



PLANET International Summer School
On AI Planning 2002

Planning and Execution

Martha E. Pollack
University of Michigan
www.eecs.umich.edu/~pollackm

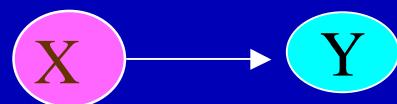
Today's Plan

- Brief Review of Lecture 1 (no slides)
- More Expressive Constraint-Based Temporal Problems (pages H-26 – H-29)
- Handling Potential Plan Failures (pages H-30 – H-48)
- *[[Deliberation Management (pages H-49 – H-59)]]*
- Conclusions (page H-60)

- Note: List of references by topic on pages H-60 – H 63

Handling Temporal Uncertainty

- TP-u (e.g., STP-u)
- Distinguish between two kinds of events:
 - Controllable: the executing agent controls the time of occurrence
 - Uncontrollable: “nature” controls the time of occurrence



Controllable edge (Y controllable event)

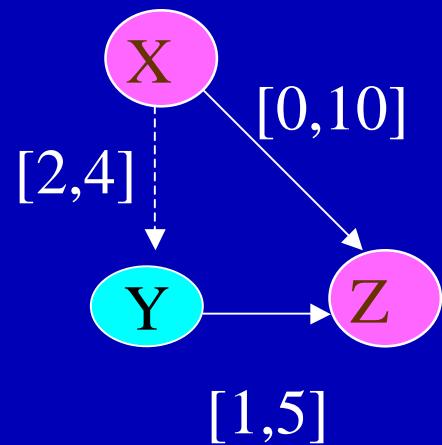


Uncontrollable edge (Y uncontrollable event)

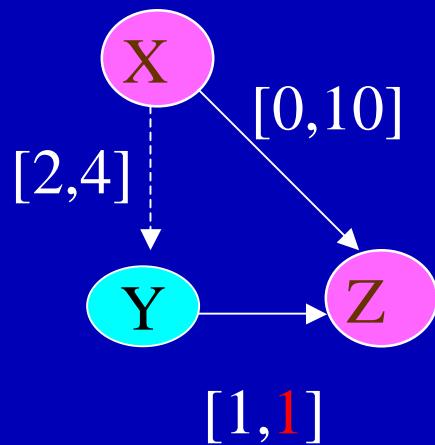
Three Notions of “Solution”

- *Strongly Controllable*: There is an assignment of time points to the controllable events such that the constraints will be satisfied regardless of when the uncontrollables occur.
- *Weakly Controllable*: For each outcome of the uncontrollables, there is an assignment of time points to the controllables such that the constraints are satisfied.
- *Dynamically Controllable*: As time progresses and uncontrollables occur, assignments can be made to the controllables such that the constraints are satisfied.

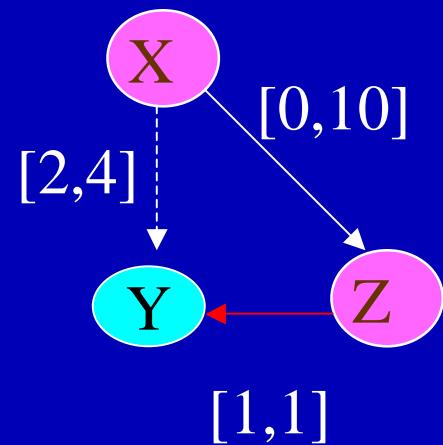
Controllability in STP-u's



Strongly Controllable
 $\{X=0, Z = 5\}$



Dynamically Controllable
 $\{X=0, Z = Y + 1\}$

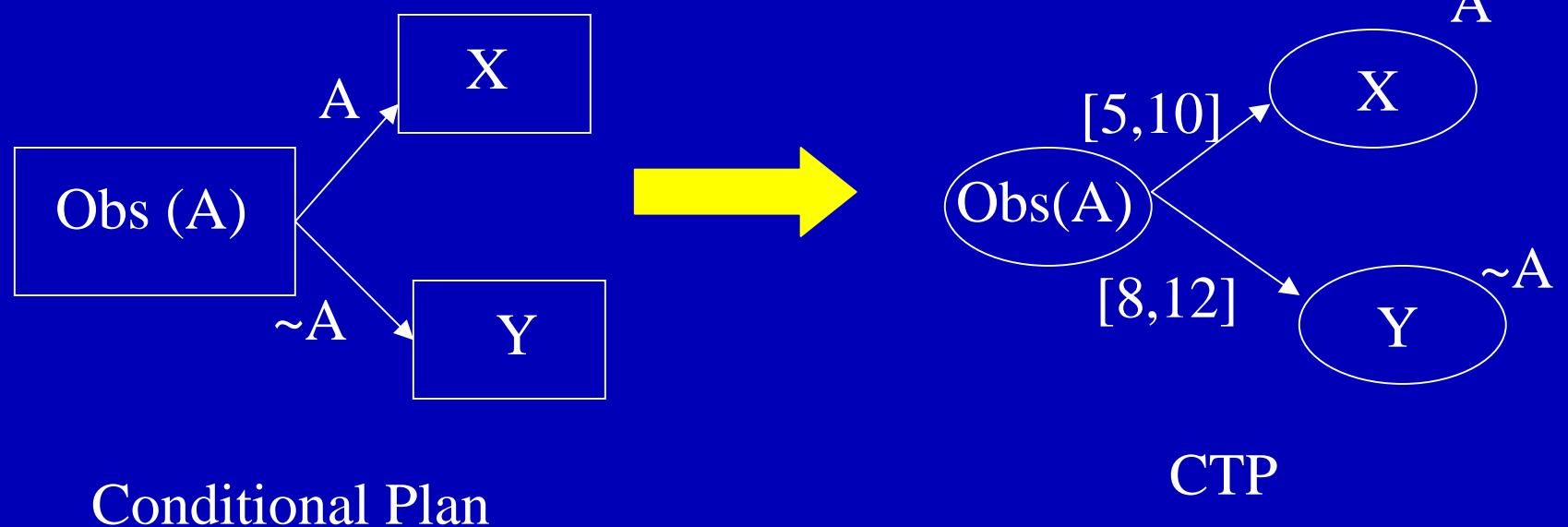


Weakly Controllable
 $\{X=0, Z = Y - 1\}$

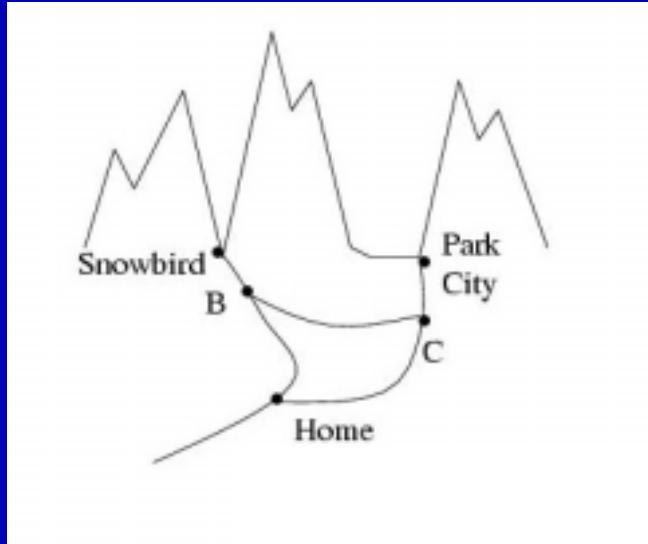
Strong \Rightarrow Dynamic \Rightarrow Weak

