Course on Automated Planning: Transformations

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AI Planning: Status

- The good news: **classical planning works!**
  - ▷ *Large problems solved very fast (non-optimally)*
- **Model simple but useful**
  - ▷ *Operators not primitive; can be policies themselves*
  - ▷ *Fast closed-loop replanning able to cope with uncertainty sometimes*
- Not so good; **limitations:**
  - ▷ *Does not model* **Uncertainty** *(no probabilities)*
  - ▷ *Does not deal with* **Incomplete Information** *(no sensing)*
  - ▷ *Does not accommodate* **Preferences** *(simple cost structure)*
  - ▷ ...

Beyond Classical Planning: Two Strategies

- **Top-down:** Develop solver for **more general class of models;** e.g., Markov Decision Processes (MDPs), Partial Observable MDPs (POMDPs), . . .

  $+$: generality
  $-$: complexity

- **Bottom-up:** Extend the scope of **current 'classical' solvers**

  $+$: efficiency
  $-$: generality

- We'll do both, starting with **transformations** for

  ▷ compiling **soft goals** away (planning with preferences)
  ▷ compiling **uncertainty** away (conformant planning)
  ▷ compiling **sensing** away (planning with sensing)
  ▷ doing **plan recognition** (as opposed to plan generation)

Compilation of Soft Goals

- Planning with **soft goals** aimed at plans π that maximize **utility**

$$u(\pi) = \sum_{p \in do(\pi, s_0)} u(p) \quad - \quad \sum_{a \in \pi} c(a)$$

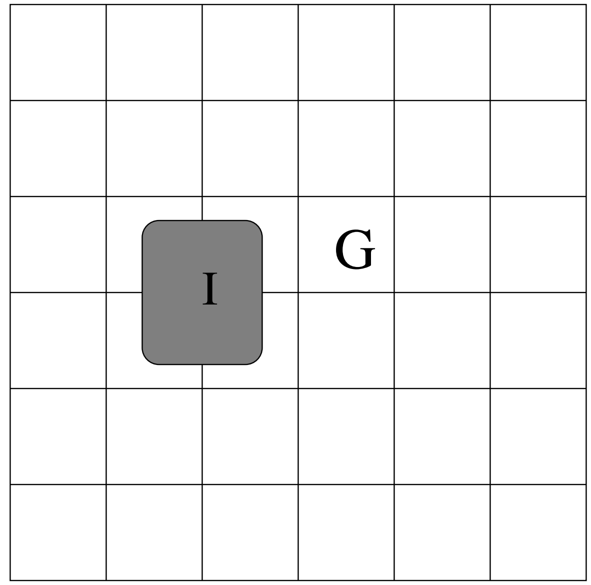
- Actions have **cost** $c(a)$, and soft goals **utility** $u(p)$
- Best plans achieve best **tradeoff** between **action costs** and **utilities**
- Model used in recent planning competitions; **net-benefit track** 2008 IPC
- Yet it turns that soft goals **do not** add expressive power, and can be **compiled away**

Compilation of Soft Goals (cont'd)

- For each soft goal p, create **new hard goal** p' initially false, and **two new actions**:
  - ▷ $collect(p)$ with precondition p, effect p' and **cost** 0, and
  - ▷ $forgo(p)$ with an empty precondition, effect p' and **cost** $u(p)$
- Plans π maximize $u(\pi)$ iff minimize $c(\pi) = \sum_{a \in \pi} c(a)$ in resulting problem
- Compilation yields better results that native soft goal planners in recent IPC (Keyder & G. 07,09)

	IPC6 Net-Benefit Track			Compiled Problems			
Domain	Gamer	HSP^*_{P}	Mips-XXL	Gamer	HSP^*_{F}	HSP^*_{0}	Mips-XXL
crewplanning(30)	4	16	8	-	8	**21**	8
elevators (30)	11	5	4	**18**	8	8	3
openstacks (30)	**7**	5	2	6	4	6	1
pegsol (30)	24	0	23	22	**26**	14	22
transport (30)	12	12	9	-	**15**	**15**	9
woodworking (30)	13	11	9	-	**23**	22	7
total	71	49	55		84	**86**	50

