



Challenges of Human-in-the-Loop Planning and Decision Support

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(google: rao asu)

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Yochan Research Group

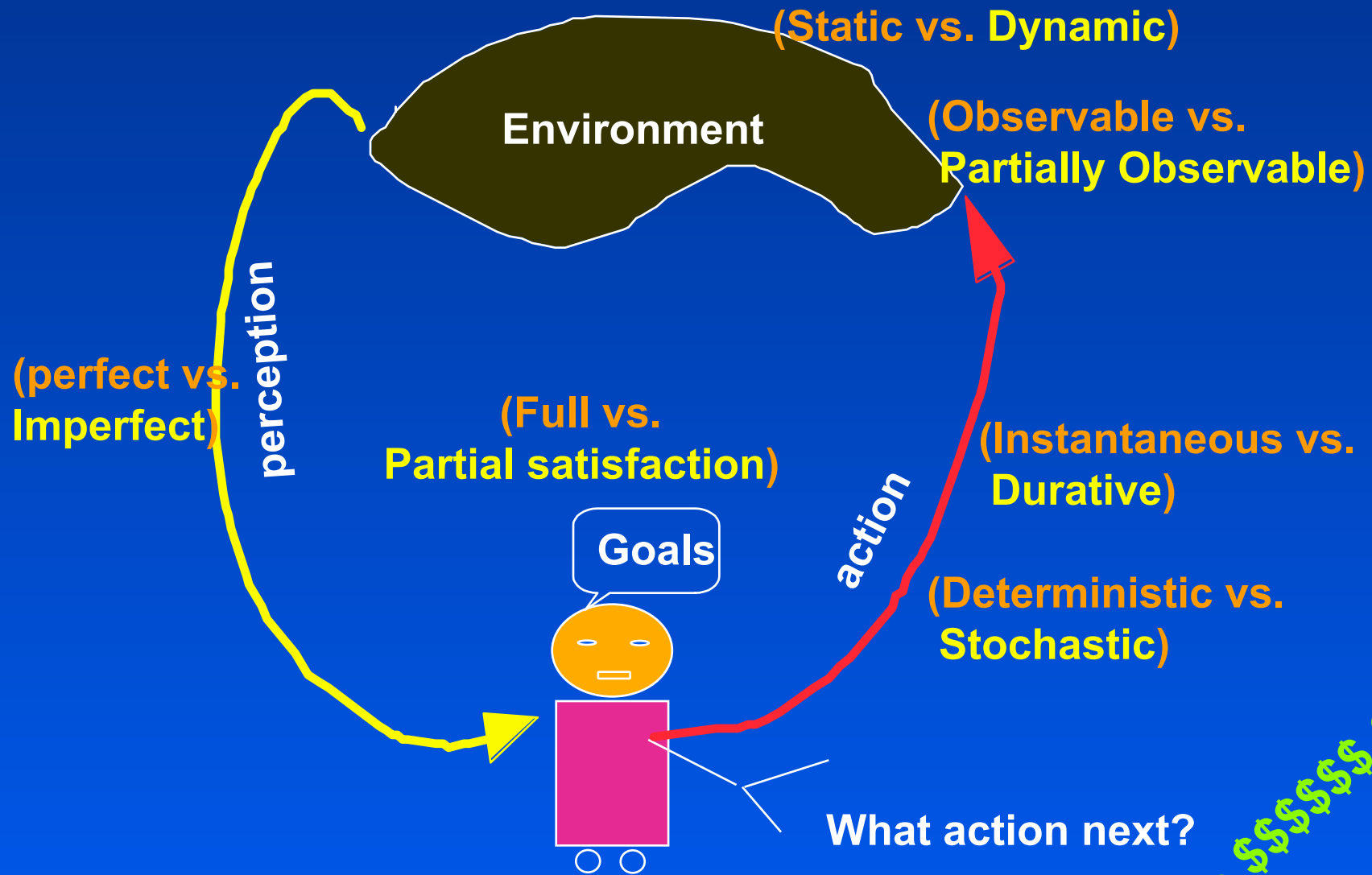
Automated Planning

- Foundations of automated planning
- Planning under a variety of domain models
 - Classical, temporal, stochastic, partially-observable
- Current Focus: Human-in-the-loop planning

Information Fusion/Integration

- Integrating structured and semi-structured data to support effective query processing
- Structured data: Probabilistic methods for imputation, rectification..
- Semi-structured data: Trust and Relevance based source selection
- Unstructured data: Analyzing and aligning social media data with event transcripts, sentiment analysis

Planning Involves Deciding a Course of Action to achieve a desired state of affairs



The \$\$\$\$\$\$ Quest

“Classical” Planning

```

(:action pick-up
  :parameters (?obj)
  :precondition (and (clear ?obj)
                    (on-table ?obj)
                    (arm-empty)
                    (block ?obj))
  :effect
  (and (not (on-table ?obj))
        (not (clear ?obj))
        (not (arm-empty))
        (holding ?obj)))
  
```

Blocks world

State variables:
 Ontable(x) On(x,y) Clear(x) hand-empty holding(x)

Init:
 Ontable(A), Ontable(B),
 Clear(A), Clear(B), hand-empty

Initial state:
 Complete specification of T/F values to state variables
 --By convention, variables with F values are omitted

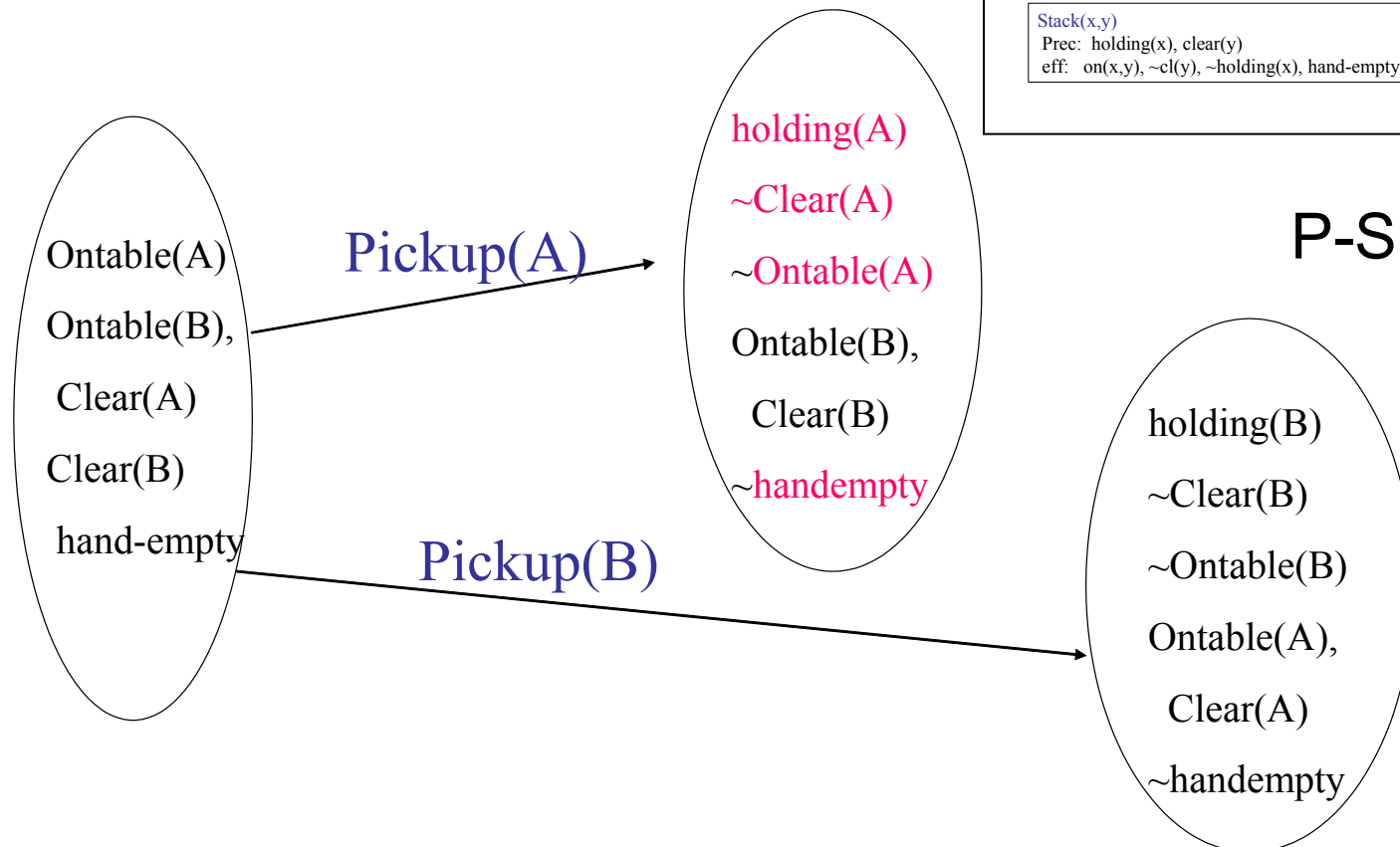
Goal state:
 A partial specification of the desired state variable/value combinations
 --desired values can be both positive and negative

Pickup(x)
 Prec: hand-empty, clear(x), ontable(x)
 eff: holding(x), ~ontable(x), ~hand-empty, ~Clear(x)

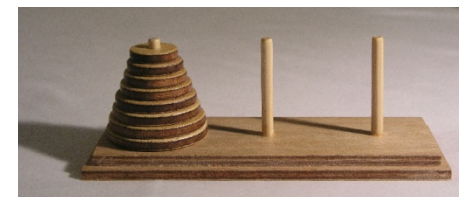
Putdown(x)
 Prec: holding(x)
 eff: Ontable(x), hand-empty, clear(x), ~holding(x)

Stack(x,y)
 Prec: holding(x), clear(y)
 eff: on(x,y), ~cl(y), ~holding(x), hand-empty

Unstack(x,y)
 Prec: on(x,y), hand-empty, cl(x)
 eff: holding(x), ~clear(x), clear(y), ~hand-empty



P-Space Complete

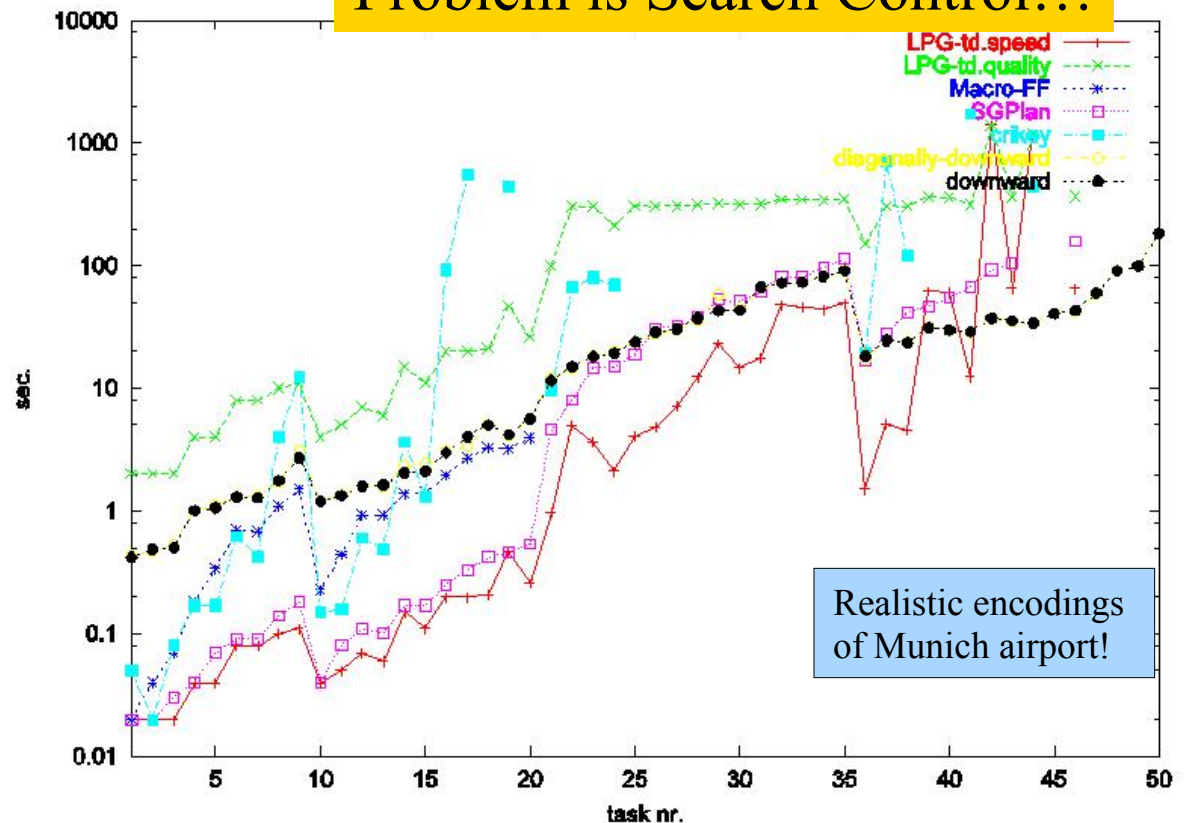


Scalability was the big bottle-neck...

