An LP-Based Approach for Goal Recognition as Planning

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PUCRS SCHOOL OF TECHNOLOGY

Table of Contents

What is it?

- **Goal Recognition** is the task of recognizing agents' goal that explains a sequence of observations of its actions;
  - Related to plan recognition, i.e. recognizing a *top-level* action
  - A specific form of the problem of abduction

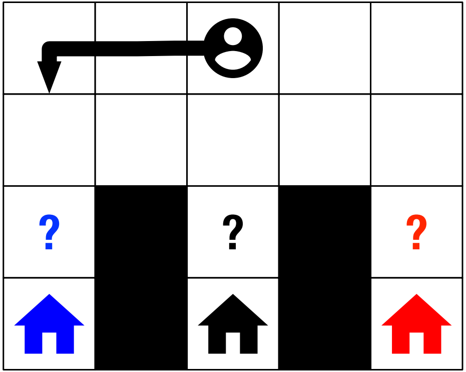


Table of Contents

Automated Planning

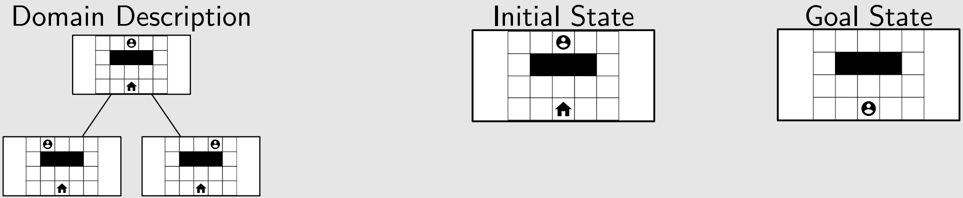
Definition (Planning)

A planning instance is represented by a triple $\Pi = \langle \mathcal{V}, \mathcal{O}, s_0, s^*, \mathrm{cost} \rangle$, in which:

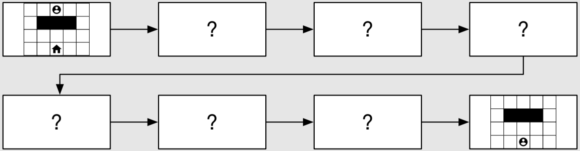
- $\mathcal{V}$ is a finite set of variables, each $v \in \mathcal{V}$ with domain $D(v)$
- $\mathcal{O}$ is a finite set of operators, where $o \in \mathcal{O}$ are tuples $o = \langle \mathrm{pre}(o), \mathrm{post}(o) \rangle$ each of which has cost $\mathrm{cost}(o)$
- s_0 is the **initial state**
- s^* is the **goal state**

Automated Planning - Less boring

Planning problems have three key ingredients



Solution



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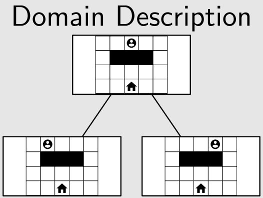
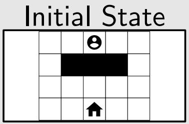
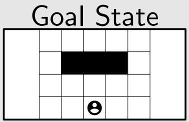
Planning problems have three key ingredients







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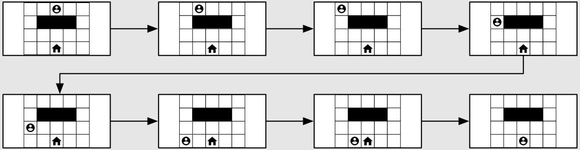


Goal Recognition Problem

Definition (Goal Recognition Problem)

A goal recognition problem is a tuple $P = \langle \Pi_{\mathrm{P}}, \Gamma, \Omega \rangle$, where:

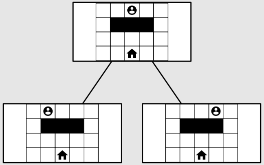
- Π_{P} is a planning task without a goal condition;
- Γ is a set of goal candidates; and
- Ω is a sequence $\langle \vec{o}_1, \ldots \vec{o}_n \rangle$ of observations, with each $\vec{o}_i \in \mathcal{O}$

