Inferring Agents Preferences as Priors for Probabilistic Goal Recognition

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Abstract

Recent approaches to goal recognition have leveraged planning landmarks to achieve high-accuracy with low runtime cost. These approaches, however, lack a probabilistic interpretation. Furthermore, while most probabilistic models to goal recognition assume that the recognizer has access to a prior probability representing, for example, an agent’s preferences, virtually no goal recognition approach actually uses the prior in practice, simply assuming a uniform prior. In this paper, we provide a model to both extend landmark-based goal recognition with a probabilistic interpretation and also the estimation of such prior probability and its usage to compute posterior probabilities after repeated interactions of observed agents. We empirically show that our model can not only recognize goals effectively but also successfully infer the correct prior probability distribution representing an agent’s preferences.

1 Introduction

Goal Recognition is the task of inferring an agent’s goals, given a potentially flawed observation of this agent’s behavior (Sukthankar et al., 2014). The area of Goal and Plan Recognition as Planning (Ramírez and Geffner, 2009) has advanced substantially over the past decade, yielding a number of approaches capable of coping with partial and noisy observations (E-Martín R. Moreno and Smith, 2015; Sohrabi, Riabov, and Udrea, 2016), and doing this efficiently (Pereira, Oren, and Meneguzzi, 2020).

Virtually, all such efforts use the model of Ramírez and Geffner (2010) as their underpinning, which defines via Bayes’ Rule the probability of a goal, given observations in terms of the probability of the observations given the goal, and some prior probability of goals, representing an agent’s preference. Comparatively, fewer efforts provide a probabilistic interpretation of the model defined by Ramírez and Geffner (Sohrabi, Riabov, and Udrea, 2016; Kaminka, Vered, and Agmon, 2018). Fewer efforts still actually use the prior probability on goals, assuming instead a uniform distribution for the goals, and ignoring the prior in their calculations. Ignoring the prior probability bakes into the goal recognition model the assumption that all goal recognition tasks are one-shot, such that agents pursue exactly one goal within a particular goal recognition domain exactly once. Such an assumption does not reflect many goal recognition tasks, such as intention recognition for elder care (Geil, 2002), assistance for activities of daily living (Sim et al., 2010), proactive user interfaces (Amir and Gal, 2013), among others.

In this paper, we expand recognition problems from the traditional one-shot setting used by all models so far into problems that assume goal hypotheses have different probability distributions representing an agent’s preferences and develop a solution for this problem by extending recent work on landmark-based goal recognition (Pereira, Oren, and Meneguzzi, 2020). Our key contributions are twofold: (1) a novel definition of goal recognition problems with a goal preference distribution; and (2) a probabilistic interpretation that relies on the concept of landmarks.

2 Background

Planning. Planning is the problem of finding a sequence of actions (i.e., a plan) that achieves a goal state from an initial state (Ghallab, Nau, and Traverso, 2004). A state is a finite set of facts that represent logical values according to some interpretation. Facts can be either positive or negated ground predicates. A predicate is denoted by an n-ary predicate symbol p applied to a sequence of zero or more terms (τ0, τ1, ..., τn). An operator is represented by a triple a = ⟨name(a), pre(a), eff(a)⟩ where name(a) represents the description or signature of a; pre(a) describes the preconditions of a — a set of facts or predicates that must exist in the current state for a to be executed; eff(a) = eff(a)+ ∪ eff(a)− represents the effects of a, with eff(a)+ an add-list of positive facts or predicates, and eff(a)− a delete-list of negative facts or predicates. When we instantiate an operator over its free variables, we call the resulting ground operator an action. A planning instance is represented by a triple Π = ⟨Σ, F, G⟩, where Σ = ⟨F, A⟩ is a planning domain definition; F consists of a finite set of facts and A a finite set of actions; F ⊆ F is the initial state; and G ⊆ F is the goal state. A plan is a sequence of actions π = ⟨a0, a1, ..., an⟩ that modifies the initial state F into one in which the goal state G holds by the successive execution of actions in π. As in Classical Planning, actions have an associated cost, and here, we assume that this cost is 1 for all actions. A plan π is considered optimal if its cost, and thus length, is minimal.

Goal Recognition as Planning. Goal Recognition is the
task of discerning the intended goal of autonomous agents or humans by observing their interactions in a particular environment (Sukthankar et al. 2014, Chapter 1). We formally define the problem of Goal Recognition as Planning by adopting the formalism proposed by Ramírez and Geffner (2009; 2010), as follows in Definition 1.

