

Accurately Determining Intermediate and Terminal Plan States Using Bayesian Goal Recognition

David Pattison and Derek Long

Department of Computer and Information Science
University of Strathclyde, Glasgow G1 1XH, UK
{david.pattison, derek.long}@cis.strath.ac.uk

Abstract

Goal Recognition concerns the problem of determining an agent’s final goal, deduced from the plan they are currently executing (and subsequently being observed). The set of possible goals or plans to be considered are commonly stored in a *library*, which is then used to propose possible candidate goals for the agent’s behaviour.

Previously, we presented AUTOGRAPH – a system which removed the need for a goal or plan library, thus making any problem solvable without the need to construct such a structure. In this paper, we discuss IGRAPH, which improves upon its predecessor by utilising Bayesian inference to determine both *terminal* and *intermediate* goals/states which the agent being observed is likely to pass through.

1 Introduction

Goal Recognition (GR) can be considered a sub-problem of Plan Recognition (PR) where only the *terminal* goal is required and the plan used to achieve this is somewhat irrelevant. Traditionally, both of these fields have made use of *libraries* (Kautz and Allen 1986; Goldman, Geib, and Miller 1999) which contain known, valid plans or goals and the plans used to achieve them, commonly represented as Hierarchical Task Networks (HTNs) (Nau, Ghallab, and Traverso 2004). Construction of these libraries by domain-expert is a time-consuming task, while automatic generation suffers the risk of being incomplete or containing irrelevant and invalid entries.

In our previous work with AUTOGRAPH (Pattison and Long 2010), we removed the need for a plan or goal library by representing the problem as a Planning task in which observations reflected movement through the *state space* of the associated domain. After each observation O a hypothesis was produced which represented a belief in the agent’s final goal. Perhaps expectedly, the accuracy of these hypotheses was often directly correlated to the number of plan steps observed so far. That is to say, more accurate hypotheses were produced towards the end of the plan, while earlier hypotheses often lacked many of the final goals as no previous observation had indicated they were a part of the true goal. Furthermore, AUTOGRAPH assumed a near-optimal (or

even optimal) plan was being observed – something which is rarely true in real-life.

This paper presents IGRAPH (Intermediate Goal Recognition with A Planning Heuristic), a recognition engine which tackles the problem of accurately determining an agent’s *intermediate* goal states – that is, states which the agent is expected to pass through **before** the end of their plan. To do this we adopt a Bayesian approach to reasoning over which goals are most likely at future timestep t , and furthermore provide a *relaxed estimate* of remaining plan length.

2 Motivation for Intermediate Goal Recognition

Tackling Goal Recognition without any form of library is a far harder task than if one were available. With such a library present the number of possible goals or plans being pursued is trivial in comparison to having to consider the entire state-space and all possible plans. However, for most real-world problems the benefits of a library-based recognition system are eclipsed by the scarcity of useful candidate plans and goals.

To motivate the need for non-library based recognition, let us consider a typical city shown in Figure 1a which is made up of many buildings, streets and services, with people in the city able to move between and interact with these. Given that we are to observe the movements of just a single person around this city, the number of possible plans which a library would have to contain for even a fixed starting location is intractable. However, if we consider each achievable fact to be a single, independent goal, then enumeration of all destinations or tasks becomes possible.

Now let us assume we begin observing an agent who starts at location A , then proceeds to walk to locations E and G before stopping at F (as shown in Figure 1b). If we assume the agent only has a single goal which is to move to another location, then as the plan progresses we can eliminate destinations which become harder to reach after each observation. For example, after the agent has moved from A to E , it can be deduced that they are probably not trying to reach B , D or H , as the route they have already chosen would mean a longer plan than had they moved directly towards one of these after starting at A .

Once the agent has reached E , we can reason that they are heading to C , G or F . Now suppose we wish to interact with

the agent **before** they achieve any of these goals. If we can deduce that they must pass through at tollbooth at X first, then we can plan to stop, hinder or help them in achieving their final destination goal.

However, the assumption in the above example that there will only ever be a single goal is both restricting and unrealistic. It is far more likely that the agent would have several goals. For instance, they may stop at location E to buy some goods, visit a relative at location G , then continue to location B . Their plan may be only 1 step long, or it may run to hundreds of actions. The ability to dynamically generate valid goal-conjunctions from otherwise unrelated goals is central to IGRAPH. This is in contrast to most previous work which assumes plans achieve a known, fixed conjunction or a single-goal (Mott, Lee, and Lester 2006; Lesh and Etzioni 1996).