We have figured out how to scale synthesis..

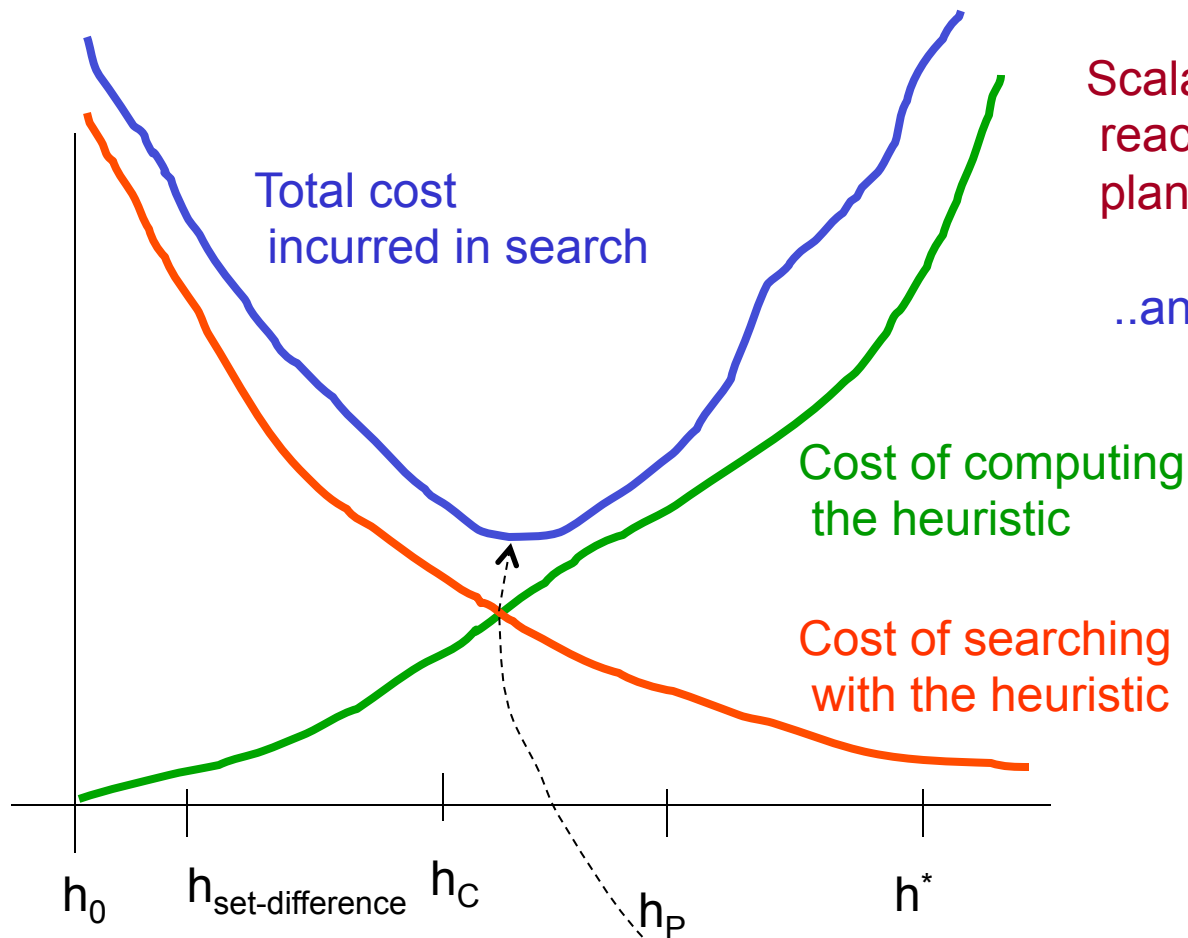
Problem is Search Control!!!

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



Realistic encodings of Munich airport!

The primary revolution in planning in the recent years has been methods to scale up plan synthesis



Scalability came from sophisticated reachability heuristics based on planning graphs..

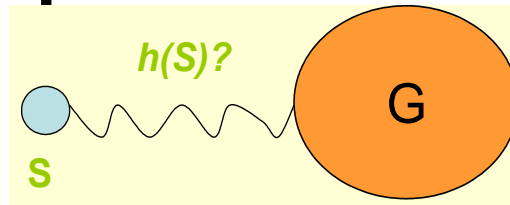
..and not from any hand-coded domain-specific control knowledge

Not always clear where the total minimum occurs

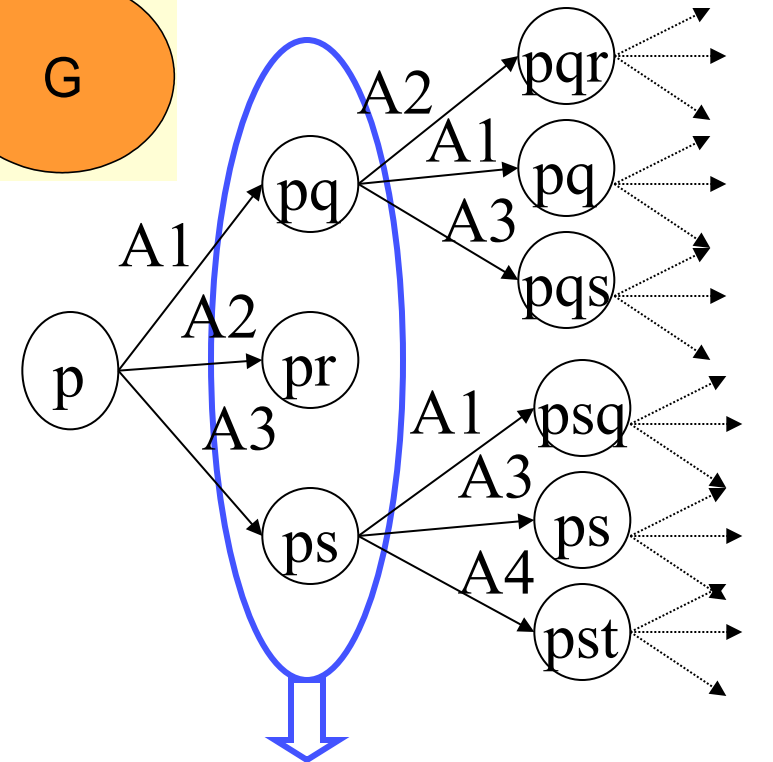
- Old wisdom was that the global min was closer to cheaper heuristics
- Current insights are that it may well be far from the cheaper heuristics for many problems
 - E.g. Pattern databases for 8-puzzle
 - Plan graph heuristics for planning

“Optimistic projection of achievability”

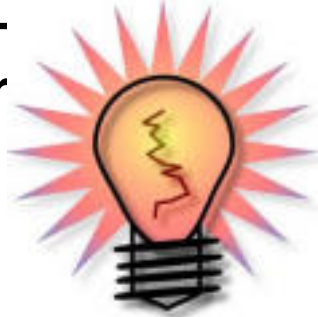
Planning Graph and Projection



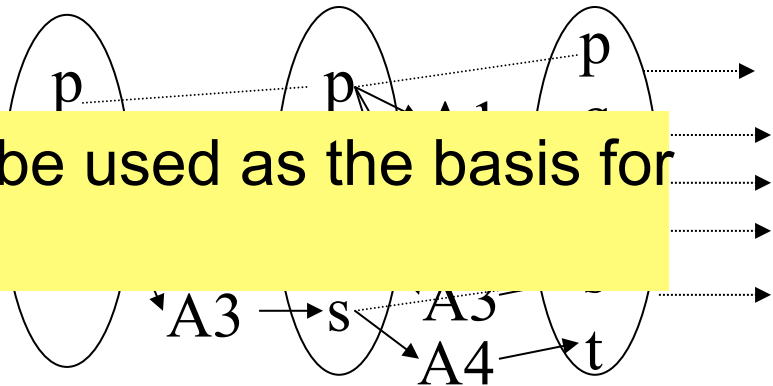
- Envelope of Progression Tree (Relaxed Progression)
 - Proposition lists: Union of states at k^{th} level
 - Mutex: Subsets of literals that cannot be part of any legal state



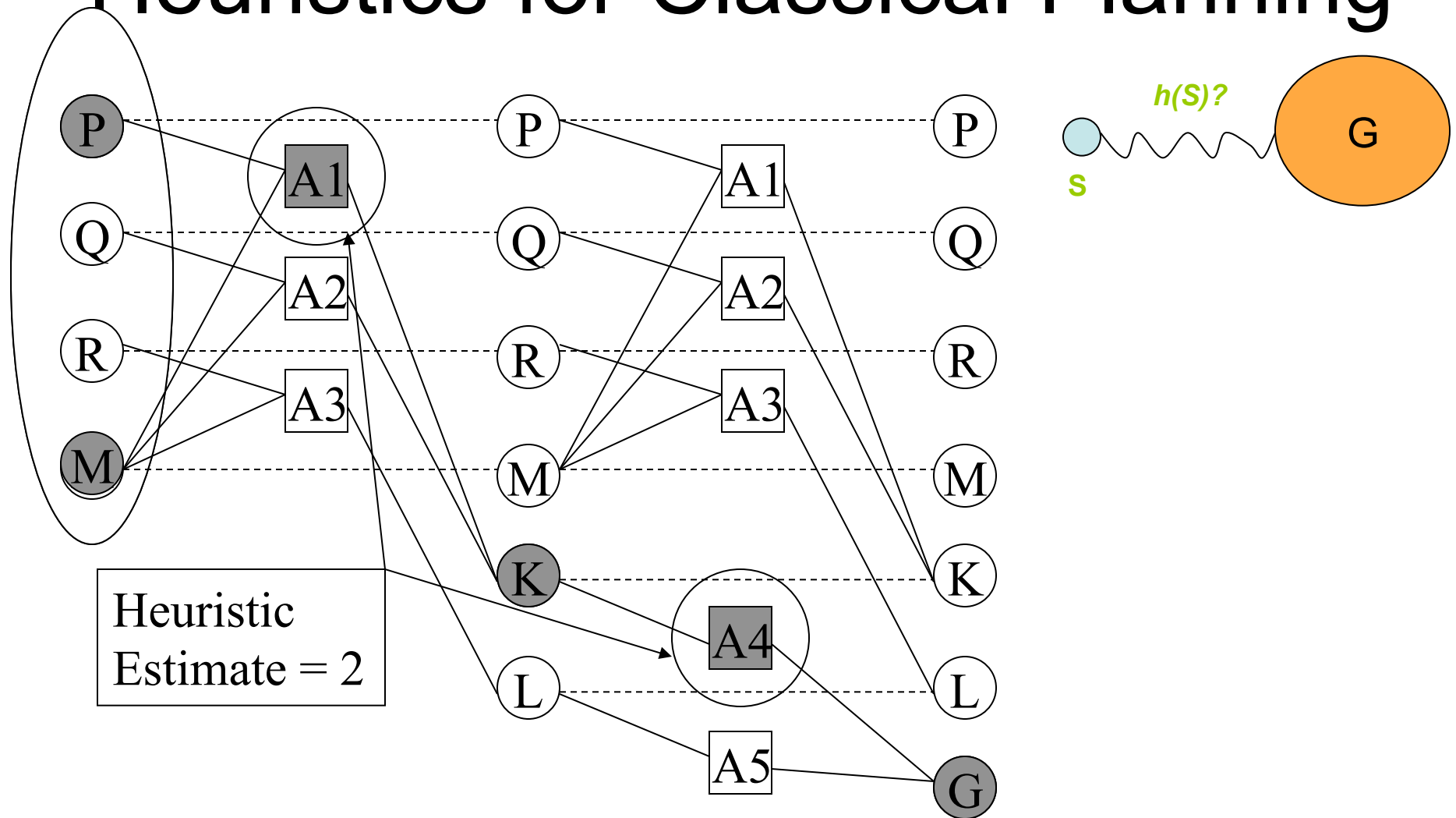
- Lower bound
- Propositional information



Planning Graphs can be used as the basis for heuristics!



