Plan and Goal Recognition in the Real World

Felipe Meneguzzi†

†Pontifical Catholic University of Rio Grande do Sul, Brazil
felipe.meneguzzi@pucrs.br

Scotland, September, 2017
# Table of Contents

1. **Introduction**
   - Motivation and Intuition

2. Goal Recognition as reasoning over Heuristics

3. Online Goal Recognition as Reasoning over Landmarks

4. Real World Applications
   - Plan Recognition using Video Data

5. Summary and Future Directions
Recognizing plans and goals of others is a critical ability for intelligent interaction:
- important for humans/agents working in the same environment
- increasingly important as we build more intelligent systems

Overall area of Plan, Activity and Intent Recognition
- Activity recognition: recognizing meaningful activities from low-level sensor data
- Plan/Intent/Goal recognition: recognizing intentional higher-level sequences of activities
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

Approaches to goal and plan recognition divided into roughly two types:
- Plan-library based (classical plan recognition)
- Domain-theory based (plan recognition as planning, or PRAP)
Flavors of Recognition Formalism

Plan Library

Domain Theory (PRAP)

(define (domain grid)
(:requirements :strips :typing)
(:types place shape key)
(:predicates (conn ?x ?y − place)
(key−shape ?k − key ?s − shape)
(lock−shape ?x − place ?s − shape)
(at ?r − key ?x − place )
(at−robot ?x − place)
(locked ?x − place)
(carrying ?k − key)
(open ?x − place)
)

(:action unlock
 :parameters (?curpos ?lockpos − place ?key − key ?shape − shape)
 :precondition (and (conn ?curpos ?lockpos) (key−shape ?k)
 (lock−shape ?lockpos ?shape) (at−robot ?curpos)
 (locked ?lockpos) (carrying ?k))
 :effect (and
 (open ?lockpos) (not (locked ?lockpos)))
)

(:action move
 :parameters (?curpos ?nextpos − place)
 :precondition (and (at−robot ?curpos) (conn ?curpos ?nextpos)
 :effect (and (at−robot ?nextpos) (not (at−robot ?curpos))
 )

(:action pickup
 :parameters (?curpos − place ?key − key)
 :precondition (and (at−robot ?curpos) (at ?key ?curpos))
 :effect (and (carrying ?key)
 (not (at ?key ?curpos)))
)
An example of Activity Recognition

![Image: How to Break an Egg](image-url)
An example of Activity Recognition
An example of Activity Recognition
An example of Activity Recognition

breaking egg
An Example of Goal/Plan Recognition

from Miquel Ramirez’s thesis

The possible goals the trainer expected to pursue:

1. Store all triangles in $b_1$
2. Store all spheres in $b_2$
3. Store all cubes in $b_3$
4. Store red objects in $b_2$
5. Store green objects in $b_3$
6. Store blue objects in $b_1$

Wooden pieces $p_1, p_2, \ldots, p_n$

Pieces have shapes and colors

Bins $b_1, b_2, \ldots, b_n$
An Example of Goal/Plan Recognition
from Miquel Ramirez’s thesis

One possible plan for the trainer to achieve task #1 (store all triangles in $b_1$):

1. Walk from B3 into A4
2. Pick $p_3$ up
3. Walk from A4 into B3
4. Walk from B3 into C2
5. Pick $p_4$ up
6. Throw $p_3$ into $b_1$
7. Throw $p_4$ into $b_1$

Wooden pieces $p_1, p_2, \ldots, p_n$
Pieces have shapes and colors
Bins $b_1, b_2, \ldots, b_n$
An Example of Goal/Plan Recognition

from Miquel Ramirez’s thesis

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>4</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>6</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td></td>
<td>3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

If sensors miss 70% of *walk* actions and half *pick* and *drop* actions, we may only see:

1. Pick $p_3$ up
2. Walk from A4 into B3

Wooden pieces $p_1, p_2, \ldots p_n$

Pieces have shapes and colors

Bins $b_1, b_2, \ldots, b_n$
An Example of Goal/Plan Recognition
from Miquel Ramirez’s thesis

Figure 1.1: Lab environment represented as a grid, each cell is referred to by its coordinates: A0, ..., E4. Clear cells are the ones the trainer can enter and exit. Numbered cylinders 1, 2 and 3 represent bins \(b_1\), \(b_2\) and \(b_3\). Note that \(b_1\) is located in a cell the trainer can traverse.

