Human Goal Recognition as Bayesian Inference: Investigating the Impact of Actions, Timing, and Goal Solvability

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ABSTRACT

Goal recognition is a fundamental cognitive process that enables individuals to infer intentions based on available cues. Current goal recognition algorithms often take only observed actions as input, but here we use a Bayesian framework to explore the role of actions, timing, and goal solvability in goal recognition. We analyze human responses to goal-recognition problems in the Sokoban domain, and find that actions are assigned most importance, but that timing and solvability also influence goal recognition in some cases, especially when actions are uninformative. We leverage these findings to develop a goal recognition model that matches human inferences more closely than do existing algorithms. Our work provides new insight into human goal recognition and takes a step towards more human-like AI models.

KEYWORDS

Goal Recognition; Problem Solving; Bayesian Inference; Solvability

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1 INTRODUCTION

Imagine that you are a security guard monitoring a camera feed, and you witness a person approaching a locked door. The situation is compatible with two potential goals: entering the conference room behind the locked door or proceeding to the lounge outside the door. If you observe the person pausing for an extended period outside the door, you might infer that they intended to access the locked conference room, a goal that is currently unachievable. However, if the person passes by the door without stopping, you might infer that they have the achievable goal of visiting the lounge.

As this example illustrates, people's ability to infer the intentions of others may be influenced by factors such as timing information in addition to observed actions [7, 18, 22]. Furthermore, individuals can sometimes infer goals that the actor cannot currently achieve. However, most existing goal recognition focus on actions alone, neglecting the broader context, and they struggle to handle situations involving unsolvable goals [10, 13, 15, 17, 24]. In this paper, we draw on behavioral experiments to explore how goal recognition in humans is influenced by three kinds of information: actions, timing, and goal solvability.

Goal recognition is the problem of inferring an actor's real goal given a sequence of observations and a set of possible goals. Two notable approaches that draw on Bayesian inference [6] have emerged in the literature. In 2009, Baker et al. [3] introduced the inverse planning Bayesian model, aimed at simulating human plan recognition by modeling human Theory of Mind formally as planning. Around the same time, Ramírez and Geffner [16] independently proposed a generative approach that uses planning algorithms over planning models and is known as plan recognition as planning (PRP).

Beyond actions alone, a small group of researchers in AI and cognitive science have explored how additional sources of information help to convey what others are thinking. Singh et al. [18] used gaze data to infer people's intentions and discovered that gaze can help uncover the hidden goals of players in a board game. Gates et al. [7] developed a Bayesian model that explains how people use response times as a cue to preferences in one-shot decision making situations. Zhang et al. [22] generalized the underlying idea and explored how timing information can be used in situations where actors generate rich sequences of actions, not just one-shot decisions. While both Zhang et al. [22] and Berke et al. [4] report that people are sensitive to timing information, there have been no comprehensive attempts to understand the extent to which timing affects human goal inferences.

Beyond actions and timing, the solvability of candidate goals provides a third relevant cue that may influence people's goal inferences. It seems plausible that people tend to assume actors are working towards achievable goals, because actors often have accurate beliefs and are unlikely to waste effort working towards goals that they believe to be unachievable. To the best of our knowledge, however, there has been little work on the impact of solvability in goal-recognition scenarios. Psychological studies of solvability judgments generally focus on tasks like unscrambling anagrams [14, 20], and planning scenarios have received little attention. We therefore consider solvability in addition to actions and timing information, and develop an experiment that aims to understand how these three factors influence goal inference in humans.

Figure 1 suggests how the three factors can be studied using goal-recognition tasks within the domain of Sokoban. In all cases the actor is required to push a box towards a goal, and the observer must infer which of two candidate goals the actor is working towards. Figure 1a is used to study the effect of observed actions. If the actor moves left at the key step shown as a pink arrow, people typically infer that the goal must be the green club, but had the

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actor moved right instead the red heart would be more probable. Figures 1c and 1b feature two identical maps with distinct green goal positions, with Figure 1c representing a solvable green goal and Figure 1b an unsolvable one. The probability assigned to the red goal may increase when the green goal is unsolvable rather than solvable. In Figure 1d, there is a single potential path towards the red heart but two possible paths towards the green club. If the agent thinks for a long time before taking the key step shown as a pink arrow, one possible inference is that the goal is green and the agent is deciding which of the two paths to pursue. In contrast, the red goal provides no plausible explanation of an extended pause before the key step.