Heuristics for Classical Planning



Relaxed plans are solutions for a relaxed problem

How far have we got?

How planners from past IPCs would have performed in IPC-8?

- In Sequential Satisficing track, [LAMA-11](#) (winner of Sequential Satisficing track of IPC-7) would have been **12th** out of 21.
- In Agile track, [LPG](#) and [FF](#) would have been, respectively, **13th** and **17th** out of 17.

..and we have done our fair bit...

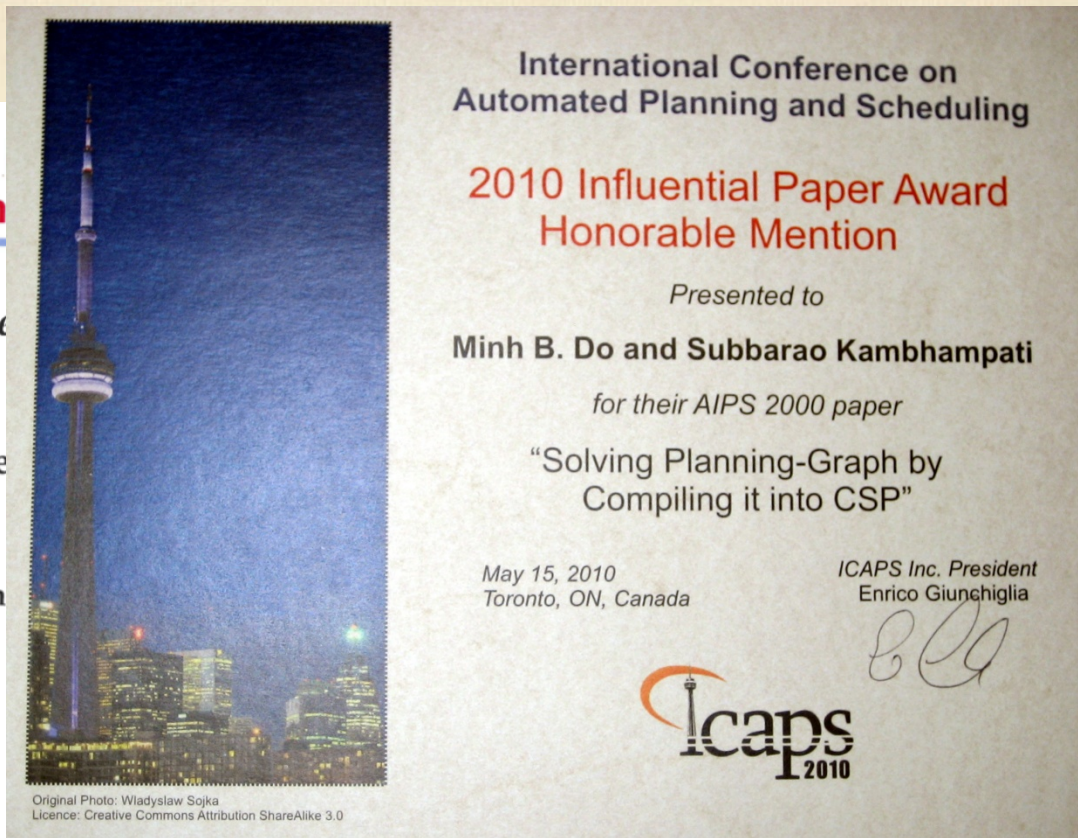


The
Autom

Outstanding Diss

Me

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Original Photo: Wladyslaw Sojka
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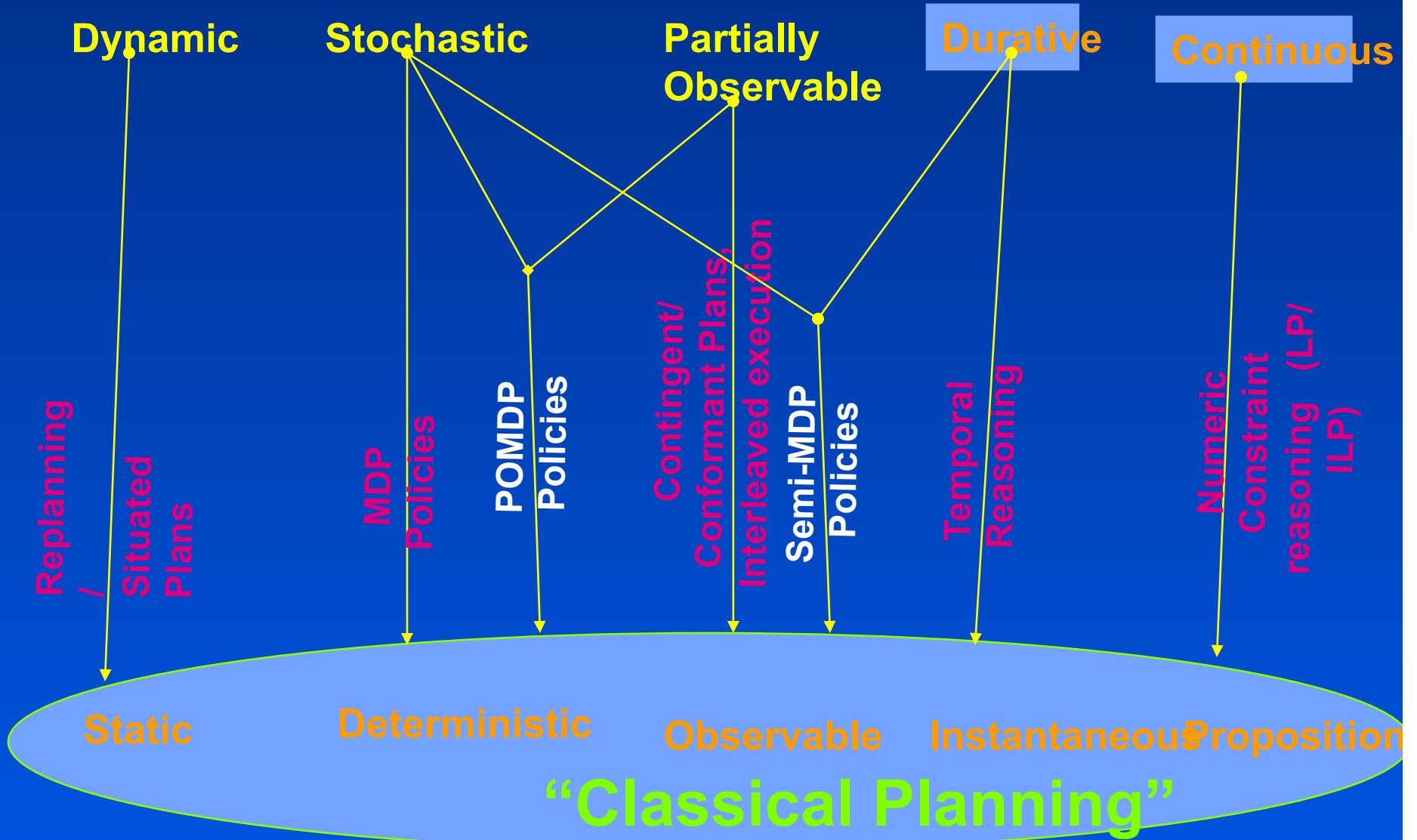
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So why the continued fascination with classical planning?

- ..of course, the myriad applications for classical STRIPS planning 😊
- But more seriously, because classical planners have become a customized substrate for “compiling down” other more expressive planning problems
 - Effective approaches exist for leveraging classical planners to do partial satisfaction planning, conformant planning, conditional planning, stochastic planning etc.

So, what next?





Compilation Substrates for Planning

SAT

- First of the substrates
 - Kautz&Selman got the classic paper award honorable mention
- Continued work on fast SAT solvers
- Limited to bounded length planning
- (Not great for metric constraints)

IP/LP

- Followed closely on the heels of SAT
- Can go beyond bounded length planning
 - Allows LP Relaxation
 - (Has become the basis for powerful admissible heuristics)
- IP solvers evolve much slower..

(Classical) Planning

- Tremendous progress on heuristic search approaches to classical planning
- A currently popular approach is to compile expressive planning problems to classical planning
 - Conformant planning, conditional planning
 - (even plan recognition)



Applications—sublime and mundane

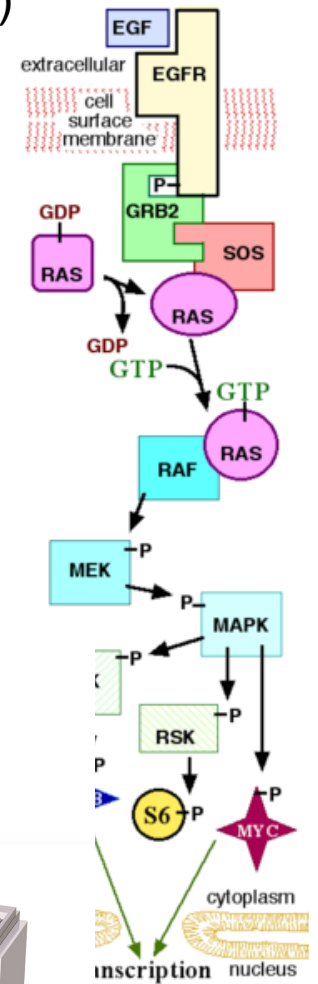
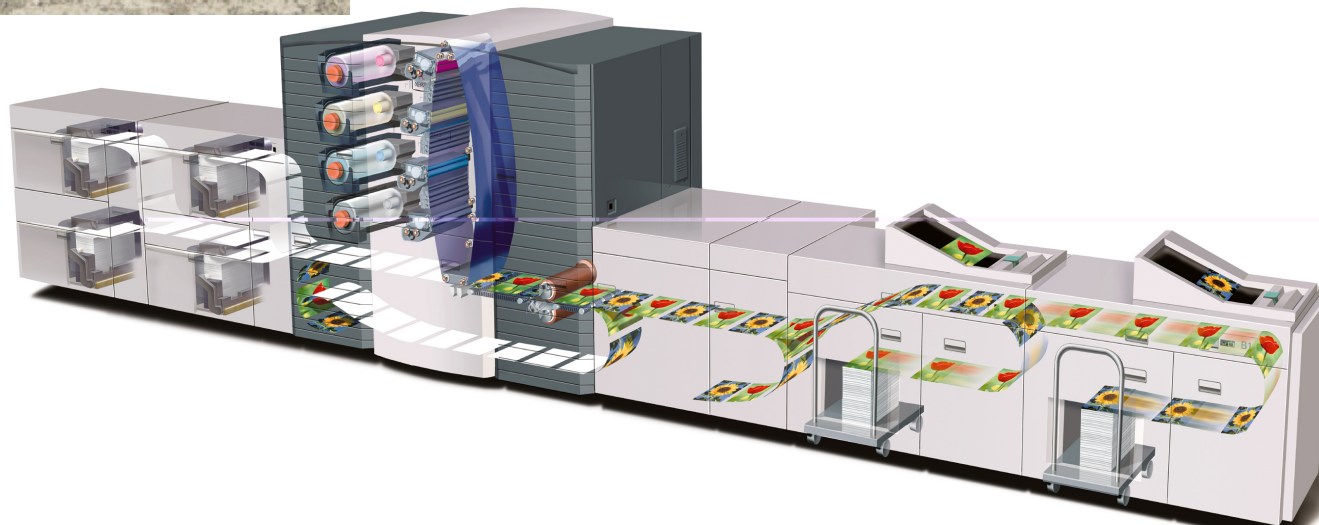
Mission planning (for rovers, telescopes)