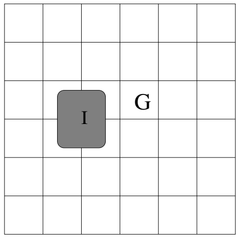
Incomplete Information: Conformant Planning



Problem: A robot must move from an **uncertain** I into G with **certainty**, one cell at a time, in a grid nxn

- Problem very much like a classical planning problem except for **uncertain** I
- Plans, however, quite different: best **conformant plan must move the robot to a corner first (localization)**

Conformant Planning: Belief State Formulation



- call a **set** of possible states, a **belief state**
- actions then map a belief state b into a bel state $b_a = \{s' \, | s' \in F(a,s) \;\&\; s \in b\}$
- **conformant problem** becomes a path-finding problem in **belief space**

Problem: number of belief state is **doubly exponential** in number of variables.

- **effective representation** of belief states b
- **effective heuristic** $h(b)$ for estimating cost in belief space

Recent alternative: translate into classical planning . . .

Basic Translation: Move to the 'Knowledge Level'

Given **conformant problem** $P = \langle F, O, I, G \rangle$

- F stands for the fluents in P
- O for the operators with effects $C \longrightarrow L$
- I for the initial situation (**clauses** over F-literals)
- G for the goal situation (set of F-literals)

Define **classical problem** $K_0(P) = \langle F', O', I', G' \rangle$ as

- $F' = \{KL, K\neg L \mid L \in F\}$
- $I' = \{KL \mid$ clause $L \in I\}$
- $G' = \{KL \mid L \in G\}$
- $O' = O$ but preconds L replaced by KL, and effects $C \longrightarrow L$ replaced by $KC \longrightarrow KL$ (**supports**) and $\neg K \neg C \longrightarrow \neg K \neg L$ (**cancellation**)

$K_0(P)$ is **sound** but **incomplete**: every classical plan that solves $K_0(P)$ is a conformant plan for P, but not vice versa.

Key elements in Complete Translation $K_{T,M}(P)$

- A set T of **tags** t: consistent sets of **assumptions** (literals) about the **initial situation** I

$$I \not\models \neg t$$

- A set M of **merges** m: **valid subsets of tags** (= DNF)

$$I \models \bigvee_{t \in m} t$$

- **New (tagged) literals** KL/t meaning that L **is true if** t **true initially**

A More General Translation $K_{T,M}(P)$

Given **conformant problem** $P = \langle F, O, I, G \rangle$

- F stands for the fluents in P
- O for the operators with effects $C \rightarrow L$
- I for the initial situation (**clauses** over F-literals)
- G for the goal situation (set of F-literals)

define **classical problem** $K_{T,M}(P) = \langle F', O', I', G' \rangle$ as

- $F' = \{KL/t\ ,\ K\neg L/t \mid L \in F$ and $t \in T\}$
- $I' = \{KL/t \mid$ if $I \models t \supset L\}$
- $G' = \{KL \mid L \in G\}$
- $O' = O$ but preconds L replaced by KL, and effects $C \rightarrow L$ replaced by $KC/t \rightarrow KL/t$ (**supports**) and $\neg K\neg C/t \rightarrow \neg K\neg L/t$ (**cancellation**), and **new merge actions**

$$\bigwedge_{t \in m, m \in M} KL/t \ \rightarrow \ KL$$

The two **parameters** T and M are the set of **tags** (assumptions) and the set of **merges** (valid sets of assumptions) . . .

Compiling Uncertainty Away: Properties

- General translation scheme $K_{T,M}(P)$ is always **sound**, and for suitable choice of the sets of **tags** and **merges**, it is **complete**.