Handling Causal Uncertainty

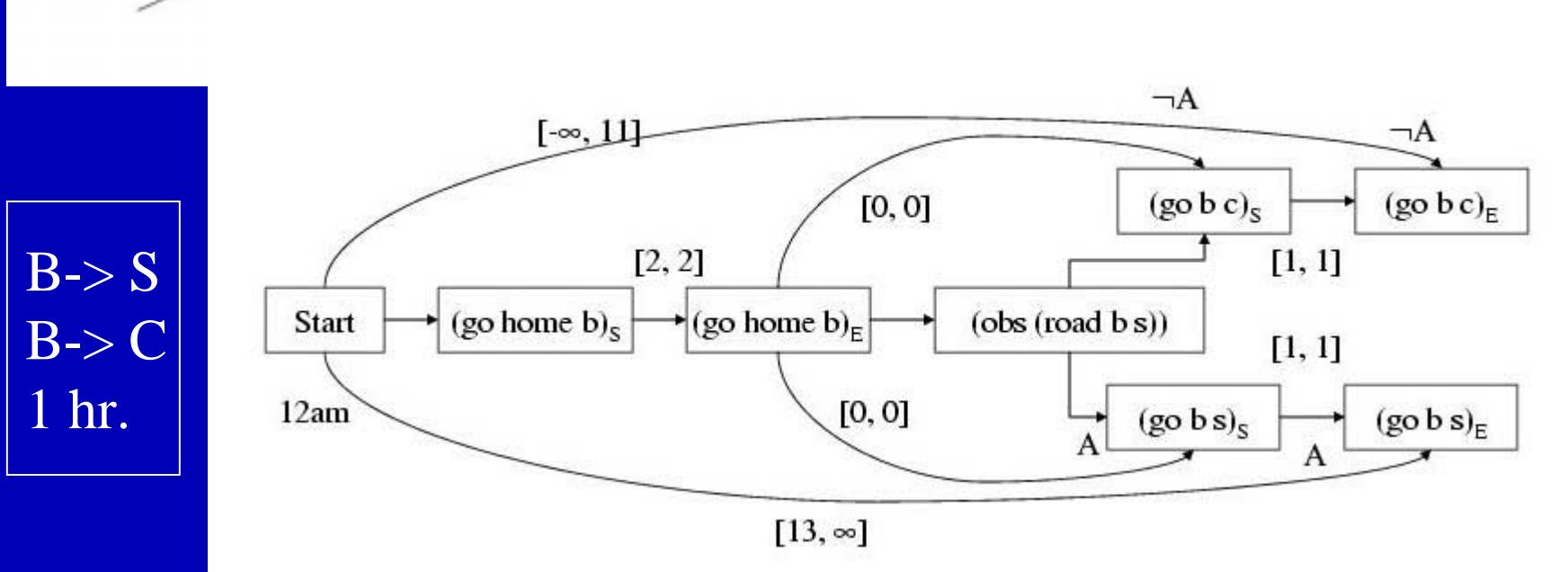
- CTP (e.g., CSTP)
- Label each node—events are executed only if their associated label is true (at a specified observation time)



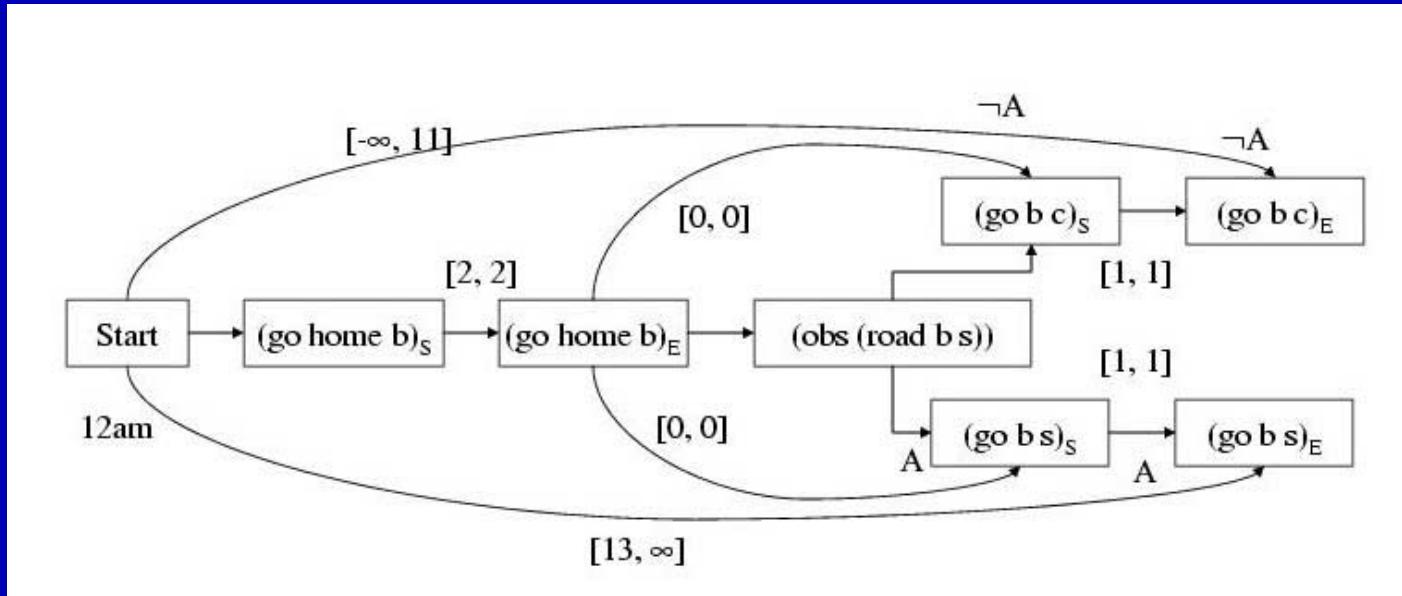
Conditional Plan as CTP



Travel from Home to S, but if the road is blocked from B to S, go to P.
If you go to S, arrive after 1p.m. (to take advantage of the discounts).
If you go to P, arrive at C by 11 a.m. (because traffic gets heavy).