Objects are represented by their shapes and colors. The red circle is denoted as \(p_1\) and the blue triangle as \(p_4\). The trainer is initially located in cell B3.

The set of possible goals that the robot knows about and expects the trainer to pursue are:
1. Store all triangles in \(b_1\).
2. Store all spheres in \(b_2\).
3. Store all cubes in \(b_3\).
4. Store red objects in \(b_2\).
5. Store green objects in \(b_3\).
6. Store blue objects in \(b_1\).

One possible plan for the trainer when she is pursuing task #1 given that she starts at cell B3 would be:
1. Walk from B3 into A4.
2. Pick \(p_3\) up.

If sensors miss 70% of walk actions and half pick and drop actions, we may only see:

1. Pick \(p_3\) up
2. Walk from A4 into B3

Here, we could deduce either task #1 or #4 (store all red objects in \(b_2\)), as other tasks are less likely.

Wooden pieces \(p_1, p_2, \ldots, p_n\)
Pieces have shapes and colors
Bins \(b_1, b_2, \ldots, b_n\)
Introduction
  • Motivation and Intuition

Goal Recognition as reasoning over Heuristics

Online Goal Recognition as Reasoning over Landmarks

Real World Applications
  • Plan Recognition using Video Data

Summary and Future Directions
Motivation

- In this work, we use a planning domain definition to represent agent behavior and environment properties;
- Previous approaches involve multiple calls to a modified planner.
- Our main contribution is twofold:
  - We obviate the need to execute a planner multiple times for recognizing goals; and
  - We develop novel goal recognition heuristics that use planning landmarks.
- We show that our approaches are more accurate and orders of magnitude faster than Ramírez and Geffner’s approach.
Our heuristics require identifying which fact landmarks have been achieved during the observed plan execution for every candidate goal $G \in \mathcal{G}$;

For every candidate goal $G \in \mathcal{G}$:
- Extract ordered landmarks for $G$;
- Use achieved landmarks of $G$ in preconditions and effects of every observed action $o \in O$;
- Under partial observability, we deal with missing actions by inferring that predecessors of observed landmarks must have been achieved;
Goal Completion $h_{gc}$ aggregates the percentage of completion of each sub-goal into an overall percentage of completion for all facts of a candidate goal;

$$h_{gc}(G, \mathcal{AL}_G, \mathcal{L}_G) = \left( \frac{\sum_{g \in G} \frac{|\mathcal{AL}_g \in \mathcal{AL}_G|}{|\mathcal{L}_g \in \mathcal{L}_G|}}{|G|} \right)$$  \hspace{1cm} (1)$$

where:

- $\mathcal{AL}_G$ achieved landmarks for goals in $G$
- $\mathcal{L}_G$ all landmarks for goals in $G$
Our second heuristic computes **landmark uniqueness**: inverse frequency of a landmark within landmarks for candidate goals:

\[
L_{Uniq}(L, \mathcal{L}_G) = \left( \frac{1}{\sum_{\mathcal{L} \in \mathcal{L}_G} |\{L | L \in \mathcal{L}\}|} \right)
\]  

(2)

\[
L_{Uniq}(L2) = \frac{1}{2} \\
L_{Uniq}(L1) = \frac{1}{3} \\
L_{Uniq}(L3) = 1
\]
Our second heuristic, called $h_{uniq}$, estimates the goal completion of a candidate goal $G$ by calculating the ratio between the sum of the uniqueness value of the achieved landmarks of $G$ and the sum of the uniqueness value of all landmarks of $G$:

$$h_{uniq}(G, \mathcal{AL}_G, \mathcal{L}_G, \Upsilon_{uv}) = \left( \frac{\sum_{A_L \in \mathcal{AL}_G} \Upsilon_{uv}(A_L)}{\sum_{L \in \mathcal{L}_G} \Upsilon_{uv}(L)} \right)$$

