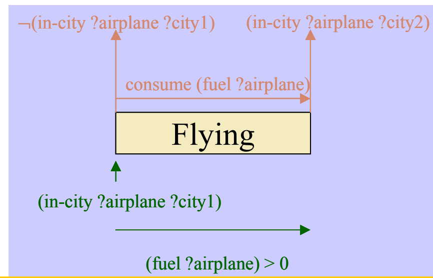
[ECP 2001; AIPS 2002; ICAPS 2003; JAIR 2003]

Search through time-stamped states

- **Goal Satisfaction**:
  $S=(P,M,\Pi,Q,t) \Rightarrow G$ if $\forall <p_i,t_i> \in G$ either:
  - $\exists <p_i,t_j> \in P$, $t_j < t_i$ and no event in Q deletes p_i.
  - $\exists e \in Q$ that adds p_i at time $t_e < t_i$.
- **Action Application**:
  Action A is applicable in S if:
  - All instantaneous preconditions of A are satisfied by P and M.
  - A's effects do not interfere with Π and Q.
  - No event in Q interferes with persistent preconditions of A.
  - A does not lead to concurrent resource change
- When A is applied to S:
  - P is updated according to A's instantaneous effects.
  - Persistent preconditions of A are put in Π
  - Delayed effects of A are put in Q.

$S=(P,M,\Pi,Q,t)$

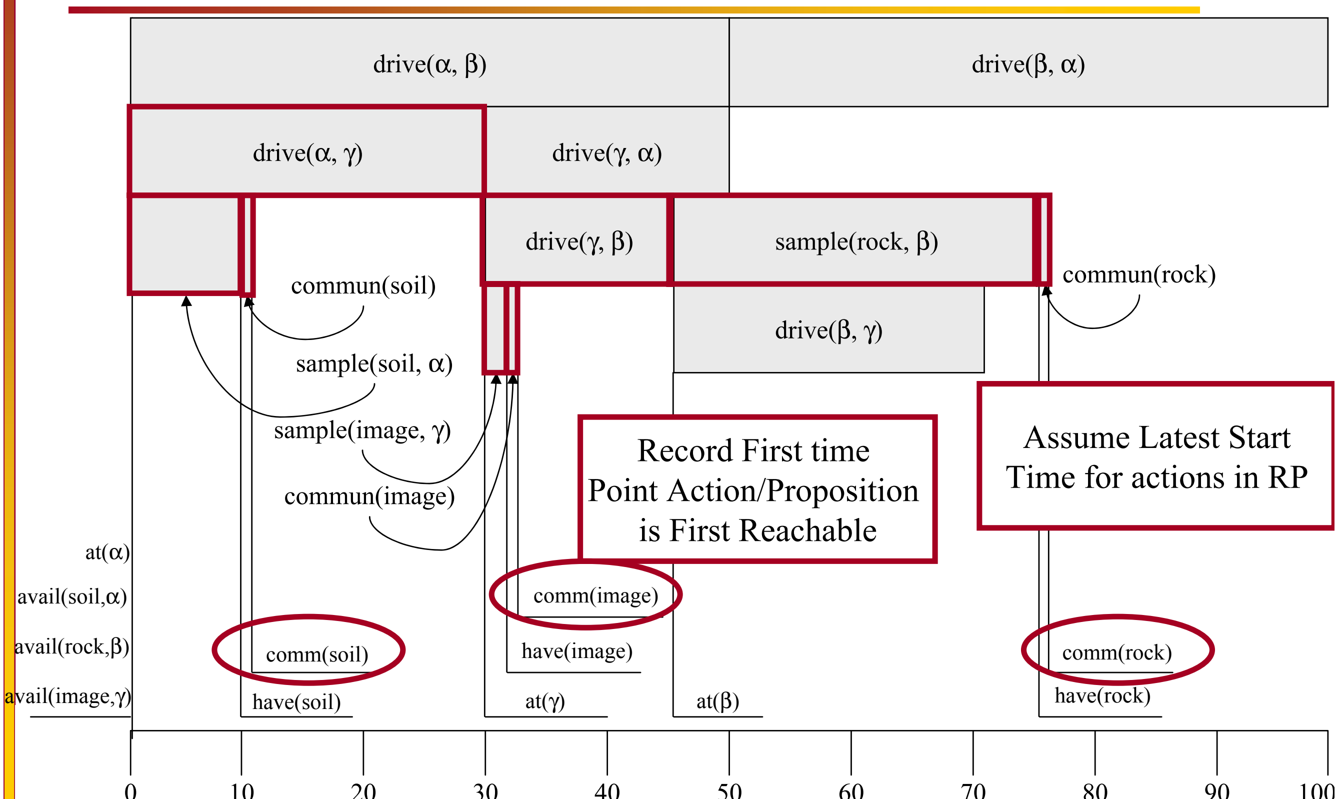
- Set <pi,ti> of predicates pi and the time of their last achievement $t_i < t$. (P)
- Set of functions represent resource values. (M)
- Set of protected persistent conditions (could be binary or resource conds). (Π)
- Event queue (contains resource as well As binary fluent events). (Q)
- Time stamp of S. (t)



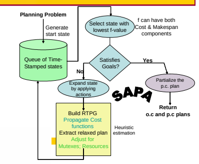
Search:

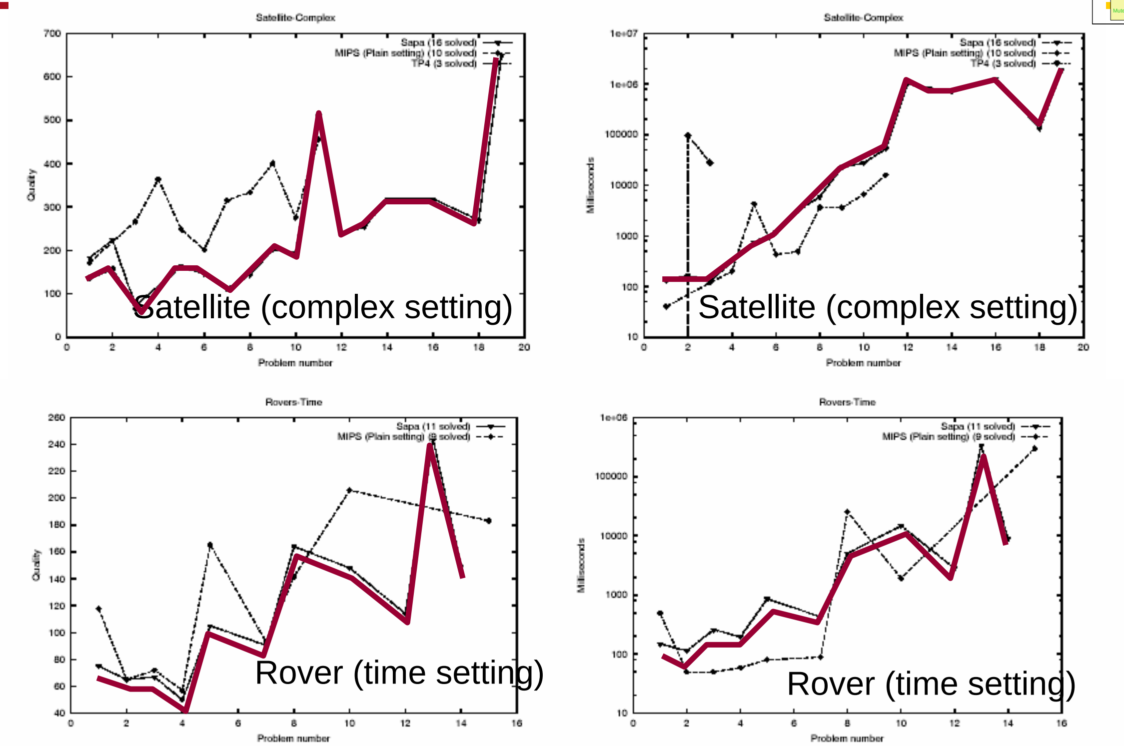
Pick a state S from the queue.
If S satisfies the goals, end
Else non-deterministically do one of
--Advance the clock
(by executing the earliest event in Qs
--Apply one of the applicable actions to S

Temporal Planning



SAPA at IPC-2002





[JAIR 2003]

Temporal Planning Conclusion

- Levels become Time Points
- Makespan and plan length/cost are different objectives
- Set-Level heuristic measures makespan
- Relaxed Plans measure makespan and plan cost

Non-Deterministic Planning

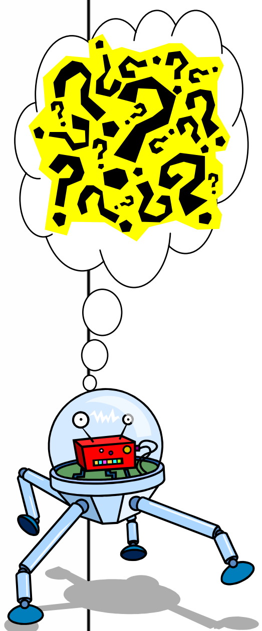
Non-Deterministic Planning

- Belief State Distance
- Multiple Planning Graphs
- Labelled Uncertainty Graph
- Implicit Belief states and the CFF heuristic

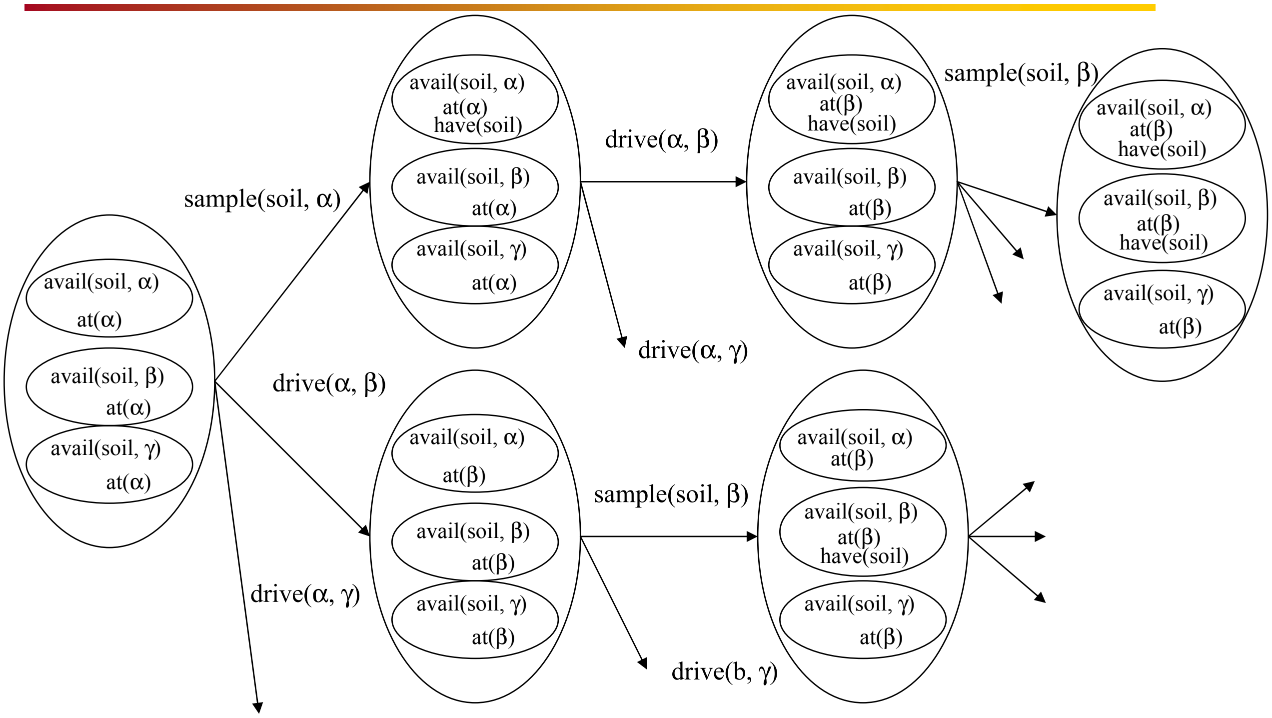
Conformant Rover Problem

```
(define (domain rovers_conformant)
  (:requirements :strips :typing)
  (:types waypoint data)
  (:predicates
          (at ?x - waypoint)
          (avail ?d - data ?x - waypoint)
          (comm ?d - data)
          (have ?d - data))
  (:action drive
   :parameters (?x ?y - waypoint)
   :precondition (at ?x)
   :effect (and (at ?y) (not (at ?x))))
  (:action commun
   :parameters (?d - data)
   :precondition (have ?d)
   :effect (comm ?d))
  (:action sample
   :parameters (?d - data ?x - waypoint)
   :precondition (at ?x)
   :effect (when (avail ?d ?x) (have ?d)))
)
```

```
(define (problem rovers_conformant1)
  (:domain rovers)
  (:objects
      soil image rock - data
      alpha beta gamma - waypoint)
  (:init (at alpha)
         (oneof (avail soil alpha)
                (avail soil beta)
                (avail soil gamma))
  (:goal (comm soil))
)
```