- $K_{S0}(P)$ is **complete instance** of $K_{T,M}(P)$ obtained by setting T to the set of **possible initial states** of P

- $K_i(P)$ is a **polynomial instance** of $K_{T,M}(P)$ that is **complete** for problems with **width** bounded by i.

  ▷ *Merges for each L in $K_i(P)$ chosen to* **satisfy** i *clauses in I relevant to L*

- The **width** of most benchmarks **bounded** and equal 1!

- This means that such problems can be solved with a **classical planner** after a **polynomial** translation (Palacios & G. 07, 09)

Planning with Sensing: Models and Solutions

Problem: Starting in one of two rightmost cells, get to B; A & B **observable**

A				B

- **Contingent Planning**
  - ▷ *A* **contingent plan** *is a* **tree** *of possible executions, all leading to the goal*
  - ▷ *A contingent plan for the problem:* $\underline{R(ight), R, R, \text{ if } \neg B \text{ then } R}$

- **POMDP planning**
  - ▷ *A* **POMDP policy** *is mapping of belief states to actions, leading to goal*
  - ▷ *A POMDP policy for problem:* $\underline{\text{If } Bel \neq B, \text{ then } R}$ $(2^5 - 1\ Bel$'s)

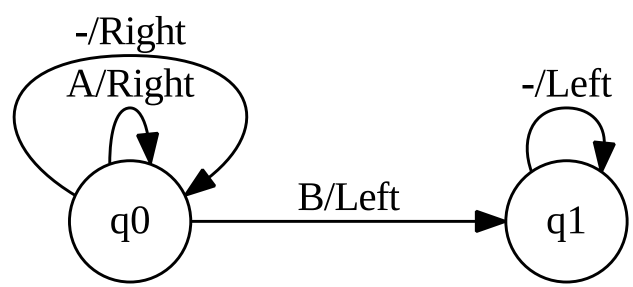
I'll focus on different **solution form**: **finite state controllers**

Finite State Controllers: Example 1

- Starting in A, move to B and back to A; marks A and B **observable.**

A				B

- This **finite-state controller** solves the problem

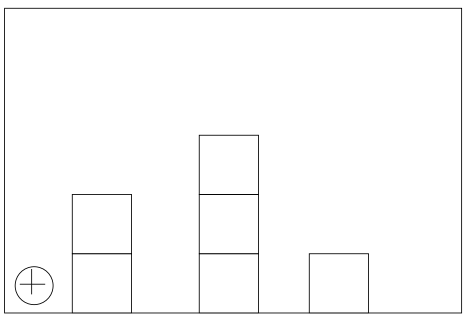


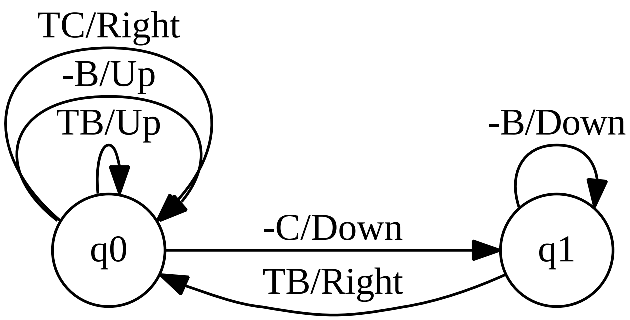
- FSC is **compact** and **general:** can add noise, vary distance, etc.
- Heavily **used in practice**, e.g. video-games and robotics, but **written by hand**
- **The Challenge:** How to get these controllers automatically

Finite State Controllers: Example 2

- **Problem** P: find **green block** using visual-marker (circle) that can move around one cell at a time (à la Chapman and Ballard)

- **Observables:** Whether cell marked contains a green block (G), non-green block (B), or neither (C); and whether on table (T) or not (–)





- Controller on the right **solves** the problem, and not only that, it's **compact** and **general**: it applies to **any number of blocks** and **any configuration**!