**Definition 1 (Goal Recognition Problem).** A goal recognition problem is a tuple \( \Pi_G^2 = (\Xi, \mathcal{I}, \mathcal{G}, \Omega) \), where: \( \Xi = (\mathcal{F}, \mathcal{A}) \) is a planning domain definition; \( \mathcal{I} \) is the initial state; \( \mathcal{G} = (G_0, G_1, \ldots, G_n) \) is the set of goal hypothesis, including the correct intended goal \( G^* \), such that \( G^* \in \mathcal{G} \); and \( \Omega = (o_0, o_1, \ldots, o_n) \) is an observation sequence of executed actions, with each observation \( o_i \in \mathcal{A} \).

The ideal solution for a goal recognition problem \( \Pi_G^2 \) is the correct intended goal \( G^* \in \mathcal{G} \) that the observation sequence \( \Omega \) of a plan execution achieves. An observation sequence \( \Omega \) can be full or partial. A full observation sequence contains all actions of agents’ plans, so all actions of a plan are observed, whereas in a partial observation sequence, only a sub-sequence of actions are observed.

Existing work on Goal Recognition as Planning considers the solution to a goal recognition problem to be either a score system associated to the set of goal hypothesis (Pereira, Oren, and Meneguzzi 2017; Pereira, Pereira, and Meneguzzi 2019; Pereira, Oren, and Meneguzzi 2020), or a probability distribution for the goal hypothesis (Ramírez and Geffner 2009; 2010; E-Martín, R.-Moreno, and Smith 2015; Sohrabi, Riabov, and Udrea 2016; Pereira et al. 2019). In this work, we extend a landmark-based approach for goal recognition and provide a probabilistic model that relies on the concept of landmarks.

### 3 Probabilistic Goal Recognition as Reasoning over Landmarks

Key to our probabilistic goal recognition approach is the concept of landmarks in planning, which has been extensively used in goal recognition approaches (Pereira and Meneguzzi 2016; Pereira, Oren, and Meneguzzi 2017; Vered et al. 2018; Pozanço et al. 2018; Shvo and McIlraith 2020). Landmarks are defined as necessary fact (or actions) that must be true (or executed) at some point along all valid plans that achieve a particular goal from an initial state (Hoffmann, Porteous, and Sebastia 2004). Landmarks are often partially ordered based on the sequence in which they must be achieved. Hoffman et al. (2004) define fact landmarks as follows:

**Definition 2 (Fact Landmark).** Given a planning instance \( \Pi = (\Xi, \mathcal{I}, G) \), a formula \( L \) is a fact landmark in \( \Pi \) iff \( L \) is true at some point along all valid plans that achieve \( G \) from \( I \). A landmark is a type of formula (e.g., a conjunctive or disjunctive formula) over a set of facts that must be satisfied at some point along all valid plan executions.

The process of generating all landmarks and deciding their ordering is proved to be PSPACE-complete (Hoffmann, Porteous, and Sebastia 2004), which is exactly the same complexity as deciding plan existence (Bylander 1994). Thus, to operate efficiently, most landmark extraction algorithms (Hoffmann, Porteous, and Sebastia 2004; Silvia Richter 2008; Keyder, Richter, and Helmer 2010) extract only a subset of landmarks for a given planning instance.

In what follows, we expand the landmark-based goal recognition framework of Pereira, Oren, and Meneguzzi (2020) by introducing a probabilistic interpretation that allows us to perform recognition repeatedly refining estimated goal probabilities over time. The recognition framework of Pereira, Oren, and Meneguzzi (2020) provides a score system that ranks the goal hypothesis \( G \) according to the ratio between the achieved landmarks and total number of landmarks. Our probabilistic interpretation model is based the well-known probabilistic model of Ramírez and Geffner (2010). The probabilistic model of Ramírez and Geffner (2010) sets the probability distribution for every goal \( G \) in the set of goals \( \mathcal{G} \), and the observation sequence \( \Omega \) to be a Bayesian posterior conditional probability, as follows:

\[
\mathbb{P}[G | \Omega] = \alpha \mathbb{P}[\Omega | G] \mathbb{P}[G]
\]

where \( \mathbb{P}[G] \) is a prior probability to goal \( G \), \( \alpha \) is a normalizing factor, and \( \mathbb{P}[\Omega | G] \) is the probability of observing \( \Omega \) when the goal is \( G \). Ramírez and Geffner (2010) compute \( \mathbb{P}[\Omega | G] \) by computing two plans for every goal \( G \), and based on these two plans, they compute a cost-difference between these plans and plug it into a Boltzmann equation. Basically, they compute a plan that complies with the observations, and another a plan that does not comply with the observations. The intuition of Ramírez and Geffner probabilistic model is that the lower the cost-difference for a goal, the higher the probability for this goal.