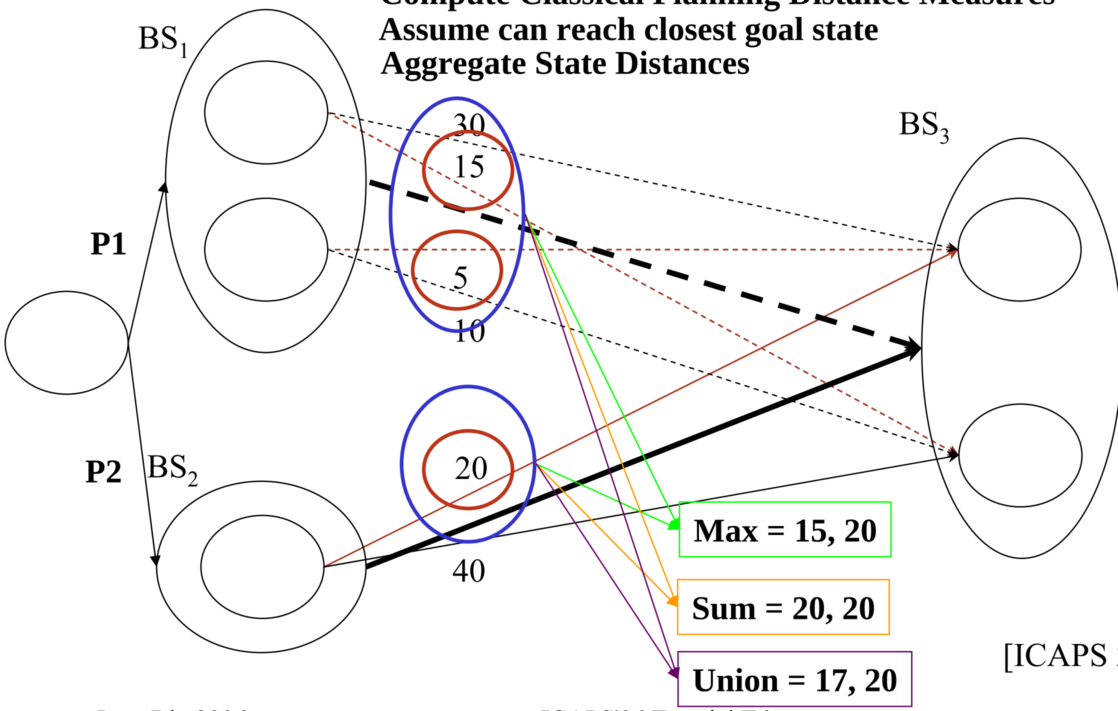


Search in Belief State Space



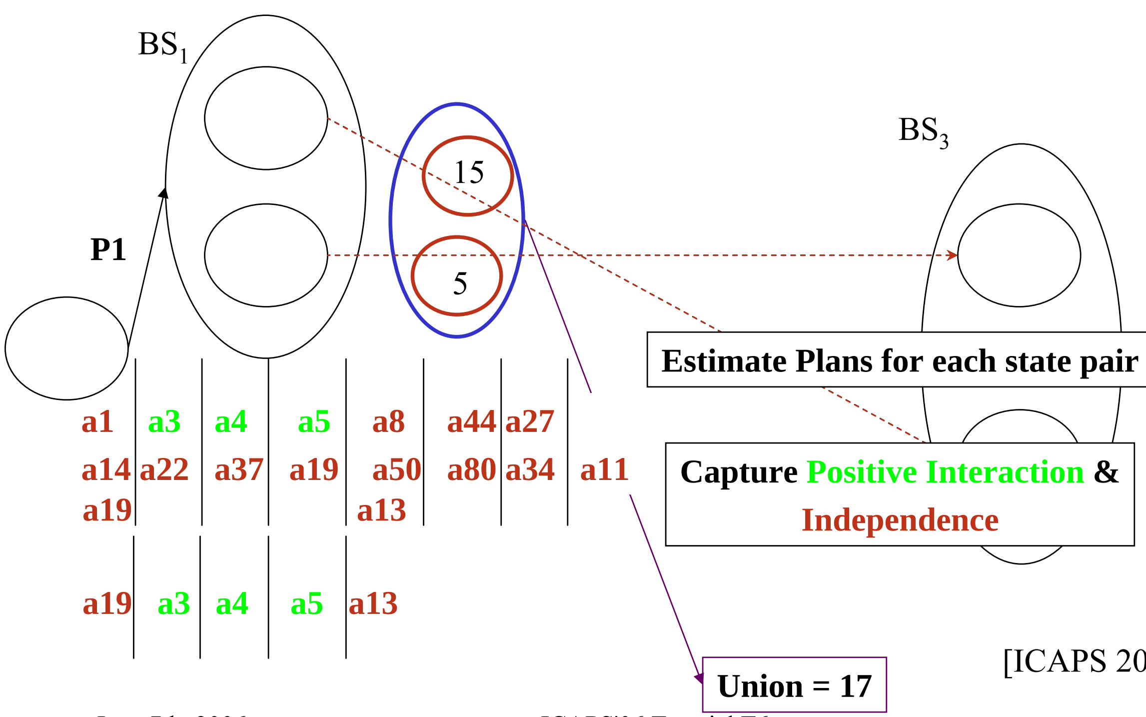
Belief State Distance

Compute Classical Planning Distance Measures
Assume can reach closest goal state
Aggregate State Distances



[ICAPS 2004]

Belief State Distance



[ICAPS 2004]

State Distance Aggregations

[Bryce *et.al*, 2005]

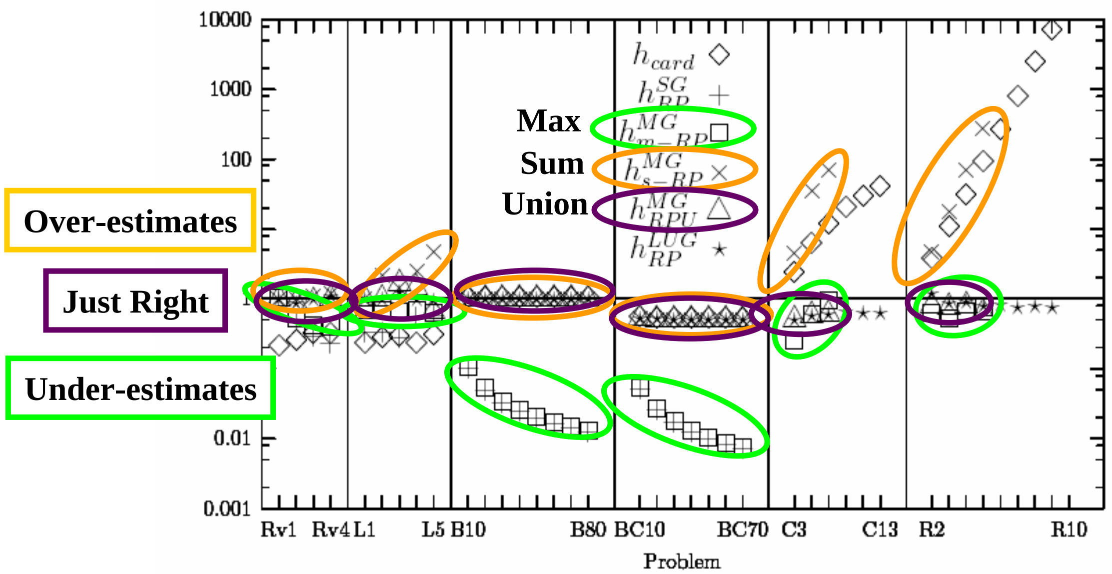
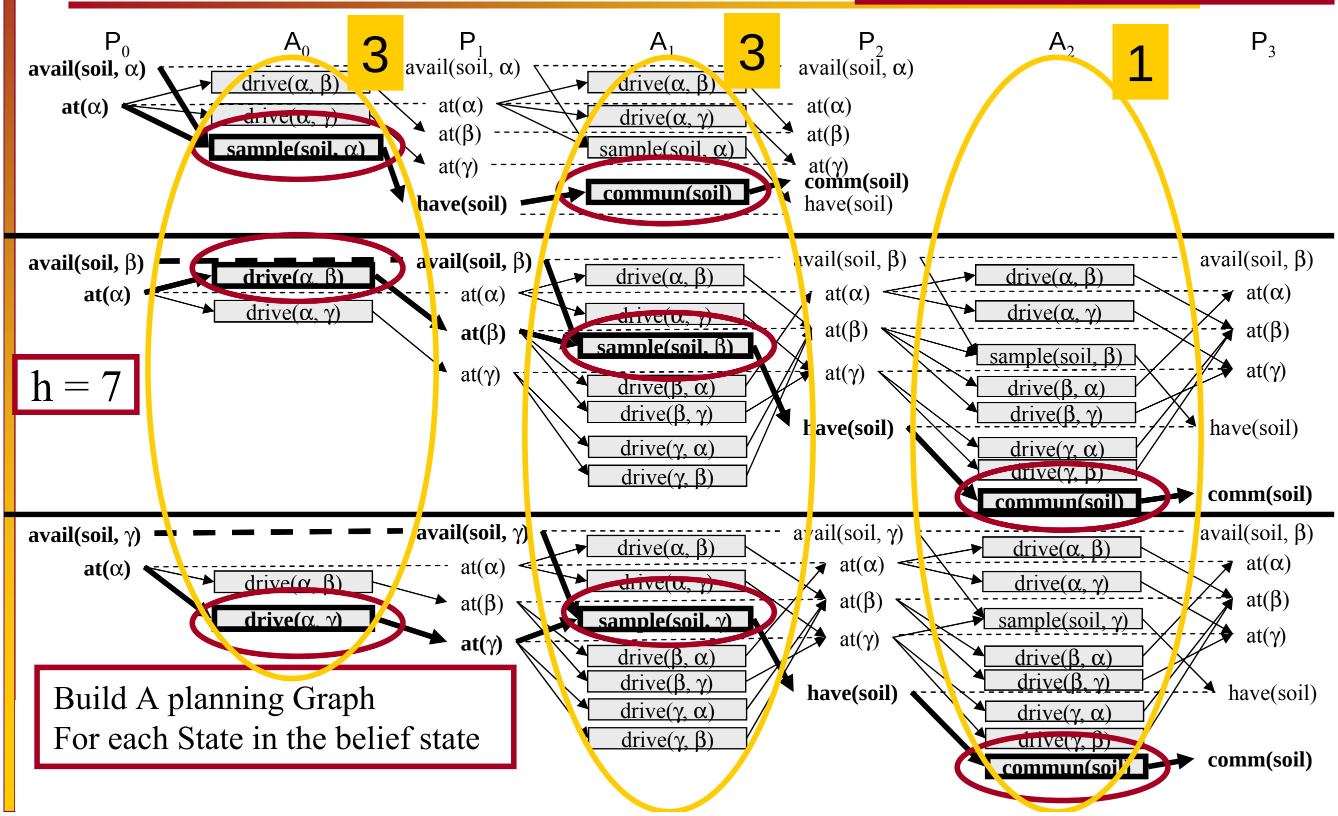


Figure 16: Ratio of heuristic estimates for distance between BS_I and BS_G to optimal plan length. Rv = Rovers, L = Logistics, B = BT, BC = BTC, C = Cube Center, R = Ring.