(3)

where:

- $\Upsilon_{uv}$ is a table of uniqueness values
- $\mathcal{AL}_G$ achieved landmarks for goals in $G$
- $\mathcal{L}_G$ all landmarks for goals in $G$
Example (1 of 4)

Observations:
- `(unstack D B); and`
- `(unstack C A).

The real goal is: `(and (ontable D) (on C D) (clear C))`
Achieved Landmarks in Observations:

1. (and (ontable D) (clear A) (on A D)), 5 out of 8:
   - [(clear A)], [(clear A) (ontable A) (handempty)],
   - [(on C A) (clear C) (handempty)], [(holding D)],
   - [(clear D) (on D B) (handempty)]

2. (and (ontable D) (clear B) (on B D)), 4 out of 7:
   - [(clear B)], [(ontable B) (handempty)],
   - [(on D B) (clear D) (handempty)], [(holding D)]

3. (and (ontable D) (clear C) (on C D)), 5 out of 7:
   - [(clear C)], [(clear C) (on C A) (handempty)], [(clear D) (holding C)]
   - [(clear D) (on D B) (handempty)], [(holding D)]
Landmark-Based Goal Completion Heuristic

- (and (ontable D) (clear A) (on A D)):
  - Goal Completion: 0.7222
- (and (ontable D) (clear B) (on B D)):
  - Goal Completion: 0.6666
- (and (ontable D) (clear C) (on C D)):
  - Goal Completion: 0.7777 (highest estimated value)
Example (4 of 4) - $h_{uniq}$

**Landmark-Based Uniqueness Heuristic**

- (and (ontable D) (clear A) (on A D)), Total$_{Uniq} = 5.5$:  
  - [(clear A)] = 1, [(clear A) (ontable A) (handempty)] = 1,  
  - [(on C A) (clear C) (handempty)] = 0.5, [(holding D)] = 0.3333,  
  - [(clear D) (on D B) (handempty)] = 0.3333  
  - $h_{uniq} = 3.1666 / 5.5 = 0.5757$

- (and (ontable D) (clear B) (on B D)), Total$_{Uniq} = 5$:  
  - [(clear B)] = 1, [(ontable B) (handempty)] = 1,  
  - [(on D B) (clear D) (handempty)] = 0.3333, [(holding D)] = 0.3333  
  - $h_{uniq} = 2.6666 / 5 = 0.5333$

- (and (ontable D) (clear C) (on C D)), Total$_{Uniq} = 4.5$:  
  - [(clear C)] = 1, [(clear C) (on C A) (handempty)] = 0.5,  
  - [(clear D) (holding C)] = 1, [(holding D)] = 0.3333  
  - [(clear D) (on D B) (handempty)] = 0.3333  
  - $h_{uniq} = 3.1666 / 4.5 = 0.71$

**Recognized** (and (ontable D) (clear C) (on C D)) with:  
$h_{uniq} = 0.71$
We evaluate our heuristics over datasets with 15 planning domains (6 of these domains from original Ramírez and Geffner paper):

- Blocks-World, Campus, Depots, Driver-Log, Dock-Worker-Robots, Easy-IPC-Grid, Ferry, Intrusion-Detection, Kitchen, Logistics, Miconic, Rovers, Satellite, Sokoban, and Zeno-Travel;

These datasets contain hundreds of goal recognition problems, varying the observability (10%, 30%, 50%, 70%, and 100%);

We compared our heuristics against the original approach of Ramírez and Geffner (Plan Recognition as Planning. IJCAI, 2009), which is their fastest and most accurate approach;
Experiments and Evaluation - ROC Space (1 of 2)