In conventional goal recognition tasks, the evidence typically comprises one or more observed actions. Here, we also consider scenarios where no actions are observed. We refer to these instances as *prior* instances, because they probe expectations in advance of observing any actions. These prior instances allow us to investigate how solvability influences goal-recognition when other sources of information are absent. For instance, in Figure 1a, in the absence of any observations, individuals may exhibit a slight preference for the solvable goal (the red heart). Previous Bayesian models of goal recognition typically assume a uniform prior [3, 17, 19, 21], but a small body of recent work has explored how actions observed in previous instances shape the priors that observers apply to new goal-recognition instances [8, 12]. Here we take a different approach, and explore how the prior reflects structural properties such as solvability and solution complexity rather than previously-observed sequences of actions.

To preview our results, we find that solvability influences people's goal-recognition judgments when no actions have been observed, but that this factor may be subsumed by a more general notion of solution complexity. When actions are observed, however, solvability appears to play a minimal role, and people's goal-recognition inferences are shaped instead by actions (as a primary factor) and timing information (as a secondary factor). We evaluate a suite of formal models and find that human goal inference is well-captured using Bayesian inference, and in particular that a Bayesian model which incorporates an online planner provides a good account of human judgments.

Our work makes several kinds of contributions. First, we carry out a comprehensive behavioral experiment aimed at thoroughly investigating the factors that influence human goal recognition. This study provides a strong foundation for the development of computational models of human goal inference. Second, we expand upon the planning model introduced by Zhang et al. [22] by integrating a component that allows the planner to recognize unsolvable goals. Third, we introduce a human-like goal recognition algorithm that relies on Bayesian inference, and show that it provides a good account of human behavior.

2 GOAL RECOGNITION AND BAYESIAN FRAMEWORK

We now formalize the problem of goal recognition and introduce a Bayesian framework for this problem. We follow the notation commonly used in the planning community [16, 19, 21], but the same general approach has been applied in the cognitive science literature [3]. Because we consider timing information, our problem formulation includes this information.

Definition 2.1. A goal recognition problem with timing information is a tuple $\langle D, G, Prior, O\rangle$, where D is a planning domain, $G = \{g_1, g_2, ..., g_n\}$ is a set of possible goals for the planning domain, $Prior$ is the prior probability $P(G)$ over G, and O is a sequence of observations $\langle a_0, t_0\rangle, ..., \langle a_m, t_m\rangle$, where $a_i \in A$ is an action, and t_i is a non-negative real number denoting the planning time used to select a_i for execution.

Goal recognition can then be carried out using

$$P(G|O) \propto Prior(G)LL(O, G), \tag{1}$$

where $P(G|O)$ is the posterior distribution over goals, $Prior(G)$ is the prior $P(G)$ and $LL(O, G)$ the likelihood $P(O|G)$. Following [22], we decompose the likelihood $LL(O, G)$ into two components: the timing component $LL_T(O, G) := P(\langle t_0, t_1, ..., t_m\rangle|G)$ and the action component $LL_A(O, G) := P(\langle a_0, a_1, ..., a_m\rangle|G)$, allowing for independent calculations.

While solvability, actions, and timing might all influence human goal inference, a Bayesian perspective suggests a fundamental distinction between solvability and the other two factors. Solvability is an inherent property of the goal and should therefore be captured by $Prior(G)$ within the Bayesian model. In contrast, actions and timing are aspects of O, the observation sequence, and should be incorporated in the likelihood $LL(O, G)$.

Because previous Bayesian accounts of goal recognition usually assume a uniform prior [3, 17, 19, 21], they focus on estimating the likelihood term $LL(O, G)$. Specifically, this involves determining the probability of generating the provided observation sequence O given the goal G. Most goal recognition models rely on standard planning algorithms that do not handle scenarios in which the goal G is unsolvable. For example, with classical planning, unsolvable goals are filtered out from consideration at the outset.