Multiple Planning Graphs

Extract Relaxed Plans from each

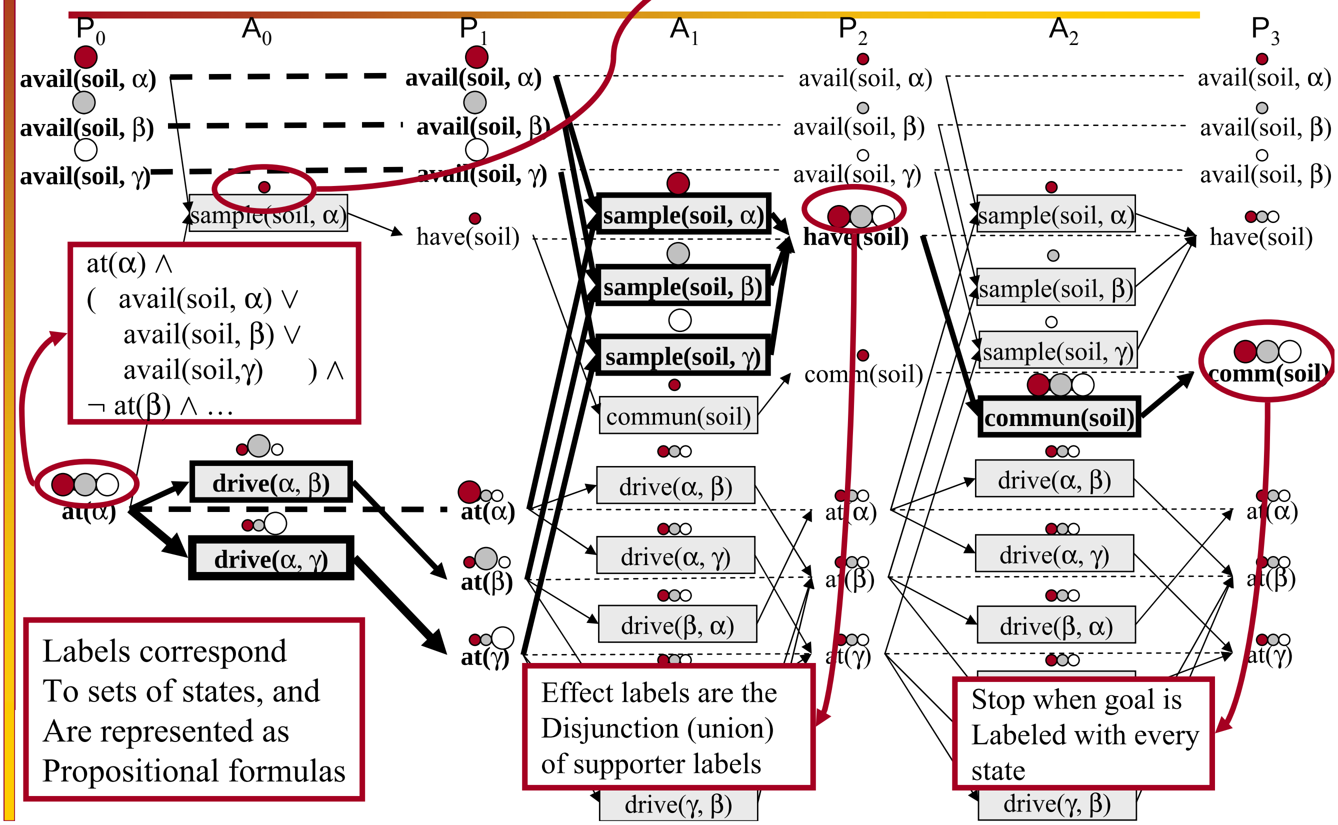
Step-wise union relaxed plans



Build A planning Graph
For each State in the belief state

Labelled Uncertainty Graph

Action labels are the Conjunction (intersection) of their Precondition labels



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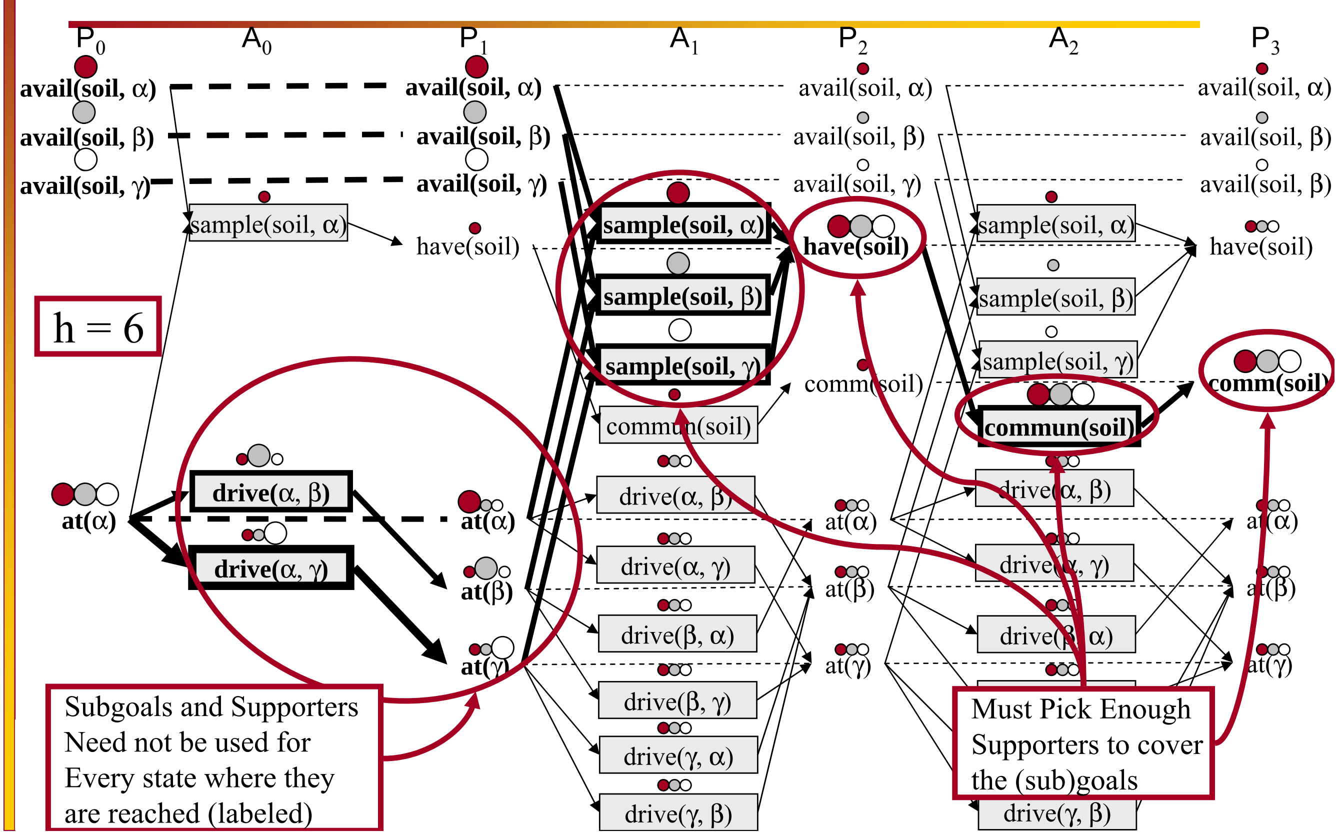
Labelled Relaxed Plan



Comparison of Planning Graph Types

[JAIR, 2006]

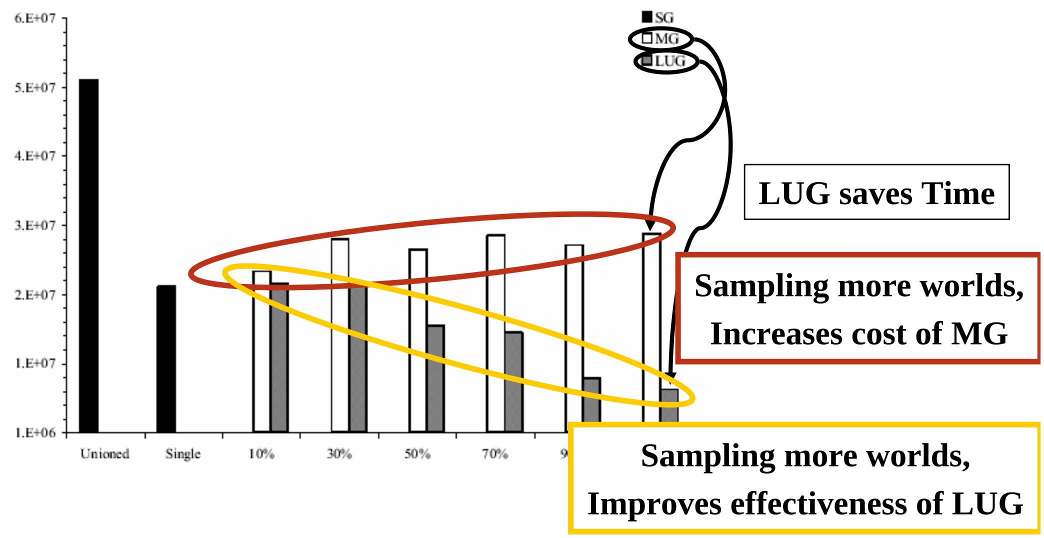


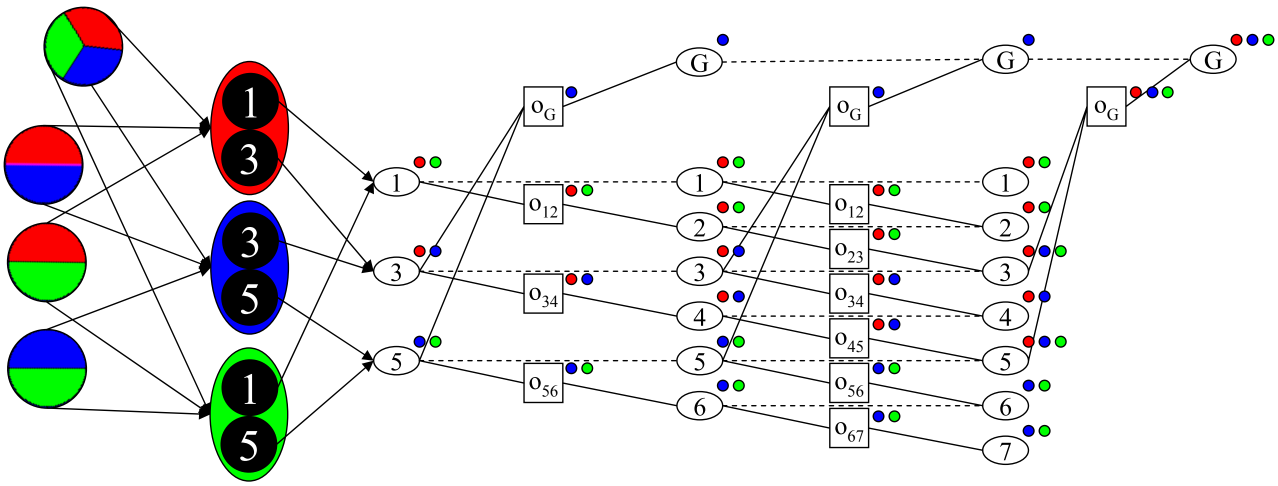
Figure 15: Total Time (ms) to solve all problems when sampling worlds to use in heuristic computation.

State Agnostic Planning Graphs (SAG)

- LUG represents multiple explicit planning graphs
- SAG uses LUG to represent a planning graph for every state
- The SAG is built once per search episode and we can use it for relaxed plans for every search node, instead of building a LUG at every node
- Extract relaxed plans from SAG by ignoring planning graph components not labeled by states in our search node.