Military planning/scheduling

Web-service/Work-flow composition

Paper-routing in copiers

Gene regulatory network intervention

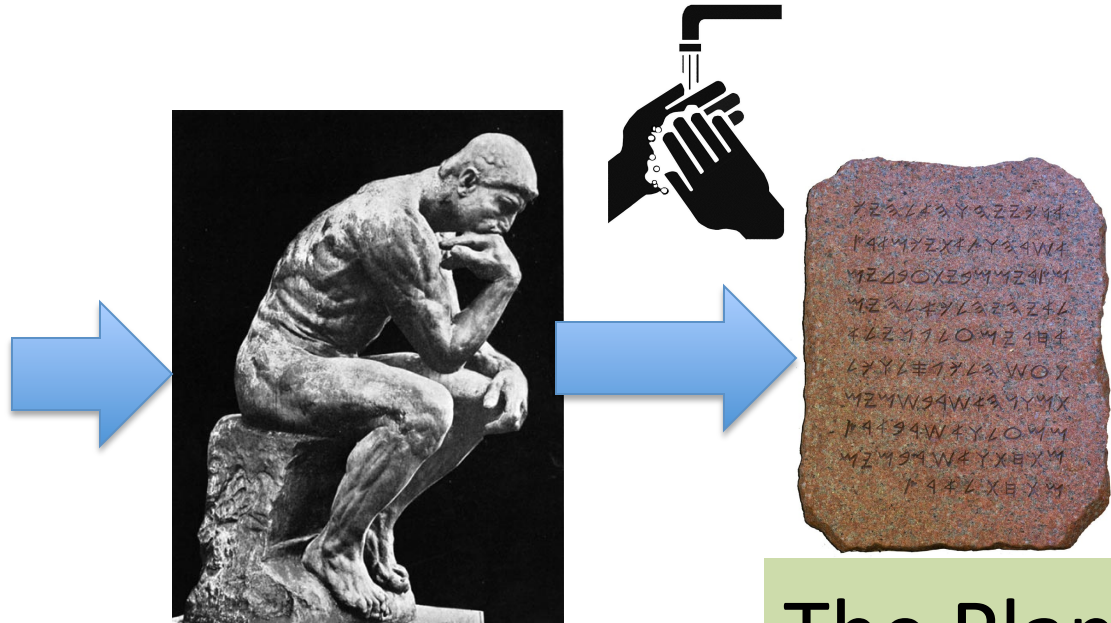




Planning: The Canonical View

A fully specified problem

- Initial state
- Goals
(each non-negotiable)
- Complete Action Model



The Plan





Need for Human-in-the-Loop/Human-Aware Planning & Decision Support

- Planners are increasingly embedded in systems that include both humans and machines
 - Human Robot Teaming
 - Petrick et al, Veloso et al, Williams et al, Shah et al, Kambhampati et al
 - Decision support systems; Crowd-planning systems; Tutorial planning systems
 - Allen et al, Kambhampati et al; L
- Necessitates Human-in-the-Loop Planning
 - But, isn't it just "Mixed-Initiative Planning"?
 - ..a lot of old MIP systems had the "Humans in the land of Planners" paradigm (the humans help planners)
 - In effective human-aware planning, planners realize they inhabit the land of humans..



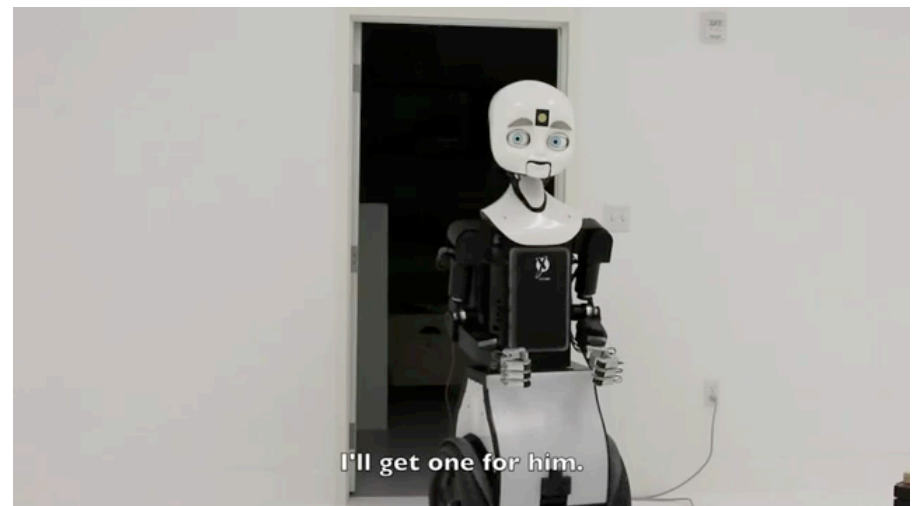
Human-Robot Teaming

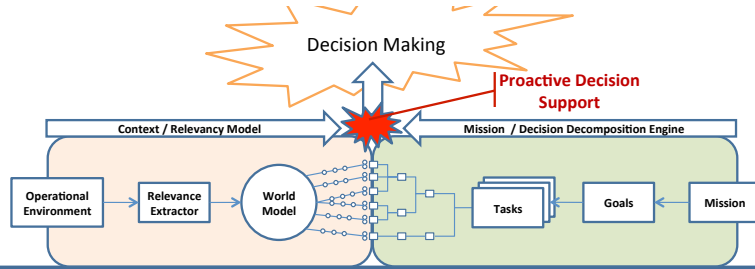


- Search and report (rescue)
- Goals incoming on the go
- World is evolving
- Model is changing



- Infer instructions from Natural Language
- Determine goal formulation through clarifications and questions





Commander View

Firefighters near Prescott Go

Prescott Firestation #1

- 20 professional people
- 8 people called to forest fire about 10 minutes ago

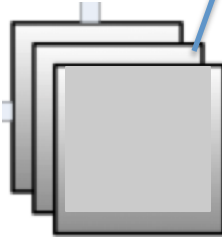
Volunteer firefighter #123

- kartik: I heard about a fire on the radio, maybe they will call me to volunteer today

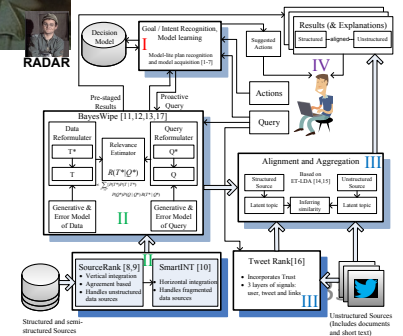
Sedona Firestation #3

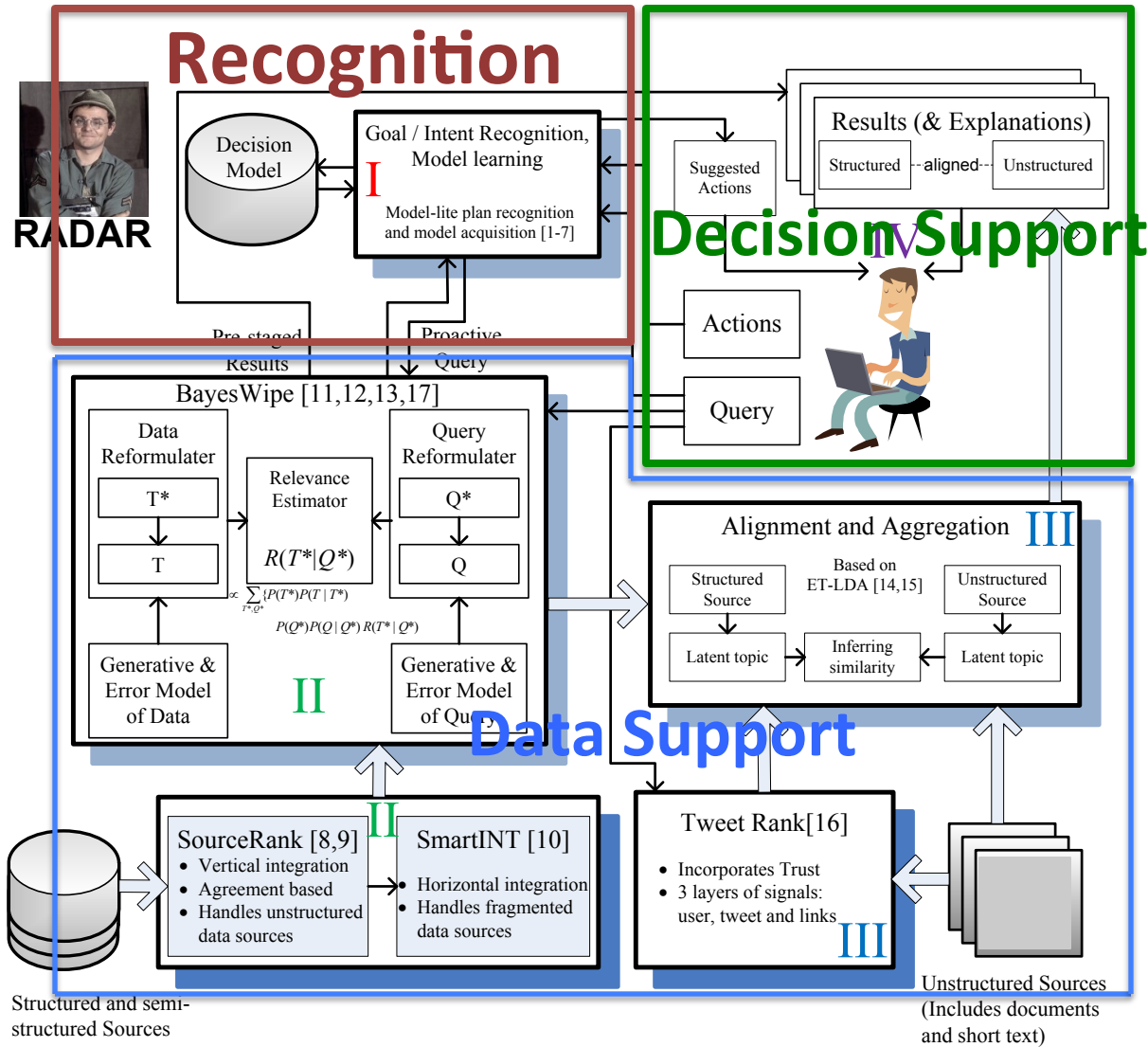


Structured Data



Unstructured Data Stream (e.g., short text)







Crowd-Sourced Planning

TourPlanner Instructions

TOUR REQUEST

Going to New York City for only a day in about a month. Where is a must to eat at that I can make reservations at? With so little time, I don't exactly want to spend it waiting for hours to get seated/get food. Also, what are the must things I should do and see in NYC? Off the beaten path things are preferred! :) I've been to NYC before, so perhaps new speaskies, restaurants and night life recommendations would be awesome.

manhattan_gettingto

#museum
#lecture

- Have a quick light lunch. Budget is 30\$. #lunch
- Do some shopping for a maximum of 2 hours. I can spend upto 300\$ on shopping. #shop
- Take a walk in some touristy place. #walk #touristy
- Have dinner and drinks at a good local restaurant. I want to spend a maximum time of 3 hours here. #dinner

TO DO Tags:

manhattan_gettingto

Getting to manhattan

museum

lunch

Add new activity »

Existing Activities:

Macys: Awesome clothes and the head quarters (10:00 hrs) (1 hours)
#shop

Manhattan: Walk near the NY public library and the charging bull (14:00 hrs) #walk

Critique existing activity »





Results: Role of Planner Module

VOTED ICAPS 2014 BEST DEMO BY ... THE CROWD!

ICAPS
2014

International Conference on Automated Planning and Scheduling

2014 ICAPS System Demonstration

People's Choice Award

Presented to
L. Manikonda, T. Chakraborti, S. De, K. Talamadupula, S.