- Controller obtained by running a **classical planner** over **transformed problem** (Bonet, Palacios, G. 2009)

Some notation: Problem and Finite State Controllers

- **Target problem** P is like a classical problem with **incomplete initial situation** I and some **observable fluents**

- **Finite State Controller** $\mathcal{C}$ is a set of tuples $t = \langle q, o, a, q' \rangle$

  tuple $t = \langle q, o, a, q' \rangle$, *depicted* $q \stackrel{o/a}{\rightarrow} q'$, *tells to do action* a
  when o *is observed in controller state* q *and then to switch to* q'

- Finite State Controller $\mathcal{C}$ **solves** P if all state trajectories compatible with P and $\mathcal{C}$ reach the goal

Question: how to derive FSC for solving P?

Idea: Finite State Controllers as Conformant Plans

- Consider set of possible tuples $t = \langle q, o, a, q' \rangle$

- Let P' be a problem that is like P but with

  1. **no observable fluents**
  2. **new fluents** o and q representing possible joint observations o and q's
  3. **actions** $b(t)$ replacing the actions a in P, where for $t = \langle q, o, a, q' \rangle$, $b(t)$ is like a but **conditional on** both q and o being true, and resulting in q'.

Theorem: The **finite state controller** $\mathcal{C}$ solves P iff $\mathcal{C}$ is the set of tuples t in the actions $b(t)$ of a **stationary conformant plan** for P'

- **Corollary:** The finite state controller for P can be obtained with **classical planner** from further transformation of P'.

- Plan π is **stationary** when for $b(t)$ and $b(t')$ in π for $t = \langle q, o, a, q' \rangle$ and $t' = \langle q, o, a', q'' \rangle$, then $a = a'$ and $q' = q''$

Intuition: Memoryless Controllers

- For simplicity, consider **memoryless** controllers where tuples are $t = \langle o, a \rangle$, meaning to do a when o observed

- In transformed problem P' the actions a in P replaced by $a(o)$ where

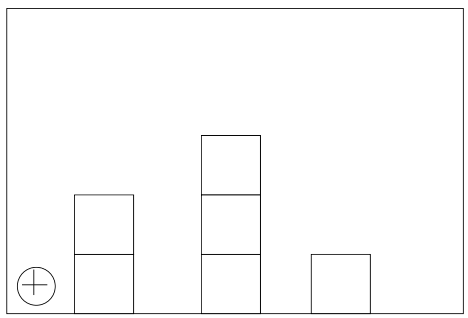
$a(o)$ is like a when o is true, else is a NO-OP

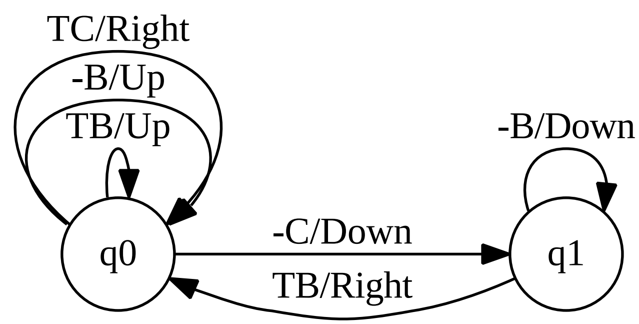
Claim: If the memoryless controller $C = \{\langle o_i, a_i \rangle \,|\, i = 1, n\}$ solves P in m steps, the sequence $a_1[o_1]$, ..., $a_n[o_n]$ **repeated** m **times** is a **conformant plan** for P'

Example: FSC for Visual Marker Problem

- **Problem** P: find **green block** using visual-marker (circle) that can move around one cell at a time (à la Chapman or Ballard)

- **Observables:** Whether cell marked contains a green block (G), non-green block (B), or neither (C); and whether on table (T) or not (–)