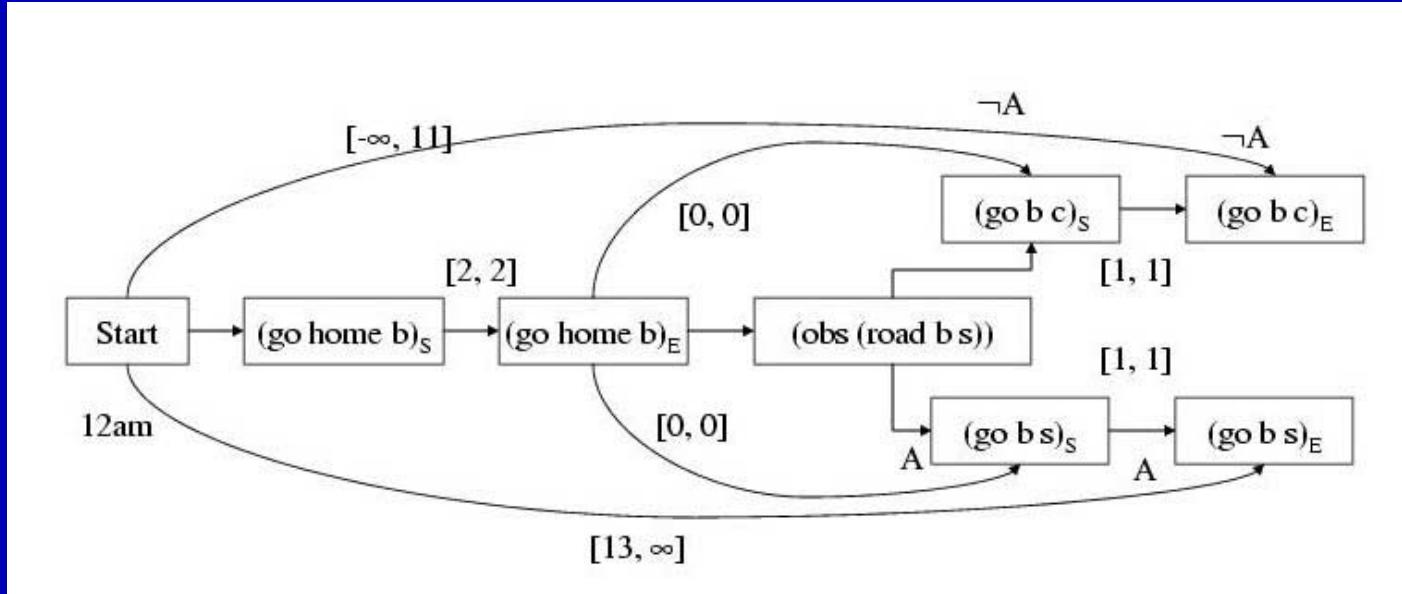


Strong Consistency



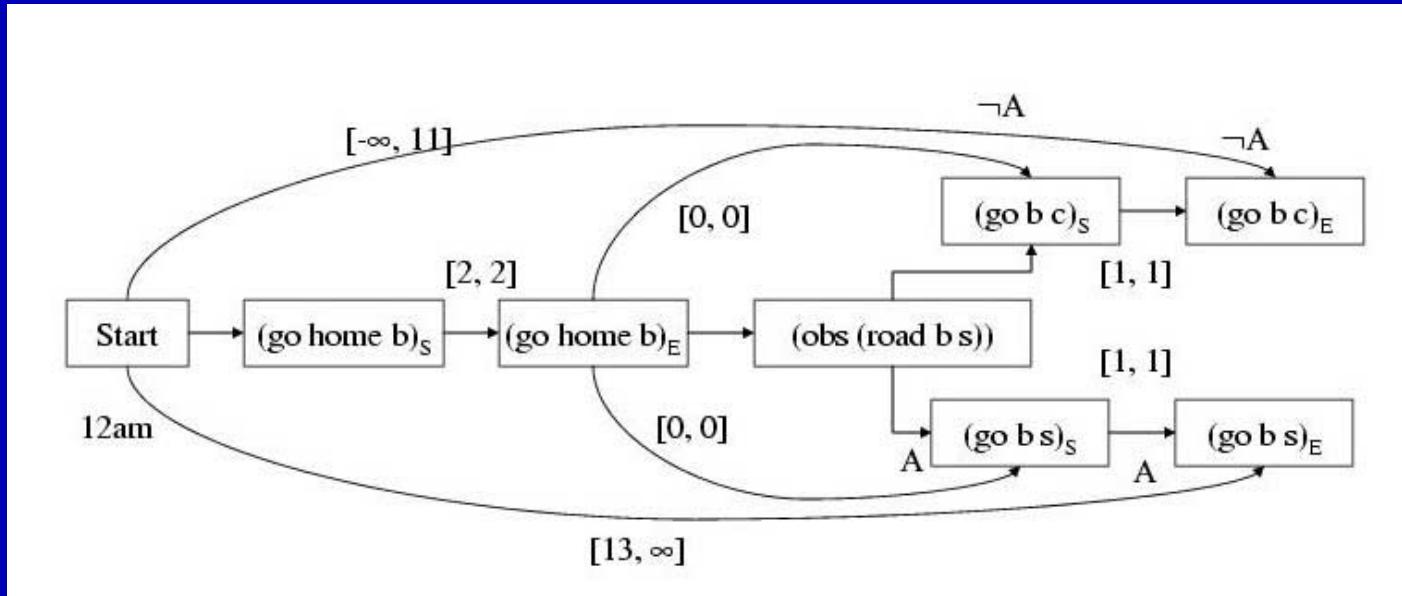
- **Not strongly consistent:** Must not be at B before 12 (if A is true); must be at B by 10 (if A is false)—and can't observe A until you're at B.

Weak Consistency



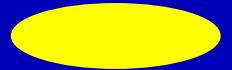
- Weakly consistent: When A is true, leave home after 10 (and all other assignments directly follow). When A is false, leave home by 9.

Dynamic Consistency



- Not dynamically consistent: Can't tell when you need to leave home until it's too late.
- Variant that is dynamically consistent: Add a parking lot at B where you can wait.

Planning and Execution



- So far: Execution Dispatch
 - Well-formed problems
 - Precise solutions that cohere
- This time: Planning and Execution
 - More open-ended questions
 - Partial answers
 - *Opportunity for lots of good research!*

Problem Characteristics

Classical planning:

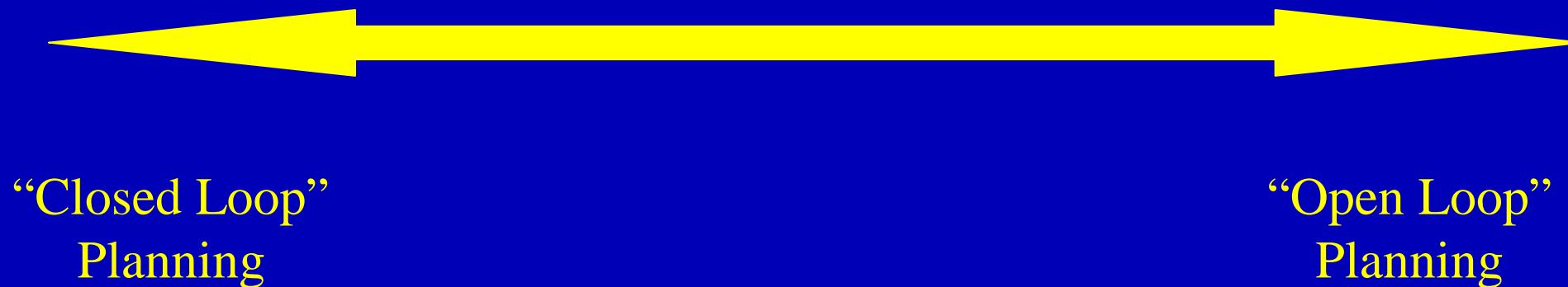
- World is static (and therefore single agent).
- Actions are deterministic.
- Planning agent is omniscient.
- All goals are known at the outset.
- *Consequently*, everything will “go as planned.

But in general:

- World is dynamic and multi-agent
- Actions have uncertain outcomes.
- Planning agent has incomplete knowledge.
- New planning problems arrive asynchronously
- So, things may not go as planned!

When Plans May Fail...

*conformant
plans*



Conformant Planning

- Construct a plan that will work regardless of circumstances
 - Sweep a bar across the desk to clear it
 - Paint both the table and chair to ensure they're the same color
- Without any sensors, may be the best you can do
- In general, conformant plans may be costly or non-existent

When Plans May Fail...

*universal
plans*

*conformant
plans*

“Closed Loop”
Planning

“Open Loop”
Planning

Universal Plans

[Schoppers]

- Construct a complete function from states to actions
- Observe state—take one step—loop
- Essentially follow a decision tree
- Assumes you can completely observe state
- May be a huge number of states!

When Plans May Fail...



*conditional
plans*
MDPs
*universal
plans*

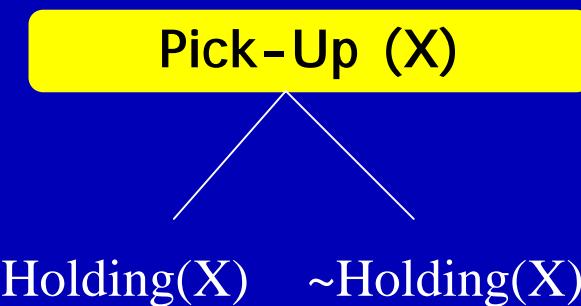
*probabilistic
plans*
*conformant
plans*