- Many solution concepts here (check the paper)
- Caveat: we may have other representations for the observations

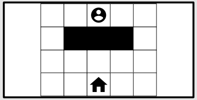
Goal Recognition Problem - Less boring

Goal/Plan Recognition problems have three key ingredients

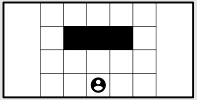
Domain Description



Initial State



Goal State



Goal Recognition Problem - Less boring

Goal/Plan Recognition problems have **four** key ingredients

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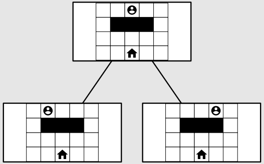

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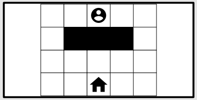
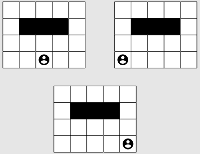
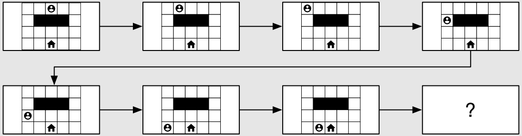


Goal **Hypotheses**



Observations



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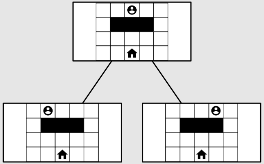

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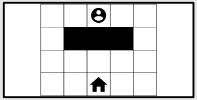

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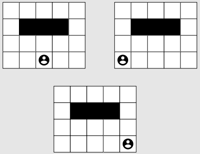

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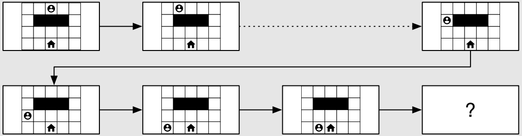

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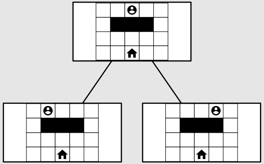

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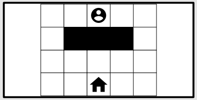

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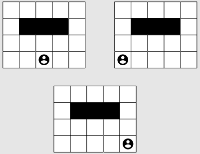

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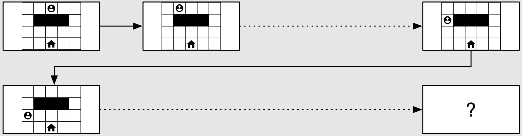

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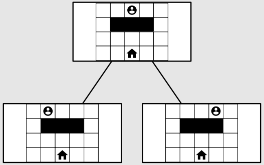

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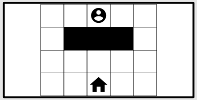

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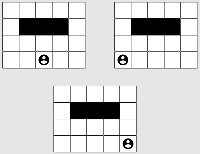

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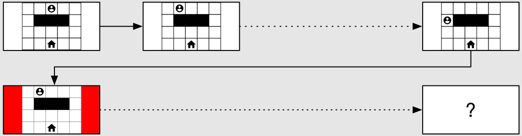
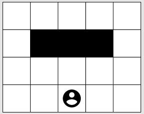


Solution

Correct Goal



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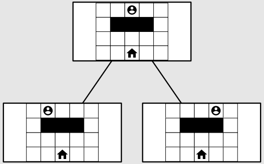

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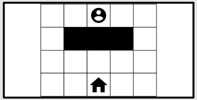

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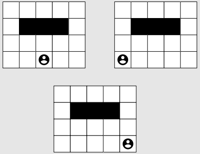
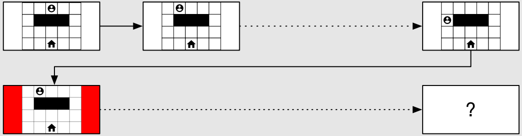
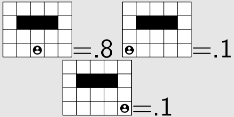