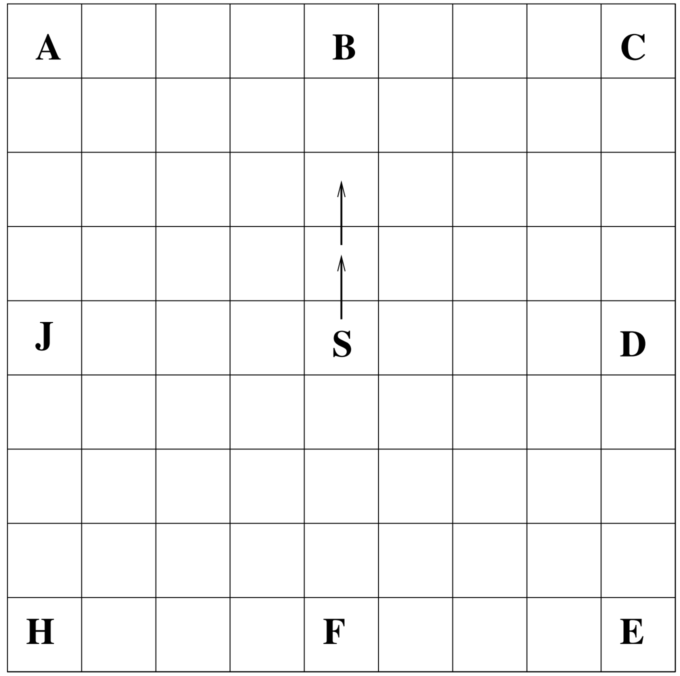




- **Controller** obtained using a **classical planner** from translation that assumes 2 controller states.

- Controller is **compact** and **general**: it applies to **any number of blocks** and **any configuration**

Plan Recognition



- Agent can **move** one unit in the four directions
- Possible **targets** are A, B, C, . . .
- Starting in S, he is **observed** to move up twice
- **Where** is he going?

Standard Plan Recognition over Libraries (Abstract View)

- A **plan recognition problem** defined by triplet $T = \langle \mathcal{G}, \Pi, O \rangle$ where
  - ▷ $\mathcal{G}$ is the set of **possible goals** G,
  - ▷ $\Pi(G)$ is the set of **possible plans** π for G, $G \subseteq \mathcal{G}$,
  - ▷ O is an **observation sequence** $a_1, \ldots, a_n$ where each a_i is an action

- A possible goal $G \in \mathcal{G}$ is **plausible** if $\exists$ plan π in $\Pi(G)$ that **satisfies** O

- An action sequence π **satisfies** O if O is a subsequence of π

(Classical) Plan Recognition over Action Theories

PR over **action theories** similar but with set of plans $\Pi(G)$ defined **implicitly**:

- A **plan recognition problem** is a triplet $T = \langle P, \mathcal{G}, O \rangle$ where
  - ▷ $P = \langle F, A, I \rangle$ is **planning domain**: fluents F, actions A, init I, **no goal**
  - ▷ $\mathcal{G}$ is a set of **possible goals** G, $G \subseteq F$
  - ▷ O is the **observation sequence** $a_1, \ldots, a_n$, all a_i in A

If $\Pi(G)$ stands for **'good plans'** for G in P (to be defined), then as before:

- A possible goal $G \in \mathcal{G}$ is **plausible** if there is a plan π in $\Pi(G)$ that **satisfies** O
- An action sequence π **satisfies** O if O is a subsequence of π

Our goal: define the **good plans** and solve the problem with a **classical planner**

Compiling Observations Away

We get rid of obs. O by transforming $P = \langle F, I, A \rangle$ into $P' = \langle F', I', A \rangle$ so that

π is a plan for G in P that **satisfies** O **iff** π is a plan for $G + O$ in P'

and

π is a plan for G in P that **doesn't satisfy** O **iff** π is a plan for $G + \overline{O}$ in P'

The transformation from P into P' is actually very simple . . .

