Goal Recognition: Models, Algorithms, Challenges

Hector Geffner
ICREA and Universitat Pompeu Fabra
Barcelona, Spain
Planning

- Planning is the **model-based** approach to action selection: behavior obtained from model of the **actions, sensors, preferences, and goals**

\[ \text{Model} \rightarrow \boxed{\text{Planner}} \rightarrow \text{Controller} \]

- Many **planning models**; many **dimensions**: uncertainty, feedback, costs, . . .
Basic Model: Classical Planning

- finite and discrete state space $S$
- a **known initial state** $s_0 \in S$
- a set $S_G \subseteq S$ of goal states
- actions $A(s) \subseteq A$ applicable in each $s \in S$
- a **deterministic transition function** $s' = f(a, s)$ for $a \in A(s)$
- positive **action costs** $c(a, s)$

A **solution** is a sequence of applicable actions that maps $s_0$ into $S_G$, and it is **optimal** if it minimizes sum of action costs (\# of steps)

Other **models** obtained by relaxing assumptions in **bold** ...
Goal MDPs are fully observable, probabilistic state models:

- a state space $S$
- initial state $s_0 \in S$
- a set $S_G \subseteq S$ of goal states
- actions $A(s) \subseteq A$ applicable in each state $s \in S$
- transition probabilities $P_a(s'|s)$ for $s \in S$ and $a \in A(s)$
- action costs $c(a, s) > 0$

- Solutions are functions (policies) mapping states into actions
- Optimal solutions minimize expected cost to goal
Partial Feedback: Partially Observable MDPs (POMDPs)

Goal POMDPs are **partially observable, probabilistic** state models:

- states \( s \in S \)
- actions \( A(s) \subseteq A \)
- transition probabilities \( P_a(s'|s) \) for \( s \in S \) and \( a \in A(s) \)
- observable goal states \( S_G \subseteq S \)
- initial belief state \( b_0 \)
- sensor model given by probabilities \( P_a(o|s) \), \( o \in O \), \( s \in S \)

- **Belief states** are probability distributions over \( S \)
- **Solutions** are policies that map belief states into actions
- **Optimal** policies minimize expected cost to go from \( b_0 \) to \( S_G \)
Example

Agent A must reach G, moving one cell at a time in known map

- If actions deterministic and initial location known, planning problem is classical
- If actions stochastic and location observable, problem is an MDP
- If actions stochastic and location partially observable, problem is a POMDP

Three problems, three models, three solution forms
From Planning to Plan/Goal Recognition

- **General idea:** solve **plan recognition** problem over **model** (classical, MDP, POMDP) using **planner** for that **model**.

- Early work in this direction using **classical** models, **MDPs**, and **POMDPs**:
Example: Classical Setting

- 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? Why?
Example (cont’d)

- From Bayes, goal posterior is \( P(G|O) = \alpha P(O|G') P(G) \), \( G \in G \)
- If priors \( P(G) \) given for each goal in \( G \), the question is what is \( P(O|G) \)
- \( P(O|G) \) measures how well goal \( G \) predicts observed actions \( O \)
- In classical setting,
  - \( G \) predicts \( O \) worst when needs to get off the way to comply with \( O \)
  - \( G \) predicts \( O \) best when needs to get off the way not to comply with \( O \)
Posterior Probabilities from Plan Costs

- From Bayes, **goal posterior** is \( P(G|O) = \alpha P(O|G) P(G) \),
- If **priors** \( P(G) \) given, set \( P(O|G) \) to monotonic function

\[
\text{function}(c(G + \overline{O}) - c(G + O))
\]

\[
\triangleright c(G + O): \text{cost of achieving } G \text{ while complying with } O
\]
\[
\triangleright c(G + \overline{O}): \text{cost of achieving } G \text{ while not complying with } O
\]

- Costs \( c(G + O) \) and \( c(G + \overline{O}) \) **computed** by classical planner
- Goals of **complying** and **not complying** with \( O \) translated into normal goals
- **Function** of cost difference set to **sigmoid**; follows from assuming action selected with Boltzmann distributions
- Posterior probabilities \( P(G|O) \) **computed in** \( 2|G| \) classical planner calls, where \( G \) is the set of possible goals (Ramirez and G. 2010)
Goal Recognition in other Settings: Example

- Two objects $A$ and $B$: $A$ can be in drawers 1 or 2; $B$ can be in 1, 2, or 3
- Agent doesn’t know where $A$ and $B$ are but has priors $P(A@i)$, $P(B@i)$
- She can move around, open and close drawers, look for object in open drawer, and grab object from drawer if known to be there
- The sensing action is not perfect, and agent may fail to see object in drawer