Some approaches avoid the assumption that the actor is rational [3, 21, 22, 24], and can therefore estimate the likelihood of an unachievable goal. We go beyond these approaches by using a novel solvability-aware planner (i.e. solvability-aware Adaptive Lookahead Planner, full details in the supplementary information) that can decide whether a goal is unsolvable. While searching through the state space, the planner maintains a closed list of previously visited states in memory, and terminates and declares the goal unachievable if no new states are encountered during a fixed number of iterations. Although we provide a limited evaluation of this planner as an account of human planning, our primary focus is on evaluating the Bayesian model of goal recognition that incorporates this planner as a likelihood estimation component.

3 EXPERIMENT CONFIGURATION

To explore how actions, timing and solvability influence goal recognition and to test competing computational models we conducted a human experiment using the Sokoban domain. Although goal recognition is our primary focus, the experiment began with a planning phase in which participants were asked to solve 23 Sokoban problems. 9 of these problems were unsolvable, and participants could press a specified button at any stage if they believed that the current instance was unsolvable.

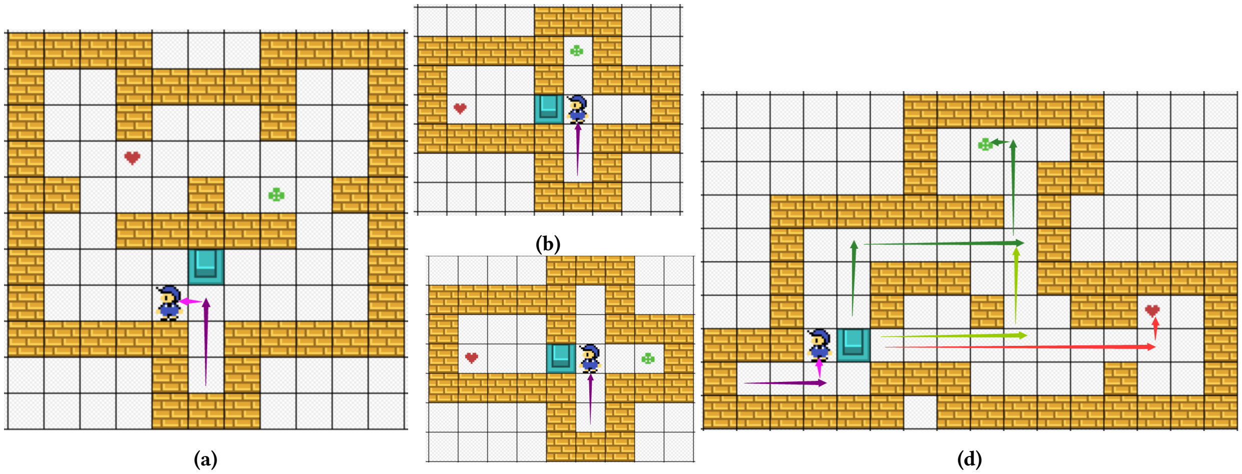


Figure 1: Examples showing three types of Sokoban maps in which action, timing and solvability might affect human goal inference. After performing two forced moves indicated by the purple arrows, the actor executes a key step indicated by the pink arrow. Complete sets of maps used in our experiment can be found in the supplementary materials. (a) An *action* map. The red goal is achievable and the green goal is not, and the actor moves left at the key step. (b) An *easy-goal* map. The red goal is easy to achieve but the green goal is not achievable. The key move (not shown) involves a push to the left. (c) A second *easy-goal* map. The red goal is easy to achieve but the path to the green goal is more complex. At the key move (again not shown) the actor pushes the box to the left. (d) A *competing-path* map. There is one good path (red arrows) to the red goal and two good paths (green arrows) to the green goal. The actor moves up at the key step.

Participants then moved on to a goal-recognition phase using the same maps presented in the planning phase. Each instance presented a Sokoban map with two possible goal positions marked as A and B. Participants were asked to infer the actor's goal, and provided responses on a six point Likert scale labeled "very confident B", "fairly confident B", "slightly confident B," "slightly confident A," and so on. For subsequent analyses we mapped these six responses to probabilities $\{0, 0.2, 0.4, 0.6, 0.8, 1\}$, where each probability represents the probability of choosing goal A [9]. For example, if three participants chose "very confident A" and two chose "slightly confident B" the average response would be $\frac{3\times1+2\times0.4}{2+3} = \frac{3.8}{5} = 0.76$.