Compiling Observations Away (cont'd)

- Given $P = \langle F, I, A \rangle$, the transformed problem is $P' = \langle F', I', A' \rangle$:

  ▷ $F' = F \cup \{\, p_a \,|\, a \in O \}$,
  ▷ $I' = I$
  ▷ $A' = A$

  where p_a is **new fluent** for the observed action a in A' with **extra effect**:

  ▷ p_a, if a is the first observation in O, and
  ▷ $p_b \rightarrow p_a$, if b is the action that immediately precedes a in O.

- The 'goals' O and $\overline{O}$ in P' are p_a and $\neg p_a$ for the **last action** a in O

- The plans π for G in P that **satisfy/don't satisfy** O are the plans in P' for $G + O / G + \overline{O}$ respectively

Planning Recognition as Planning: First Formulation

Define the set $\Pi(G)$ of 'good plans' for G in P, as the **optimal plans** for G in P.

- Then $G \in \mathcal{G}$ is a **plausible goal** given observations O

  iff there is an **optimal plan** π for G in P that satisfies O;
  iff there is an **optimal plan** π for G in P that is a plan for $G + O$ in P';
  iff cost of G in P equal to **cost** of $G + O$ in P' abbreviated

$$c_{P'}(G + O) = c_P(G)$$

- It follows that **plausibility** of G can be **computed exactly** by calling an **optimal planner** twice: one for computing $c_{P'}(G + O)$, one for computing $c_P(G)$.

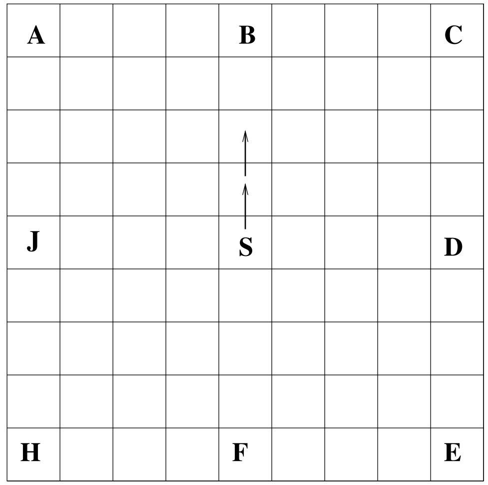
- In turn, this can be **approximated** by calling **suboptimal planner** just once (Ramirez & G. 2009). We pursue a **more general** approach here . . .

Plan Recognition as Planning: A More General Formulation

- Don't **filter** goals G as **plausible**/**implausible**,
- Rather **rank** them with a **probability distribution** $P(G|O)$, $G \in \mathcal{G}$
- From **Bayes Rule** $P(G|O) = \alpha \, P(O|G) \, P(G)$, where
  - ▷ α is a normalizing constant
  - ▷ $P(G)$ assumed to be **given** in problem specification
  - ▷ $P(O|G)$ defined in terms of **extra cost** to pay **for not complying** with the observations O:

$$P(O|G) = \mathbf{function}(c(G + \overline{O}) \; - \; c(G + O))$$

Example: Navigation in a Grid Revisited



If $\Delta(G, O) \stackrel{\text{def}}{=} c(G + \overline{O}) - c(G + O)$:

- For $G = B$, $c(B + O) = c(B) = 4$; $c(B + \overline{O}) = 6$; thus $\Delta(B, O) = 2$
- For $G = C$ or A, $c(C + O) = c(C + \overline{O}) = c(C) = 8$; thus $\Delta(C, O) = 0$
- For all others G, $c(G + O) = 8$; $c(G + \overline{O}) = c(G) = 4$; thus $\Delta(G, O) = -4$

If $P(O|G)$ is a **monotonic function** of $\Delta(G, O)$, then

$$P(O|B) > P(O|C) = P(O|A) > P(G) \text{ , for } G \notin \{A, B, C\}$$

Defining the Likelihoods $P(O|G)$

- Assuming Boltzmann distribution and writing $exp\{x\}$ for e^x, likelihoods become

$$\begin{aligned} P(O|G) &\stackrel{\text{def}}{=} \alpha\, exp\{-\beta\, c(G+O)\} \\ P(\overline{O}|G) &\stackrel{\text{def}}{=} \alpha\, exp\{-\beta\, c(G+\overline{O})\} \end{aligned}$$

  where α is a normalizing constant, and β is a positive constant.