For the ICAPS 2014 System Demonstration

AI-Mix: How a Planner can Help Guide Hur
Towards a Better Crowdsourced Plan

June 24, 2014, Portsmouth, New Hampshire, US



GOAL

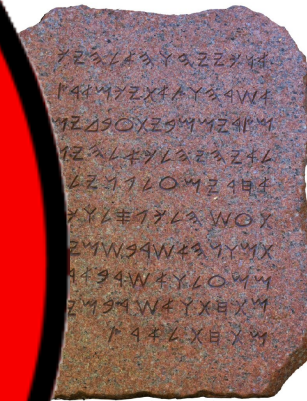




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- Complete Action



The Plan





Challenges in Human-in-the-Loop/Human-Aware Planning & Decision Support

- Interpret what humans are doing
 - Plan/goal/intent recognition
- Plan with incomplete domain models
 - Robust planning with “lite” models
 - (Learn to improve domain models)
- Continual planning/Replanning
 - Commitment sensitive to ensure coherent interaction
- Explanations/Excuses
 - Excuse generation can be modeled as the (conjugate of) planning problem
- Asking for help/elaboration
 - Reason about the information value

Eigen
Slide

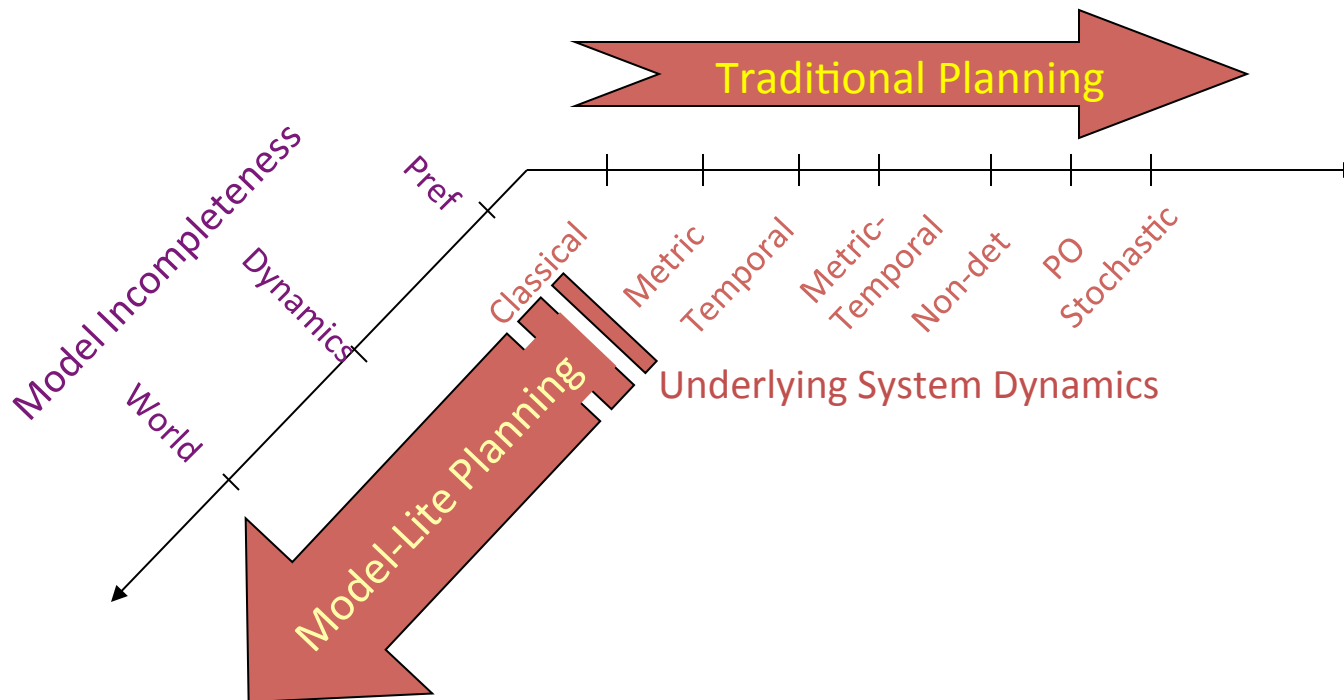


Violated Assumptions:

- ~~Complete~~ Action Descriptions (fallible domain writers)
- ~~Fully Specified~~ Preferences (uncertain users)
- ~~Packaged~~ planning problem (Plan Recognition)
- ~~One-shot~~ planning (continual revision)

Planning is no longer a pure inference problem ☹

☹ But humans in the loop can ruin a really a perfect day ☹



Effective ways to handle the more expressive planning problems by exploiting the deterministic planning technology

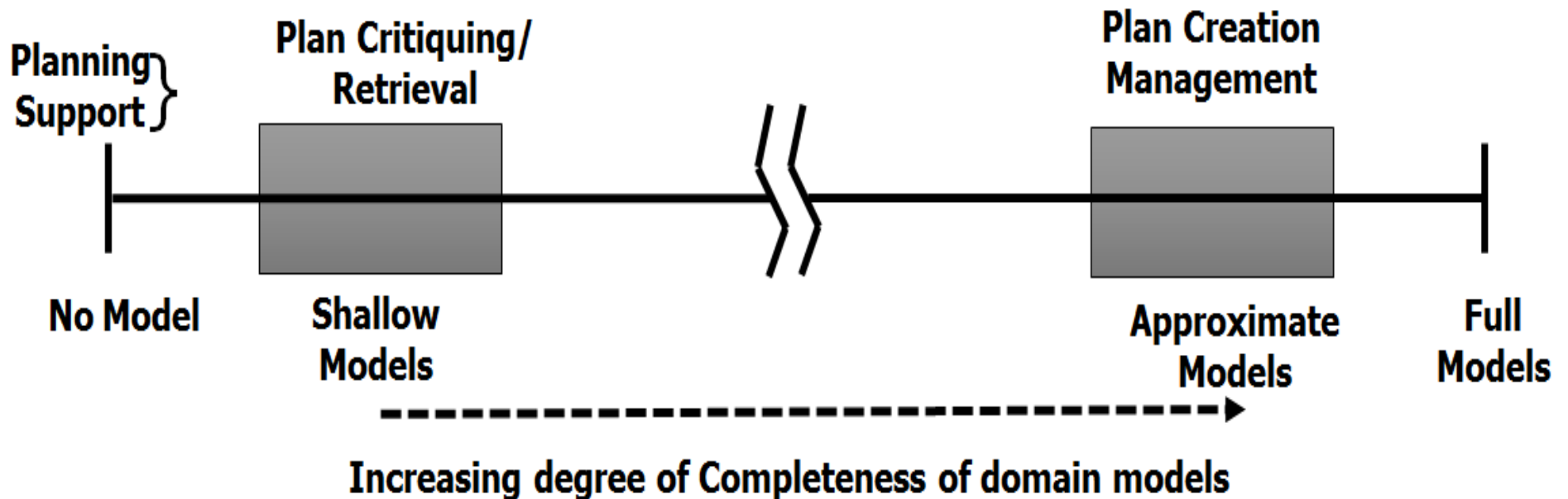


Learning is useful but not the (sole) answer..

- A tempting way to handle incompleteness is to say that we should wait until the full model is obtained
 - Either through learning
 - (We do have work in Model Learning: E.g. Zhuo et al. IJCAI 2013)
 - Or by the generosity of the domain writer..
- Problem: Waiting for complete model is often times not a feasible alternative
 - The model may never become complete...
 - We need to figure out a way of maintaining incomplete models, and planning with them (pending learning..)



MODELS V. PLANNING CAPABILITIES



I/O types
Task dependency
(e.g. workflows management,
web service composition)

Missing some preconditions/
effects of actions
(e.g. Garland & Lesh, 2002)

Approaches for Planning with Incomplete Models (1)

Incompleteness annotations are available

- One way to make-up for model incompleteness is to expect annotations circumscribing the extent of incompleteness
- In this case, we can explicitly reason with the correctness of candidate plans over all possible models
 - Nguyen et. al. ICAPS 2014; NIPS 2013

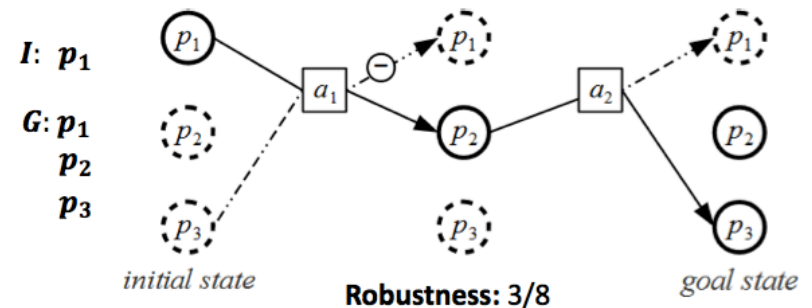
Problem Formulation

- ❖ Incomplete domain: $\tilde{D} = \langle F, A \rangle$
- ❖ Each partially specified action $a \in A$:
 - Known preconditions, effects: $Pre(a), Add(a), Del(a)$
 - Possible preconditions, effects: $\tilde{Pre}(a), \tilde{Add}(a), \tilde{Del}(a)$
 - Optional weights: $w_a^{pre}(p), w_a^{add}(p), w_a^{del}(p) \in (0,1)$
- ❖ Exponential number of candidate complete models: $\ll \tilde{D} \gg$
 - One of which is the *true* model.
- ❖ Planning problem: $\tilde{P} = \langle \tilde{D}, I, G \rangle$

Incomplete ≠ Stochastic

Robustness measure for plans

$$R(\pi, \tilde{P}: \langle \tilde{D}, I, G \rangle) = \sum_{D_i \in \ll \tilde{D} \gg, \gamma(\pi, I, D_i) = G} \Pr(D_i)$$



A Spectrum of robust planning problems

- ❖ Robustness assessment
- ❖ Maximally robust plan generation
- ❖ Generating plan with desired level of robustness
- ❖ Cost-sensitive robust plan generation
- ❖ Incremental robustification

Robustness Assessment as Weighted Model Counting

❖ Causal-proof based correctness constraints Σ

Establishment constraints

➤ Unsupported known preconditions must be supported:

➤ So do possible preconditions, if realized:

Protection constraints

➤ Known preconditions deleted by realized effects must be re-established:

➤ So do possible preconditions, if realized:

$$\begin{aligned}
 & p_{a_i}^{pre} \Rightarrow \bigvee_{C_p^i \leq k \leq i-1, p \in \overline{Add}(a_k)} p_{a_k}^{add} \\
 & p_{a_m}^{del} \Rightarrow \bigvee_{C_p^i \leq k \leq i-1, p \in \overline{Add}(a_k)} p_{a_k}^{add} \\
 & p_{a_i}^{pre} \Rightarrow (p_{a_m}^{del} \Rightarrow \bigvee_{C_p^i \leq k \leq i-1, p \in \overline{Add}(a_k)} p_{a_k}^{add})
 \end{aligned}$$

- ❖ Plan robustness = Weighted model counting $WMC(\Sigma)$.
- ❖ **Complexity:** Assessing plan robustness is #P-complete.

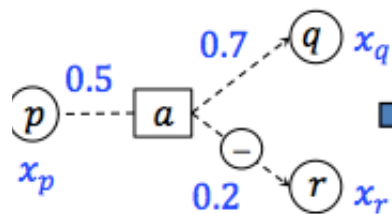
Robust Plan Synthesis: A Compilation Approach

Incomplete model
Complete world state



Complete model
Belief state

(Conformant Probabilistic Planning)



Resulting action a' with eight conditional effects.