- Results of our heuristics use threshold $\theta = 20\%$;
- We compare Ramírez and Geffner’s approach over ROC space, which shows the trade-off between TPR and FPR;
- We aggregate multiple domains and plot these goal recognition results in ROC space.
Experiments and Evaluation - Recognition Time

The graph illustrates the recognition time (in seconds) as a function of observation length. The x-axis represents the observation length, while the y-axis shows the recognition time. Several curves are plotted, each representing different metrics:

- $h_{gc}$
- $h_{uniq}$
- R&G
- Filter 10% + R&G

Each curve shows how recognition time increases with observation length.
Experiments and Evaluation - Recognition Time with Noise

![Recognition Time Graph](image)

- **$h_{gc}$**
- **$h_{uniq}$**
- **R&G**

**Observation Length** vs. **Recognition Time (s)**
Contributions and Limitations

- **Contribution so far:**
  - Use planning landmarks for goal recognition;
  - Obviate the need to run a planner during goal recognition, resulting in much faster and highly accurate recognition; and
  - Robust dataset to evaluate goal recognition algorithms

- **Limitations:**
  - Sensitive to the presence of landmarks; and
  - Low accuracy with very few observations, i.e., 10% of observability;
Table of Contents

1 Introduction
   • Motivation and Intuition

2 Goal Recognition as reasoning over Heuristics

3 Online Goal Recognition as Reasoning over Landmarks

4 Real World Applications
   • Plan Recognition using Video Data

5 Summary and Future Directions
Motivation for Efficient Online Goal Recognition

Most goal recognition approaches using domain models have three key limitations:

1. assumption of a discrete state-space in a PDDL-like formalism
   - not viable for use with path planning scenarios
2. assume all access to all observations at once
   - approaches do not consider the time to recognition
3. need to call a planner multiple times per goal to rank hypotheses
   - PRAP is computationally expensive, impractical for long plans
Online vs. Offline Plan Recognition

- Offline plan recognition:
  - All observations received at once;
  - Observations may be incomplete or noisy;
  - One-shot recognition;

- Online plan recognition:
  - Observations received incrementally;
  - Observations may be incomplete or noisy;
  - Objective is to recognize goal as soon as possible, without the full observation sequence.

\[ O = \{O_1\} \quad \text{Time} \quad O = \{O_1, O_2\} \quad O = \{O_1, O_2, O_3\} \]
Efficient Online Goal Recognition

Our approach:
- is efficient for online goal recognition;
- works in both discrete and continuous domains;
- minimizes planner calls;
- reasons about landmarks to minimize the number of goal hypotheses;
- returns reliable goal ranking as soon as possible
Landmarks in Continuous Domains

We need a notion of landmark in continuous domains

- Redefine landmarks as areas surrounding goals
  - Goals – Black dots
  - Surrounding Rectangles – continuous landmark areas

- To reach a goal the observed motion must intersect (go through) the corresponding landmark area.

- In this work, landmark areas roughly correspond to rooms partitioned as rectangular Voronoi diagrams
  - Other notions of numeric landmarks may apply (e.g. Scala et al. IJCAI 2017)
Online Recognition with Landmarks

- Generate the ordered set of achieved landmarks
- Maintain the group of goals eliminated due to landmarks
- For every observation:
  - Check if it “achieved” a landmark
  - If observations backtrack, re-instate goals
- Rank goals using the landmark completion heuristic $h_{gc}$
Goal Mirroring with Landmarks

Combines landmark reasoning with goal mirroring

- Compute landmarks and optimal plans for all goals
- For every observation:
  - Compute plan prefix, and for every goal
    - Either prune goals that have passed the last landmark; or
  - Compute plan suffix (from last observation) using planner
  - Compute cost ratio between prefix+suffix and optimal plan

- Rank unpruned goals based on a normalized cost ratio
- Ranks $P(g_k | O)$ using a normalizing factor $\eta 1/ \sum_{g_k \in G} rank(g_k)$
- Approximates $P(g | O) = \eta \sum_{g_k \in G} P(O | g_k)P(g_k)$ for all goals, assuming $P(g_k) = 0$ for pruned goals
Continuous Evaluation