Observations



Solution

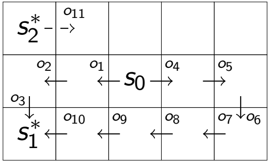
Probability Distribution



Running Example

Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
- Reference goal s_1^*



- $\Omega_1 = \langle \vec{o}_1 \rangle$ is an optimal observation sequence from optimal plan $\pi_1 = \langle o_1, o_2, o_3 \rangle$
- $\Omega_2 = \langle \vec{o}_5, \vec{o}_7, \vec{o}_9 \rangle$ and $\Omega_3 = \langle \vec{o}_4, \ldots, \vec{o}_{10} \rangle$ are suboptimal observation sequences from suboptimal plan $\pi_2 = \langle o_4, \ldots, o_{10} \rangle$,
- $\Omega_4 = \langle \vec{o}_4, \ldots, \vec{o}_{10}, \vec{o}_{11} \rangle$ is a suboptimal and noisy observation sequence (with added $\vec{o}_{11}$)

Reference Solutions

Reference Solution Set

- *Goal recognition task* $\langle \Pi_P, \Gamma, \Omega \rangle$
- Π is a planning task with the reference goal $s^* \in \Gamma$
- π^* is the optimal plan for Π, and π plan for Π that generates Ω
- $h^*_\Omega(s_0, s^*_i)$ is the cost of an optimal plan for Π that complies with Ω, $h^*(s_0, s^*_i)$ is the cost of an optimal plan for Π, both with $s^*_i \in \Gamma$

The reference solution is

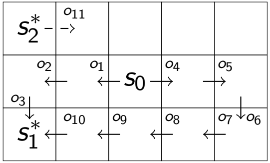
$$\Gamma^* = \{s^*_i \in \Gamma \mid \frac{h^*_\Omega(s_0, s^*_i)}{h^*(s_0, s^*_i)} \leq \frac{\text{cost}(\pi)}{\text{cost}(\pi^*)} \land h^*_\Omega(s_0, s^*_i) \neq \infty\}$$

The *reference solution set* includes goal candidates that have plans as sub-optimal as or less than the plan that generated the observations for the reference goal.

Reference Solution Example

Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
- Reference goal s_1^*
- $\Omega_1 = \langle \vec{o}_1 \rangle$ from $\pi_1 = \langle o_1, o_2, o_3 \rangle$
- $\Omega_2 = \langle \vec{o}_5, \vec{o}_7, \vec{o}_9 \rangle$ and $\Omega_3 = \langle \vec{o}_4, \dots, \vec{o}_{10} \rangle$ from $\pi_2 = \langle o_4, \dots, o_{10} \rangle$
- $\Omega_4 = \langle \vec{o}_4, \dots, \vec{o}_{10}, \vec{o}_{11} \rangle$ from $\pi_2 = \langle o_4, \dots, o_{10} \rangle$ (with added $\vec{o}_{11}$)



$\Gamma_i^* = \{s_1^*\}$, for $\Omega_1, \Omega_2, \Omega_3, \Omega_4$ since

- $h^*_{\Omega_4}(s_0, s_1^*) = 7$, $h^*_{\Omega_4}(s_0, s_2^*) = 9$
- $\mathrm{cost}(\pi_2) / \mathrm{cost}(\pi^*) = 7/3$

A Canned History of Current Approaches

Ramirez and Geffner (2009 and 2010)

- First approaches to goal recognition: Plan Recognition as Planning (PRAP)
- Probabilistic model aims to compute $P(G \mid O)$
- Following Bayes Rule $P(G \mid O) = \alpha P(O \mid G)P(G)$
- Given $P(G)$ as a prior, key bottleneck is computing $P(O \mid G)$

Sohrabi et al. (2016)

- Conceptually similar to Ramirez and Geffner
- Compilation into **multiple planning** problems (one for each G)

Pereira, Oren and Meneguzzi (2017):

- **Obviate the need to execute a planner multiple times** for recognizing goals; and
- Novel goal recognition heuristics that use **planning landmarks**.
- **More accurate** and **orders of magnitude faster** than all previous approaches.