The stimuli for the goal recognition phase belong to one of three types, and included 20 *prior* instances, 40 *observation* instances and 9 *filler* instances. The presentation order of these instances was fully randomized. Identical map configurations and goal positions were used for the prior and observation instances, but the prior instances required participants to infer the actor's goal without having observed any actions. In all *filler* instances participants observed the player pressing the button to declare the instance unsolvable. Responses to these instances will not be analyzed, and they were included only to reinforce the possibility that the goal might be unsolvable.

The *observation* instances included pairs that share identical maps and potential goal positions but differ in a single key step (see Figures 1a and 1d). This key step refers to the first step at which a player who does not backtrack has multiple options. Within each pair, either the action for this step or the response time for the action at this step can vary. There are 20 pairs in total, corresponding to the 20 instances in the *prior* type.

The observation instances can be organized into three subtypes. *Action* pairs differ based on the action taken for the key step (see Figure 1a). We hypothesize that changing the action at this step will influence human inferences regardless of the solvability of the potential goals.

The remaining two subtypes allow us to study the influence of timing information. *Easy-goal* pairs use maps where one goal is easy to solve and the other goal is either solvable or unsolvable (Figure 1c and 1b). In this subtype, the thinking time for the key step varies. We hypothesize that increasing the thinking time at this step will decrease the participant's confidence that the actor is aiming for the easy goal, because achieving the easy goal should not require a prolonged pause at any stage.

Competing-path pairs (the third and final subtype) include cases in which one goal (e.g. the green goal in Figure 1d) requires a choice between two possible actions at the key step, but the other goal suggests only one natural action at this step. As for easy-goal pairs, we vary the thinking time observed at the key step. We hypothesize that increasing the thinking time at this step will suggest that the actor is choosing between two paths, and therefore aiming for the competing-path goal rather than the alternative.

For each map configuration, we started with a goal-recognition instance featuring two solvable goals. We then created additional instances by moving each solvable goal in turn to either an adjacent unsolvable position or an unsolvable position with similar properties (e.g. Manhattan Distance from the start position). Figure 1c shows an original instance with two solvable goals, and Figure 1b is a variant in which the green goal is unsolvable. Manipulating solvability in this way allows us to explore the influence of solvability on human goal inference.

The experiment was pre-registered on AsPredicted. We recruited 100 standard sample participants (63 females and 37 males with a median age of 28) on Prolific, and 5 were excluded because they had more than 3 abnormal responses in the problem solving phase. For each instance, responses more than 3 standard deviations away from the mean total time and total steps for that instance were considered abnormal.

4 HUMAN PROBLEM SOLVING BEHAVIOUR

The problem-solving phase in the experiment serves three primary purposes. Firstly, it aims to validate the effectiveness of our manipulation of observations (i.e. actions or thinking times) in the goal recognition phase. Secondly, it seeks to analyze participants' strategies when faced with an unsolvable goal. Lastly, it involves a comparative assessment of the performance between solvability-aware Adaptive Lookahead Planner (A-LH) and human participants across Sokoban instances. The number of iterations generated by A-LH was converted into seconds by normalizing, ensuring that the total planning time for all instances remains the same across humans and A-LH.

Across the *action* maps, the majority of participants (88%) make choices that match our manipulation in the goal recognition phase, which is consistent with the model's prediction (82%) as shown in Figure 2a. Across *easy-goal* maps (e.g. Figure 2b), participants spend less time on the easy goal, with an average of 2.84 seconds compared to 7.75 seconds for the harder goal. The model's prediction shows a similar trend: 1.41 seconds for the easy goal and 8.24 seconds for the hard goal. Across *competing-path* maps, both human participants and the model show a small but statistically significant difference in planning times for the two goals. Human planning times increase from 5.94 seconds to 6.83 seconds, and the model predicts an increase from 5.68 to 7.04 seconds (see Figure 2c). These results indicate that the manipulations in our experiments are well-grounded and also suggest that the A-LH planner provides a good account of human behavior in the Sokoban domain.