- Cubicles environment and robot (OMPL)
- 11 points spread evenly over the environment
- 220 problems
Discrete Evaluation

- Dataset expanded from Ramirez and Geffner’s original work
- Domains extracted from the IPC competition
- Hundreds of goal recognition problems

Domains

- Blocks-World
- Campus
- Depots
- Driver-Log
- Dock-Worker-Robots
- Easy-IPC-Grid
- Ferry
- Intrusion-Detection
- Kitchen
- Logistics
- Miconic
- Rovers
- Satellite
- Sokoban; and
- Zeno-Travel
Performance Results

![Performance Results Graph]

- **True Positive Rate** vs **False Positive Rate**
- **Random Guess**
- **Goal Mirroring**
- **Goal Mirroring With Landmarks**
- **Online Recog. With Landmarks**

**Legend**:
- Random Guess (Dotted Line)
- Goal Mirroring (Crosses)
- Goal Mirroring With Landmarks (Orange Squares)
- Online Recog. With Landmarks (Circles)

**Axes**:
- **False Positive Rate** on the X-axis
- **True Positive Rate** on the Y-axis

**Notes**:
- Variability in performance metrics across different methods.
- Higher True Positive Rates suggest better accuracy in recognition.
- Lower False Positive Rates indicate fewer incorrect recognitions.
Efficiency Results

- Average Number of Calls to Planner
- Goal Mirroring
- Goal Mirroring with Landmarks
- Online Recognition with Landmarks

- Time Improvement Percent
- Goal Mirroring with Landmarks
- Online Recognition with Landmarks
Contributions and Limitations

- **Contribution so far:**
  - Extended the idea of landmarks for continuous domains; and
  - Developed online algorithms able to recognize plans in discrete and continuous domains;
  - Very efficient in both discrete and continuous domains.

- **Limitations:**
  - Naive notion of spatial landmarks;
  - Much better performance on discrete domains.
Table of Contents

1 Introduction
   • Motivation and Intuition

2 Goal Recognition as reasoning over Heuristics

3 Online Goal Recognition as Reasoning over Landmarks

4 Real World Applications
   • Plan Recognition using Video Data

5 Summary and Future Directions
Plan Recognition using Video Data

- **Plan recognition**
  - Task of recognizing the plan (i.e., the sequence of actions) the observed agent is following in order to achieve his intention (Sadri, 2012)

- **Activity recognition**
  - The task of recognizing the independent set of actions that generates an interpretation to the movement that is being performed (Poppe, 2010)
  - Such task is particularly challenging in the real physical world

- Much research effort focuses on activity and plan recognition as separate challenges;
- We develop a hybrid approach that comprises both activity and plan recognition;
- The approach infers, from a set of candidate plans, which plan a human subject is pursuing based exclusively on fixed-camera video.

Sadri, Fariba. Intention Recognition in Agents for Ambient Intelligence: Logic-Based Approaches. Ambient Intelligence and Smart Environments, pp. 197-236, 2012.
A Hybrid Architecture for Activity and Plan Recognition

- Conceptually divided in two main parts
  - CNN-based activity recognition (CNN)
  - CNN-backed symbolic plan recognition (SBR)
Experiments: Dataset

- **ICPR 2012 Kitchen Scene Context based Gesture Recognition dataset (KSCGR)**
- **5 recipes for cooking eggs in Japan**
  - Ham and Eggs, Omelet, Scrambled-Egg, Boiled-Egg and Kinshi-Tamago
  - Each recipe is performed by 7 subjects (5 in training set, 2 in testing set)
- **9 cooking activities composes the dataset**
  - Breaking, mixing, baking, turning, cutting, boiling, seasoning, peeling, and none
Summary of the Results

Conducted experiments on two levels:

- **Activity Recognition**
  - Accuracy lower than 50% (in 9-label classification) for infrequent activities
  - Very good accuracy to identify “no-action”

- **Overall Plan Recognition**
  - Low accuracy for overall plan recognition using plan-libraries
Contributions and Future Work

We developed a hybrid architecture for activity and plan recognition.