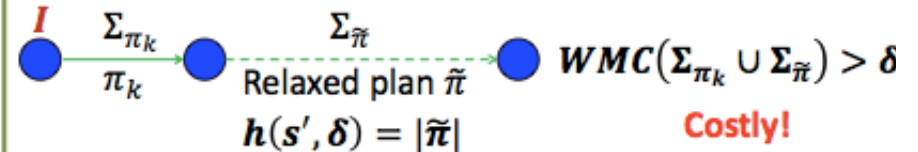
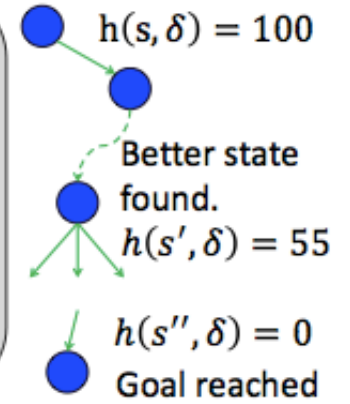
Cond: $x_p \wedge p \wedge x_q \wedge x_r$ Eff: $q \wedge \neg r$

Initial belief state

Robust Plan Synthesis: A Heuristic Approach

❖ Anytime approach

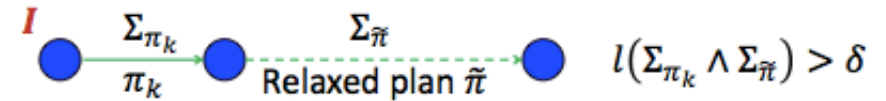
1. Initialize: $\delta = 0$
2. Repeat
 - ❖ Find plan π s.t. $R(\pi) > \delta$
 - ❖ If plan found: $\delta = R(\pi)$
3. Return π and $R(\pi)$ if plan found



❖ Approximate plan robustness

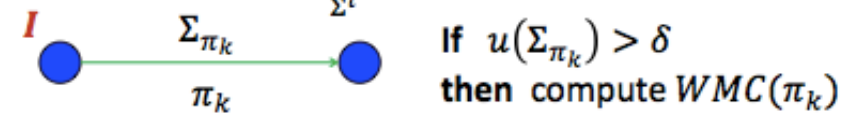
- Lower bound: Σ as monotone clauses

$$l(\Sigma) = \prod_{c \in \Sigma} \Pr(c) \leq WMC(\Sigma)$$



- Upper bound: divide Σ into independent sets Σ^i

$$u(\Sigma) = \prod_{\Sigma^i} \min_{c \in \Sigma^i} \Pr(c) \geq WMC(\Sigma)$$



❖ Evaluation

Approaches for Planning with Incomplete Models (2)

Library of cases is available

- Sometimes, we may have access to “cases”/previous successful plans
- ML-CBP exploits cases directly during planning (by transferring case fragments into a skeletal plan generated w.r.t. M')
 - Zhuo Et al AAI 2013
- An alternative approach would be to use the cases C to *refine* the model M' into a more accurate model M'' (where M'' is a better approximation of M^*)
 - M'' contains both primitive and macro-operators
 - Zhuo et. Al. IJCAI 2013

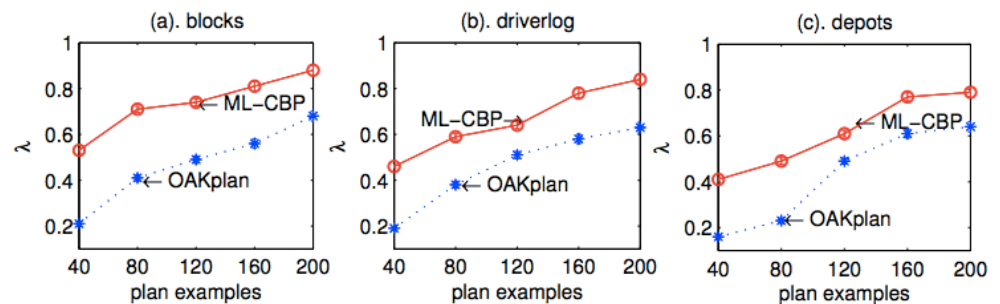
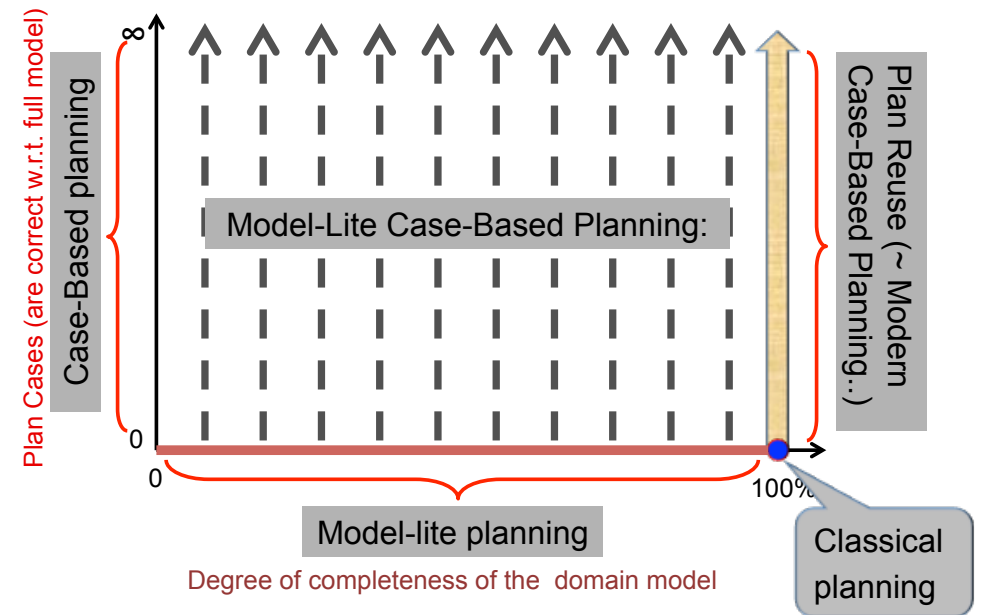


Figure 3: Accuracy w.r.t. number of plan cases.

Approaches for Planning with Incomplete Models (2)

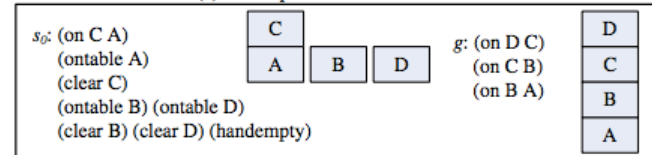
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```

pickup (?x - block)
pre: (handempty) (clear ?x) (ontable ?x)
eff: (holding ?x) (not (handempty)) (not (clear ?x)) (not (ontable ?x))
putdown (?x - block)
pre: (holding ?x)
eff: (ontable ?x) (clear ?x) (handempty) (not (holding ?x))
unstack (?x ?y - block)
pre: (handempty) (on ?x ?y) (clear ?x)
eff: (holding ?x) (clear ?x) (not (clear ?x)) (not (on ?x ?y)) (not (handempty))
stack (?x ?y - block)
pre: (clear ?y) (holding ?x)
eff: (on ?x ?y) (clear ?x) (handempty) (not (clear ?y)) (not (holding ?x))
    
```

(a). Incomplete action models



(b). Initial state s_0 and goal g

```

p1: {(clear b1) (clear b2) (clear b3) (clear b4) (ontable b1) (ontable b2)
(ontable b3) (ontable b4) (handempty)}, pickup(b3) stack(b3 b2) pickup(b1)
stack(b1 b3) pickup(b4) stack(b4 b1), {(on b4 b1) (on b1 b3) (on b3 b2)}
p2: {(clear b1) (ontable b2) (on b1 b3) (on b3 b2) (handempty)}, unstack(b1
b3) putdown(b1) unstack(b3 b2) putdown(b3) pickup(b1) stack(b1 b2)
pickup(b3) stack(b3 b1), {(on b3 b1) (on b1 b2)}
p3: ...
    