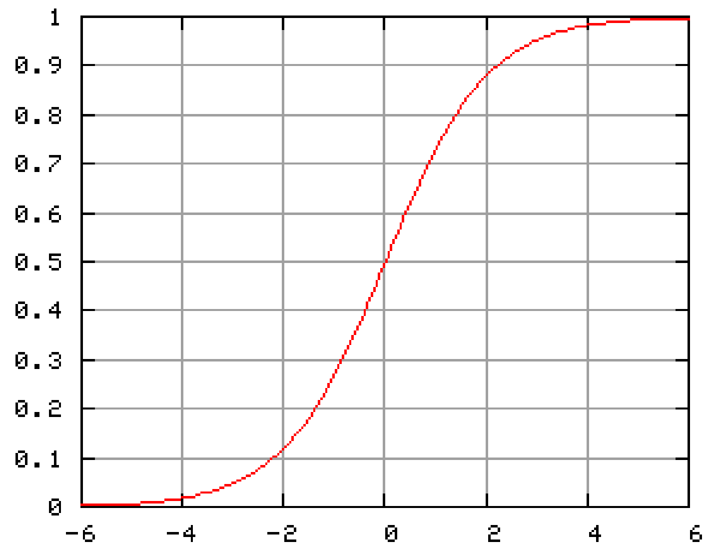
- Taking ratio of two equations, it follows that

$$P(O|G)/P(\overline{O}|G) = exp\{\beta\, \Delta(G,O)\}$$

  and hence

$$P(O|G) = 1/(1 + exp\{-\beta\, \Delta(G,O)\}) = sigmoid(\beta\, \Delta(G,O))$$

Defining Likelihoods $P(O|G)$ (cont'd)



$$
\begin{aligned}
P(O|G) &= sigmoid(\beta\,\Delta(G,O)) \\
\Delta(G,O) &= c(G+\overline{O}) - c(G+O)
\end{aligned}
$$

