PLAYGROUND- System Demo of Goal Recognition Design

Sarah Keren and Avigdor Gal and Ran Harari

Erez Karpas

{sarahn@tx,avigal@ie,srharari@t2}.technion.ac.il karpase@csail.mit.edu
Technion — Israel Institute of Technology
Massachusetts Institute of Technology

Abstract

We describe PLAYGROUND, an interactive game developed for demonstrating the concepts of *goal recognition design* (*grd*). *grd* is a recently formulated task that involves the off-line analysis of goal recognition models. As such *grd* involves formulating measures that assess the ability to perform goal recognition within a model and finding efficient ways to compute and optimize them. PLAYGROUND is designed as a walk-through introduction to the concepts of goal recognition design by engaging the user in a goal recognition task before and after goal recognition design has been applied. This setting allows the user to have a hands-on experience with improving the design of goal recognition tasks.

Introduction

Goal recognition (also termed plan recognition (Pattison and Long 2011), aims at discovering the goals (and sometimes plans) of an agent according to observations of its actions, collected online. *Goal recognition design (grd)* (Keren, Gal, and Karpas 2014; 2015) is a newly formulated problem which involves the offline analysis of goal recognition models, by formulating measures that assess the ability to perform goal recognition within a model and finding efficient ways to compute and optimize them.

Goal recognition design is relevant to any domain for which quickly performing goal recognition is essential and in which the model design can be controlled. Applications of goal recognition design may be found in problems such as intrusion detection (Jarvis, Lunt, and Myers 2004), assisted cognition (Kautz et al. 2003), natural language processing (Geib and Steedman 2007) and computer games ((Kabanza et al. 2010))

At a nutshell, the *grd* analysis consists of two stages. Given a model of a domain and a set of possible goals the first stage is to determine to what extent do actions, performed by an agent within the model, reveal his objective. The second stage is to find the best way to modify the model so that an agent acting within it will implicitly reveal his objective as early as possible. *grd* accomplishes the first stage by offering an offline solution for assessing the *worst case distinctiveness (wcd)* of a model, which represents the maximal number of observations that need to be collected in order to assure the goal of an agent in the system is recognized.



Figure 1: Examples of a goal recognition design scenarios

The second stage consists of minimizing the *wcd* by modifying the model. Modification is done by disallowing actions in the model which correspond, for example, to placing barriers or screens in order to direct the flow of passengers in an airport. As a way to guarantee user comfort, the *grd* is assigned a modification budget and computes a solutions that minimizes the change introduced to the model.

To demonstrate the novel concepts of *grd*, PLAY-GROUND is designed as an interactive game with stages corresponding to those of the *grd* analysis. Being assigned the task of recognizing the objectives of agents acting in the system, the user is offered a chance to experience the difference in performing recognition in a model before and after *grd* analysis. In addition, the user can engage in the *grd* analysis process and offer ways to improve the design.

PLAYGROUND

The objective of PLAYGROUND is to expose the user to the novelty of the *grd* approach by experiencing the analysis process and its contribution to the goal recognition task. Towards this end we choose to formulate the game as an interactive walk-through of the *grd* process in which the user assumes the task of recognizing the objectives of agents acting in the system before and after applying the *grd* design. In addition, the user shall participate in the design stage, getting a chance to fully appreciate the potential of the grd analysis on the recognition process. We start by presenting the domains of the game and then describe its dynamics.

Example Scenarios

In order to assure the PLAYGROUND highlights the contribution of the *grd* process in a straightforward way we choose to demonstrate it on two simple examples, which are both adaptations of goal recognition tasks presented in (Ramirez and Geffner 2009). In both settings we rely on three simplifying assumptions namely that agents in the system are optimal, the system is fully observable and the actions are deterministic.

setting is based on The first the GRID-NAVIGATION benchmark and depicted in Figure 1(a). The setting consists of a room (or airport) with a single entry point, marked as 'Start' and two possible exit points (boarding gates), marked as 'Goal 1' (domestic flights) and 'Goal 2' (international flights). An agent can move vertically or horizontally from 'Start' to one of the goals. Notice that for each of the goals there are several optimal paths, some of which share a common prefix with an optimal path to the other goal. In the presented example the goal of the agent becomes clear once turning left or right. Therefore, the wcd is 5 since in the worst case an optimal agent can move up 5 steps before it is obliged to turn towards its goal. As shown in Figure 1(b), The wcd can be reduced to 0 by placing a single barrier in front of the entry point obliging the user to make a decision as he enters the room.