```

(c). Plan examples

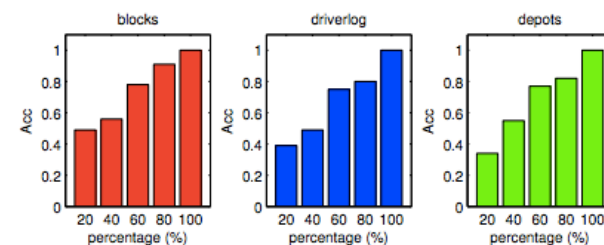


Figure 3: Accuracies w.r.t. completeness of action models.



Challenges in Human-in-the-Loop/Human-Aware Planning & Decision Support

- Interpret what humans are doing
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- Plan with incomplete domain models
 - Robust planning with “lite” models
 - (Learn to improve domain models)
- Continual planning/Replanning
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- Explanations/Excuses
 - Excuse generation can be modeled as the (conjugate of) planning problem
- Asking for help/elaboration
 - Reason about the information value

Eigen
Slide



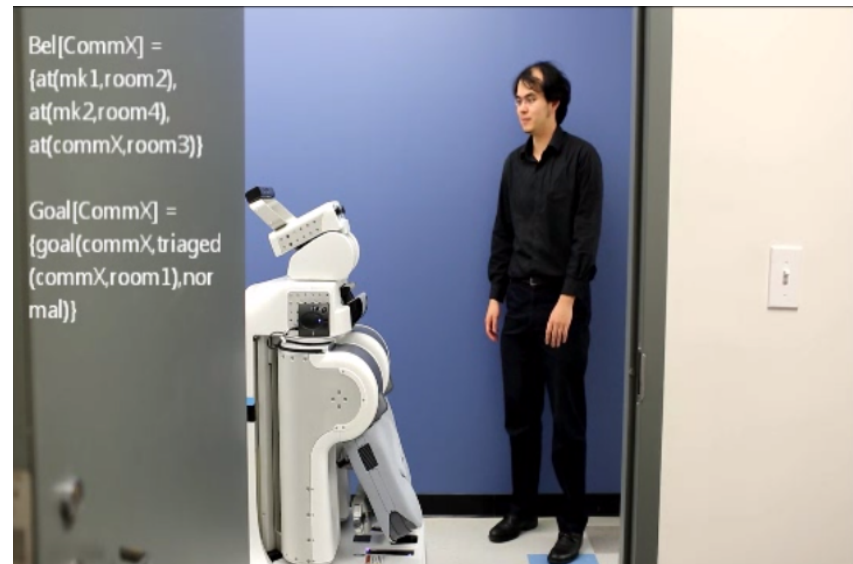
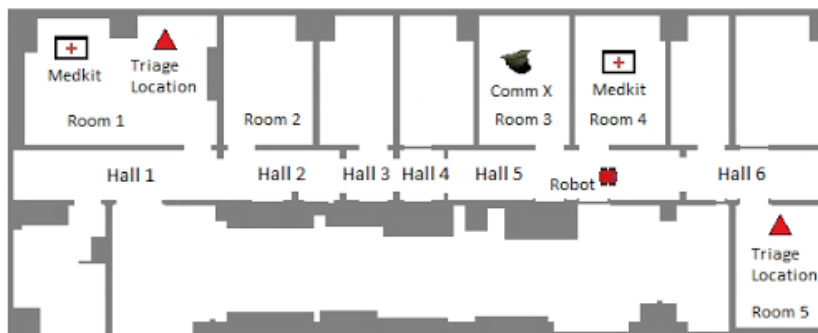
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COORDINATION IN HUMAN-ROBOT TEAMS USING MENTAL MODELING AND PLAN RECOGNITION

Presented at IROS 2014



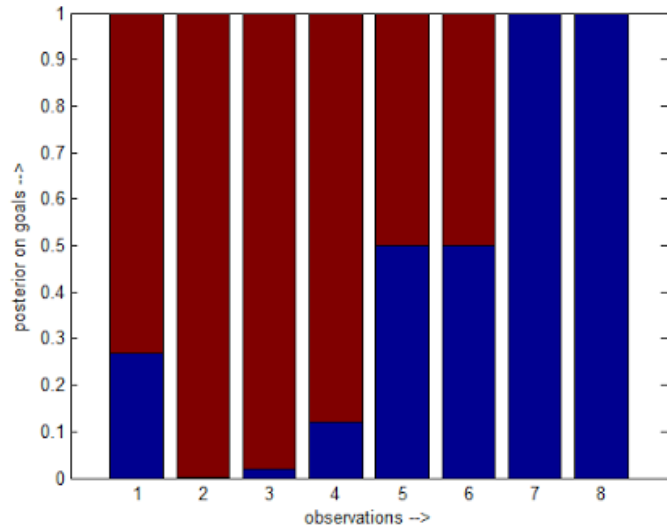
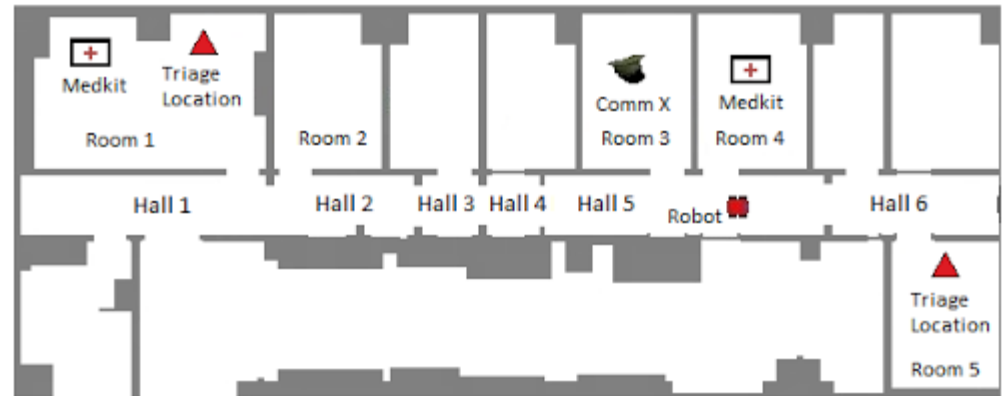
Talamadupula et al. – Arizona State
University & Tufts University
Coordination in Human-Robot Teams Using
Mental Modeling & Plan Recognition



Plan Recognition

BELIEF IN GOAL

(conducted_triage commX room1)
 (conducted_triage commX room5)



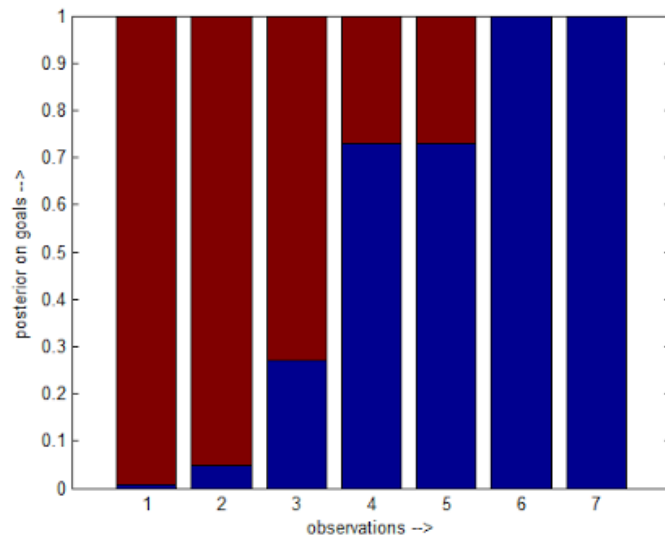
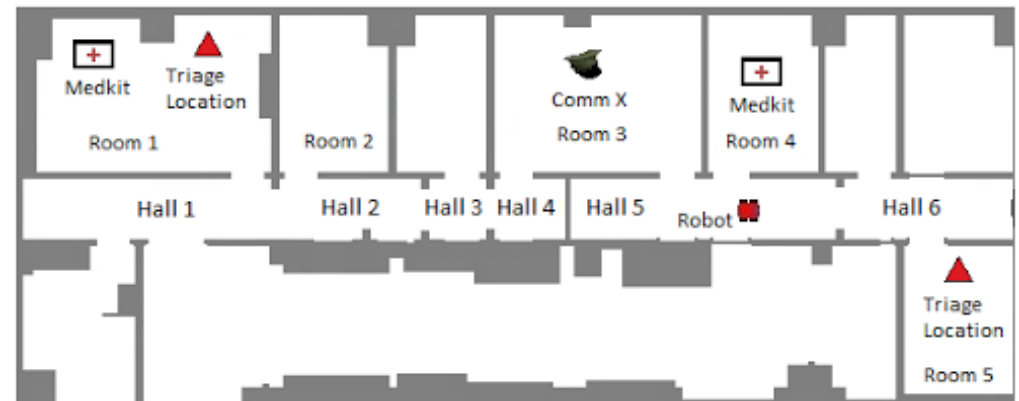
observations -
 move commx room3 hall5
 move_reverse commx hall5 hall4
 move_reverse commx hall4 hall3
 move_reverse commx hall3 hall2
 move_reverse commx hall2 hall1
 move_reverse commx hall1 room1
 pick_up_medkit commx mkeast room1
 conduct_triage commx room1



Plan Recognition

BELIEF IN GOAL

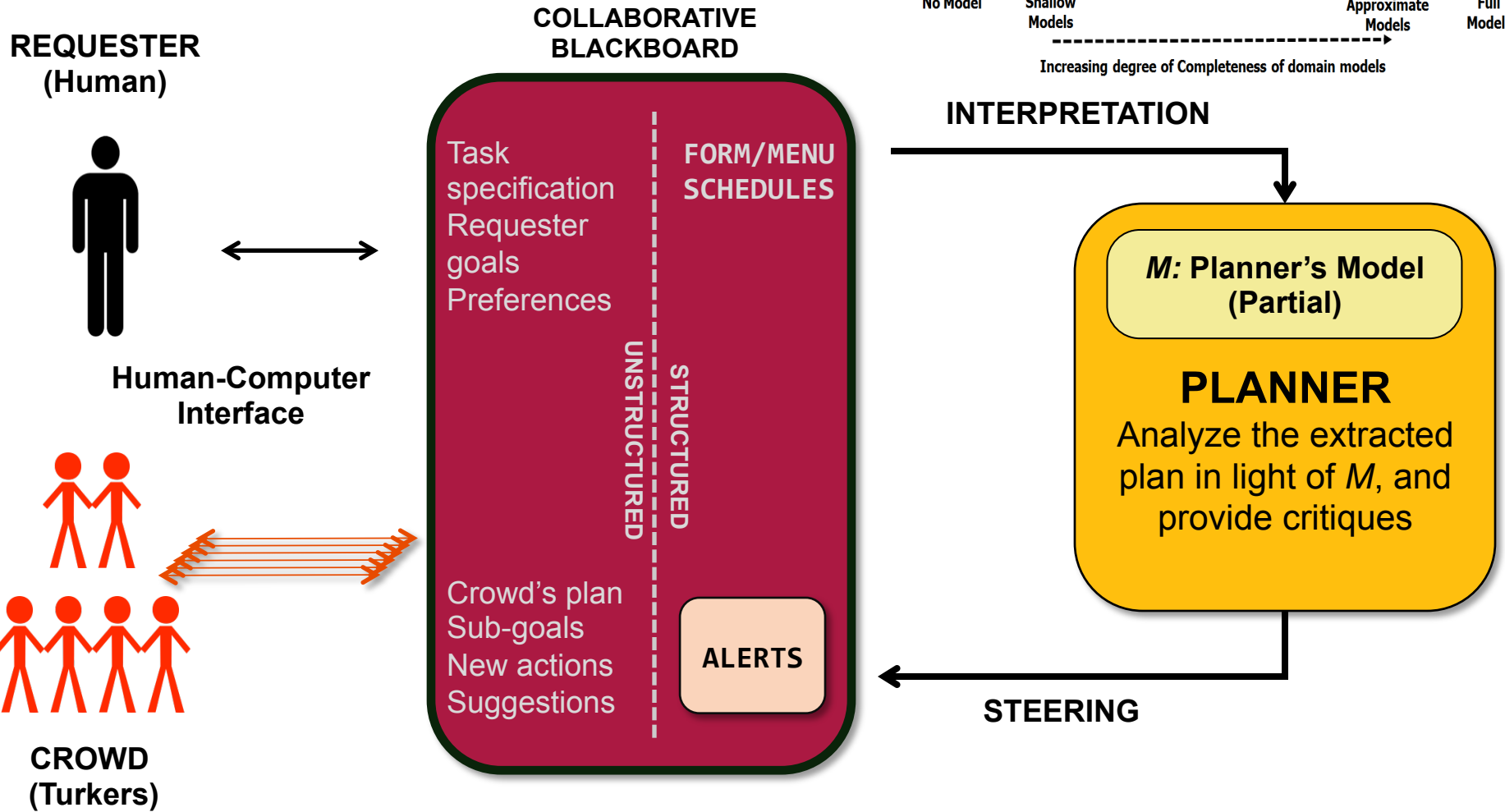
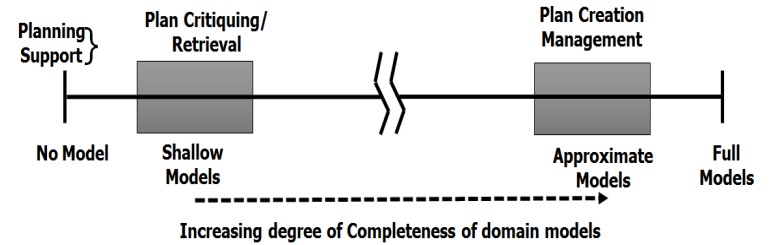
(conducted_triage commX room1)
 (conducted_triage commX room5)



observations -
 move commx room3 hall4
 move_reverse commx hall4 hall3
 move_reverse commx hall3 hall2
 move_reverse commx hall2 hall1
 move_reverse commx hall1 room1
 pick_up_medkit commx mkeast room1
 conduct_triage commx room1



AI-MIX: SYSTEM SCHEMATIC

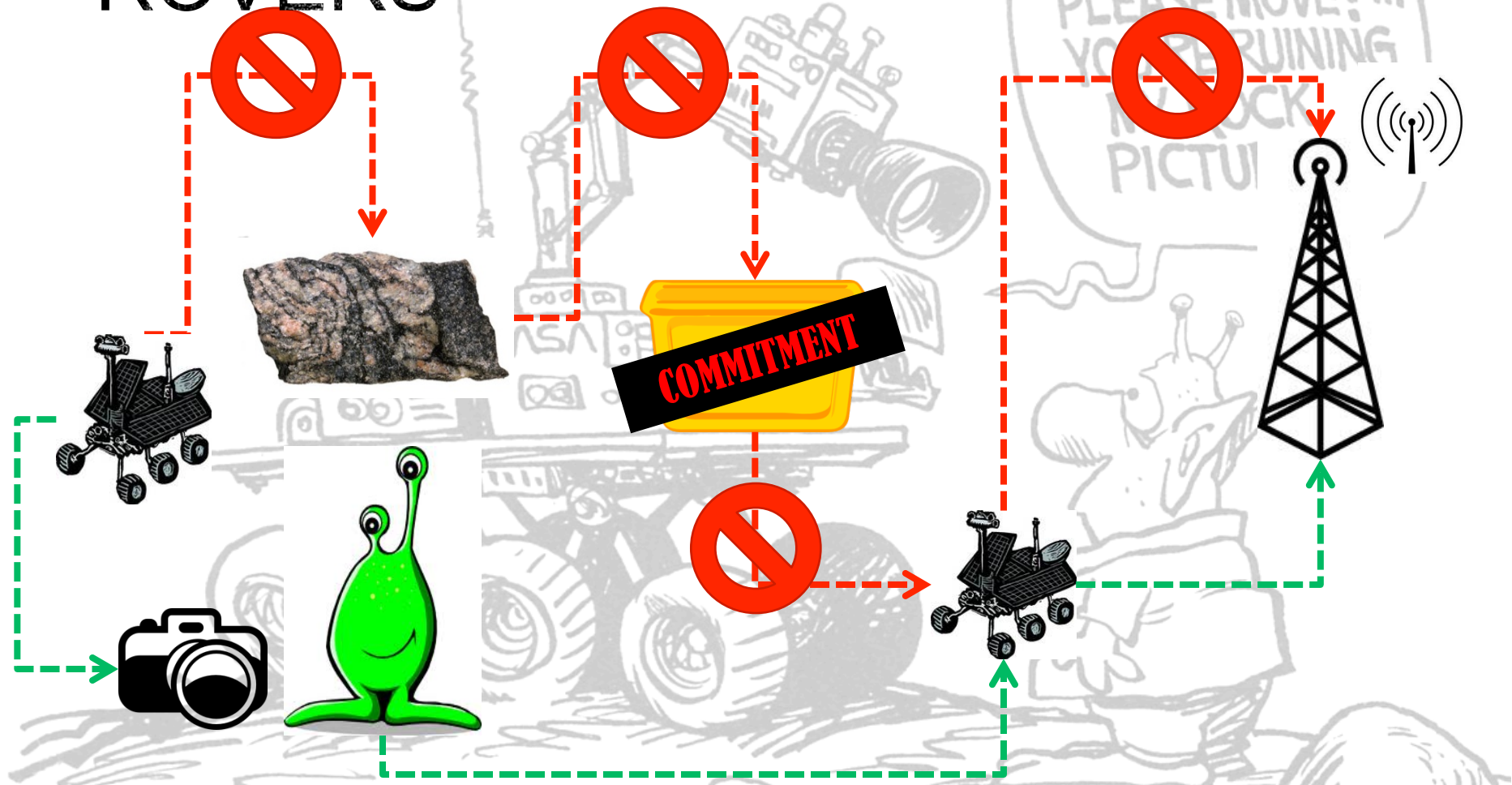


Challenges in Human-in-the-Loop/Human-Aware Planning & Decision Support

- Interpret what humans are doing
 - Plan/goal/intent recognition
- Plan with incomplete domain models
 - Robust planning with “lite” models
 - (Learn to improve domain models)
- Continual planning/Replanning
 - Commitment sensitive to ensure coherent interaction
- Explanations/Excuses
 - Excuse generation can be modeled as the (conjugate of) planning problem