We further examined the number of steps taken before participants became aware that unsolvable instances were in fact unsolvable. The results in Figure 2d demonstrate a positive correlation between the model's predictions and human responses. The majority of participants demonstrated behavior resembling that of online planners, taking an average of 15.23 steps, indicating that participants take approximately 15 steps before recognizing the unsolvability of the goal. The model predicted a much higher average of 35.78 steps. This divergence might be attributed to participants' general lack of patience during online experiments. A minority of participants do recognize goals as unsolvable before carrying out any actions, and failing to capture the responses of these participants may also contribute to the difference between model predictions and average human responses. Nevertheless, our data strongly suggest that the majority of people should be characterized as online planners in our experimental context.

5 HUMAN GOAL RECOGNITION

We use mixed effects models to fit the human responses in the goal recognition phase. In these models, the variable *CL* represents the confidence level towards goal A, ranging from 0 to 1. The variables *soA* and *soB* correspond to the solvability of goals A and B, respectively, with 1 denoting solvability and -1 denoting unsolvability. In the *action* maps, goal A represents the rightmost goal, while goal B represents the leftmost goal. In *easy-goal* maps, goal A is designated as the easy goal, while goal B is identified as the hard goal. In *competing-path* maps, goal A signifies the no-competion goal, while goal B denotes the competing-paths goal. The variable *obs* indicates whether the observation (i.e. action or planning time) is consistent with goal A (1 denotes consistent, -1 denotes inconsistent) if available. The model also includes random effects for participant and map configuration. All p-values subsequently reported are based on log-likelihood ratio tests, where M_0 serves as the null model. The models and summary of regression results can be found in Table 1.

5.1 Prior Instances

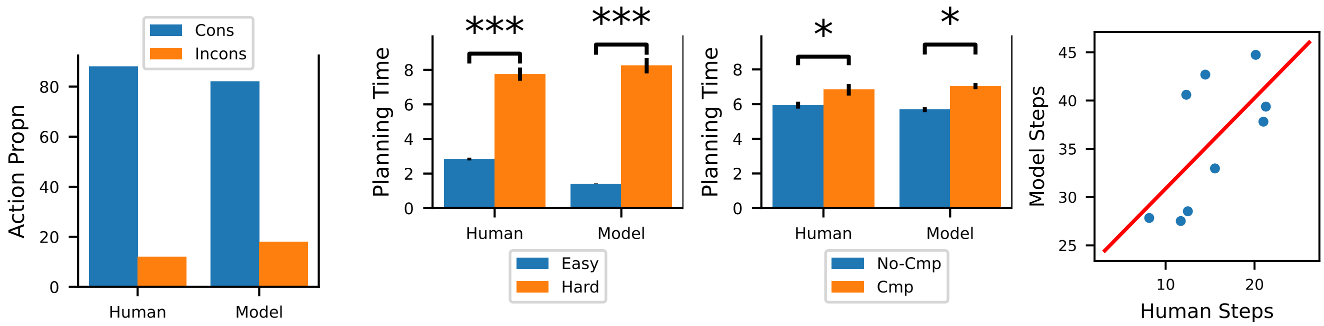
In *prior* instances, we present a map without any observed actions to determine how solvability or other static properties would influence the human prior $Prior_{\mathcal{H}}(G)$ over the potential goals. Our hypothesis is that humans will prefer solvable goals in cases where one goal is solvable and the other is unsolvable. As shown in Figure 3, the overall choice percentage of solvable goals stands at 61.16% (the sum of blue bars), and the average response is 0.59. This result confirms a clear preference for goals that can be solved.

The log-likelihood ratio test of prior instances yields $\chi^2(3) = 44.185, p < 0.001$. Model M1 demonstrates a strong fit, implying that the impact of solvability is evident. Specifically, the 95% Confidence Interval (CI) for the regression coefficient of soA is [-0.05, -0.02], while the 95% CI for soB is [0.02, 0.05]. These findings confirm our hypothesis — when one target is solvable, participants are more likely to infer that the solvable target represents the actual goal.