Table of Contents

Operator Counting Heuristics

- Based on the idea of *Cost Partitioning for Landmarks*
- Represents cost of a planning problem in terms of linear constraints:[1]
  - **Variables:** Count_o for each operator o
  - **Objective:** Minimize $\sum_{o} \text{Count}_o \cdot \text{cost}(o)$, subject to
    - $\sum_{o \in L} \text{Count}_o \geq 1$ for all landmarks L
    - $\text{Count}_o \geq 0$ for all operators o
  - Numbers of operator occurrences in any plan satisfy constraints
  - Minimizing total cost $\rightarrow$ admissible heuristic

[1] Adapted from Helmert and Röger's planning course

Operator Counting

Operator-counting Constraints[2]

- *linear constraints* whose variables denote *number of occurrences* of a given operator
- must be satisfied by every plan

Examples:

- $\text{Count}_{o1} + \text{Count}_{o2} \geq 1$ "must use o_1 or o_2 at least once"
- $\text{Count}_{o1} - \text{Count}_{o3} \leq 0$ "cannot use o_1 more often than o_3"

Motivation:

- declarative way to **represent knowledge** about the solution
- allows **reasoning about solutions** to derive heuristic estimates
- elegant framework to combine information from multiple heuristics

[2] Adapted from Helmert and Röger's planning course

Operator Counting Constraints for Goal Recognition

Motivation:

- Operator counting constraints represent knowledge about solutions
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Operator Counting Constraints for Goal Recognition

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- allows **reasoning about solutions** that **comply with additional constraints**:

Operator Counting Constraints for Goal Recognition

Motivation:

- Operator counting constraints represent knowledge about solutions
- allows **reasoning about solutions** that **comply with additional constraints**:
    - **actual** observations
    - **missing** observations
    - **noisy** observations
    - goal hypotheses
    - other constraints

Operator Counting Heuristic for Goal Recognition

Satisfying IP/LP heuristic

The *satisfying* integer program IP_Ω^C for a set of operator-counting constraints C, a set of *observation-counting constraints*, and sequence of observations Ω for state s is

$$\text{minimize} \sum_{o \in O} \text{cost}(o)\text{Y}_o \qquad \text{subject to } C,$$

$$\text{Y}_{\vec{o}} \leq occur_\Omega(o) \qquad \text{for all } o \in \mathcal{O} \tag{1}$$

$$\text{Y}_{\vec{o}} \leq \text{Y}_o \qquad \text{for all } o \in \mathcal{O} \tag{2}$$

$$\sum_{\text{Y}_{\vec{o}} \in \mathcal{Y}^\Omega} \text{Y}_{\vec{o}} \geq |\,\Omega\,| \tag{3}$$

$$\text{Y}_o, \text{Y}_{\vec{o}} \in \mathbb{Z}_0^+.$$

The *satisfying* IP *heuristic* h_Ω^{IP} is the objective value of IP_Ω^C, and the *satisfying* LP *heuristic* h_Ω is the objective value of its linear relaxation. If the IP or LP is infeasible, the heuristic estimate is ∞.

Constraints for Goal Recognition

We define a new heuristic h_Ω based on the existing operator counting framework using:

- Observations Ω for a state s,
  where $occur_\Omega(o)$ is the $\#$ of occurrences of $o \in \Omega$
- Variables $\mathsf{Y}_{\vec{o}}$ for each $\vec{o} \in \mathcal{O}$

with additional constraints:

- $\mathsf{Y}_{\vec{o}} \leq occur_\Omega(o)$, for all $o \in \mathcal{O}$
- $\mathsf{Y}_{\vec{o}} \leq \mathsf{Y}_o$ for all $o \in \mathcal{O}$
- $\sum_{\mathsf{Y}_{\vec{o}} \in \mathcal{Y}^\Omega} \mathsf{Y}_{\vec{o}} \geq |\Omega|$

Constraints for Goal Recognition

We define a new heuristic h_Ω based on the existing operator counting framework using:

- Observations Ω for a state s,
  where $occur_\Omega(o)$ is the # of occurrences of $o \in \Omega$
- Variables $\mathsf{Y}_{\vec{o}}$ for each $\vec{o} \in \mathcal{O}$

with additional constraints:

- $\mathsf{Y}_{\vec{o}} \leq occur_\Omega(o)$, for all $o \in \mathcal{O}$ $\rightarrow$ limits occurrences of observations
- $\mathsf{Y}_{\vec{o}} \leq \mathsf{Y}_o$ for all $o \in \mathcal{O}$ $\rightarrow$ binds Ω to operators in the OC heuristic
- $\sum_{\mathsf{Y}_{\vec{o}} \in \mathcal{Y}^\Omega} \mathsf{Y}_{\vec{o}} \geq |\,\Omega\,|$ $\rightarrow$ ensures observations are satisfied

The h_Ω heuristic

- Y_o acts as an upper bound for $Y_{\vec{o}}$
- The only difference of h_Ω to the OC heuristic are the *observation-counting constraints*
  - $h \rightarrow$ lower bound on optimal plans
  - $h_\Omega \rightarrow$ lower bound on optimal plans that satisfy observations

Computing solutions using h_Ω

- We compute the cost difference between observation-complying Operator Counts h_Ω and the OCs lower bound on optimal plan cost h

$$\delta_{\min} = \min_{s_i^* \in \Gamma \,:\, h_\Omega(s_0, s_i^*) < \infty} \{h_\Omega(s_0, s_i^*) - h(s_0, s_i^*)\}$$

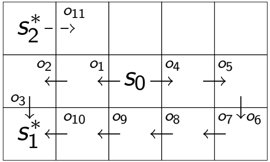
- And select goals for which the observation-complying plans have the least additional cost over the optimal plan

$$\Gamma^{\text{LP}} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\min}\}$$

Computing solutions using h_Ω

Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
- Reference goal s_1^*
- $\Omega = \langle \vec{o}_5, \vec{o}_7, \vec{o}_9 \rangle$



$$\Gamma^{LP} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\min}\}$$

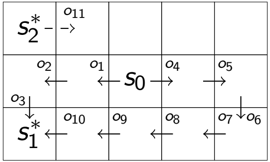
- $h_\Omega(s_0, s_1^*) = 7$ and $h(s_0, s_1^*) = 3$
- $h_\Omega(s_0, s_2^*) = 9$ and $h(s_0, s_2^*) = 3$
- $\delta_{\min} = 4$, so $\Gamma^{LP} = \{s_1^*\}$

Table of Contents

Noisy Observations

Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
- Reference goal s_1^*
- $\Omega = \langle \vec{o}_4, \ldots, \vec{o}_{10}, \vec{o}_{11} \rangle$



$$\Gamma^{\mathsf{LP}} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\mathsf{min}}\}$$

- $h_\Omega(s_0, s_1^*) = 13$ and $h(s_0, s_1^*) = 3$
- $h_\Omega(s_0, s_2^*) = 11$ and $h(s_0, s_2^*) = 3$
- $\delta_{\mathsf{min}} = 8$, so $\Gamma^{\mathsf{LP}} = \{s_2^*\}$

Noisy Observations

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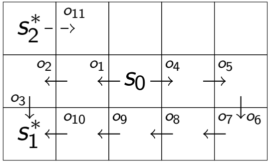

$$\Gamma^{\mathrm{LP}} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\min}\}$$

- $h_\Omega(s_0, s_1^*) = 13$ and $h(s_0, s_1^*) = 3$
- $h_\Omega(s_0, s_2^*) = 11$ and $h(s_0, s_2^*) = 3$
- $\delta_{\min} = 8$, so $\Gamma^{\mathrm{LP}} = \{s_2^*\}$ ← this is a problem, as $\vec{o}_{11}$ very unlikely

Dealing with Noisy Observations

- Noisy Observations $\rightarrow$ Suboptimal or Spurious
  - Unlikely to be part of an optimal plan
  - Expensive to detect
- We estimate which observations are noisy in polynomial time in the linear relaxation in a new heuristic h_{Ω}^{ϵ}