Expanding this example to that of a real-world formulation, GR is often associated with monitoring and tracking (Huntemann et al. 2008; Geib and Goldman 2001) or in military and video game simulations (Schadd, Bakkes, and Spronck 2007; Kabanza et al. 2010; Albrecht, Zukerman, and Nicholson 1998; Cheng and Thawonmas 2004). While determining the agent’s **final** goal is the crux of GR, in all of these cases it would be beneficial to know the **intermediate** states or goals which the agent being observed is most likely to pass through on their way to achieving their final goals. Having this knowledge could be used to prevent the agent from achieving specific undesirable goals, or as an aid to plan deduction by using these intermediate states in a similar manner to *landmarks* (Porteous, Sebastia, and Hoffmann 2001; Richter, Helmert, and Westphal 2008). Conversely, in a co-operative domain with two or more agents in which communication has been lost but execution is continuing, the ability to pre-empt another agent’s intermediate goals could allow for co-operative tasks to be executed with minimal interruption and aid plan repair.

Many applications of GR relate strongly to *adversarial* recognition, wherein agents actively try to block their plans or goals from being recognised by the observer (Geib and Goldman 2001). Yet the majority of this work is related to simply the *detection* of adversarial behaviour, not the prevention of the outcome. It is also true that much of this has been directed towards plan recognition as opposed to goal recognition. Conceptually, this means that the problem of detecting intermediate goals is a moot point, as any plan hypothesis will allow intermediate states to be computed without probabilistic reasoning being required. This is the case in Blaylock and Allen’s work (2006), in which they experiment with the use of HTNs containing a high-level goal at the root, which decomposes into ordered subgoals (which may also decompose themselves). Intermediate and high level goals are inferred by noting that a subgoal at layer n has been achieved after an observation, and producing a *goal chain* – a path from the subgoal to the root.

Recently, the field of *interactive entertainment* has produced several works on recognition, based on Bayesian inference (Charniak and Goldman 1993) where the intention is to determine the goals of an agent (commonly the player), such that a personal story can be crafted around their expe-

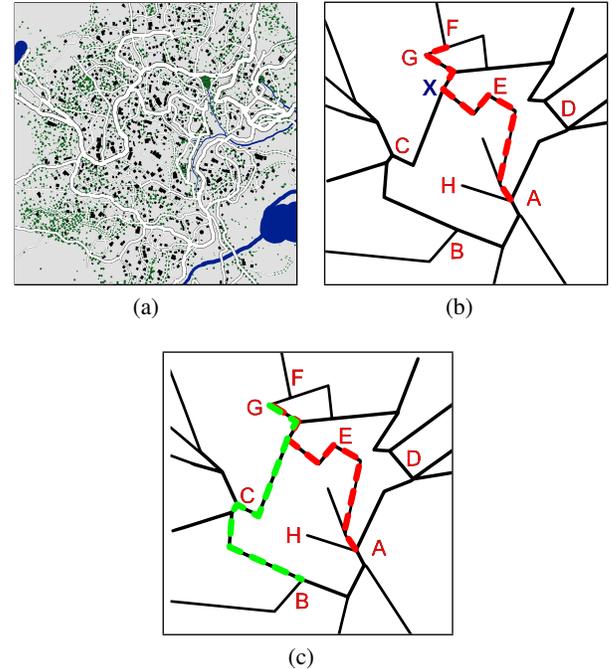


Figure 1: A small city map and several example plans displayed on a heavily-simplified version.

rience. In (Albrecht, Zukerman, and Nicholson 1998), Dynamic Belief Networks were used to generate predictions of a player’s next action and current quest in the context of a text-based virtual-reality game, which were trained using recordings of observed plans and actions. Mott *et al* (2006) offer another Bayesian approach to GR in the detection of goals in an interactive narrative environment. Their results show that goals can be incrementally converged upon as more evidence is provided, but that only single-goals are considered. More recently, (Kabanza et al. 2010) have presented HICOR, a PR system for detecting an opponent’s intentions in a real-time strategy game. While HICOR can present multiple, concurrent plans as a single hypothesis, testing has been performed using only mutually-exclusive single goals (although detecting multiple goals is possible).