“Closed Loop”
Planning

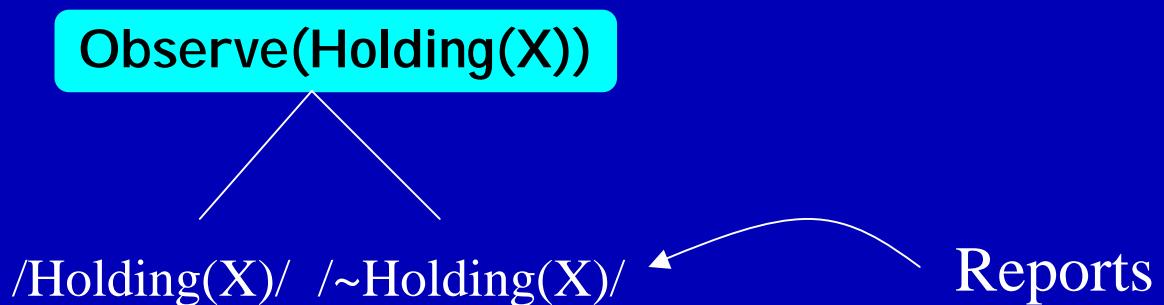
“Open Loop”
Planning

Conditional Planning

- Some causal actions have alternative outcomes



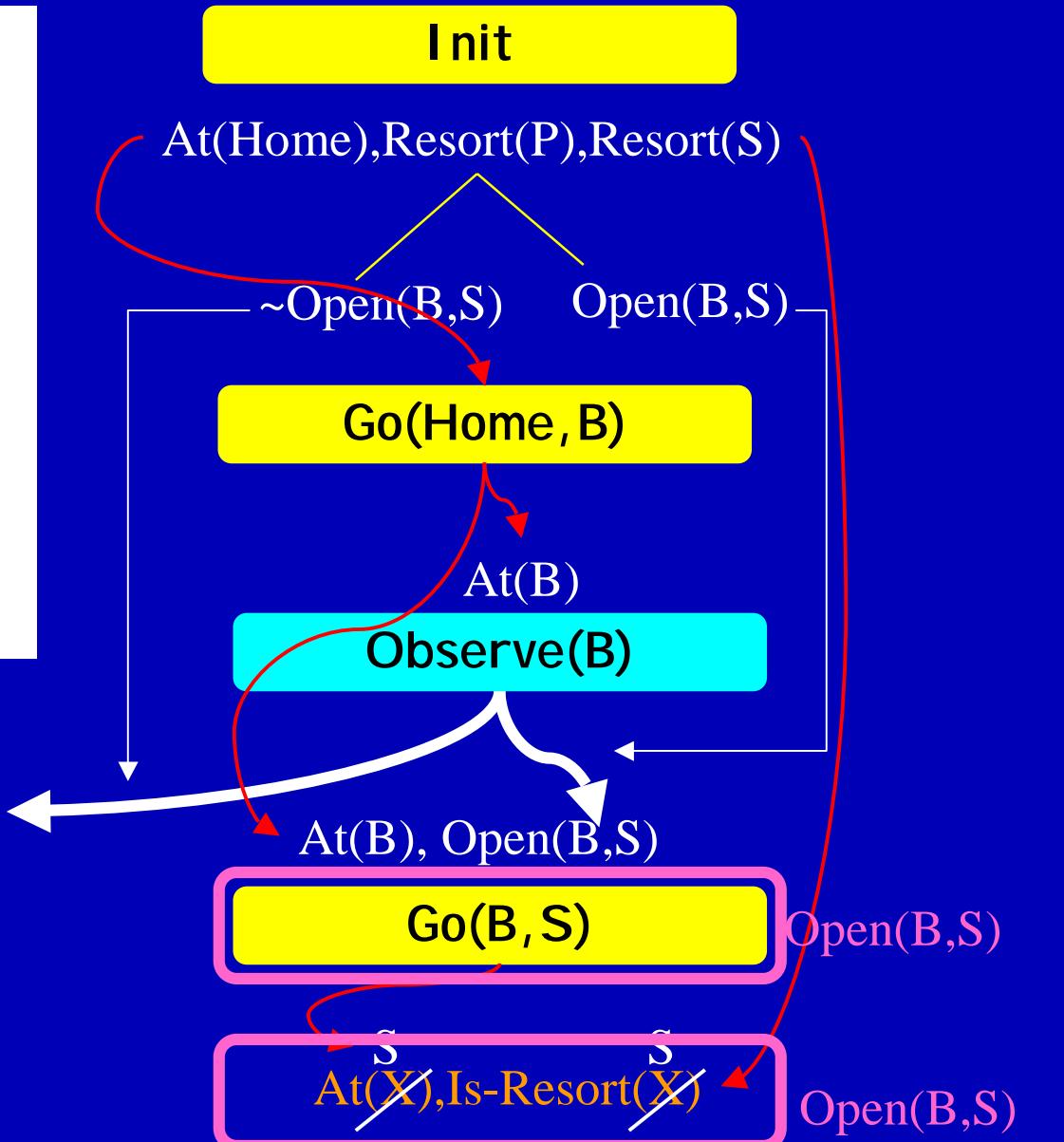
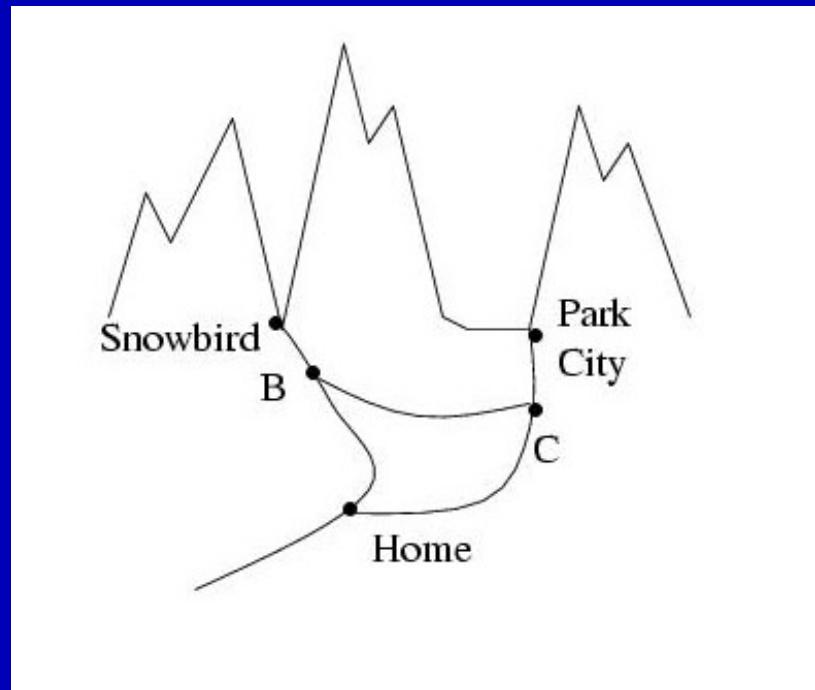
- Observational actions detect state



Plan Generation with Contexts

- *Context* = possible outcome of conditional steps in the plan
- Generate a plan with branches for every possible outcome of conditional steps
 - Do this by creating a new goal state for the negation of the current contexts

Conditional Planning Example



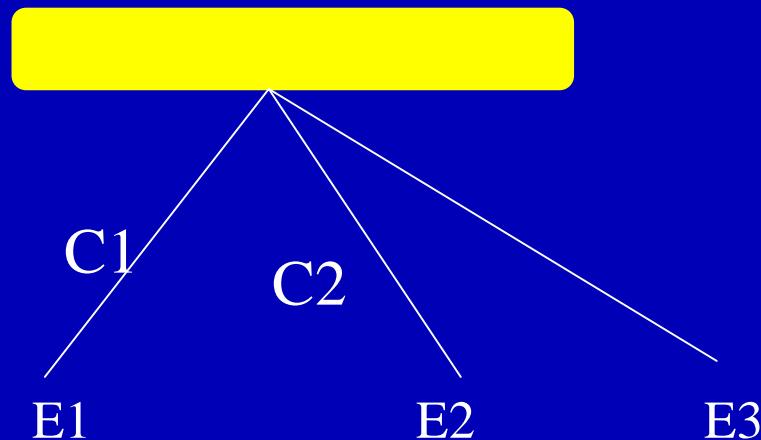
Corrective Repair

- “Correct” the problems encountered, by specifying what to do in alternative contexts
- Requires observational actions, but not probabilities
- Plan for $C_1; \neg C_1 \wedge C_2; \neg C_1 \wedge \neg C_2 \wedge C_3; \dots$
- Disjunction of contexts is a tautology—cover all cases!
 - In practice, may be impossible

Preventive Repair



- Prevent problems from occurring
- “Confrontation” as a threat resolution strategy



When Plans May Fail...

*conditional
plans*

MDPs

*universal
plans*

*probabilistic
plans*

*conformant
plans*

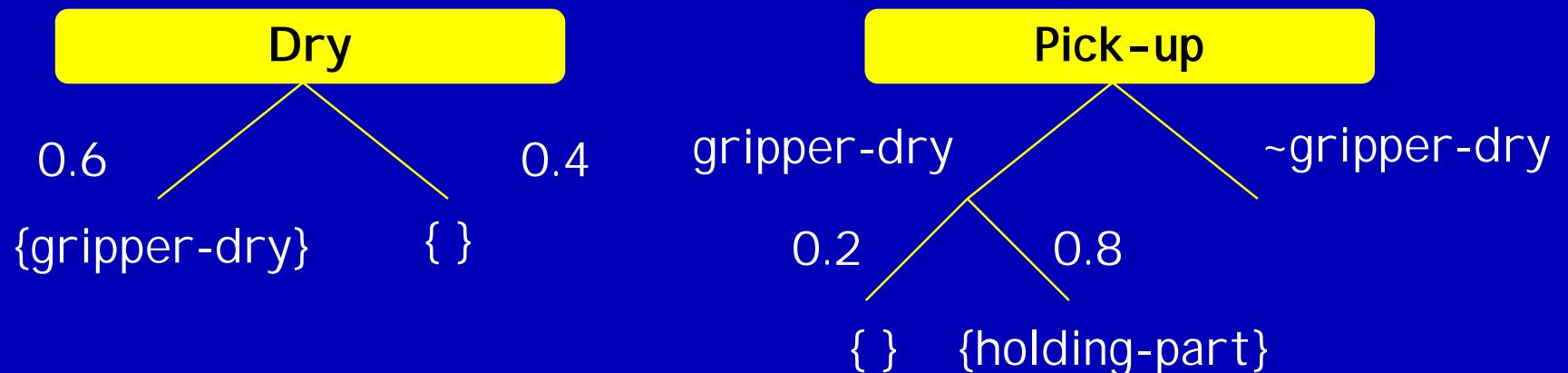


“Closed Loop”
Planning

“Open Loop”
Planning

Probabilistic Planning

- Again, causal steps with alternative outcomes, but this time, know probability of each