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- Noisy Observations $\rightarrow$ Suboptimal or Spurious
  - Unlikely to be part of an optimal plan
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- We estimate which observations are noisy in polynomial time in the linear relaxation in a new heuristic h^{ϵ}_{Ω}
- Recall constraint forcing observation counts to satisfy all observations

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Dealing with Noisy Observations

- Noisy Observations $\rightarrow$ Suboptimal or Spurious
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  - ϵ corresponds to an **error rate**
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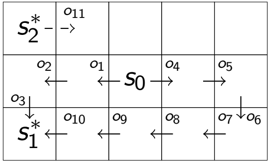
Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
- Reference goal s_1^*
- $\Omega = \langle \vec{o}_4, \ldots, \vec{o}_{10}, \vec{o}_{11} \rangle$



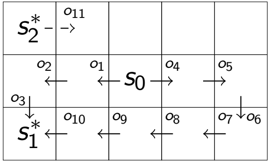
$$\Gamma^{\mathrm{LP}} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\min}\}$$

- $h_\Omega(s_0, s_1^*) = 13$ and $h(s_0, s_1^*) = 3$
- $h_\Omega(s_0, s_2^*) = 11$ and $h(s_0, s_2^*) = 3$
- $\delta_{\min} = 8$, so $\Gamma^{\mathrm{LP}} = \{s_2^*\}$ $\leftarrow$ this is a problem, as $\vec{o}_{11}$ very unlikely

Computing solutions using h^{ϵ}_{Ω}

Goal Recognition task with:

- $\Gamma = \{s^*_1, s^*_2\}$
- Reference goal s^*_1
- $\Omega = \langle \vec{o}_4, \ldots, \vec{o}_{10}, \vec{o}_{11} \rangle$



$$\Gamma^{\epsilon} = \{s^*_i \in \Gamma \mid h^{\epsilon}_{\Omega}(s_0, s^*_i) - h(s_0, s^*_i) = \delta_{\min}\}$$

- Assuming $\epsilon = 0.2$
- $h_{\Omega}(s_0, s^*_1) = 7$ and $h(s_0, s^*_1) = 3$
- $h_{\Omega}(s_0, s^*_2) = 9$ and $h(s_0, s^*_2) = 3$
- $\delta_{\min} = 4$, so $\Gamma^{\epsilon} = \{s^*_1\}$

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- Recognizing goals is hard with low observability, most existing approaches have either
  - Low accuracy while maintaining low spread
  - High accuracy while having high spread
- Our approach modulates the accuracy/spread tradeoff in response to lower observability

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$$\mu = 1 + \frac{\max\limits_{s_i^* \in \Gamma^{\mathrm{LP}}} \{h_\Omega(s_0, s_i^*)\} - |\Omega|}{\max\limits_{s_i^* \in \Gamma^{\mathrm{LP}}} \{h_\Omega(s_0, s_i^*)\}}$$

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$$\Gamma^{\mathrm{LP}} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\min}\}$$

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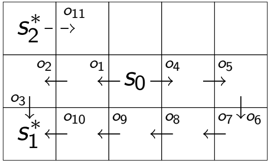
$$\Gamma^\mu = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) \leq \delta_{\min} * \mu\}$$

Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
- Reference goal s_1^*
- $\Omega = \langle \vec{o}_6 \rangle$



$$\Gamma^{LP} = \{s_i^* \in \Gamma \mid h_\Omega(s_0, s_i^*) - h(s_0, s_i^*) = \delta_{\min}\}$$

- $h_\Omega(s_0, s_1^*) = 7$ and $h(s_0, s_1^*) = 3$
- $h_\Omega(s_0, s_2^*) = 9$ and $h(s_0, s_2^*) = 3$
- $\delta_{\min} = 4$, so $\Gamma^{LP} = \{s_1^*\}$

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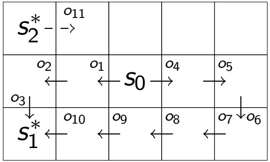

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- $h_\Omega(s_0, s_2^*) = 9$ and $h(s_0, s_2^*) = 3$
- $\delta_{\min} = 4$, so $\Gamma^{\mathrm{LP}} = \{s_1^*\}$ ← this is also problematic: $|\Omega| = 1$!