Ramírez and Geffner (2010) also present a Planning-based model of GR similar to IGRAPH, which computes goal probability based on heuristic estimates after each observation. Probability likelihoods are based on *cost differences*, which represent the cost of achieving $P(G|O)$ versus $P(G|\neg O)$. While their work allows for multiple plans achieving multiple goals, it is evaluated using domains which comprise of only a few hundred actions and goals, while IGRAPH can handle thousands or even tens-of-thousands of goals.

3 Problem Definition

We begin by defining our representation of the problem. As in the original AUTOGRAPH we use a propositional Planning model similar to a STRIPS encoding (Fikes and Nilsson 1971), which we derive from a PDDL domain and problem

definition (McDermott et al. 1998; Fox and Long 2003).

Definition 1. Goal Recognition Problem Base

A goal recognition problem base is a triple $\langle F, A, I \rangle$, where F is a set of primitive (propositional) facts, A is a set of actions and $I \subseteq F$ is the initial state for the problem. Each action $a \in A$ is a triple $\langle a_{pre}, a_{add}, a_{del} \rangle$, where $a_{pre}, a_{add}, a_{del} \subseteq F$ are the preconditions, add effects and delete effects of a , respectively.

We also require a *Goal Recognition Problem* representing the plan being observed. Unlike AUTOGRAPH we do not assume that the plan being observed is optimal, near-optimal, or even rational. However, we do retain the assumptions that the plan is fully-observable and totally-ordered, but that we do not know its length. As we will discuss shortly, this final assumption is key to the operation of IGRAPH.

Definition 2. Goal Recognition Problem

A goal recognition problem is a triple $\langle \mathcal{G}, \mathbb{H}_I, P \rangle$, where \mathcal{G} is a goal recognition problem base, \mathbb{H}_I is an initial probability distribution over the hypothesis space \mathbb{H} and $P = \langle o_1, \dots, o_n \rangle$ is the sequence of plan actions observed one-by-one during the problem.

Enumeration of \mathbb{H} is intractable for all but the most trivial of problems, as it is a superset of the state-space. Thus, we define a *relaxed hypothesis space*, \mathcal{H} , which contains each individual *reachable fact*, f , and note sets of known mutually-exclusive facts¹ in order to keep the probability distribution over $f \cup \text{mutex}(f)$ normalised. However, while we only enumerate individual goals, we still allow for multiple facts to be considered as the goal of plan P , i.e. goal G_1 can be achieved, then goals G_2 and G_3 achieved in later observations. The mechanics of this last point are discussed in Section 4.

Before recognition begins, we may assign a *uniform probability distribution* over all mutually-exclusive facts, which become the *prior probabilities* for Bayesian inference. Alternatively, we may assign a *weighted probability distribution* using the same domain analysis techniques used in AUTOGRAPH (Pattison and Long 2010). Once all goals have an initial probability we compute their *heuristic estimate* $h(G)$ – an approximate measure of the number of actions required to achieve G .

As the agent executes actions, they move through the state-space and subsequently will move closer to achieving certain facts/goals and further away from others. This movement can be used as an indication of which subset of \mathbb{H} is being pursued. We update the heuristic estimate for all goals $G \in \mathcal{H}$ after each observation. These new estimates are then used to compute the *posterior probability* $P(G|O)$.

4 Heuristic Estimates as Bayesian Likelihoods

In AUTOGRAPH we also made use of heuristic estimation to determine the probability of a fact f being the true goal.

¹IGRAPH does not assume that *all* mutually-exclusive facts for a given domain are known, although not knowing this may affect the accuracy of the final probability distribution.

However, due to the assumption of having an optimal/near-optimal plan, if $h(f)$ increased after an observation its probability of being a goal was reduced to zero regardless of its previous value. This behaviour is also in line with use of an optimal heuristic, something which does not exist, thus hypothesis quality could be affected by inaccurate estimates.

For IGRAPH we have adopted an *interpolated* Bayesian approach to probability updates which has been inspired by work in Information Retrieval (IR) (Zhai and Lafferty 2004). We use observation O to update the probability of each goal $P(G|O)$ by computing the *likelihood function* $P(O|G)$ using $h(G)$. This determines the probability of O being relevant if G is assumed to be the true goal. By using interpolated smoothing to compute $P(G|O)$ we remove the ability for $(O|G)$ and thus $P(G)$ to equal zero. This shift to evidence-based probability updates means that goals can no longer be completely eliminated from the set of hypothesis *goal candidates*. Furthermore, it allows the agent to revisit sections of the search-space after having achieved a goal in another section.