In contrast, our probabilistic model reasons over the evidence of landmarks, and follows the intuition of Pereira, Oren, and Meneguzzi (2020), where goals \( G \) are ranked according to their score, namely, the most likely goals are the ones that have achieved most of their landmarks in the observations. Thus, replicating this ranking in a probabilistic setting entails assigning probabilities to the observation of landmarks. If we consider an arbitrary goal \( G \) and represent its landmarks as a set \( L_G \), where \( L_G \subseteq L_G \) is an individual landmark for \( G \), we can reason about the probabilistic properties of observing such landmarks. First, since landmarks are necessary conditions to achieve a goal, the probability of observing all landmarks in a set of observations for a given goal should be 1, as we formally define in Equation 2:

\[
\mathbb{P}[L_G \mid G] = \sum_{L_G \in L_G} \mathbb{P}[L_G \mid G] = 1
\]

Without any additional evidence, we can also infer that the probability of observing any given individual landmark in an observation sequence \( \Omega \) should be uniformly distributed as shown in Equation 3.
\[ \mathbb{P}[L_G \mid G] = \frac{1}{|L_G|} \quad (3) \]

If we completely ignore the ordering of the landmarks in observations, and consider only the probabilities of observing landmarks, we can compute the probability of a particular set of observations \( \Omega \) towards a goal \( G \) using Equation 4.

\[ \mathbb{P}[\Omega \mid G] = \sum_{L_G \in (L_G \cap \Omega)} \mathbb{P}[L_G \mid G] \quad (4) \]

Thus, we use landmarks as a proxy for the probability of the entire set of observations \( \Omega \) given a goal \( G \). We can plug \( \mathbb{P}[\Omega \mid G] \) defined in Equation 4 into the Bayesian formulation of [Ramírez and Geffner](2009) from Equation 1. Since we assume the set of goal hypotheses to be exhaustive and mutually exclusive, we can compute instead a normalizing factor \( \alpha \), which we obtain from Equation 5.

\[ \alpha = \frac{1}{\sum_{G \in \mathcal{G}} \mathbb{P}[\Omega \mid G] \cdot \mathbb{P}[G]} \quad (5) \]

When no priors \( \mathbb{P}[G] \) are informed, we can assume that their distribution is uniform, and compute them through \( \mathbb{P}[G] = \frac{1}{|G|} \). In Section 4, we show how we infer prior probabilities by observing repeated goal recognition episodes.

4 Prior Estimation by Repeated Episodes

We now expand the probabilistic model of Section 3 to compute posterior goal probabilities when the prior goal probabilities follow a non-uniform distribution over repeated goal-recognition episodes. The resulting model allows us to converge towards the actual probability distribution that can be used as a prior for further goal recognition episodes. We formalize the extended version of such problem in Definition 3.

Definition 3 (Repeated Goal Recognition Problem). A repeated goal recognition problem is a tuple \( \Pi_\mathcal{G} = (\Xi, \mathcal{I}, \mathcal{G}, \Omega^\mathcal{G}) \), where: \( \Xi = (\mathcal{F}, \mathcal{A}) \) is a planning domain definition; \( \mathcal{I} \) is the initial state; \( \mathcal{G} = (G_0, G_1, \ldots, G_n) \) is the set of goal hypothesis; and \( \Omega^\mathcal{G} = \{\Omega_0, \Omega_1, \ldots, \Omega_n\} \) is a set of observation sequences, where each \( \Omega_i \in \Omega^\mathcal{G} \) is an observation sequence \( (o_0, o_1, \ldots, o_m) \) of executed actions, with each observation \( o_j \in \mathcal{A} \). Observation sequences \( \Omega_i \) are projections of plans \( \pi_i \) for planning tasks \( (\Xi, \mathcal{I}, G_i) \) such that the intended goal \( G_i \in \mathcal{G} \) is drawn from a probability distribution \( \mathbb{P}[G] \) with probability \( \mathbb{P}[G \mid G_i] \).

The solution for a repeated goal recognition problem is the correct probability distribution \( \mathbb{P}[G] \) that generated the set of observation sequences \( \Omega \) in the problem of Definition 3. Here, \( \mathbb{P}[G] \) does not represent the result of a single episode of goal recognition, but rather the goal preferences of the agent under observation under repeated episodes.