SAG

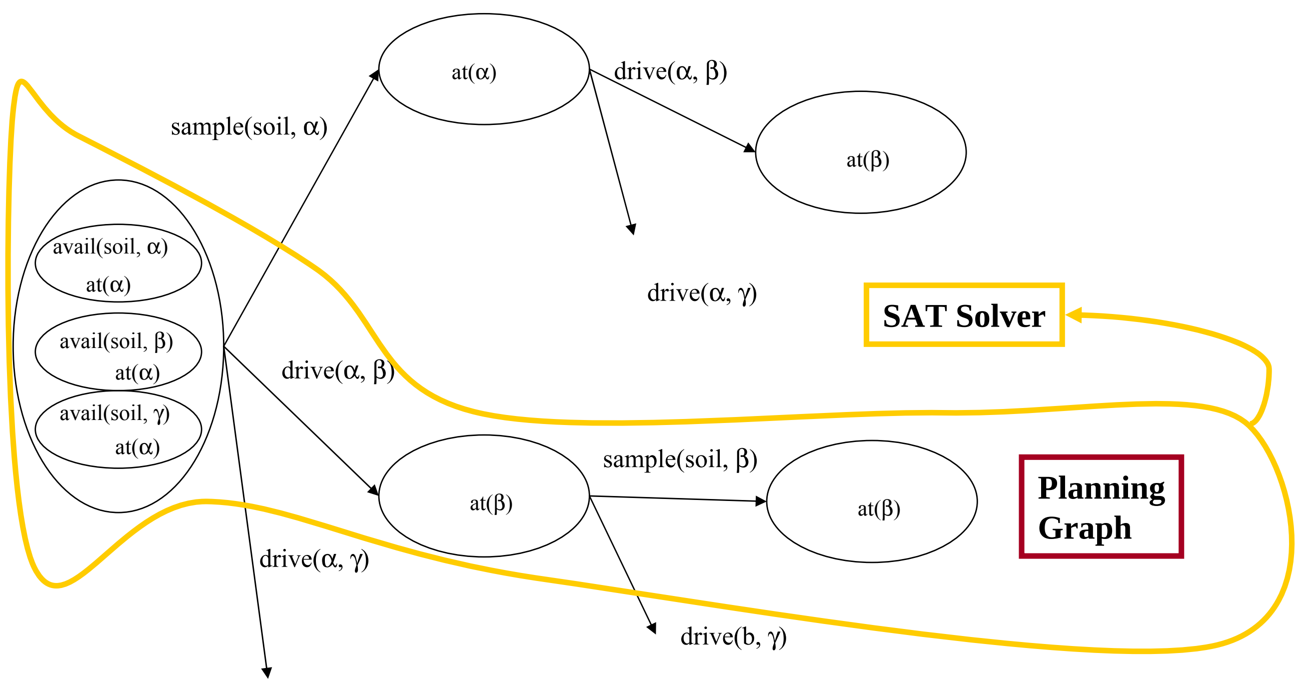
Build a LUG for all states (union of all belief states)

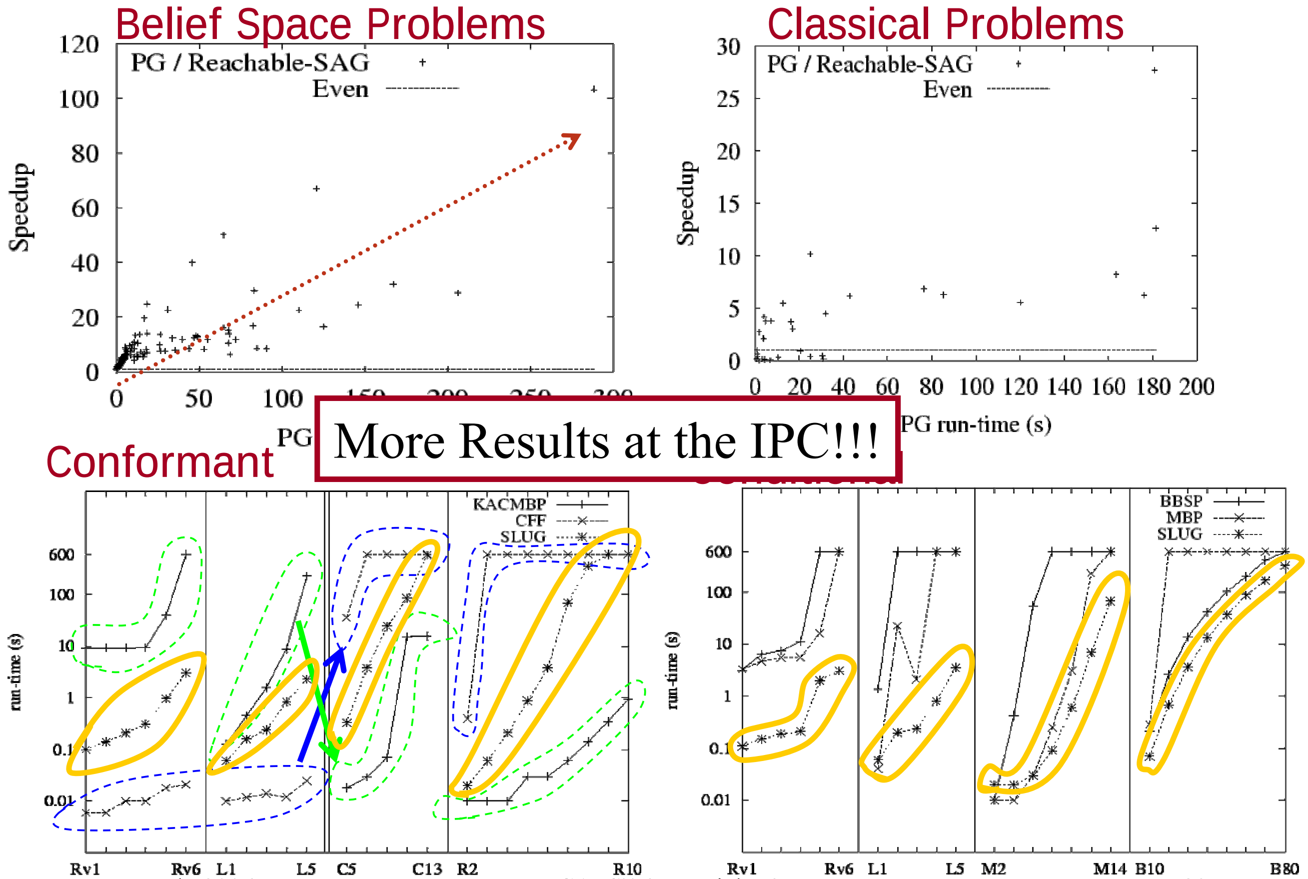


- Ignore irrelevant labels
- Largest LUG == all LUGs

[*AAAI*, 2005]

CFF (implicit belief states + PG)





Conditional Planning

- Actions have Observations
- Observations branch the plan because:
  - Plan Cost is reduced by performing less “just in case” actions – each branch performs relevant actions
  - Sometimes actions conflict and observing determines which to execute (e.g., medical treatments)
- We are ignoring negative interactions
  - We are only forced to use observations to remove negative interactions
  - Ignore the observations and use the conformant relaxed plan
    - Suitable because the aggregate search effort over all plan branches is related to the conformant relaxed plan cost

Non-Deterministic Planning Conclusions

- Measure positive interaction and independence between states co-transitioning to the goal via overlap
  - Labeled planning graphs and CFF SAT encoding efficiently measure conformant plan distance
- Conformant planning heuristics work for conditional planning without modification

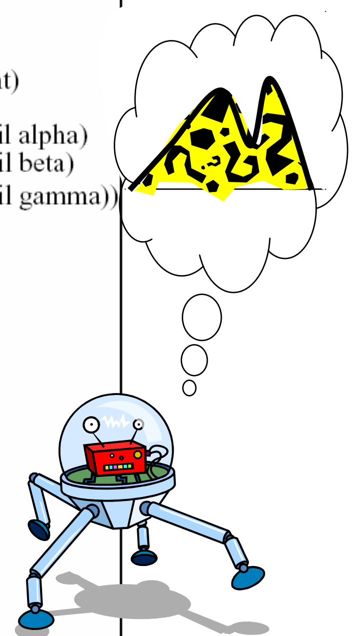
Stochastic Planning

Stochastic Rover Example

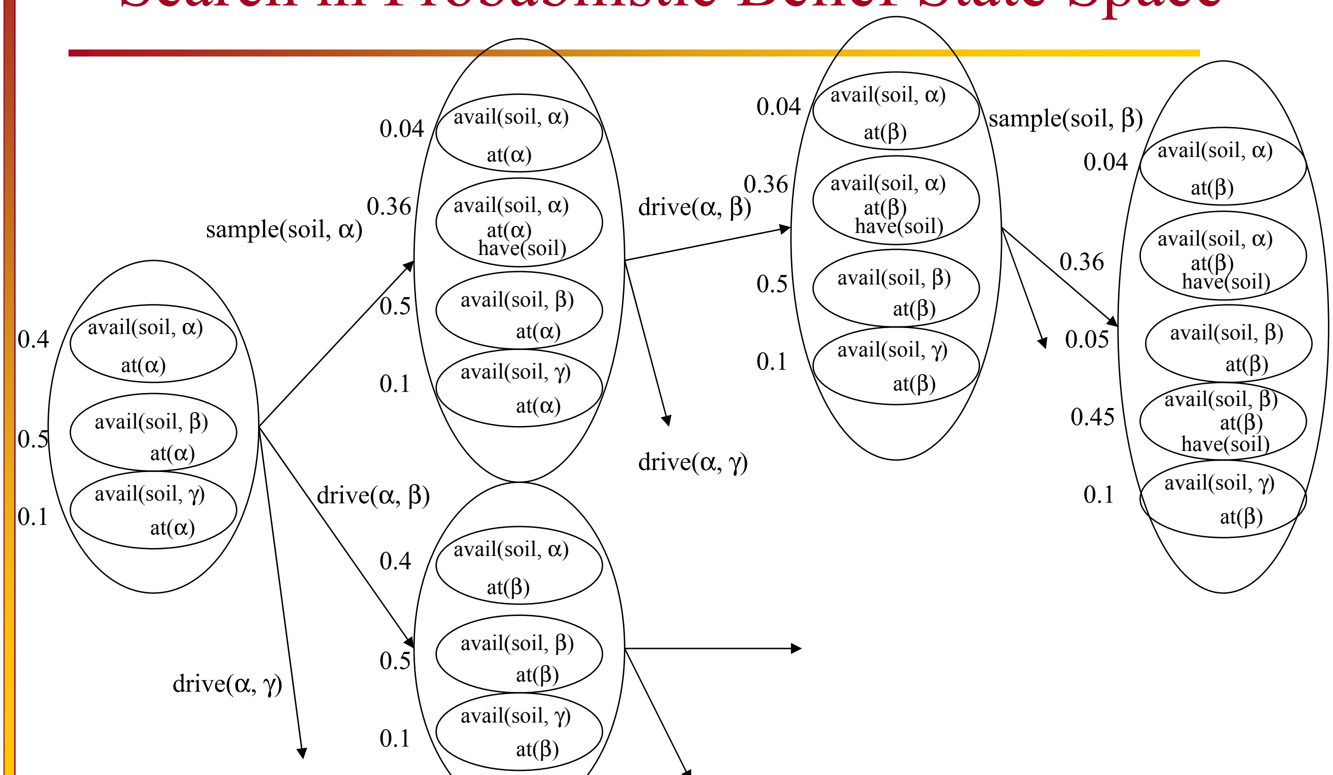
[ICAPS 2006]

```
(define (domain rovers_stochastic)
  (:requirements :strips :typing)
  (:types waypoint data)
  (:predicates
          (at ?x - waypoint)
          (avail ?d - data ?x - waypoint)
          (comm ?d - data)
          (have ?d - data))
  (:action drive
   :parameters (?x ?y - waypoint)
   :precondition (at ?x)
   :effect (and (at ?y) (not (at ?x))))
  (:action commun
   :parameters (?d - data)
   :precondition (have ?d)
   :effect (probabilistic 0.8 (comm ?d)))
  (:action sample
   :parameters (?d - data ?x - waypoint)
   :precondition (at ?x)
   :effect (when (avail ?d ?x)
                  (probabilistic 0.9 (have ?d))))
)
```

```
(define (problem rovers_stochastic1)
  (:domain rovers)
  (:objects
       soil image rock - data
       alpha beta gamma - waypoint)
  (:init (at alpha)
         (probabilistic 0.4 (avail soil alpha)
                        0.5 (avail soil beta)
                        0.1 (avail soil gamma)))
  (:goal (comm soil) 0.5)
)
```



Search in Probabilistic Belief State Space



Handling Uncertain Actions

[ICAPS 2006]

- Extending LUG to handle uncertain actions requires label extension that captures:
  - State uncertainty (as before)
  - Action outcome uncertainty
    - Problem: Each action at each level may have a different outcome. The number of uncertain events grows over time – meaning the number of joint outcomes of events grows exponentially with time
    - Solution: Not all outcomes are important. Sample some of them – keep number of joint outcomes constant.