We now define the amount of work expended on a goal G after an observation has been processed. Given observation O and a set of mutually-exclusive goals \bar{G} , the proportion of work which has been expended in moving towards achieving G is shown in Equation 1, where λ is a smoothing factor $\lambda \in [0 : 1]$ and \bar{G}^{nearer} is a set of mutually-exclusive goals (including G) whose heuristic estimate has lowered after A_t has been observed, or whose estimate has been zero for at least the past two observations.

$$W(G|O) = \begin{cases} \frac{1}{|\bar{G}^{nearer}|} & \text{if } h_t(G) < h_{t-1}(G), \\ \frac{1}{|\bar{G}^{nearer}|} & \text{if } h_t(G) = h_{t-1}(G) = 0, \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

In Section 2 we discussed the requirement of being able to have **any** valid conjunction of goals $G \in \mathcal{H}$ in a hypothesis. We implement this by introducing a relaxation in the assignment of $W(G|O)$. By providing goals which have remained true over timesteps t and $t - 1$ with a *bonus* of 1, we encourage goals which have been achieved to remain valid goal candidates. Consider the simple ZENOTRAVEL problem shown in Figure 2, in which the plan being observed will pick up passenger 1 from city 2, drop them off at city 1, fly to pick up passenger 1 in city 3, then return to city 1. After observing action 7: [fly city2 city1], the goal (at city1 passengerA) will have been true for 3 timesteps and no mutually-exclusive facts will have become heuristically closer. However, once action 7 has been observed, the heuristic estimate to (in plane passenger1) starts to reduce again. Without the bonus being applied to facts which have remained true in the intermediate timesteps, the probability of these goals reduces (as $P(O|G)$ is low), while the probability of others can increase.

This example also highlights another assumption made by IGRAPH – namely that once achieved, an agent will strive to keep the goal true if possible. We refer to this as the *stability*

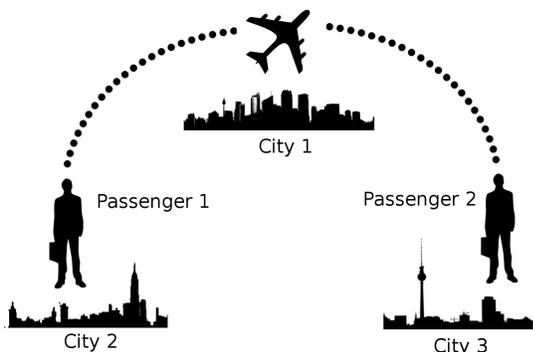


Figure 2: A small ZENOTRAVEL problem which highlights the need for a bonus being applied to goals which have remained true over $n > 0$ consecutive timesteps.

of the goal (see Equation 2). The stability of a goal $S(G)$ indicates how often it has been achieved, then *unachieved* in a later observation, with the first achievement being denoted as G_t^{true} and $\sum G_i^{true}$ the total number of timesteps G has been true since first achievement. In the above example, (at `city1 plane1`) is unachieved and re-achieved several times, giving it a low stability relative to other goals such as (at `city1 passengerA`).

We note that the use of bonus scores is not without its risks. Consider a variable with 2 mutually-exclusive transitions $\{F_1, F_2\}$, and that F_1 is true initially. If F_1 can transition to F_2 at any time during the observation of the first k plan steps (i.e. $h(F_2) = 1$), then the probability of F_2 will never increase, while $P(O|F_1)$ will receive a bonus after every observation. If after k observations, the final plan action is observed which transitions F_1 to F_2 , the probability increment for F_2 will be so small as to make no difference to hypothesis generation – more evidence would be needed to rule out F_1 as the true goal.

While this behaviour is perceivable for some problems, in general the above example would be unlikely. It is also arguable that if F_1 holds true for a long time before transitioning on the last known observation O_k , that it is probable F_1 was the goal for the plan observed until O_k , and that now a different plan with different goals is being pursued – or at the very least F_1 was an intermediate goal.