- Asking for help/elaboration
 - Reason about the information value

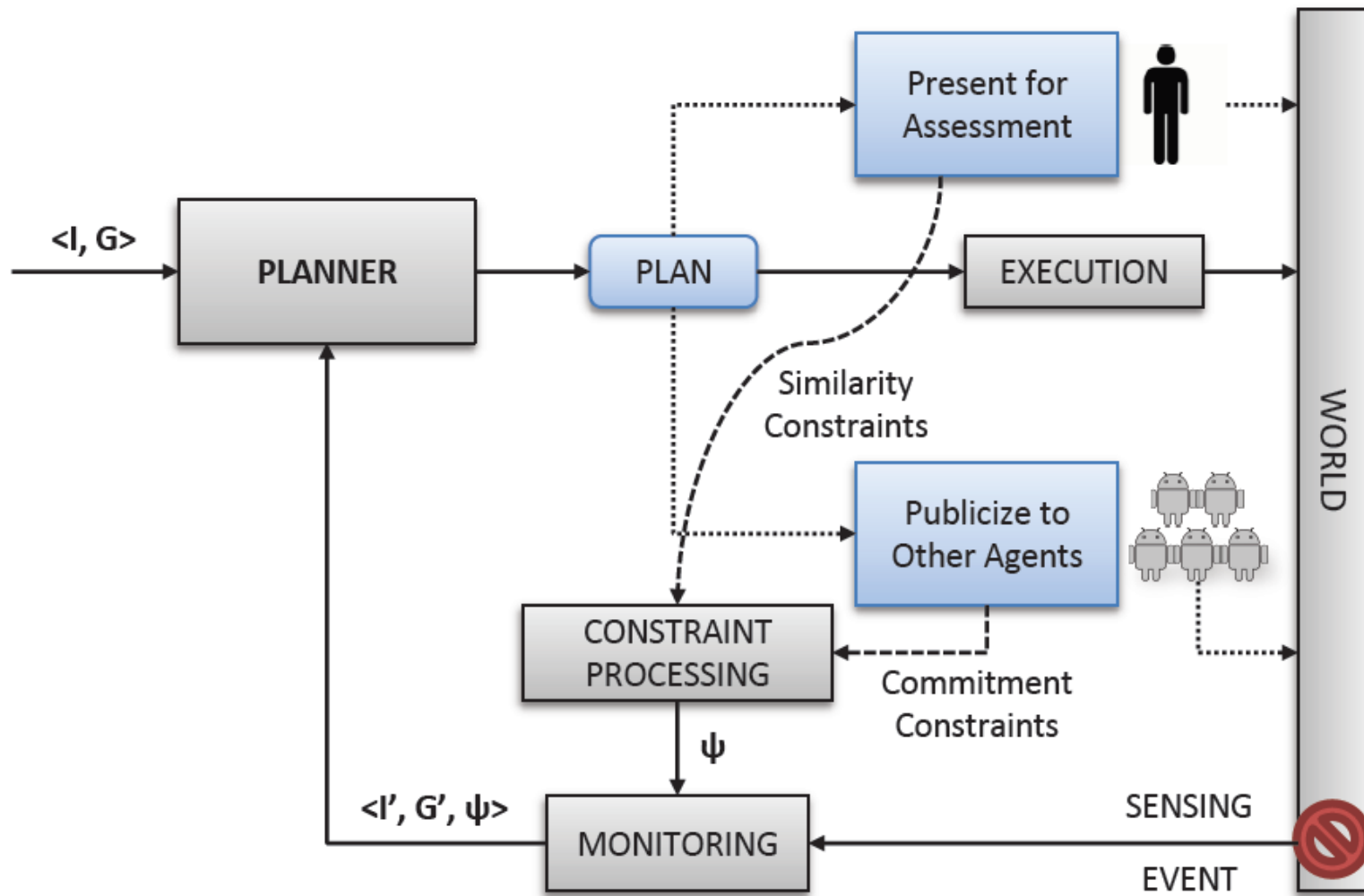
Eigen
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REPLANNING EXAMPLE: ROVERS



reward for photograph of something interesting far exceeds penalty for violating drop-off commitment

A GENERALIZED MODEL OF REPLANNING



REPLANNING CONSTRAINTS

<p>M1 REPLANNING AS RESTART (From scratch)</p>	<p>› No Constraints</p>
<p>M2 REPLANNING AS REUSE (Similarity)</p>	<p>› Depends on the similarity metric between plans</p> <p>› ACTION SIMILARITY</p> <p style="text-align: center;">$\min \pi \Delta \pi'$</p> <p>› CAUSAL SIMILARITY</p> <p style="text-align: center;">$\min CL(\pi) \Delta CL(\pi')$</p>
<p>M3 REPLANNING TO KEEP COMMITMENTS</p>	<p>› Dependencies between π and other plans</p> <p>› Project down into commitments that π' must fulfill</p> <p>› Exact nature of commitments depends on π</p> <p>› E.g.: Multi-agent commitments (between rovers)</p>

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Minecraft USAR Simulation



- Minecraft was chosen for its ease in flexibility and variability in its virtual environment.
- Office environment created in Minecraft for the purpose of simulating a search and rescue task.
- Minecraft allows for complex and changing environments and many internal participants for future iterations.





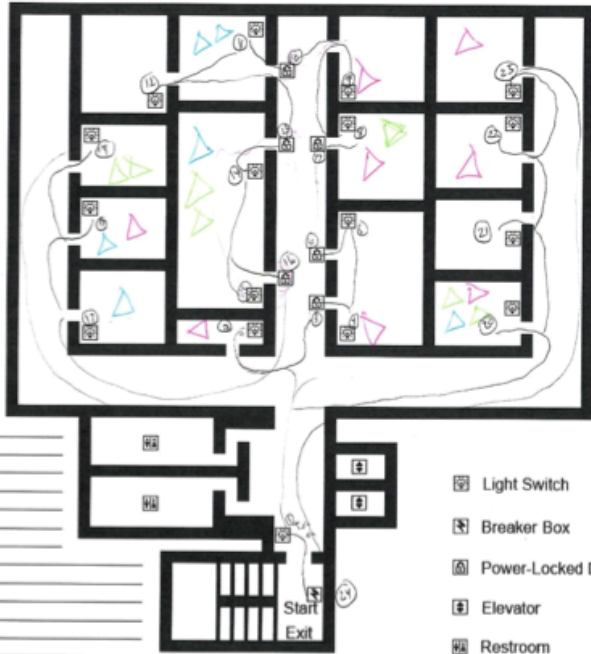
Example Maps



Run 14 Remote 7-17-2014

Notes

Notes section with horizontal lines for text entry.



- Light Switch
- Breaker Box
- Power-Locked Door
- Elevator
- Restroom



NOT
SIPANTS

- Light Switch
- Breaker Box
- Power-Locked Door
- Elevator
- Restroom

KEY

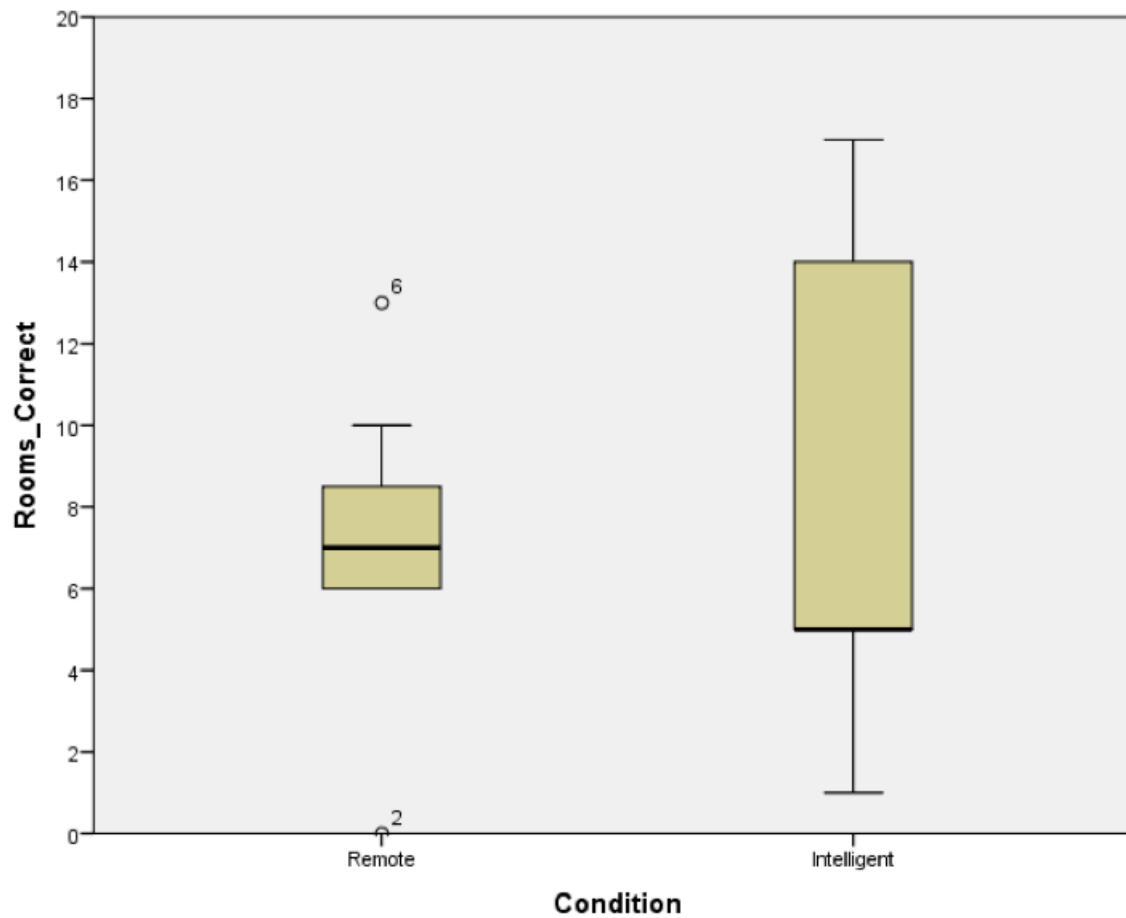




Results: Situation Awareness



External Situation Awareness = number of rooms correct (i.e., correct number and color of boxes on the map) slightly lower for Intelligent and more variability



Note: *Data collection is in progress - results are preliminary*



Human-in-the-Loop Planning is making inroads at ICAPS..

- Several papers that handle these challenges of Human-Aware Planning have been presented at the recent ICAPS (and AAI and IJCAI)
 - Significant help from applications track, robotics track and demonstration track
 - Several planning-related papers in non-ICAPS venues (e.g. AAMAS and even CHI) have more in common with the challenges of Human-aware planning
- ..so consider it for your embedded planning applications



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