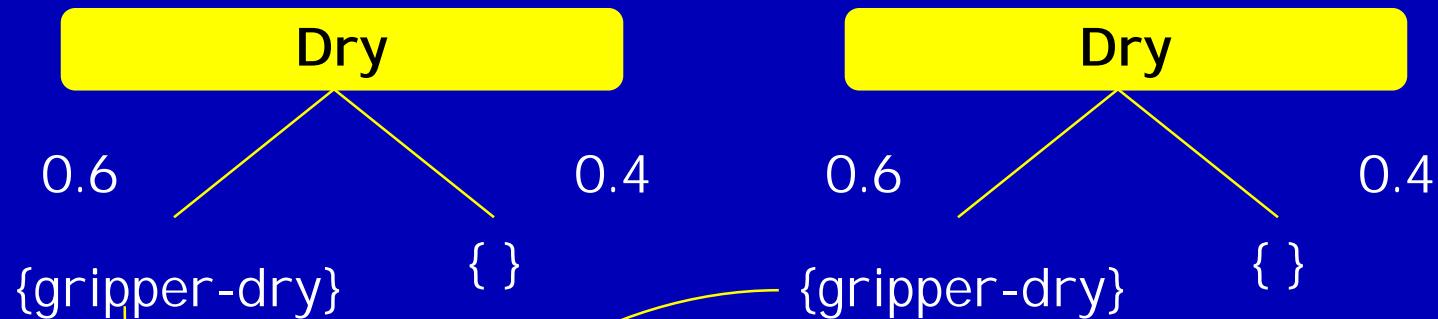


Planning to a Guaranteed Threshold

- Generate a plan that achieves goal with probability exceeding some threshold
- Don't need observation actions

Probabilistic Planning Example

$$P(\text{gripper-dry}) = .5$$



$$T=.3$$

$$.5*.8 = .4$$

$$T=.6$$

$$.5*.8 + .5*.6*.8 = .64$$

Goal: holding-part

$$T=.7$$

$$.5*.8 + .5*.6*.8 + .2*.6*.8 = .73$$

Preventive Repair

- Probabilistic planning “prevents” problems from arising
- Success measured w.r.t. a threshold
- Don’t require observational actions (although in practice, may allow them)
- Exist SAT-based probabilistic planners
 - MAXPLAN

Combining Correction and Prevention

PLAN (init, goal, T)

plans = {make-init-plan (*init*, *goal*)}

while $plan-time < T$ and $plans$ is not empty do

CHOOSE a plan P from *plans*

SELECT a flaw f from P , add all refinements of P to $plans$:

plans = *plans* U new-step(*P,f*) U step-reuse (*P,f*)

if f is an open condition

plans = *plans* U *demote*(*P,f*) U *promote*(*P,f*) U *confront* (*P,f*)

U constrain-to-branch(P, f) if f is a threat

plans = *plans* U corrective-repair(*P,f*) U preventive-repair(*P,f*)

if f is a dangling edge

return (*plans*)

When Plans May Fail...

*conditional
plans*
MDPs
*universal
plans*

*cond-prob plans with
contingency selection*

*probabilistic
plans*

*conformant
plans*

“Closed Loop”
Planning

“Open Loop”
Planning

POP QUIZ !!!

- Don't flip the page in your lectures.

A Very Quick Decision Theory Review

	Lecture is Good	Lecture is Bad
Go to Beach		
Go to Lecture		

A Very Quick Decision Theory Review

	Lecture is Good	Lecture is Bad
Go to Beach	+suntan (V=10) -knowledge (V = -40)	+suntan (V=10)
Go to Lecture	-suntan (V=-5) +knowledge (V=50)	-suntan (V=-5) bored (V=-10)

A Very Quick Decision Theory Review

	Lecture is Good p	Lecture is Bad 1-p
Go to Beach	+suntan (V=10) -knowledge (V = -40)	+suntan (V=10)
Go to Lecture	-suntan (V=-5) +knowledge (V=50)	-suntan (V=-5) bored (V=-10)

A Very Quick Decision Theory Review

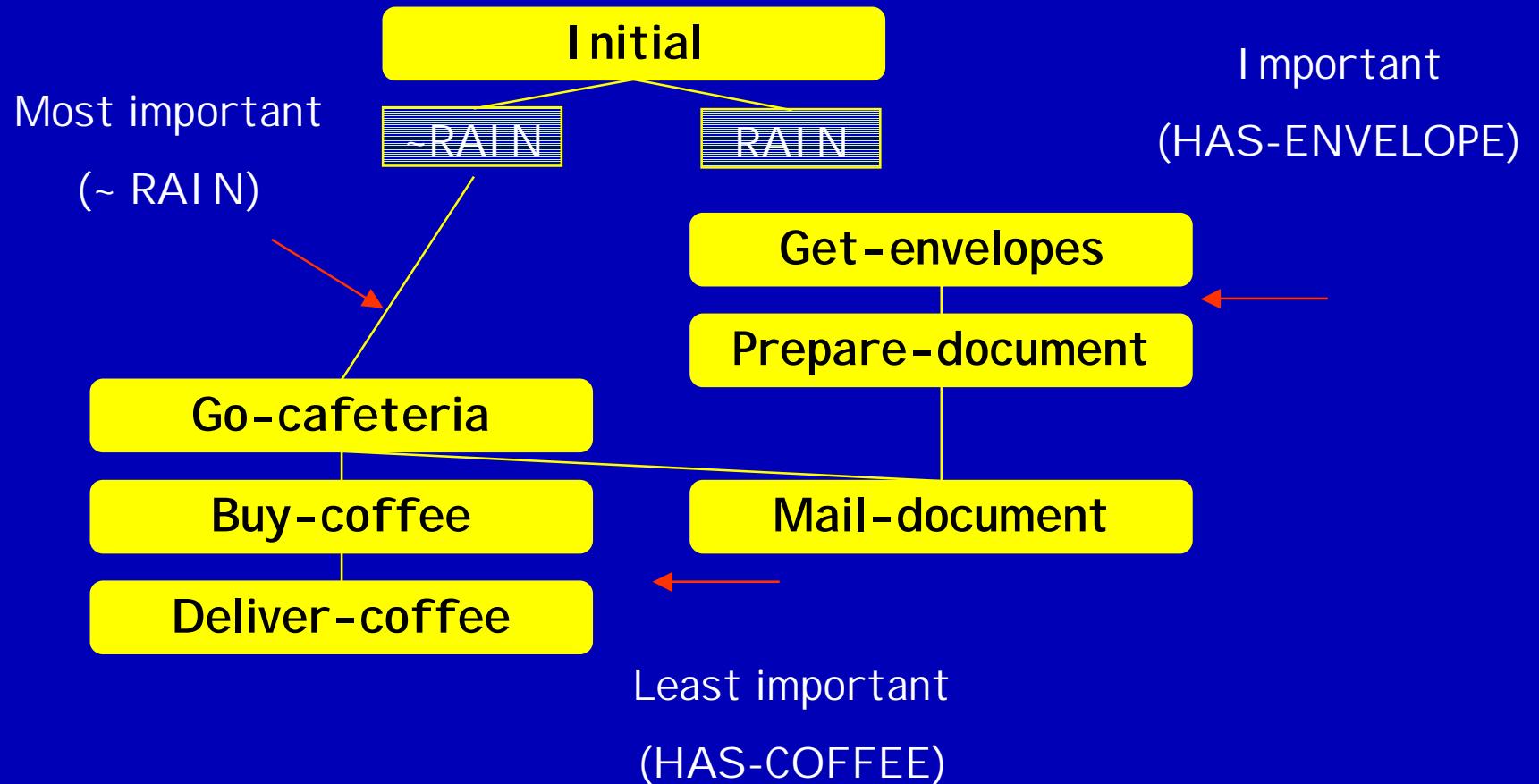
	Lecture is Good p	Lecture is Bad 1-p
Go to Beach	+suntan (V=10) -knowledge (V = -40)	+suntan (V=10)
Go to Lecture	-suntan (V=-5) +knowledge (V=50)	-suntan (V=-5) bored (V=-10)

$$EU(\text{Beach}) = p*(-30) + (1-p)*10 = 10-40p$$

$$EU(\text{Lecture}) = p*(45) + (1-p)*(-15) = 60p-15$$

$$EU(\text{Lecture}) \geq EU(\text{Beach}) \text{ iff } 60p-15 \geq 10-40p, \text{ i.e. } p \geq 1/4$$