We incorporate the stability of a goal into the Bayesian likelihood function when computing the new posterior probability for each goal.

$$S_t(G) = \begin{cases} 1 & \text{if } G \text{ unachieved in } P, \\ \frac{|Obs| - G_t^{true}}{\sum G_i^{true}} & \text{otherwise} \end{cases} \quad (2)$$

$$P(O|G) = \lambda * W(G|O) * S(G) + (1 - \lambda) * \frac{1}{|\bar{G}|} \quad (3)$$

$$P(G|O) = \frac{P(G)P(O|G)}{\sum P(G_i)P(O|G_i)} \quad \forall G_i \in \bar{G} \quad (4)$$

Given a goal G and the set of goals which are mutually-exclusive $mutex(G)$, the *interpolated likelihood function* shown in Equation 3 defines the probability of O being relevant to the achievement of G with respect to all other goals $G_i \in \bar{G}$, where $\bar{G} = G \cup mutex(G)$. The smoothing factor λ prevents any goal from receiving a value of zero for $P(O|G)$, with low values causing the probability distribution over \mathcal{H} to be more evenly spread amongst mutually-exclusive facts.

As a special case, if a goal has no mutexes Equation 3 will not suffice as $P(O|G)$ for any stable goal which has moved closer will be 1. For this we use *laplace smoothing*, another IR scoring technique shown in Equation 5, where $\mu \in \mathbb{Z}^+$ and $|O_{helpful}|$ is number of observations which have lowered the original estimate $h(G)$, or maintained it at zero over $n \geq 2$ steps.

$$W(G|O) = \frac{|O_{helpful}| + \mu}{|O| + \mu} \quad \text{iff } |mutex(g)| = 0 \quad (5)$$

We now describe how this Bayesian approach to GR is used to generate both *intermediate* and *terminal* hypotheses.

5 Hypotheses as Intermediate States

Once the probability of every goal has been updated after each observation, we can attempt to estimate the number of remaining steps within the plan $\varepsilon \in \mathbb{Z}^+$. This is computed by generating an *immediate goal hypothesis* H_I , which is simply the set of mutually-exclusive facts that have the highest probabilities within \mathcal{H} , then heuristically estimating the number of steps required to achieve the hypothesis, $\varepsilon = h(H_I)$.

After ε has been computed, a *bounded hypothesis* can be generated for the next n steps, which is equivalent to the set of facts that are expected to be true at time $t + n$ (or which of the facts in the current state are the goal if $n = 0$). If the hypothesis contains a value from every set of mutually-exclusive facts, it is a *bounded intermediate state*, while if $n = \varepsilon$ it is a *terminal hypothesis*.

Definition 3. Bounded Goal Hypothesis

A *bounded goal hypothesis* H_t^n is a set of non-mutually-exclusive facts $\{G_1, G_2 \dots G_k\}$, where $H_t^n \in \mathbb{H}$ produced at time t on the rationale that H will be true at time $t + n$, and that $0 \leq n \leq \varepsilon$.

Facts which are a member of the relaxed-goal-space \mathcal{H} are selected for a bounded hypothesis based on the probability of an action A which achieves them being observed in the next n steps (see Equations 6 and 7). As an actions pre-conditions A_{pre} must all be satisfied before it can be applied and thus its effects added, the probability of these being an intermediate goal must also be considered.

$$P^n(A) = \begin{cases} 0 & \text{if } h(A_{pre}) > n, \\ \max P(f) \quad \forall f \in A_{add} & \text{otherwise} \end{cases} \quad (6)$$

$$P^n(G) = \max P^n(A) \quad \forall A \in \text{achievers}(G) \quad (7)$$

6 Evaluation

IGRAPH has been tested on the propositional versions of the DRIVERLOG, ZENOTRAVEL and ROVERS domains taken from the 3rd International Planning Competition along with their best-known-plan solutions (Long and Fox 2003). The FF heuristic (Hoffmann and Nebel 2001) has been used for evaluation, although any heuristic would suffice. A smoothing constant of $\lambda = 0.8$ was used for Bayesian updates, while $\mu = 1$ was used in the computation of $W(G|O)$ if $|\text{mutex}(G)| = 0$.

Tests were conducted in Ubuntu 9.10 on a quad core 2.8GHz Intel i5 with 4GB of RAM using the latest Java Virtual Machine (1.6.0_20), and were given as much time as necessary to complete each stage of the recognition process.

6.1 Intermediate Bounded Hypotheses

As in AUTOGRAPH, intermediate hypotheses produced by IGRAPH have been evaluated using *precision and recall* (P/R). However, while previously the P/R of a hypothesis was compared with the agent’s true final goal, here they are compared against the **state** encountered at time $t + n$.