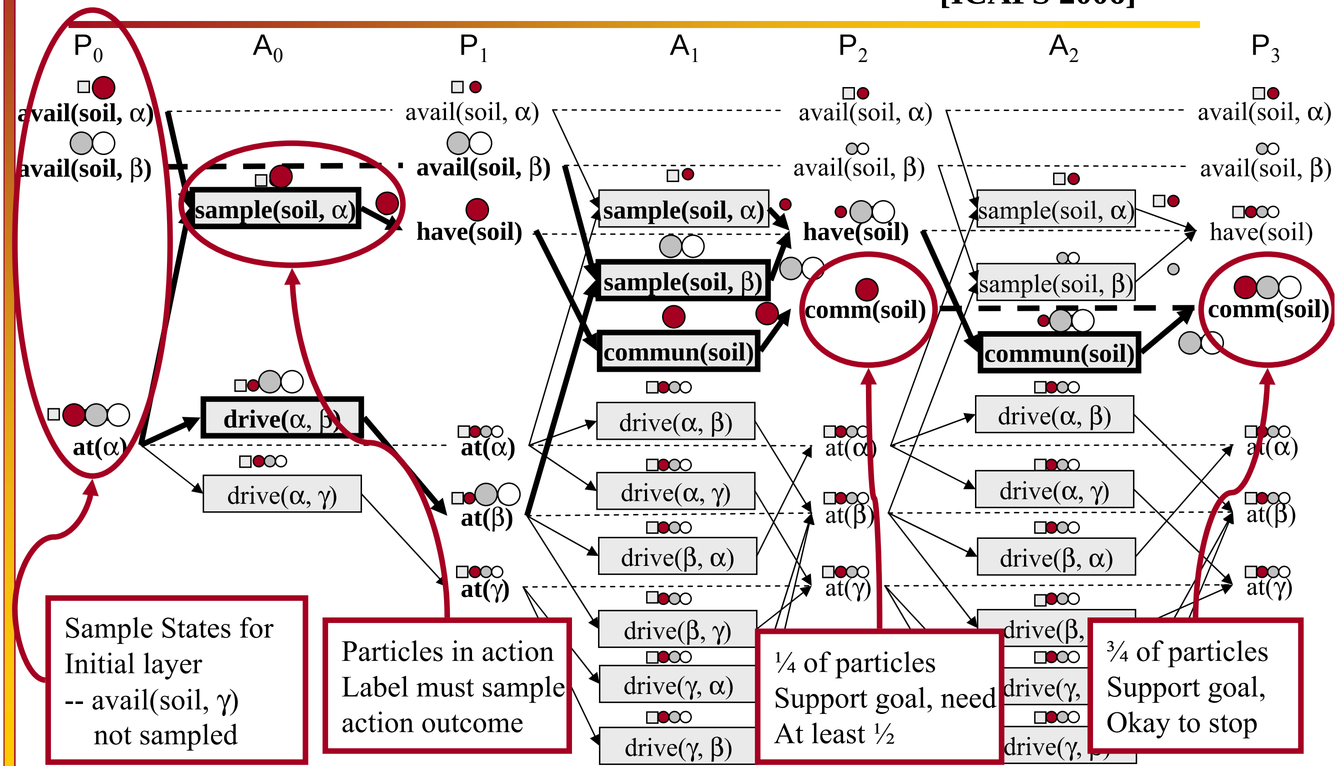
Monte Carlo LUG (McLUG)

[ICAPS 2006]

- Use Sequential Monte Carlo in the Relaxed Planning Space
  - Build several deterministic planning graphs by sampling states and action outcomes
  - Represent set of planning graphs using LUG techniques
    - Labels are sets of particles
    - Sample which Action outcomes get labeled with particles
    - Bias relaxed plan by picking actions labeled with most particles to prefer more probable support

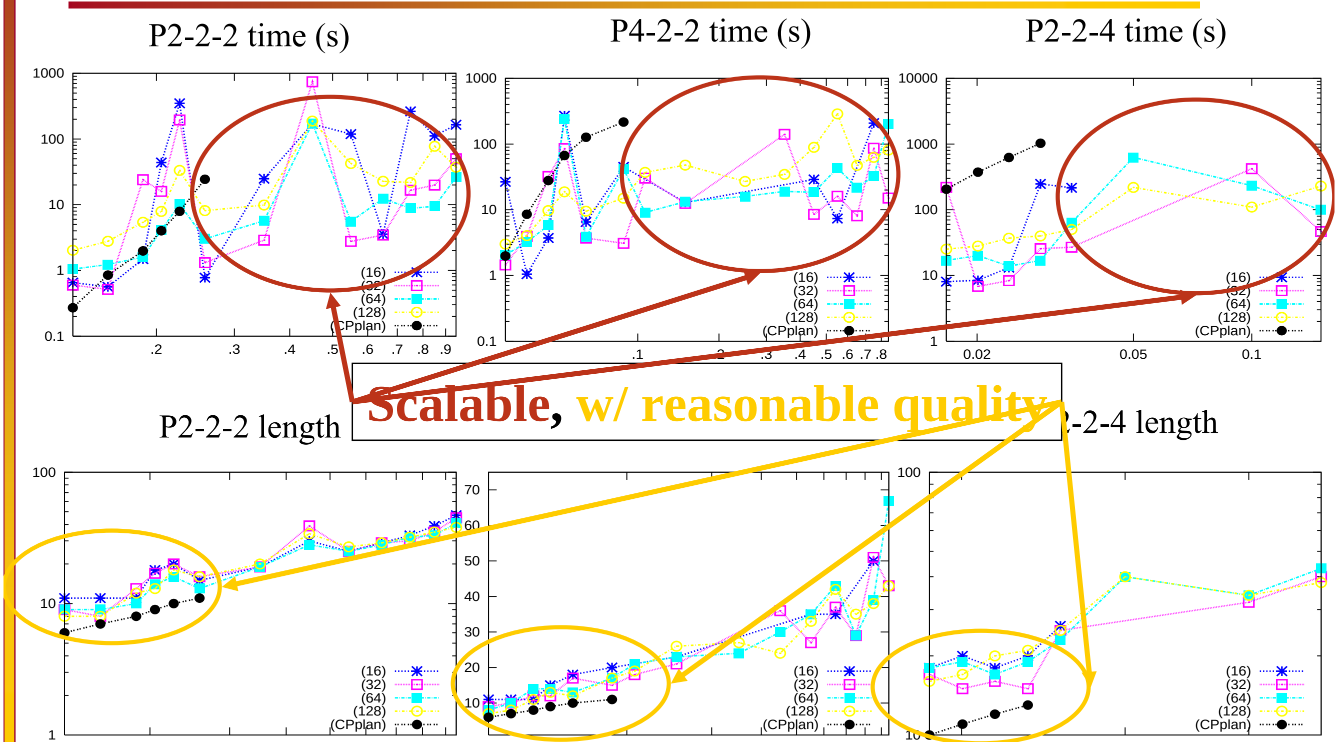
McLUG for rover example

[ICAPS 2006]



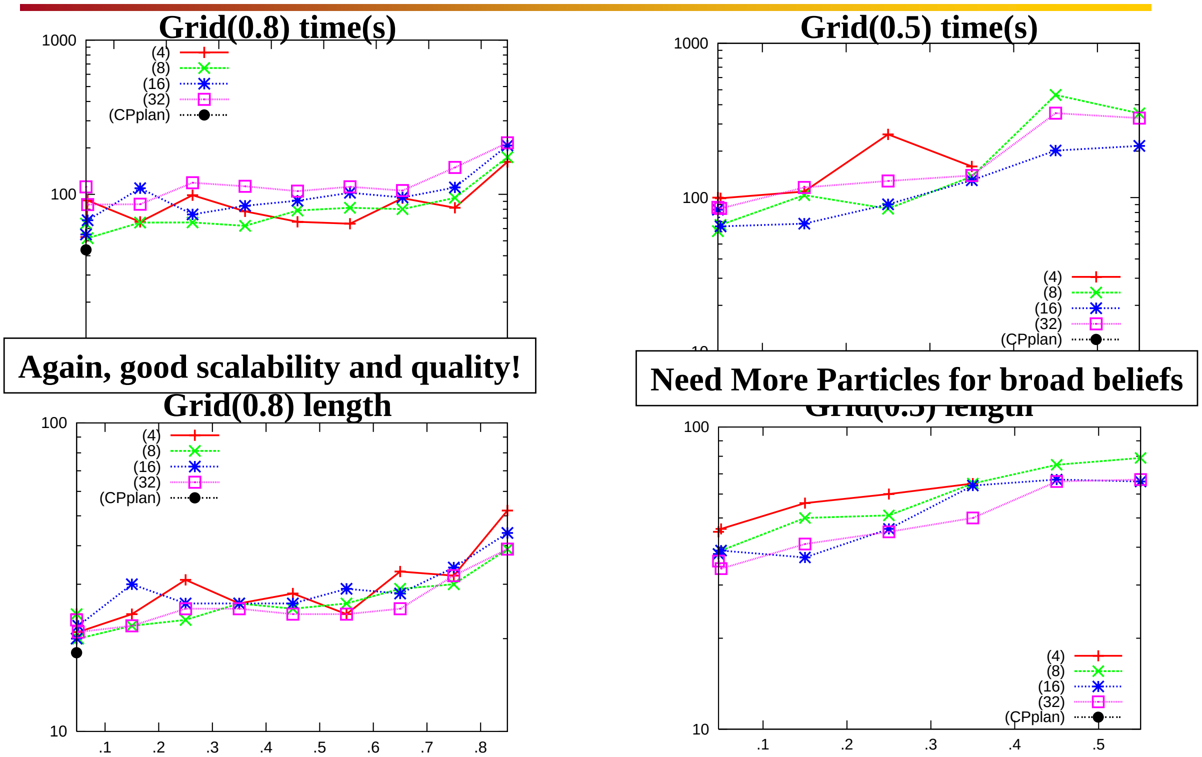
Logistics Domain Results

[ICAPS 2006]



Grid Domain Results

[ICAPS 2006]



Direct Probability Propagation

- Alternative to label propagation, we can propagate numeric probabilities
  - Problem: Numeric Propagation tends to assume only independence or positive interaction between actions and propositions.
    - With probability, we can vastly under-estimate the probability of reaching propositions
  - Solution: Propagate Correlation – measures pair-wise independence/pos interaction/neg interaction
    - Can be seen as a continuous mutex

Correlation

- $C(x, y) = Pr(x, y)/(Pr(x)Pr(y))$
- If :
  - $C(x, y) = 0$, then x, y are mutex
  - $0 < C(x, y) < 1$, then x, y interfere
  - $C(x, y) = 1$, then x, y are independent
  - $1 < C(x, y) < 1/Pr(x)$, then x, y synergize
  - $C(x, y) = 1/Pr(x) = 1/Pr(y)$, then x, y are completely correlated

Probability of a set of Propositions

- $Pr(x1, x2, \ldots, xn) = \Pi_{i=1..n} Pr(xi|x1 \ldots xi\text{-}1)$ **Chain Rule**
  - $Pr(xi|x1 \ldots xi\text{-}1) = \frac{Pr(x1 \ldots xi\text{-}1 \mid xi)\, Pr(xi)}{Pr(x1 \ldots xi\text{-}1)}$ **Bayes Rule**

$$\approx \frac{Pr(x1|xi) \ldots Pr(xi\text{-}1|xi)Pr(xi)}{Pr(x1) \ldots Pr(xi\text{-}1)}$$ **Assume Independence**

$$= \frac{Pr(xi|x1)}{Pr(xi)} \ldots \frac{Pr(xi|xi\text{-}1)}{Pr(xi)} Pr(xi)$$ **Bayes Rule**

$$= Pr(xi)\, C(xi, x1) \ldots C(xi, xi\text{-}1)$$ **Correlation**

$$= Pr(xi)\, \Pi_{j = 1..i-1} C(xi, xj)$$

- $Pr(x1, x2, \ldots, xn) = \Pi_{i=1..n} Pr(xi)\, \Pi_{j = 1..i-1} C(xi, xj)$

Probability Propagation

- The probability of an Action being enabled is the probability of its preconditions (a set of propositions).
- The probability of an effect is the product of the action probability and outcome probability
- A single (or pair of) proposition(s) has probability equal to the probability it is given by the best set of supporters.
- The probability that a set of supporters gives a proposition is the sum over the probability of all possible executions of the actions.