Pipeline includes:

- A CNN for activity recognition that feeds directly into:
  - a modified (SBR) approach that uses the CNN to index activities in the plan library

Approach limited by the plan library in the plan recognizer.

Next steps:

- Employ other deep learning architectures such as Long-Short Term Memory networks (LSTM) and 3D CNNs
- Use a more flexible approach for plan recognition, such as PRAP
- Explore object recognition to provide additional clues of the activity that is being performed

Demo video: https://youtu.be/BoiLjU1vg3E
Table of Contents

1 Introduction
   • Motivation and Intuition

2 Goal Recognition as reasoning over Heuristics

3 Online Goal Recognition as Reasoning over Landmarks

4 Real World Applications
   • Plan Recognition using Video Data

5 Summary and Future Directions
Papers reporting these results

FRAGA PEREIRA, Ramon; MENEGUZZI, Felipe. Landmark-based Plan Recognition. ECAI, 2016.

PEREIRA, Ramon F.; OREN, Nir; and MENEGUZZI, Felipe. Landmark-Based Heuristics for Goal Recognition. AAAI, 2017.

PEREIRA, Ramon F.; OREN, Nir; and MENEGUZZI, Felipe. Monitoring Plan Optimality using Landmarks and Domain-Independent Heuristics. PAIR Workshop@AAAI, 2017.

GRANADA, Roger L.; PEREIRA, Ramon F.; MONTEIRO, Juarez; BARROS, Rodrigo; RUIZ, Duncan; and MENEGUZZI, Felipe. Hybrid Activity and Plan Recognition for Video Streams. PAIR Workshop@AAAI, 2017.

PEREIRA, Ramon F.; OREN, Nir; and MENEGUZZI, Felipe. Detecting Commitment Abandonment by Monitoring Plan Execution. AAMAS, 2017.


VERED, Mor; PEREIRA, Ramon F.; MAGNAGUAGNO, Maurício C.; KAMINKA, Gal; and MENEGUZZI, Felipe. Online Goal Recognition Combining Landmarks and Planning. GRW@IJCAI, 2017.
Summary

- We progressively relaxed many assumptions about plan recognition:
  - Domain knowledge
  - Quality of observations
  - Exclusively discrete domains
  - Precise domain knowledge

- We illustrated applications of these techniques:
  - Real world video-data
  - Multiagent systems
Future Directions

- **Plan Recognition with Domain Theories**
  - Use different landmark extraction algorithms;
  - Extend landmark-based heuristics to temporal and non-uniform-cost domains
  - Experiment with more advanced notions of numeric landmarks (e.g. Scala et al.)

- **Applications of Plan Recognition**
  - Use object recognition techniques (deep learning) to generate fact observations in video
  - Couple the above with plan recognition in domain theories
  - Do plan recognition in latent space
Thanks and Acknowledgement

People involved in this research

- Ramon Fraga Pereira (PhD Student)
- Mor Vered (PhD Student, Bar Ilan University)
- Maurício Magnaguagno (PhD Student)
- Juarez Monteiro (MSc Student)
- Roger Granada (Postdoc)
- Gal Kaminka (Bar Ilan University)
- Nir Oren (University of Aberdeen)
- Rodrigo Barros (PUCRS colleague)
- Duncan Ruiz (PUCRS colleague)

Institutions

- The Scottish Informatics and Computer Science Alliance (SICSA) Distinguished Visiting Fellowship (DVE)
- Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) – PQ Fellowship
If this talk was interesting and you want to know more, please come to:

Plan Recognition Master Class

University of Aberdeen – 16th October 2017

We will cover:

- Detailed algorithms
- Worked out examples
- Plan recognition with incomplete domains
- Much more
Thank you!
Questions?