Our prior estimation consists of processing each observation sequence \( \Omega_i \in \Omega^\mathcal{G} \) and count the number of times we recognize each candidate goal as the actual goal of an observation sequence \( \Omega_i \). We recognize the goals of each observation sequence independently, ignoring any priors in order to avoid biasing the count (Line 5). After each run, we check whether we correctly recognize the goal for sample \( \Omega_i \) (Line 5), which we do in a supervised way. Each correctly recognized goal \( G \) for a sample results in an increment of the corresponding counter \( C_G \). After repeating the process for all samples, we compute the prior for every candidate using the counter values and a form of Laplace smoothing (marquis de Laplace 1825) shown in Line 6, where \( k \) is the number of ghost samples we include to prevent any goal from having a probability of exactly 0. Algorithm 1 formally describes how our prior estimation process works.

Algorithm 1 Prior Estimation.

1: function \texttt{ESTIMATEPRIOR}(\Pi_\mathcal{G})
2: \hspace{1em} \( C_G \leftarrow 0 \) for all \( G \in \mathcal{G} \)
3: \hspace{1em} for \( \Omega \in \Omega^\mathcal{G} \) do
4: \hspace{2em} \( G \leftarrow \texttt{RECOGNIZE}(\Pi_\mathcal{G}) \)
5: \hspace{2em} if \( G \in \mathcal{G} \) then \( C_G \leftarrow C_G + 1 \) for all \( G \in \mathcal{G} \)
6: \hspace{2em} \( \mathbb{P}[G] \leftarrow \frac{(k+\sum_{G \in \mathcal{G}} C_G}{(k+|\mathcal{G}|)} \)
7: return \( \mathbb{P}[G] \) \quad \triangleright \text{Return probability distribution.}

5 Experiments and Evaluation

We empirically evaluate our probabilistic model over the recognition datasets from [Ramírez and Geffner](2009). These datasets comprise hundreds of recognition problems for four planning domains (BLOCKS-WORLD, EASY-IPCGRID, INTRUSION-DETECTION, and LOGISTICS), having recognition problems with both partial and full observability. Recognition problems with partial observability have four observation levels: 10\%, 30\%, 50\% and 70\%.

Repeated Goal Recognition Setup

To evaluate our repeated goal recognition algorithm, we develop a recognition problem generator that generates a set of samples that comprises \( \Omega^\mathcal{G} \) from a set of possible goal hypotheses \( \mathcal{G} \). Essentially, we produce a number of planning tasks \( \Pi_i = (\Xi, \mathcal{I}, G_i) \), such that the solution for each \( \Pi_i \) is a plan \( \pi_i \) from which we generate observations \( \Omega_i \) subject to the desired level of observability, including it in \( \Omega^\mathcal{G} \). We use Fast Downward [Helmert 2011] to generate the plans from which we project the observations. The goal state \( G_i \in \mathcal{G} \), and \( G \) is drawn from a probability distribution \( \mathbb{P}[G] \). For our experiments, we generate \( 10 \cdot |G| \) samples per repeated goal recognition problem. The probability distribution \( \mathbb{P}[G] \) is known only to the generator. We use two different probability distributions to generate such samples: a normal distribution with \( \mu = 1 \) and \( \sigma = 0 \), which we denote as NORMAL-SINGLE distribution, where all samples have the same goal state; and a normal distribution, such that a single (preferred) goal \( G_i \) has \( \mathbb{P}[G_i] = 0.5 \), and the probabil-

To generate the samples, we compose planning tasks based on initial states \( \mathcal{I} \) and goals hypothesis \( \mathcal{G} \) of the recognition problems in the datasets from [Ramírez and Geffner](2009).
we show the results for all four domains using the recognition time including the landmark extraction process.

We use three metrics in our evaluation: Accuracy (Acc %), representing the fraction of problems in which the correct intended goal is among the goals with the highest posterior probability; Spread in $\mathcal{G}$ ($S$ in $\mathcal{G}$), representing the average number of goals recognized as the most likely; and recognition time (Time) in seconds, representing the recognition time including the landmark extraction process.

We use two additional metrics when evaluating our probabilistic model with prior probabilities. Max-Norm is the largest difference between corresponding probabilities in the distribution that generated the samples and the estimated distribution of priors, used to evaluate the distance between these two distributions. If we can infer the priors exactly right, Max-Norm = 0. The second metric is a $\Delta$ metric, which is the difference between the $P(G | \Omega)$ of the real goal when using priors and when not using priors and gives us an insight on how helpful the priors are in one-shot recognition.