Results

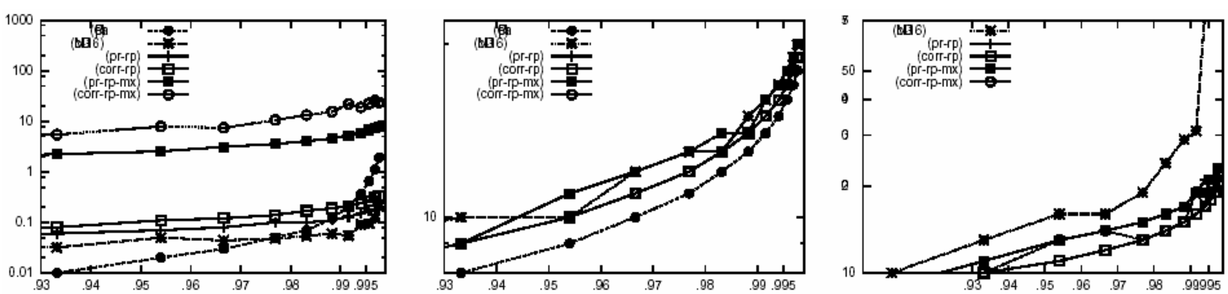


Figure 2: *Run times (s), Plan lengths, and Expanded Nodes vs. probability threshold for sandcastle-67*

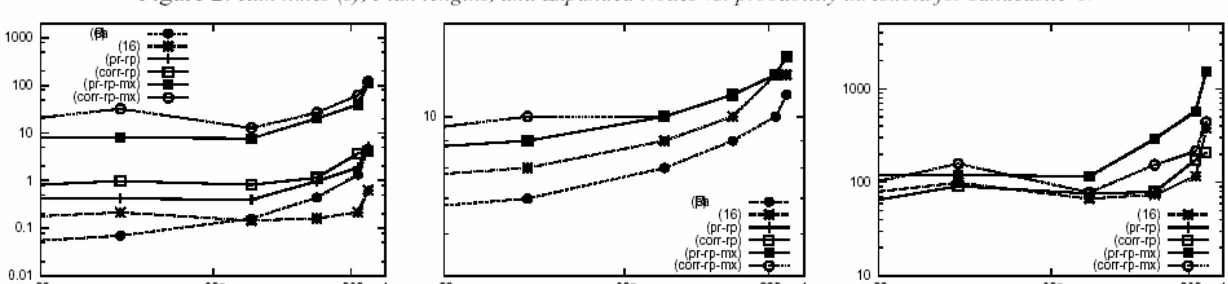


Figure 3: *Run times (s), Plan lengths, and Expanded Nodes vs. probability threshold for slippery gripper*

Stochastic Planning Conclusions

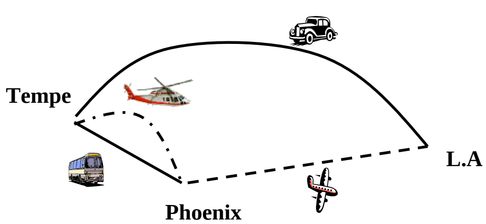
- Number of joint action outcomes too large
  - Sampling outcomes to represent in labels is much faster than exact representation
- SMC gives us a good way to use multiple planning graph for heuristics, and the McLUG helps keep the representation small
- Numeric Propagation of probability can better capture interactions with correlation
  - Can extend to cost and resource propagation

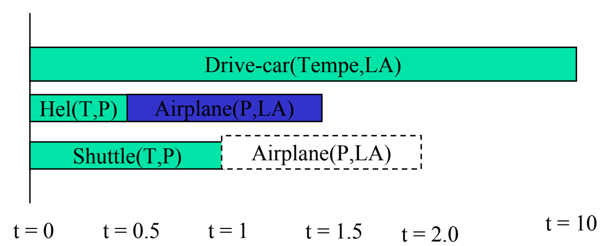
Hybrid Planning Models

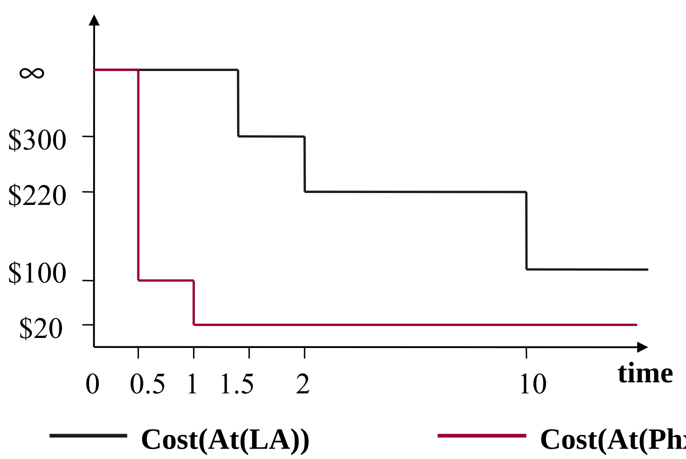
Hybrid Models

- Metric-Temporal w/ Resources (SAPA)
- Temporal Planning Graph w/ Uncertainty (Prottle)
- PSP w/ Resources (SAPA^{MPS})
- Cost-based Conditional Planning (CLUG)

Propagating Temporal Cost Functions







Shuttle(Tempe,Phx):
Cost: $20; Time: 1.0 hour
Helicopter(Tempe,Phx):
Cost: $100; Time: 0.5 hour
Car(Tempe,LA):
Cost: $100; Time: 10 hour
Airplane(Phx,LA):
Cost: $200; Time: 1.0 hour

Heuristics based on cost functions

Direct

- If we want to minimize makespan:
  - $h = t_0$
- If we want to minimize cost
  - $h = CostAggregate(G, t_\infty)$
- If we want to minimize a function f(time,cost) of cost and makespan
  - $h = \min f(t, Cost(G,t))$ s.t. $t_0 \le t \le t_\infty$
    - E.g. f(time,cost) = 100.makespan + Cost then h = 100x2 + 220 at $t_0 \le t = 2 \le t_\infty$

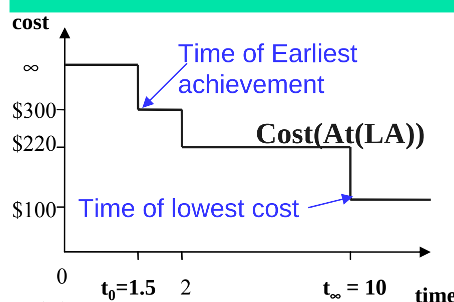
Using Relaxed Plan

- Extract a relaxed plan using h as the bias
  - If the objective function is f(time,cost), then action A (to be added to RP) is selected such that:

    f(t(RP+A),C(RP+A)) + f(t(G_{new}),C(G_{new}))

    is minimal

$G_{new} = (G \cup Precond(A)) \setminus Effects)$



Phased Relaxation

The relaxed plan can be adjusted to take into account constraints that were originally ignored

Adjusting for Mutexes:

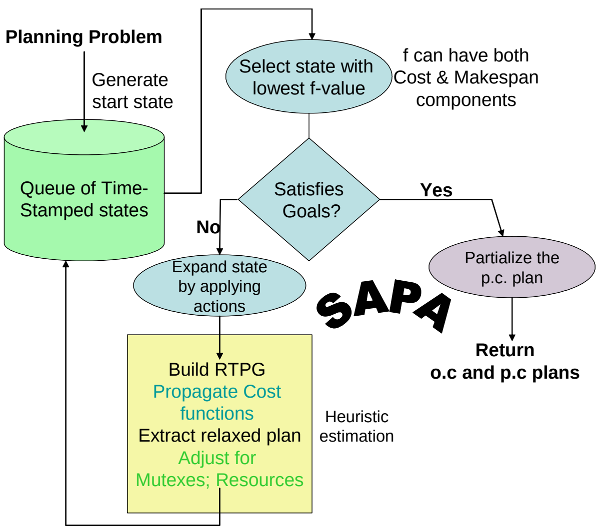
Adjust the make-span estimate of the relaxed plan by marking actions that are mutex (and thus cannot be executed concurrently

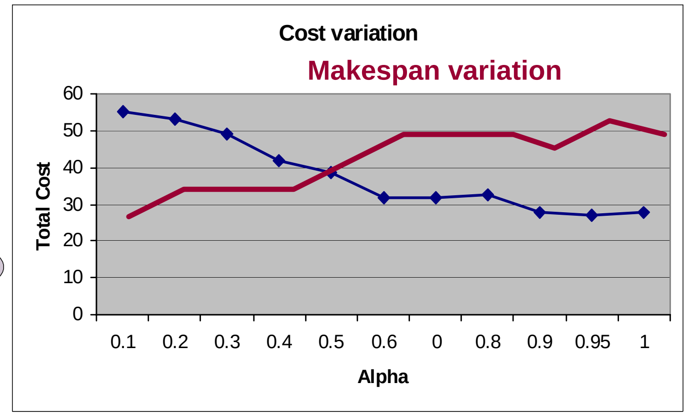
Adjusting for Resource Interactions:

Estimate the number of additional resource-producing actions needed to make-up for any resource short-fall in the relaxed plan

$$C = C + \Sigma_R \lceil (Con(R) - (Init(R)+Pro(R)))/\Delta_R \rceil * C(A_R)$$

Handling Cost/Makespan Tradeoffs





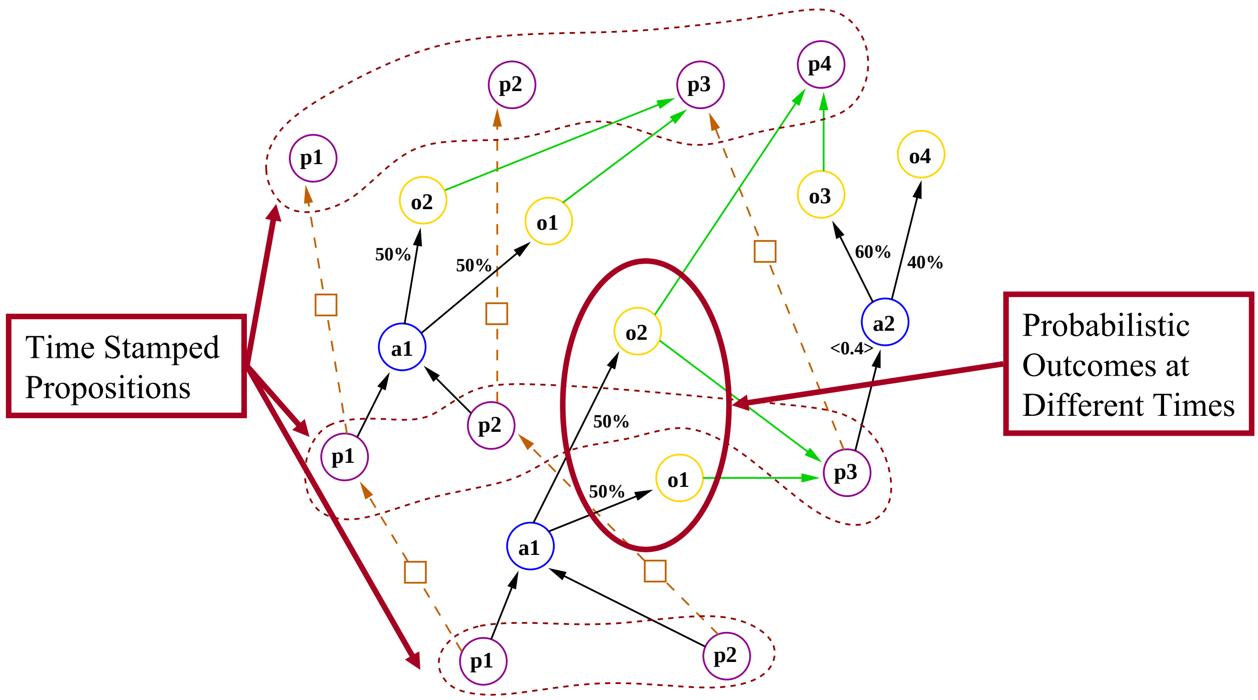
Results over 20 randomly generated temporal logistics problems involve moving 4 packages between different locations in 3 cities:

$$O = f(time,cost) = \alpha.Makespan + (1- \alpha).TotalCost$$

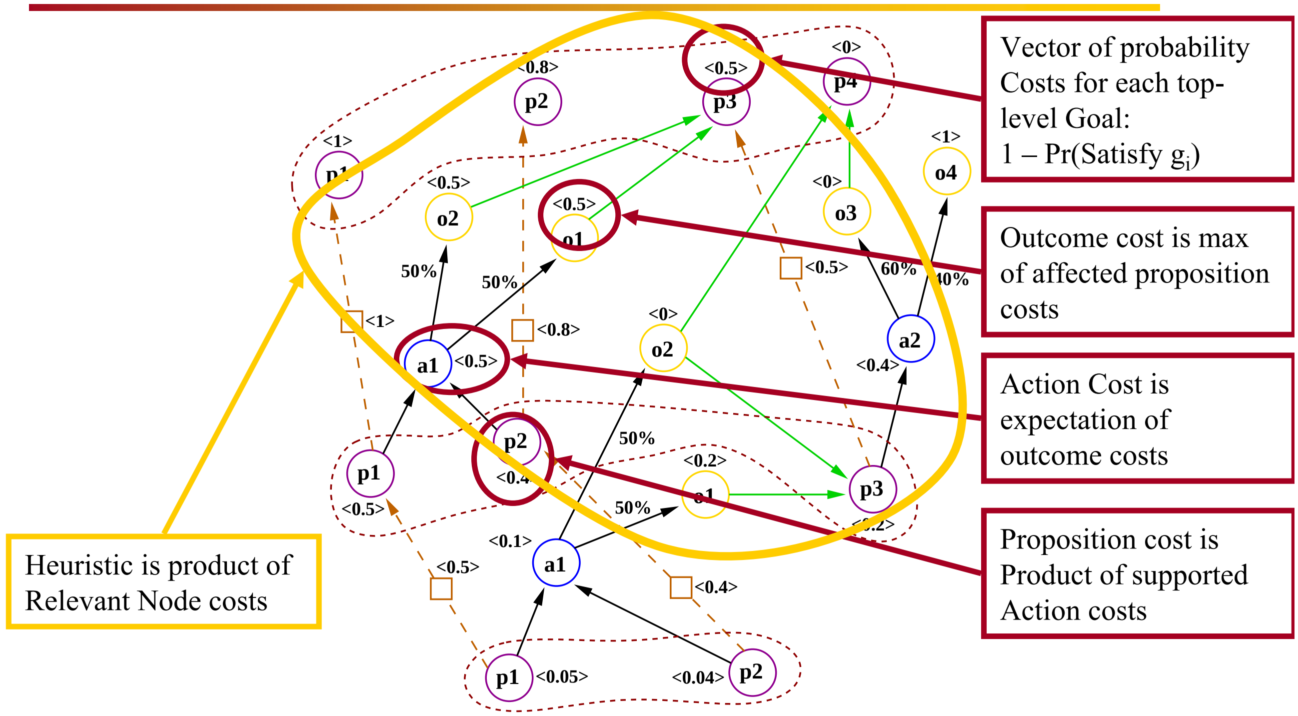
Prottle

- SAPA-style (time-stamped states and event queues) search for fully-observable conditional plans using L-RTDP
- Optimize probability of goal satisfaction within a given, finite makespan
- Heuristic estimates probability of goal satisfaction in the plan suffix

Prottle planning graph



Probability Back-Propagation



Prottle Results

problem	horizon	ε	time1	time2	cost1	cost2	states1	states2
AI	100	0.3	-	103	-	0.344	-	346,100
AI	120	0.6	-	404	-	0.222	-	1,319,229
MS	15	0.0	-	272	-	0.027	-	496,096
MS	15	0.1	-	171	-	0.114	-	309,826
MS	15	0.2	2,431	21	0.119	0.278	13,627,753	6,759
MS	15	0.3	367	235	0.278	0.278	1,950,134	434,772
MZ	10	0.0	195	10	0.178	0.178	1,374,541	13,037
MZ	**10**	**0.1**	**185**	**2**	**0.193**	**0.178**	**1,246,159**	**2,419**
MZ	10	0.2	64	1	0.197	0.193	436,876	669
MZ	10	0.3	62	2	0.202	0.193	414,414	1,812
TP	20	0.0	442	< 1	0.798	0.798	3,565,698	3,676
TP	20	0.1	456	< 1	0.798	0.798	3,628,300	2,055
TP	20	0.2	465	< 1	0.798	0.798	3,672,348	2,068
TP	20	0.3	464	< 1	1.000	0.798	3,626,404	1,256

PSP w/ Resources

- Utility and Cost based on the values of resources
- Challenges:
  - Need to propagate cost for resource intervals
  - Need to support resource goals at different levels

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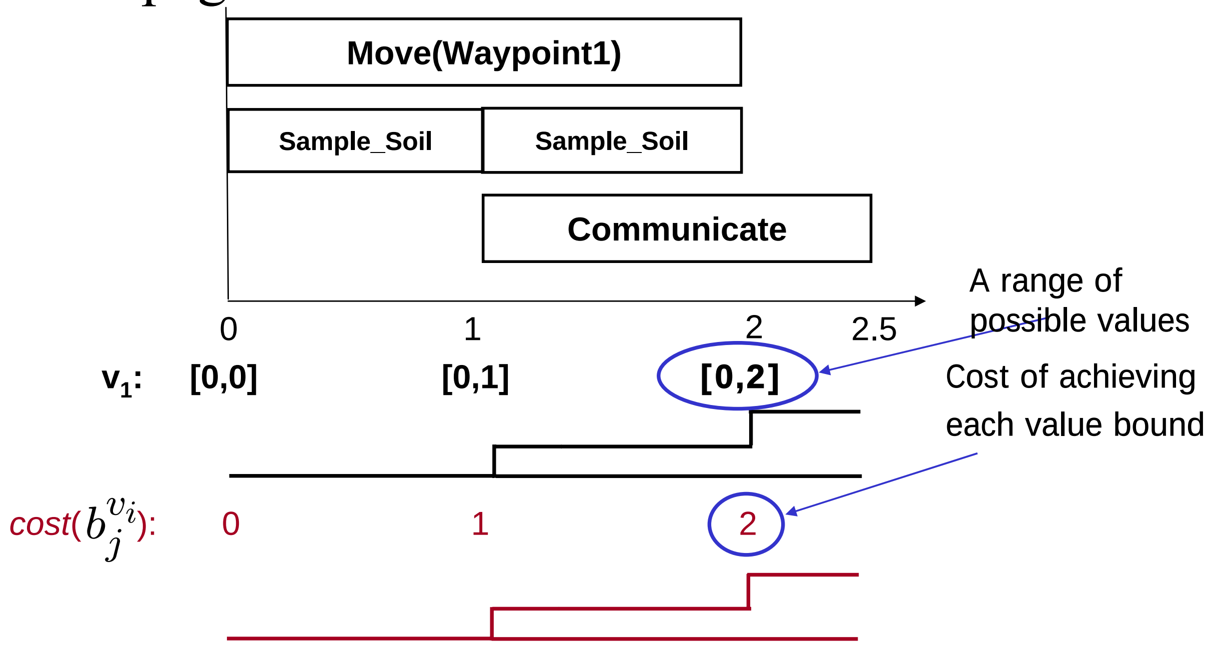
Resource Cost Propagation

- Propagate reachable values with cost



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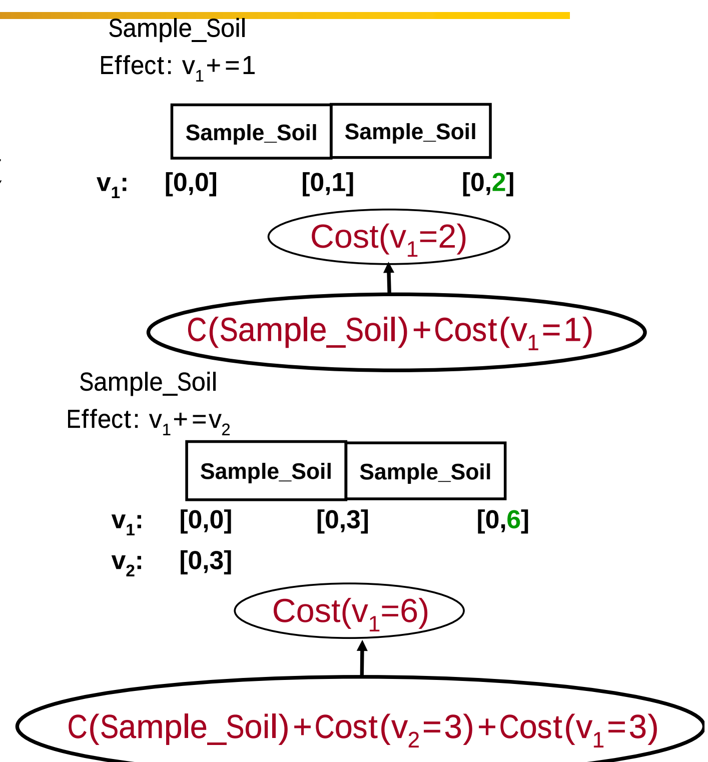
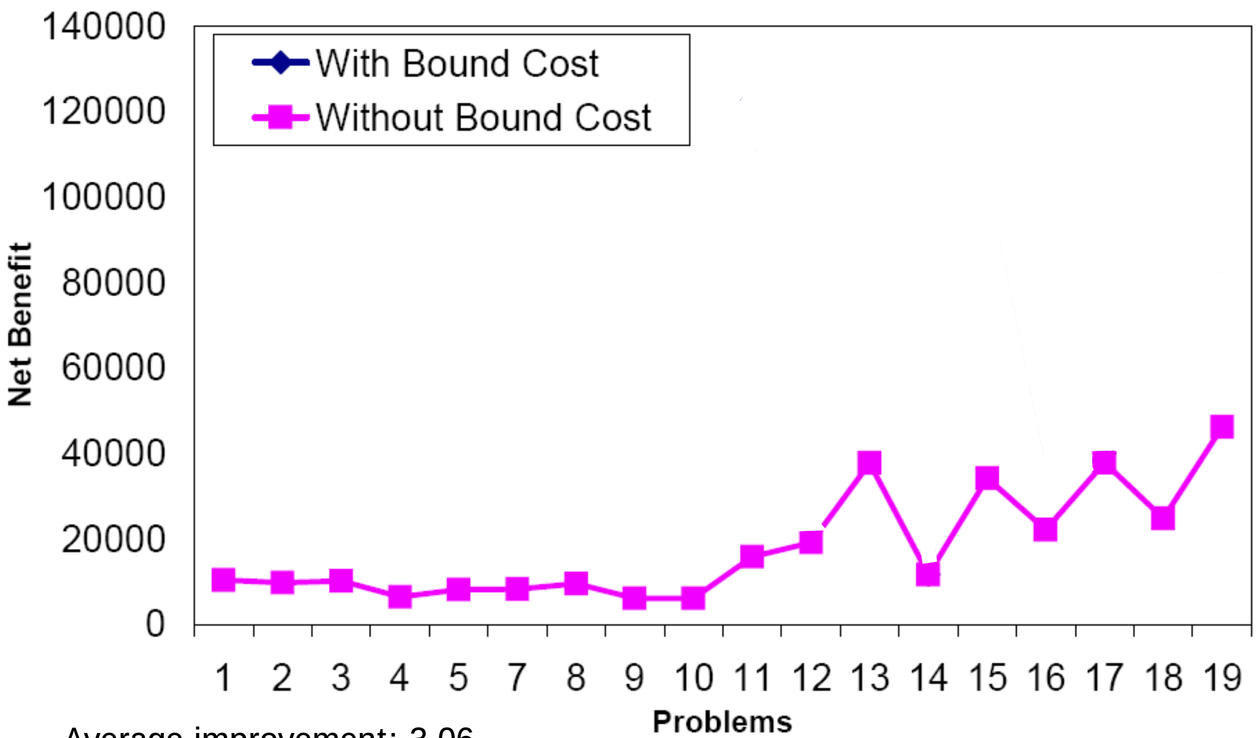
Cost Propagation on Variable Bounds

- Bound cost dependent upon
  - action cost
  - previous bound cost - current bound cost adds to the next
    - Cost of all bounds in expressions