When we look deeper into the differences between various types of scenarios, we notice that distinct map layouts affect how much participants rely on solvability (see Figure 3c). Specifically, in the *action* maps, where the primary contrast between the goals is solvability, a consistent pattern emerges: participants tend to lean toward solvable goals. Most participants, however, express only a slightly confident viewpoint. This suggests that even though participants recognize the importance of solvability, the evidence supporting it might not be strong enough to firmly guide their conclusions.

In the *easy-goal* maps, the findings reveal a substantial number of participants who exhibit strong confidence in favor of the target being solvable rather than unsolvable. This finding, however, prompts the question of whether this confidence stems solely from solvability or is influenced by other characteristics within the *easy-goal* maps. As mentioned already, within these maps the solvable goal coincides with the easier goal. In order to further explore the possible role of easiness, we compared responses to maps that were similar except that the hard goal was solvable rather than unsolvable. We found that solvability itself does not significantly impact human inference; rather, individuals consistently lean towards the easier goal, irrespective of the solvability status of the other goal.

For *competing-path* maps, solvability continues to shape human judgments, but in a different way. Among the responses, 54.74% show a preference for the solvable goal, resulting in a mean confidence level of 0.57. This is even higher than the 0.56 confidence level in the *action* maps. Interestingly, when participants choose a solvable goal, their behavior stands out from when they pick an unsolvable one. While they don't seem very sure about choosing



(a) (b) (c) (d)

Figure 2: Results for the planning phase. (a) Proportion of participant choices for the action in *action* maps. *Cons* means consistent with our manipulation in the goal recognition phase. The model employs softmax action selection with a temperature parameter set to 5. (b) Average Planning time for *easy* and *hard* goals in *easy-goal* maps. The effect of thinking time is significant for both humans and the model ($p < 0.001$). For both (b) and (c), error bars show the standard deviation of the mean planning time (measured in seconds). (c) Average Planning time for *competing* and *no-competing* goals in *competing-path* maps. The effect of thinking time is significant for both human and model ($p < 0.05$). (d) Number of steps taken in unsolvable instances for humans (x-axis) and the model (y-axis). Human responses and model predictions are strongly correlated ($r(7) = 0.65, p = 0.05$).

Model	Model String ($CL \sim$)	Prior	Action	Easy-goal	Competing-path
M0	$(1\|participant) + (1\|map)$	6762.8	6252.6	2591.2	5463.8
M1	$soA + soB + soA * soB + (1\|participant) + (1\|map)$	**6741.3**	6272.5	2597.1	**5439.5**
M2	$obs + (1\|participant) + (1\|map)$	N/A	**4621.3**	**2552.4**	5466.2
M3	$soA + soB + soA * soB + obs + (1\|participant) + (1\|map)$	N/A	4636.9	2558.3	5441.7

Table 1: Bayesian Information Criterion (BIC) scores of models in regression analysis. The best model for each set of instances (i.e. each column) is shown using bold. The dependent variable CL is the probability assigned to goal A.

an unsolvable goal, their confidence is more balanced when they opt for a solvable goal.

Our findings indicate that human goal inference is shaped by both the solvability and inherent difficulty of goals. An unsolvable goal might represent an extreme version of a difficult goal. To test this idea, we developed a simple model called the *Easiness Prior Model* to fit the human prior. In this model, we operationalize the difficulty of each solvable goal g as the sum of the optimal path length $opt(g)$ and a smoothing parameter o (set to 5 in our analyses). This parameter captures the baseline cognitive effort demanded by the task (e.g. effort to process the map, recognize the actor and goal locations, etc). We further assume that unsolvable goals have the same difficulty score ($c = 26$) as the most difficult solvable goal in our experiments. Overall, the difficulty score for goal g is defined as $s_g = o + min(c, opt(g))$. Let s_A and s_B represent the cognitive difficulty values for goals A and B respectively in the prior instances. To reflect the notion that easier goals (with shorter optimal paths) have a higher prior, we use

$$\langle Prior(A), Prior(B) \rangle = \langle \frac{s_B}{(s_A + s_B)}, \frac{s_A}{(s_A + s_B)} \rangle. \tag{2}$$

As shown in Figure 3b, our model closely aligns with the actual prior probabilities observed in the prior instances (Pearson correlation test: $r(18) = 0.91, p < 0.001$). This finding suggests that our simple easiness model can effectively mimic human decision-making when no observations are available.