The results of all intermediate hypotheses over each domain tested are shown in Figure 3. P/R results have been rounded to the nearest two decimal places in order to group together results for easier reading. The radius of a circle indicates the number of results in each grouping.

In the case of DRIVERLOG, clustering results are largely grouped above P/R = 0.5/0.5 indicating that the majority of *intermediate hypotheses* are reasonably accurate for their target bound. Results for ROVERS are primarily distributed across R = 0.45, while ZENOTRAVEL also displays strong clustering around P/R = 0.5/0.5.

Figure 4 displays intermediate clustering results in relation to their bound n . For example, column 1 relates to the accuracy of all hypotheses with $n = 1$ (hypotheses which are expected to be true after 1 further observation). These results reveal two details: that the majority of results are above 50% accurate, but also that there is a large number of P/R scores equal to (0.5/0.5) and that the estimation of remaining plan steps is often only a few steps from the current state (with $\varepsilon = 7$ being the highest observed). With regard to the former, the exact reason for the clustering around (0.5/0.5) is currently unknown as these results are spread across all three test domains. The latter observation can be explained by a combination of the accuracy of the heuristic used for estimation and the assumption that we have no knowledge of when the plan will terminate.

6.2 Short Lookahead Estimation

The nature of the FF heuristic means that estimates to goals which are far from the current state will often be much lower than their true distance, while goals that are closer will have a more accurate estimate. In fact, it is not uncommon for the estimate to distant goals to remain the same (or even increase) over multiple observations, despite the fact they are actually becoming closer. This apparent lack-of-progress towards a goal G alone is enough to eliminate it as a candidate for hypotheses, as its probability will likely be low. This

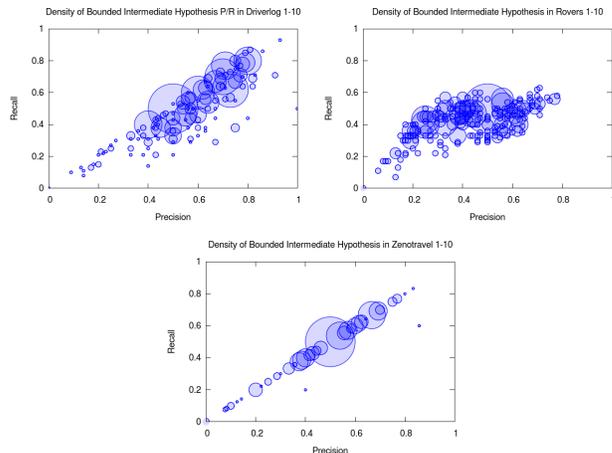


Figure 3: Density of P/R rounded to 2 d.p. over problems 1-15 and over all intermediate hypotheses for DRIVERLOG, ROVERS and ZENOTRAVEL. Circle radius is a reflection of the number of results at a specific P/R value.

is further compounded by the chance of multiple mutually-exclusive facts becoming closer after each observation.

Poor heuristic estimates for distant goals can also explain low values for ε , as only a consistent decrease in $h(G)$ will ensure they are considered as part of the *immediate hypothesis* from which ε is deduced.

6.3 Terminal Hypotheses

As stated previously, while intermediate goal hypotheses are undoubtedly useful, the ultimate task in GR is to determine the agent’s final goal. Thus, we produce a single *terminal hypothesis* after each observation which is equivalent to the *immediate hypothesis* produced to detect ε . The P/R results of these hypotheses when computed at various stages of plan observation is displayed in Table 1.

The results show a high average value for *recall* over all problems, while *precision* is often lower. However, as previously stated, while *bounded hypotheses* are tested against full states, *terminal hypotheses* are tested against the true goal only. As both hypothesis types are generated from the same algorithm, the precision for terminal hypotheses will often be much lower than the bounded equivalent.