### Goal Recognition Results

Table 1 shows the results for executions with **no priors** (traditional one-shot recognition, denoted as NO PRIORS), with priors generated through a **single-goal** samples distribution (NORMAL-SINGLE), and with priors generated through **normal** samples distribution (NORMAL-DIVERSE). We show the results for all four domains using the recognition datasets from Ramirez and Geffner 2009. For each domain, we show the number of problems (under the domain name), the average number of candidate goals $|\mathcal{G}|$, the average number of extracted landmarks $|\mathcal{L}|$, and the average number of observations $|\Omega|$. For each of the three prior setups, we show recognition time, accuracy, and Spread in $\mathcal{G}$.

| Domain       | $|\mathcal{G}|$ | $|\mathcal{L}|$ | $|\Omega|$ | Acc % | $S$ in $\mathcal{G}$ | Time (sec) | Max-Norm | $\Delta$ |
|--------------|----------------|----------------|-----------|-------|-----------------|------------|----------|----------|
| Blocks-World | 20.3           | 12.0           |           | 10    | 0.238           | 21.9%      | 0.364    | 0.158    |
|              | 30             | 2.9            | 39.3%     | 1.2   | 0.157           | 96.5%      | 0.363    | 0.161    |
|              | 50             | 4.3            | 59.0%     | 1.2   | 0.164           | 96.7%      | 0.280    | 0.166    |
|              | 70             | 6.4            | 80.9%     | 1.2   | 0.169           | 97.8%      | 0.229    | 0.173    |
|              | 100            | 8.6            | 100.0%    | 1.5   | 0.176           | 100.0%     | 0.257    | 0.185    |
| Easy-IP-Grid | 8.3            | 6.8            |           | 10    | 0.343           | 33.1%      | 0.283    | 0.246    |
|              | 30             | 4.4            | 47.5%     | 1.6   | 0.375           | 97.8%      | 0.355    | 0.352    |
|              | 50             | 7.0            | 67.6%     | 1.2   | 0.640           | 100.0%     | 0.194    | 0.660    |
|              | 70             | 9.8            | 98.9%     | 1.0   | 0.632           | 100.0%     | 0.132    | 0.644    |
|              | 100            | 13.4           | 148.0%    | 1.0   | 0.655           | 100.0%     | 0.079    | 0.655    |
| Intrusion-Detection | 16.7 | 13.8 |           | 10    | 0.378           | 75.6%      | 0.293    | 0.336    |
|              | 30             | 4.5            | 49.1%     | 1.0   | 0.337           | 100.0%     | 0.107    | 0.334    |
|              | 50             | 6.7            | 46.7%     | 1.0   | 0.346           | 100.0%     | 0.086    | 0.344    |
|              | 70             | 9.5            | 46.0%     | 1.0   | 0.385           | 100.0%     | 0.085    | 0.404    |
|              | 100            | 13.1           | 52.4%     | 1.0   | 0.360           | 100.0%     | 0.085    | 0.367    |
| Logistics    | 10.0           | 14.3           |           | 10    | 0.344           | 62.2%      | 0.313    | 0.350    |
|              | 30             | 5.9            | 66.6%     | 1.3   | 0.532           | 100.0%     | 0.281    | 0.553    |
|              | 50             | 9.6            | 70.1%     | 1.1   | 0.543           | 100.0%     | 0.168    | 0.557    |
|              | 70             | 13.5           | 45.9%     | 1.0   | 0.551           | 100.0%     | 0.115    | 0.572    |
|              | 100            | 18.7           | 67.5%     | 1.0   | 0.590           | 100.0%     | 0.082    | 0.607    |

Table 1: Experimental results comparing our landmark-based probabilistic model with no prior probability distribution, normal single-goal probability distribution, and normal probability distribution.

**6 Conclusions**

In this paper, we have developed a novel probabilistic model for Goal Recognition as Planning that relies on the concept of landmarks, and a prior estimation process that infers prior probabilities from past recognition episodes. We have shown that our probabilistic model clearly benefits when using prior probabilities that have been inferred from past
recognition episodes.

Our landmark-based probabilistic model can be used not only in Classical Planning settings, but also in other planning settings that define the concept of landmarks, i.e., Temporal Planning landmarks [Karpas et al. 2015], Numeric Planning landmarks [Scala et al. 2017]. Our prior estimation mechanism is completely independent of the underlying goal recognition algorithm, and any such algorithm (even a non-probabilistic one) could be used in estimating the priors.

As future work, we intend to expand our prior estimation algorithm to non-classical planning settings, as well as to settings where the agent under observation is adversarial, for example, deliberately choosing undesired goals to skew the prior probability away from the preference relation.

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