- Agent observed to do the actions:

  $$O = \{\text{open}(1), \text{open}(2), \text{open}(1)\}$$

- What’s the agent goal? Is she looking for object $A$ or object $B$?
Unified Formulation for Classical, MDP, and POMDP Models

\[ O_i = \langle a_i, o_{i+1} \rangle: \text{action } a_i, \text{ observation token } o_{i+1} \text{ by (observed) actor} \]

**Posterior probabilities:** using Bayes’ rule

\[
P(G|O_1, \ldots, O_n) = \alpha P(O_1, \ldots, O_n|G)P(G)
\]

**Likelihood** \( P(O_1, \ldots, O_n|G) \) from

\[
= P(O_n|O_1, \ldots, O_{n-1}, G)P(O_1, \ldots, O_{n-1}|G) \\
= P(o_{n+1}|a_1, \ldots, a_n, o_1, \ldots, o_n, G)P(a_n|a_1, \ldots, a_{n-1}, o_1, \ldots, o_{n-1}, G)P(O_1, \ldots, O_{n-1}|G) \\
= P(o_{n+1}|a_n, \text{bel}_n)P(a_n|\text{bel}_n, G)P(O_1, \ldots, O_{n-1}|G); \text{bel}_i \text{ is belief at time } i
\]

- \( P(o_n|a_n, \text{bel}_n) \) computed from POMDP parameters
- \( P(a|b, G) = \alpha' \exp\{-\beta Q_G(a, b)\} \) is prob of selecting action \( a \) for \( G \) in \( b \):
  - \( Q_G(a, b) = c(a, b) + \sum_{o \in O} b_a(o)V_G(b'_a) \), and
  - \( V_G(b) \) computed by planner represents expected cost from \( b \) to \( G \)
Assumptions and Special Cases

\[ P(O_1, \ldots, O_n|G) = P(o_n|a_n, bel_n) P(a_n|bel_n, G) P(O_1, \ldots, O_{n-1}|G) \]

**Assumptions**

*Observer* can track beliefs of *actor*: *model, priors, actions, and observations*

**Special Cases**

- For *MDPs*, beliefs \( b_i \) and observations \( o_i \) replaced by *states* \( s_i \):
  \[ P(O_1, \ldots, O_n|G) = P(s_{n+1}|a_n, s_n) P(a_n|s_n, G) P(O_1, \ldots, O_{n-1}|G) \]

- For *classical model* (*deterministic*), no need to observe actions and *states*:
  \[ P(O_1, \ldots, O_n|G) = P(a_n|s_n, G) P(O_1, \ldots, O_{n-1}|G) \]
Limitations and Challenges

- **Scalability:**
  - precompute $v$-functions $V_G(b)$ ($V_G(s)$) for all $b$ ($s$) or call planner as needed
  - $2|G|$ planner calls in classical setting approx’ed by single poly $IW(2)$ call?

- **Lack of knowledge**
  - what if no access to actions, observations, model, or priors of *actor*
  - what if *observer* has to act to get such observations (active goal recognition)

- **Role of intention recognition for general planning agent**
  - why intentional agent needs to infer intentions of others?
  - e.g., MDP agents with common goal: why infer other’s subgoals?

- **From goal recognition to story understanding**
  - general formulation to explain children stories (Little Red Riding Hood)?
  - It’s all about plans, intentions, and interactions unfolding . . .
  - why so simple for people . . . and children (!), and not yet in reach?
**Little Red Riding Hood**

| Characters: | Little Red Riding Hood (good, kind, skipping), Wolf (bad, scary, gobbles), Grandma (good), Woodcutter (good, strong, brave). |
| Setting: | Woods (birds singing, sunny), Grandma’s house (small, tidy, quaint) |
| Introduction: | LRRH walking through woods on way to Grandma’s - taking cakes (fairy, delicious) Meets wolf asks where going (growls, frightens) |
| Build-Up: | Wolf goes to Grandma’s house (knocks on wooden door). Gobbles her up (tasty, licks lips). Dresses in her clothes, gets into bed. Waits for LRRH |
| Climax: | LLRH arrives - door open (cautiously, carefully). Talks to the wolf - eyes, hands, teeth (dialogue). He jumps out and chases her into the woods. (running, tripping, screaming). |
| Resolution: | Woodcutter hears her cries and kills the wolf with axe. (striding, swings axe, happily ever after). |
Summary

- **Model-based approach to goal recognition:** use planning model and planners to infer goals of an agent

- Many models depending on **uncertainty** and **feedback** like classical, MDPs, and POMDPs

- Most work assumes that **model of observer and actor suitably aligned**; convenient but unrealistic

- Many open questions:
  - what role for intention recognition for a general planning agent?
  - what general and effective model for understanding simple multigent stories?