In both DRIVERLOG and ZENOTRAVEL, P/R results show a faster *convergence* upon the correct goal than previously displayed in AUTOGRAPH. ROVERS results display both the lowest average precision yet perfect recall. The nature of typical goals in a ROVERS problem is what causes these static results. Most often the goal is to achieve communication of a rock sample or photograph, but that this can be performed in several ways. In the case of an image, once obtained it can be transmitted at a low or high resolution, or in colour, but that crucially any combination of these is possible. Thus as an agent progresses through a plan wherein they move to a sample and photograph it, the probability of communicating the image in all forms increases at the same rate, as each type of communicated goal is non-mutex. This means that hypotheses will include all types

7 Discussion

We have presented IGRAPH, an extension of AUTOGRAPH which attempts to move the state-of-the-art forward in goal recognition by tackling the problem of recognising multiple unrelated goals and estimation of intermediate plan goals/states. This is done without the need of a plan or goal library, making it applicable in a wide range of situations with only minimal prior effort.

By generating both accurate intermediate and terminal hypotheses, we have laid the groundwork for expanding into non-library-based *plan recognition*. As each bounded hypothesis is essentially a stepping-stone towards the final goal state, the ability to determine action selection becomes a much simpler task. Indeed, initial experiments have shown that IGRAPH can produce highly accurate *next-action prediction*. By chaining these predictions together we may be able to derive a *predicted plan* without resorting to fully-blown planning.

References

- [Albrecht, Zukerman, and Nicholson 1998] 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.
- [Blaylock and Allen 2006] Blaylock, N., and Allen, J. F. 2006. Fast hierarchical goal schema recognition. In *Proc. Nat. Conf. on AI (AAAI)*, 796-801.
- [Charniak and Goldman 1993] Charniak, E., and Goldman, R. P. 1993. A Bayesian model of plan recognition. *J. AI Res.* 64(1):53-79.
- [Cheng and Thawonmas 2004] Cheng, D. C., and Thawonmas, R. 2004. Case-based plan recognition for real-time strategy games. In *Proceedings of the Game-On International Conference*, 36-40.
- [Fikes and Nilsson 1971] Fikes, R., and Nilsson, N. J. 1971. STRIPS: A new approach to the application of theorem proving to problem solving. In *Proc. Int. Joint Conf. on AI*, 608-620.
- [Fox and Long 2003] Fox, M., and Long, D. 2003. PDDL2.1: An extension to PDDL for expressing temporal planning domains. *J. AI Res.* 20:61-124.
- [Geib and Goldman 2001] Geib, C. W., and Goldman, R. P. 2001. Plan recognition in intrusion detection systems.
- [Goldman, Geib, and Miller 1999] Goldman, R. P.; Geib, C. W.; and Miller, C. A. 1999. A new model of plan recognition. *J. AI Res.* 64:53-79.
- [Hoffmann and Nebel 2001] Hoffmann, J., and Nebel, B. 2001. The FF planning system: Fast plan generation through heuristic search. *J. AI Res.* 14:253-302.
- [Huntemann et al. 2008] Huntemann, A.; Demeester, E.; van Brussel, H.; and Nuttin, M. 2008. Can Bayes help disabled users? A Bayesian approach to plan recognition and shared control for steering an electrical wheelchair. In *Proc. ACM/IEEE Human-Robot Interaction Conf.*, 67-70.
- [Kabanza et al. 2010] Kabanza, F.; Bellefeuille, P.; Bisson, F.; Benaskeur, A. R.; and Irandoust, H. 2010. Opponent behaviour recognition for real-time strategy games.
- [Kautz and Allen 1986] Kautz, H. A., and Allen, J. F. 1986. Generalized plan recognition. In *Proc. of AAAI-86*, 32-37.
- [Lesh and Etzioni 1996] Lesh, N., and Etzioni, O. 1996. Scaling up goal recognition. In *KR*, 244-255.
- [Long and Fox 2003] Long, D., and Fox, M. 2003. The 3rd international planning competition: Results and analysis. *J. AI Res.* 20:1-59.
- [McDermott et al. 1998] McDermott, D.; Ghallab, M.; Howe, A.; Knoblock, C.; Ram, A.; Veloso, M.; Weld, D.; and Wilkins, D. 1998. PDDL - the planning domain definition language. Technical report, Yale Center for Computational Vision and Control.
- [Mott, Lee, and Lester 2006] Mott, B.; Lee, S.; and Lester, J. 2006. Probabilistic goal recognition in interactive narrative environments. In *Proc. Nat. Conf. on AI (AAAI)*, 187-192.
- [Nau, Ghallab, and Traverso 2004] Nau, D.; Ghallab, M.; and Traverso, P. 2004. *Automated Planning: Theory & Practice*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.
- [Pattison and Long 2010] Pattison, D., and Long, D. 2010. Domain Independent Goal Recognition. In *STAIRS 2010: Proceedings of the Fifth Starting AI Researchers' Symposium*, volume 222, 238 - 250. IOS Press.
- [Porteous, Sebastia, and Hoffmann 2001] Porteous, J.; Sebastia, L.; and Hoffmann, J. 2001. On the extraction, ordering, and usage of landmarks in planning. In *Proc. European Conference on Artificial Intelligence*, 37-48.
- [Ramírez and Geffner 2010] Ramírez, M., and Geffner, H. 2010. Probabilistic plan recognition using off-the-shelf classical planners. In *AAAI*.
- [Richter, Helmert, and Westphal 2008] Richter, S.; Helmert, M.; and Westphal, M. 2008. Landmarks revisited. In *AAAI*, 975-982.
- [Schadd, Bakkes, and Spronck 2007] Schadd, F.; Bakkes, S.; and Spronck, P. 2007. Opponent modeling in real-time strategy games. In *8th International Conference on Intelligent Games and Simulation (GAME-ON 2007)*, 61-68.
- [Zhai and Lafferty 2004] Zhai, C., and Lafferty, J. 2004. A study of smoothing methods for language models applied to information retrieval. *ACM Trans. Inf. Syst.* 22:179-214.