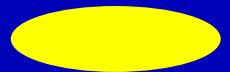
Contingency Selection Example



Influences on Contingency Selection

Factor	Directly Available?
Expected increase in utility	YES
Expected cost of executing contingency plan	NO
Expected cost of generating contingency plan	NO
Resources available at execution time	NO

Expected Increase in Plan's Utility



s_i

c

$$\sum_{g \in \text{Goals}} \{ \text{value}(g) * \text{prob}(s_i \text{ executed and } c \text{ is not true and } g \text{ is not true}) \}$$

1. Construct a plan, possibly with dangling edges.
2. For each dangling edge $e = \langle s_i, c \rangle$, compute expected increase in plan utility for repairing/preventing e .
3. Repair or prevent e with maximal expected utility increase.
4. If expected utility does not exceed threshold, loop.

Build Observations and Reactions into Plan

*conditional
plans*

MDPs

*universal
plans*

*cond-prob plans with
contingency selection*

*probabilistic
plans*

*conformant
plans*

Observe Everything
“Closed Loop”
Planning

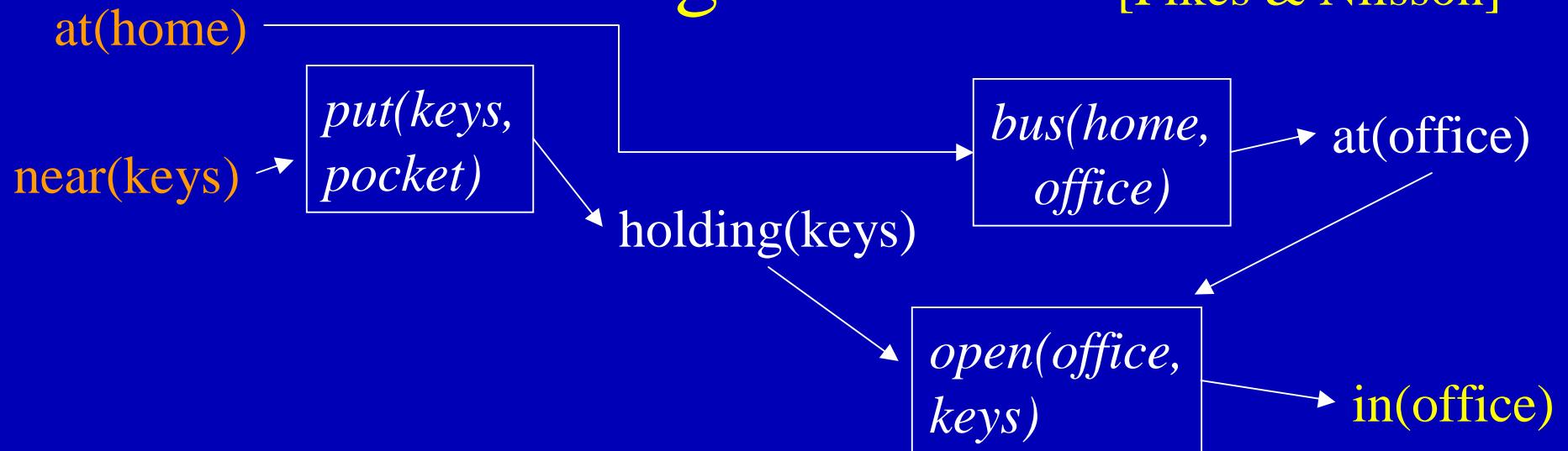
*classical
execution
monitoring*

Observe Nothing
“Open Loop”
Planning

Handle Observations and Reactions Separately

Triangle Tables

[Fikes & Nilsson]



init		put(keys, pocket)	bus(home, office)	open(office, keys)
1	near(keys)			
2	at(home)			
3		holding(keys)	at(home)	
4			at(home)	in(home)

Find largest n s.t. n^{th} kernel enabled \rightarrow
Execute n^{th} action.

Triangle Tables

- Advantages:
 - Allow limited opportunistic reasoning
- Disadvantages:
 - Assumes a totally ordered plan
 - Expensive to check *all* preconditions before every action
 - Otherwise is silent on what preconditions to check when
 - Checks only for preconditions of actions in the plan

Monitoring for Alternatives

[Veloso, Pollack, & Cox]

- May want to change the plan even if it can still succeed
- Monitor for conditions that caused rejection of alternatives during planning
- May be useful during planning as well as during execution

Alternative Monitoring Example



Preference Rule: Use frequent flier miles when cost > \$500.

T1: Cost = \$450; Decide to purchase tickets.

T2: Cost = \$600; Decide to use frequent flier miles???

Depends on whether execution has begun, and if so, on the cost of plan revision.

Monitoring for Alternatives

- Classes of monitors:
 - Preconditions
 - Usability Conditions
 - take the bus (vs. bike) because of rain
 - Quantified Conditions
 - number of cars you need to move to use van goes to 0
 - Preference Conditions
- Problems
 - Oscillating conditions
 - Ignores cost of plan modification, especially after partial execution
 - Still doesn't address timing and cost of monitoring

Build Observations and Reactions into Plan

*conditional
plans*
MDPs
*universal
plans*

*conditional plans with
contingency selection*

*probabilistic
plans*

*conformant
plans*

Observe Everything
“Closed Loop”
Planning

*classical
execution
monitoring*

*selective execution
monitoring*

Observe Nothing
“Open Loop”
Planning

Handle Observations and Reactions Separately

Decision-Theoretic Selection of Monitors [Boutilier]

- Monitor selection is actually a sequential decision problem
- At each stage:
 - Decide what (if anything) to monitor
 - Update beliefs on the basis of monitoring results
 - Decide whether to continue or abandon the plan
 - If continue, update beliefs after acting
- Formulate as a POMDP

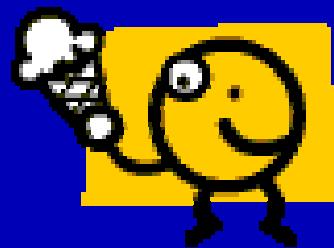
Required Information

- Probability that any precondition may fail (or may become true) as the result of an exogenous action
- Probability that any action may fail to achieve its intended results
- Cost of attempting to execute a plan action when its preconditions have failed
- Value of the best alternative plan at any point during plan execution
- Model of the monitoring processes and their accuracy

Heuristic Monitoring

- Solving the POMDP is computationally quite costly
- Effective alternative: Construct and solve a separate POMDP for each stage of the plan; combine results online