Measuring Uncertainty and Computing Solutions

Goal Recognition task with:

- $\Gamma = \{s_1^*, s_2^*\}$
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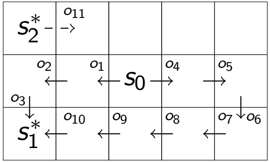

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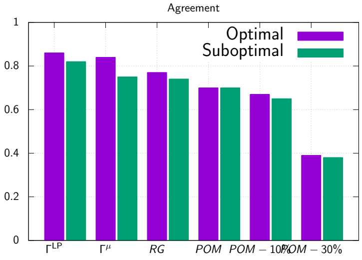
- $h_\Omega(s_0, s_1^*) = 7$ and $h(s_0, s_1^*) = 3$
- $h_\Omega(s_0, s_2^*) = 9$ and $h(s_0, s_2^*) = 3$
- $\mu = 1 + 8/9$
- $\delta_{\min} = 4$, so $\Gamma^\mu = \{s_1^*, s_2^*\}$

Table of Contents

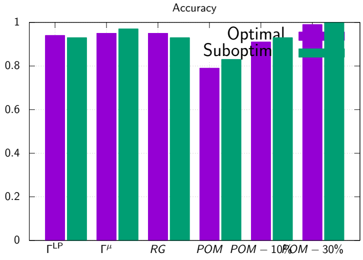
Experiments

New Benchmark:

- Based on our previous work
- Metric we use: agreement ratio
- Optimal and suboptimal plans
- Noisy and Missing Observations



Agreement
Optimal
Suboptimal
1
0.8
0.6
0.4
0.2
0
Γ^{LP}
Γ^{μ}
RG
POM
$POM - 10\%$
$POM - 30\%$



Accuracy
Optimal
Suboptimal
1
0.8
0.6
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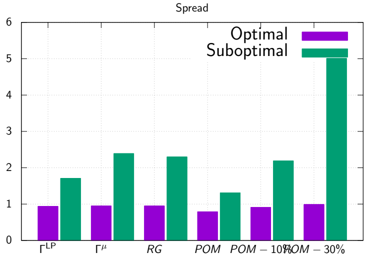
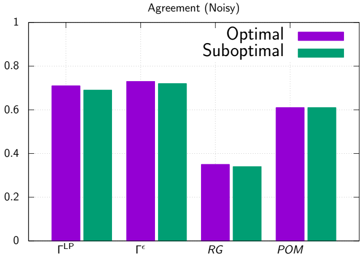
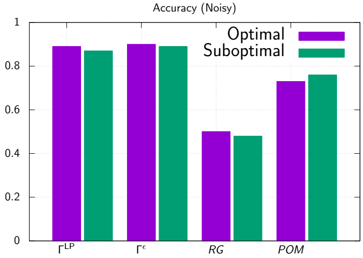
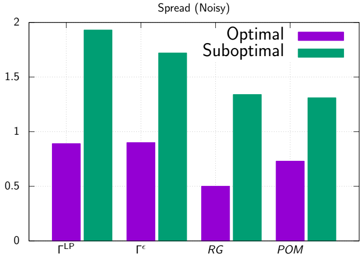


Spread
Optimal
Suboptimal
6
5
4
3
2
1
0
Γ^{LP}
Γ^{μ}
RG
POM
$POM - 10\%$
$POM - 30\%$

Agreement/Accuracy/Spread - Noisy Observations







Conclusions

We developed a new class of goal recognition methods:

- Based on linear programming models
  - Provably polynomial-time solutions
- Leverage operator counting framework
  - Opens up many **new possibilities** for goal recognition
  - Leverages the best of previous state of the art in **Runtime** and **Accuracy**

Code available at:

`https://bit.ly/lp-goal-recognition`