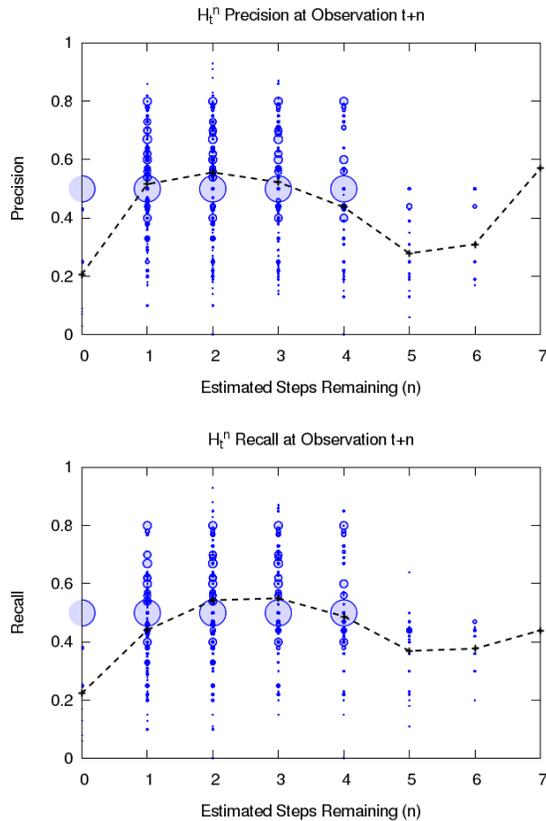


Figure 4: Density and averages for P/R of all hypotheses for all tests over all domains, when compared against the state encountered after n further observations.

of communicated goal, despite there often only being a single one required.

Finally, we note that average recall results for IGRAPH are considerably higher than those of AUTOGRAPH, with an average of 59% recall without any observations even being required. However, while recall has increased over all domains, precision has lowered for $|P| = 25 - 100\%$. This is caused by *terminal hypotheses* being produced in the same manner as *bounded hypotheses*, wherein the hypothesis is closer to a full state specification rather than a subset of goals. In AUTOGRAPH, many more restricting assumptions were made about the set of goals considered as candidates, which ultimately allowed for more concise hypotheses.

Domain	$ P = 0\%$	$ P = 25\%$	$ P = 50\%$	$ P = 75\%$	$ P = 100\%$
Driverlog	0.22/0.3	0.33/0.45	0.46/0.6	0.55/0.69	0.66/0.84
Rovers	0.28/1	0.28/1	0.28/1	0.28/1	0.32/1
Zenotravel	0.28/0.46	0.23/0.39	0.25/0.43	0.36/0.63	0.4/0.68
IGRAPH Avg.	0.26/0.59	0.28/0.61	0.33/0.68	0.4/0.77	0.46/0.84
AUTOGRAPH Avg.	0.02/0.02	0.45/0.12	0.64/0.27	0.76/0.48	0.88/0.73

Table 1: A compilation of averaged P/R scores for all *terminal hypotheses* over all domains tested at 0%, 25%, 50%, 75% and 100% plan completion.