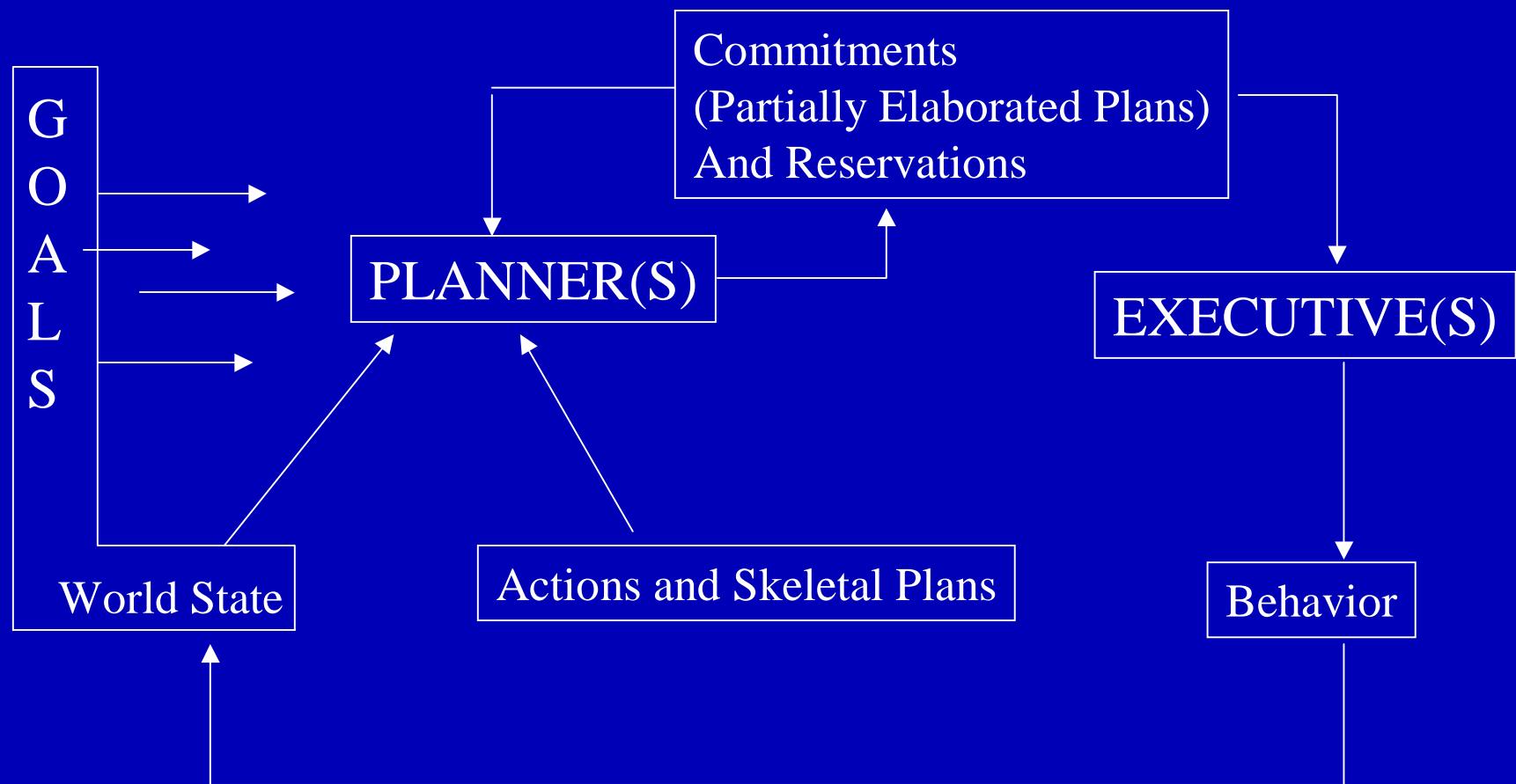
Conclusion



Today's Outline

- ✓ 1. Handling Potential Plan Failures
- 2. Managing Deliberation Resources

Integrated Model of Planning and Execution



Deliberation Management

- Have planning problems for goals $G1, G2, \dots, Gn$, and possibly competing execution step X .
- What should the agent do?
- A decision problem: can we apply decision theory?

DT Applied to Deliberation

		PROBLEM 1. Hard to specify the conditions until the planning is complete.
Plan for G1 now		
Plan for G2 now	PROBLEM 2. The DT problem takes time, during which the environment may change.	
Plan for G3 now		(Not unique to DT for deliberation: Type II Rationality)
Perform action X now		

Bounded Optimality

[Russell & Subramanian]

- Start with a method for *evaluating* agent behavior
- Basic idea:
 - Recognize that all agents have computational limits as a result of being implemented on physical architecture
 - Treat an agent as (boundedly) optimal if it performs at least as well as other agents with identical architectures

Agent Formalism

Percepts: O

Percept History: O^T

Actions: A

Action History: A^T

Agent Function: $f: O^t \rightarrow A$ s.t. $A^T(t) = f(O^T)$

World States: X

State History: X^T

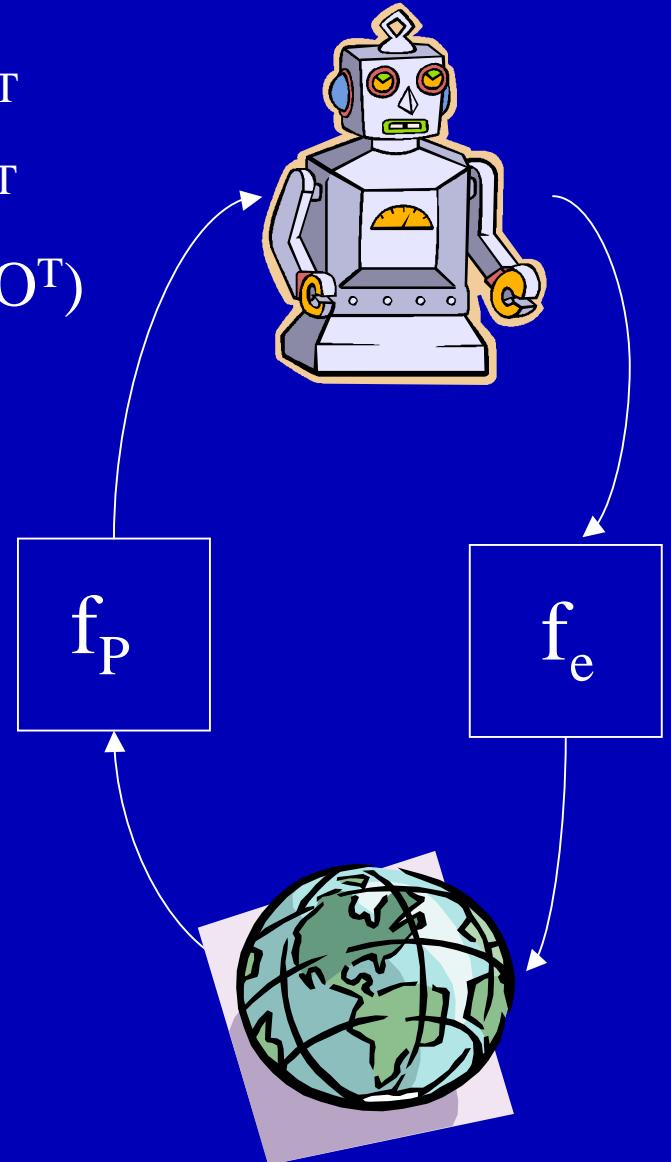
Perceptual Filtering Function: $f_P(x)$

Action Transition Function: $f_e(a,x)$

$X^T(0) = X_0$

$X^T(t+1) = f_e(A^T(t), X^T(t))$

$O^T(t) = f_P(X^T(t))$



Agent Implementations

- A given architecture M can run a set of programs L_M
- Every program $l \in L_M$ implements some agent function f
- But not every agent function f can be implemented on a given architecture M
- So define:

$$Feasible(M) = \{f \mid \exists l \in L_M \text{ that implements } f\}$$

Rational Programs

- Given a set of possible environments \mathbf{E} , we can compute the expected value, V , of an agent function f , or a program l
- Perfectly rational agent for \mathbf{E} has *agent function* $f_{OPT} = \text{argmax}_f(V(f, \mathbf{E}))$
- Boundedly optimal agent for \mathbf{E} has an *agent program* $l_{OPT} = \text{argmax}_{l \in L_M} V(l, \mathbf{M}, \mathbf{E})$
- So bounded optimality is the best you can hope for, given some fixed architecture!

Back to Deliberation Management

“The gap between theory and practice is bigger in practice than in theory.”

Bounded Optimality not (yet?) applied to the problem of deciding amongst planning problems.

Has been applied to certain cases of deciding amongst decision procedures (planners).

Bounded Optimality Result I

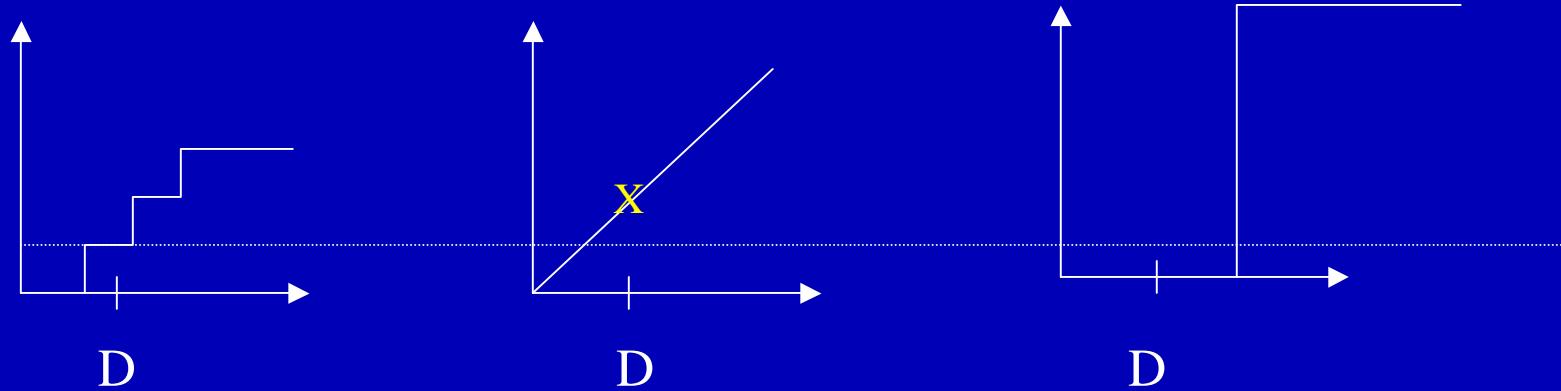
- Given an episodic real-time environment with fixed deadlines
 - the best program is the single decision procedure of maximum quality whose runtime is less than the deadline.