The second setting is based on a simplified adaptation of the LOGISTICS domain which is depicted in Figure 1(c). The setting includes a descriptions of locations, trucks and objects. An object is either at specified destination or can be moved by loading it onto the truck and unloading it in their destination after the truck reaches it. A goal in this setting is defined according to the distribution of packages in the locations. In the depicted example setting there are three locations, two trucks $Truck_1$ and $Truck_2$ which are initially located at position Loc_1 , and three objects that are initially placed such that O_1, O_2 and O_3 are in locations Loc_1, Loc_2 and Loc_3 , respectively. There are two goals: 1) all objects at $Loc_2(q_1)$ and 2) all objects at $Loc_3(q_2)$. In the initial setting wcd = 1, since O_1 can be loaded to any of the trucks. In order to visually clarify the concept of disallowing actions in this setting we constraint the loading actions according to a color assigned to trucks and some of objects. If colored, an object can only be picked up by a truck with the same color. This setting corresponds to cargo regulations that may be applied on trucks of certain types. Using this method we mark $Truck_1$ and O_3 with a dashed blue line and $Truck_2$ and O_2 with a solid red line $(O_1 \text{ is uncolored and can be loaded on})$ either truck). This setting, which is depicted in 1(d) reduces the wcd to 0, since in the goal is revealed by the identity of the truck that loads O_1 .

The Game

In correspondence with the *grd* analysis process, PLAY-GROUND consists of three stages. First, the user is pre-

sented with a setting in which agents act in order to achieve their objectives. The user accumulates points by successfully recognizing an agent's goal and is encouraged to perform recognition as early as possible by assigning a high score for early detection. In contrast, if the user mistakenly recognizes the goal of an agent for which the goal is not clear yet or if the goal is incorrect, the player looses points.

We exploit the GRID-NAVIGATION setting to demonstrate the effect of *grd* analysis on a busy setting. In this setting one of the goals is selected and the user needs to mark the agents that are aiming at the chosen goal. Several agents may appear on the screen simultaneously and with varying velocities.

The analysis stage presents to the user his success rate, and engages him in an attempt to identify the factors that hindered the recognition process. The *wcd* of the model is revealed and the user is then asked to find a way to modify the model so that the *wcd* is minimized. The system offers its solution for minimizing the *wcd*. The final stage, engages the user in a second recognition phase, where he needs to perform recognition on the modified model. When this stage is completed, the user's success rate is compared to the initial rate and the *grd* impact is demonstrated.

References

Albrecht, D. W.; Zukerman, I.; and Nicholson, A. E. 1998. Bayesian models for keyhole plan recognition in an adventure game. *User modeling and user-adapted interaction* 8(1-2):5–47.

Geib, C. W., and Steedman, M. 2007. On natural language processing and plan recognition. In *Proceedings of the Twentieth International Joint Conference on Artificial Intelligence (IJCAI 2007)*, 1612–1617.

Jarvis, P. A.; Lunt, T. F.; and Myers, K. L. 2004. Identifying terrorist activity with ai plan recognition technology. In *Proceedings of the Sixteenth National Conference on Innovative Applications of Artificial Intelligence (IAAI 2004*, 858–863. AAAI Press.

Kabanza, F.; Bellefeuille, P.; Bisson, F.; Benaskeur, A. R.; and Irandoust, H. 2010. Opponent behaviour recognition for real-time strategy games. In *AAAI Workshop on Plan, Activity, and Intent Recognition (PAIR 2010).*

Kautz, H.; Etzioni, O.; Fox, D.; Weld, D.; and Shastri, L. 2003. Foundations of assisted cognition systems. *University of Washington, Computer Science Department, Technical Report.*

Keren, S.; Gal, A.; and Karpas, E. 2014. Goal recognition design. In *ICAPS Conference Proceedings*.

Keren, S.; Gal, A.; and Karpas, E. 2015. Goal recognition design for non optimal agents. In *Proceedings of the Conference of the American Association of Artificial Intelligence (AAAI 2015)*.

Pattison, D., and Long, D. 2011. Accurately determining intermediate and terminal plan states using bayesian goal recognition. *Proceedings of the First Workshop on Goal, Activity and Plan Recognition(GAPRec 2011)* 32.

Ramirez, M., and Geffner, H. 2009. Plan recognition as planning. In *Proceedings* of the Twenty-First International Joint Conference on Artificial Intelligence (IJCAI 2009).