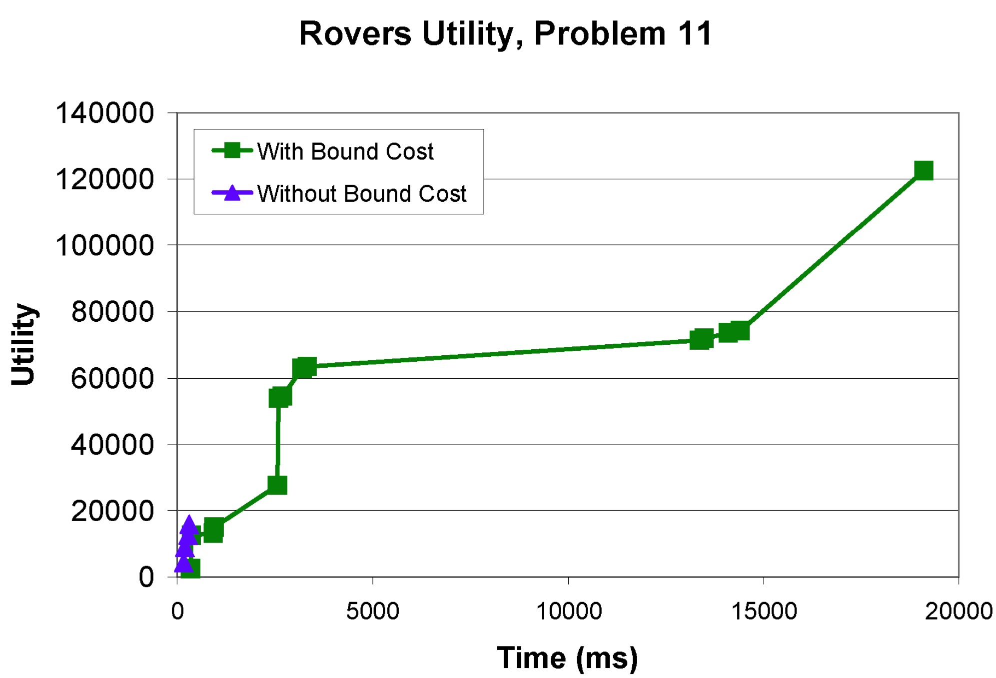


Results – *Modified* Rovers (numeric soil)

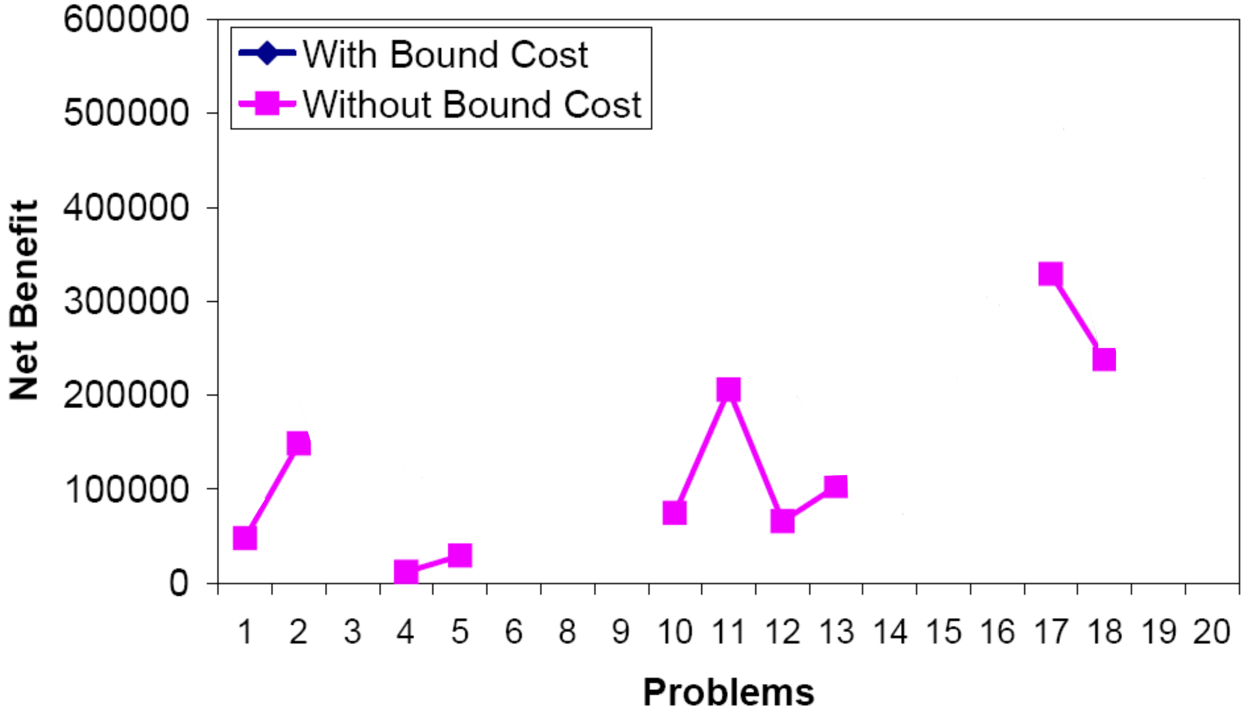


Average improvement: 3.06

Anytime A* Search Behavior



Results – *Modified* Logistics (#of packages)

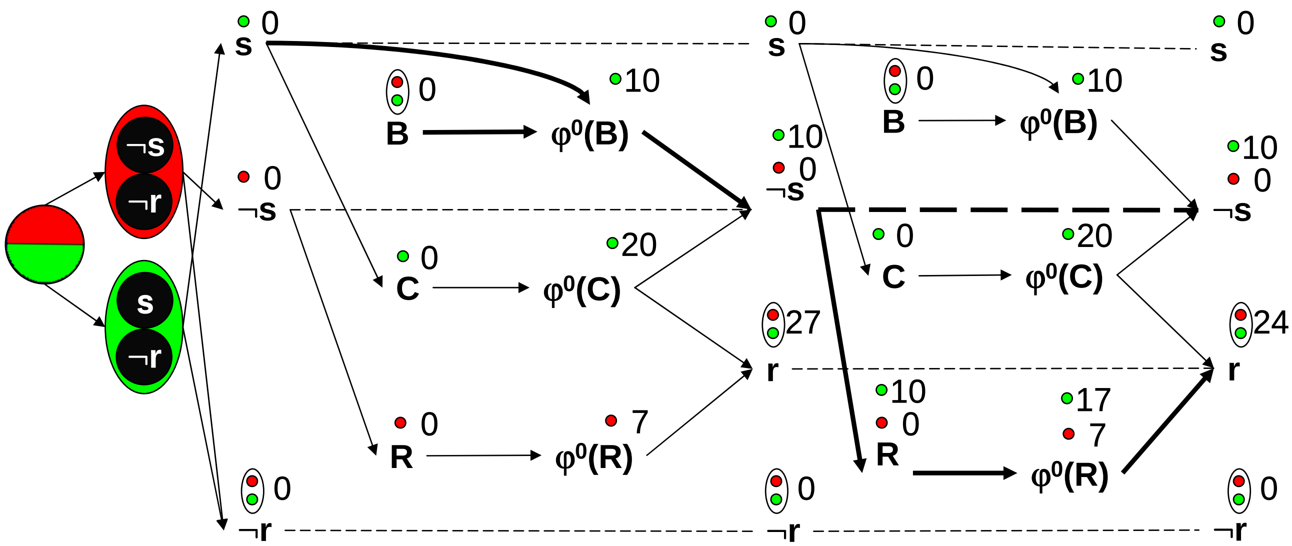


Average improvement: 2.88

Cost-Based Conditional Planning

- Actions may reduce uncertainty, but cost a lot
  - Do we want more "just in case" actions that are cheap, or less that are more expensive
- Propagate Costs on the LUG (CLUG)
  - Problem: LUG represents multiple explicit planning graphs and the costs can be different in each planning graph.
    - A single cost for every explicit planning assumes full positive interaction
    - Multiple costs, one for each planning graph is too costly
  - Solution: Propagate cost for partitions of the explicit planning graphs

Cost Propagation on the LUG (CLUG)



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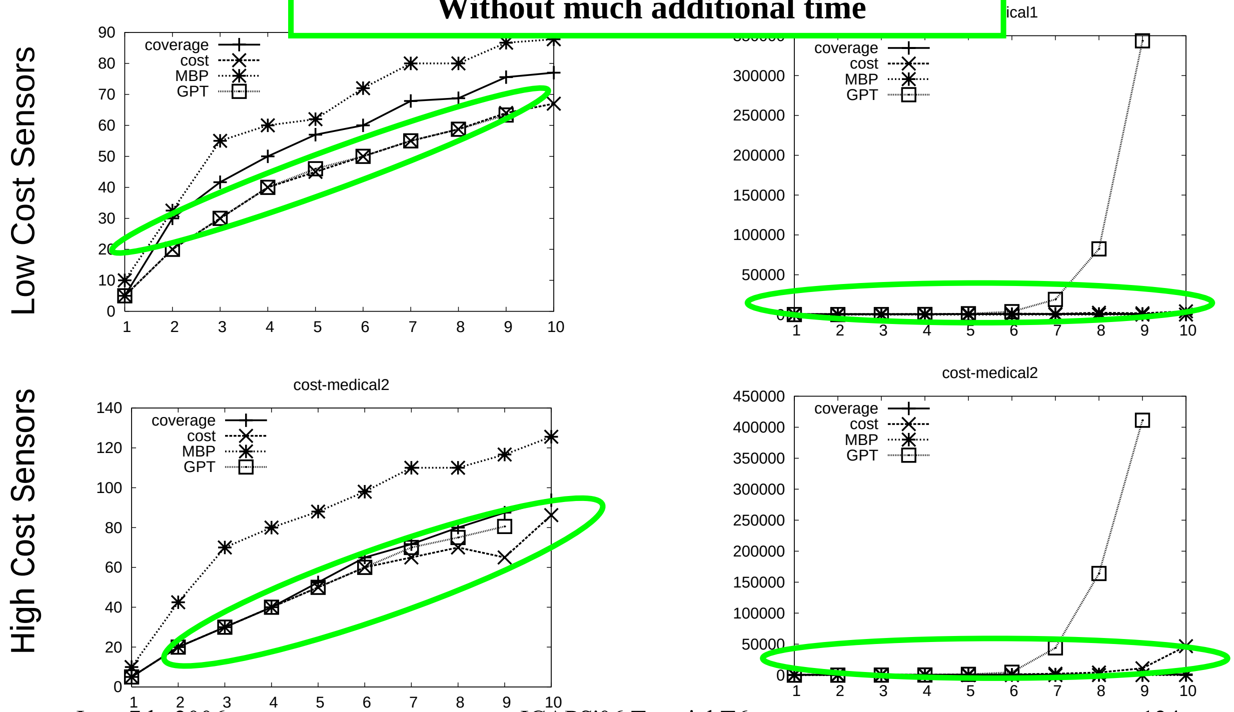
Relaxed Plan (bold)

Cost = c(B) + C(R) = 10 + 7 = 17

The Medical Specialist [Bryce & Kambhampati, 2005]

Using Propagated Costs Improves Plan Quality, Without much additional time

Average Path ... me



Overall Conclusions

- Relaxed Reachability Analysis
  - Concentrate strongly on positive interactions and independence by ignoring negative interaction
  - Estimates improve with more negative interactions
- Heuristics can estimate and aggregate costs of goals or find relaxed plans
- Propagate numeric information to adjust estimates
  - Cost, Resources, Probability, Time
- Solving hybrid problems is hard
  - Extra Approximations
  - Phased Relaxation
  - Adjustments/Penalties

Why do we love PG Heuristics?

- They work!
- They are “forgiving”
  - You don't like doing mutex? okay
  - You don't like growing the graph all the way? okay.
- Allow propagation of many types of information
  - Level, subgoal interaction, time, cost, world support, probability
- Support phased relaxation
  - E.g. Ignore mutexes and resources and bring them back later…
- Graph structure supports other synergistic uses
  - e.g. action selection
- Versatility…

Versatility of PG Heuristics

- PG Variations
  - Serial
  - Parallel
  - Temporal
  - Labelled
- Propagation Methods
  - Level
  - Mutex
  - Cost
  - Label
- Planning Problems
  - Classical
  - Resource/Temporal
  - Conformant
- Planners
  - Regression
  - Progression
  - Partial Order
  - Graphplan-style

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