An action taken any time up to the deadline gets the same value; no value after that

State history is divided into a series of episodes, each terminated by an action.

Bounded Optimality Result I

- Given an episodic real-time environment with fixed deadlines
 - the best program is the single decision procedure of maximum quality whose runtime is less than the deadline.



Bounded Optimality Result II

- Given an episodic real-time environment with fixed time costs
 - the best program is the single decision procedure whose quality net of time cost is highest.

The value of an action decreases linearly with the time at which it occurs

Bounded Optimality Result III

- Given an episodic real-time environment with stochastic deadlines
 - can use Dynamic Programming to compute an optimal sequence of decision procedures, whose rules are in nondecreasing order of quality.

Like fixed deadlines, but the time of the deadline is given by a probability distribution

Challenge

- Develop an account of bounded optimality for the deliberation management problem!

An Alternative Account

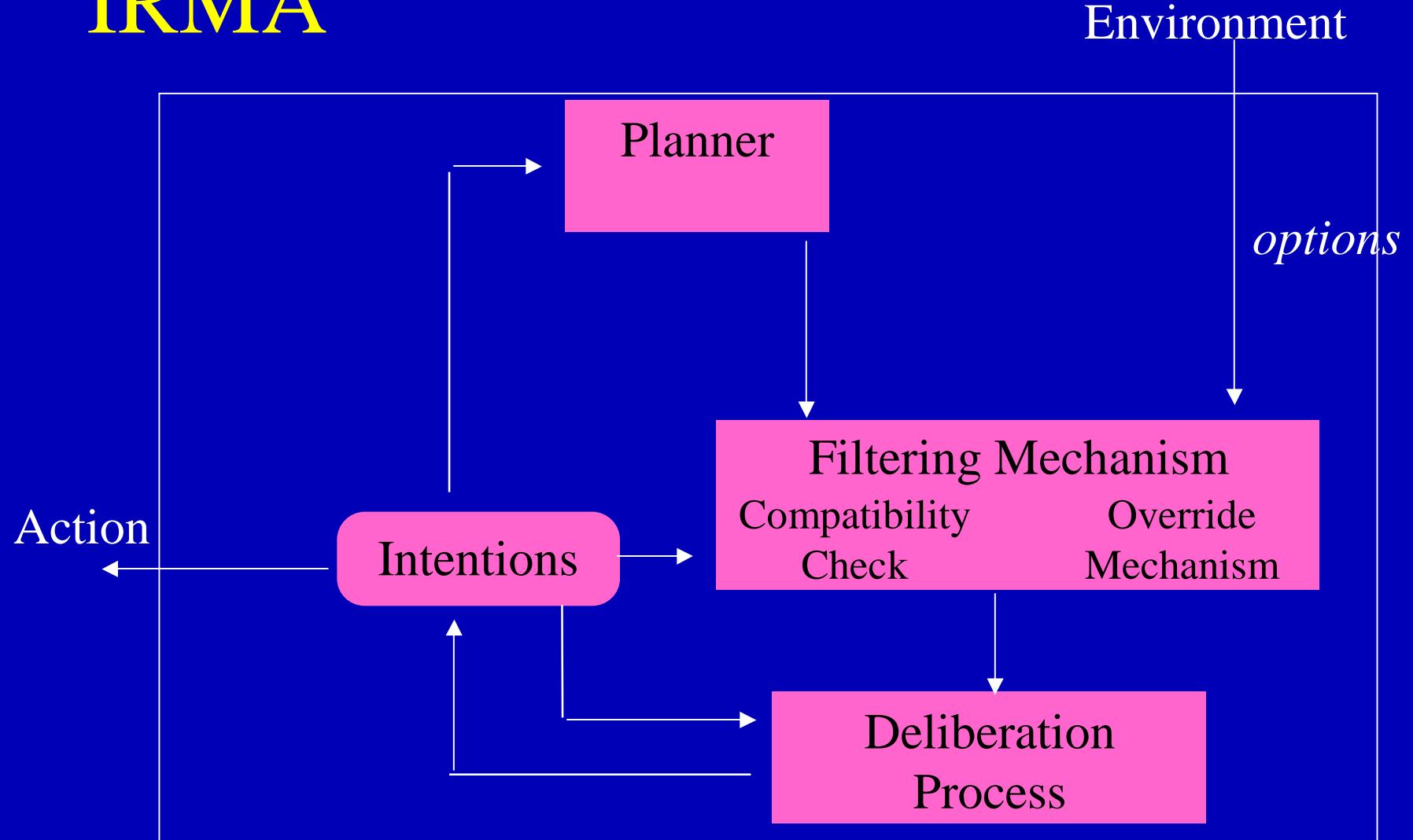
[Bratman, Pollack, & Israel]

- Heuristic approach, based on BDI (Belief-Desire-Intention) theory
- Grew out of philosophy of intention
- Was influential in the development of PRS (Procedural Reasoning System)

The Philosophical Motivation

- Question: Why Plan (Make Commitments)?
 - Metaphysically Objectionable (action at a distance) *or*
 - Rationally Objectionable (if commitments are irrevocable) *or*
 - A Waste of Time (if you maintain commitments only when you’re form the commitment anyway)
- One Answer: Plans help with deliberation management, by constraining future actions

IRMA



Filtering

- Mechanism for maintaining stability of intentions in order to focus reasoning
- Designer must balance appropriate sensitivity to environmental change against reasonable stability of plans
- Can't expect perfection: Need to trade occasional wasted reasoning and locally suboptimal behavior for overall effectiveness

The Effect of Filtering

	Survives compatibility check	Triggers override	Deliberation leads to change of plan	Deliberation <i>would have</i> led to change of plan
1	N	Y	Y	
2	N	Y	N	
3	N	N		N
4	N	N		Y
5	Y			

Situations 1 & 2: Agent behaves *cautiously*

Situations 3 & 4: Agent behaves *boldly*

Situation 2: Wasted computational effort

Situation 4: Locally suboptimal behavior

The Effect of Filtering

	Survives compatibility filter	Triggers filter override	Deliberation leads to change of plan	Deliberation <i>would have</i> led to change of plan	Deliberation worthwhile
1a		N	Y	Y	Y
1b	N	Y	Y		N
2	N	Y	N		
3	N	N		N	
4a		N	N		Y Y
4b	N	N		Y	N
5	Y				

Situations 1 & 2: Agent behaves *cautiously* (In 1a, caution pays!)

Situations 3 & 4: Agent behaves *boldly* (In 3 & 4b, boldness pays!)

Situation 1b & 2: Wasted computational effort

Situation 4a: Locally suboptimal behavior

From Theory to Practice

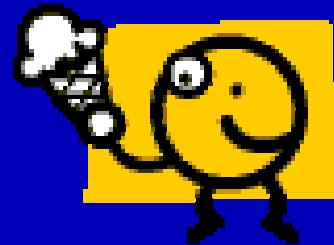
“The gap between theory and practice is bigger in practice than in theory.”

- Most results were shown in an artificial, simulated environment: The Tileworld
- More recent work:
 - Refined account in which filtering is not all-or-nothing: the greater the potential value of a new option, the more change to the background plan allowed.
 - Based on account of computing the cost of actions *in the context of other plans.*

Planning and Execution—Other Issues

- Goal identification
- Cost/benefit assessment of plans
- Replanning techniques and priorities
- Execution Systems: PRS
- Real-Time Planning Systems: MARUTI, CIRCA

Conclusion



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