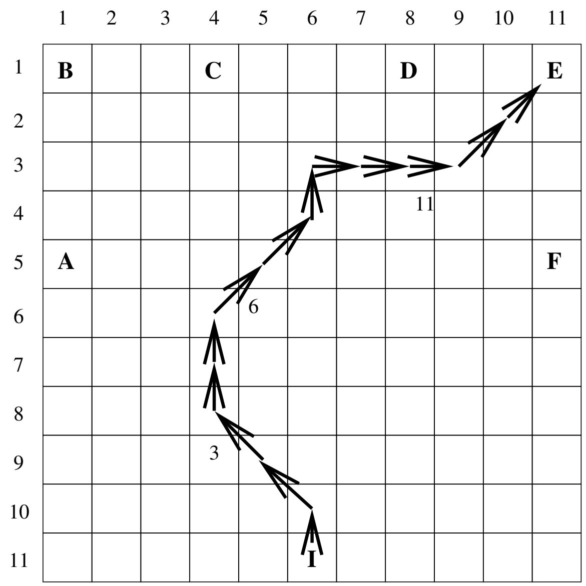
E.g.,

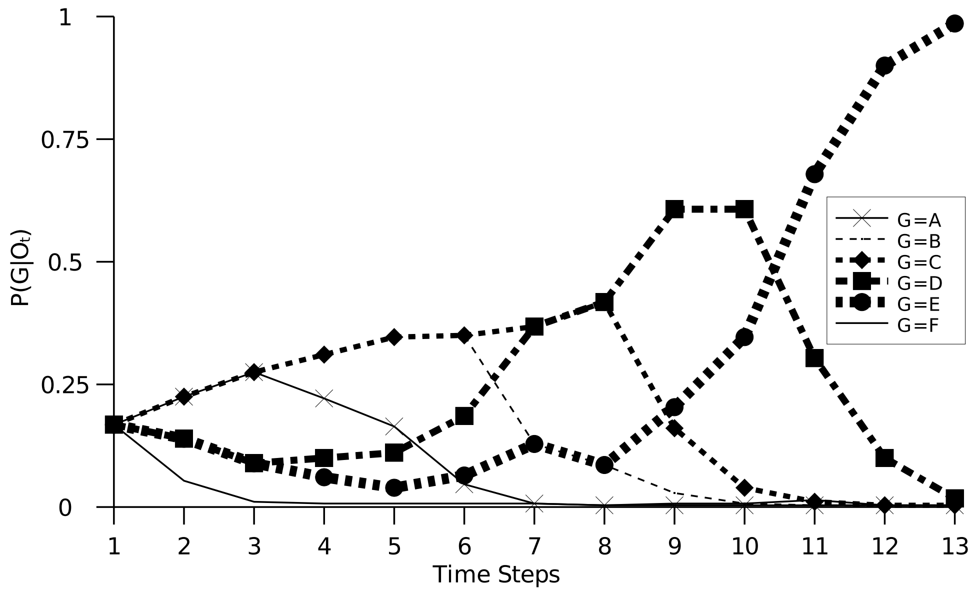
$$
\begin{array}{ll}
P(O|G) < P(\overline{O}|G) & \text{if } c(G+\overline{O}) < c(G+O) \\
P(O|G) = 1 & \text{if } c(G+O) < c(G+\overline{O}) = \infty
\end{array}
$$

Probabilistic Plan Recognition as Planning: Summary

- A **plan recognition problem** is a tuple $T = \langle P, \mathcal{G}, O, Prob \rangle$ where
  - ▷ P is a **planning domain** $P = \langle F, I, A \rangle$
  - ▷ $\mathcal{G}$ is a set of **possible goals** G, $G \subseteq F$
  - ▷ O is the **observation sequence** $a_1, \ldots, a_n$, $a_i \in O$
  - ▷ $Prob$ is **prior distribution** over $\mathcal{G}$
- **Posterior distribution** $P(G|O)$ obtained from
  - ▷ **Bayes Rule** $P(G|O) = \alpha\, P(O|G)\, Prob(G)$ and
  - ▷ **Likelihood** $P(O|G) = sigmoid\{\beta\, [c(G + \overline{O}) - c(G + O)]\}$
- Distribution $P(G|O)$ **computed** exactly or approximately:
  - ▷ exactly using **optimal planner** for determining $c(G + O)$ and $c(G + \overline{O})$,
  - ▷ approximately using **suboptimal planner** for $c(G + O)$ and $c(G + \overline{O})$
- In either case, $2 \cdot |\mathcal{G}|$ planner calls are needed.

Example: Noisy Walk





Graph on the left shows 'noisy walk' and possible targets; curves on the right show **posterior** $P(G|O)$ of each possible target G as a **function of time**

Summary: Transformations

- **Classical Planning** solved as **path-finding** in state state
  - ▷ Most used techniques are **heuristic search** and **SAT**
- **Beyond classical planning:** two approaches
  - ▷ **Top-down:** solvers for richer models like MDPs and POMDPs
  - ▷ **Bottom-up:** compile non-classical features away
- We have follow second approach with **transformations** to eliminate
  - ▷ **soft goals** when planning with preferences
  - ▷ **uncertainty** in conformant planning)
  - ▷ **sensing** for deriving finite-state controllers
  - ▷ **observations** for plan recognition
- Other transformations used for **LTL plan constraints**, **control knowledge**, etc.