5.2 Observation Instances

The observation instances consists of pairs that share identical maps and potential goal configurations but differ in a single key step. This key step refers to the first action where a player who does not backtrack has multiple options. Within each pair, either the action for this step or the response time for the action can vary. Each pair also corresponds to a prior instance which shares the same map and goal configurations without including any observations.

There are three specific subtypes within the observation pairs, which also corresponds to three different types of maps in the prior instances. In what follows we consider the three subtypes separately.

5.2.1 Action Pairs. The result confirm our hypothesis: solvability rarely contributes to the final decision in goal choice when actions are informative. Regardless of whether the goal is solvable or unsolvable, the shift in goal preference, compared to the prior (that slightly favors the solvable goal), aligns with the guidance provided by action observations. When the action moves to the unsolvable goal, the confidence level to the solvable goal shifts from 0.56 to 0.24, and when the action moves to the solvable goal, the confidence level to that goal increases to 0.81. We also ran a log-likelihood ratio test to verify the hypothesis (see Table 1).

Among the models considered, Model M2 demonstrates the best fit (($\chi^2(1) = 1638.7, p < 0.001$)), as evidenced by its lowest Bayesian

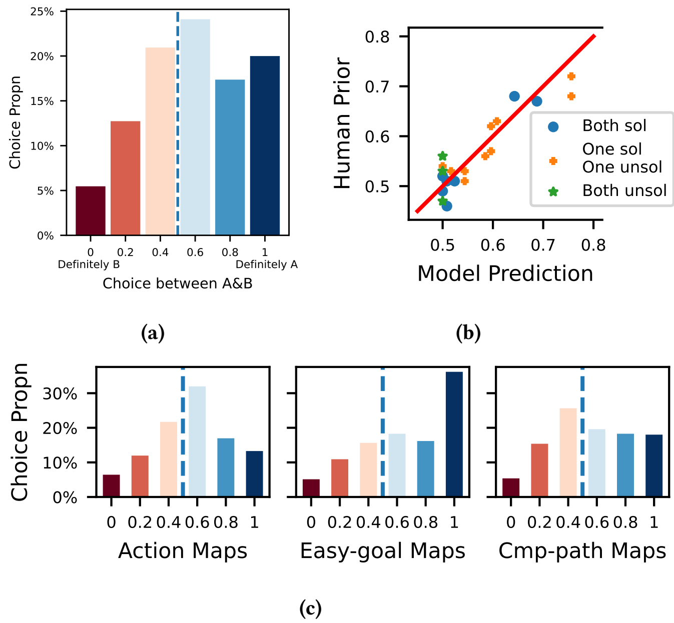


Figure 3: Results for prior instances in the goal-recognition phase. (a) Response distribution for prior instances where goal A is solvable and goal B is not. Blue bars indicate a preference for solvable goal A while red bars represent a preference for unsolvable goal B. (b) Comparison between human responses and the easiness model. The x-axis represents the model's predicted probability of choosing the easy goal, and the y-axis represents the human prior observed in the experiment. The instances are represented as circles, crosses or stars based on whether neither, one or both goals are unsolvable. (c) Response distribution from panel (a) broken down by the three subtypes.

Information Criterion (BIC) value. The 95% CI for the regression coefficient of *obs* falls within the range of [-0.32, -0.3]. Conversely, neither *soA* nor *soB* contributes meaningful information to the confidence level in this context. Notably, Model M1 even exhibits a higher BIC value than the baseline model (M0), indicating that solvability fails to enhance the model fit.

5.2.2 Easy-goal Pairs. Compared to the prior condition, regardless of the time actors take to think about the key steps, human responses shift towards the easy goal in the presence of observations. This shift is evident as the confidence level to the easy goal changes from 0.69 to 0.86 given short thinking time. However, when a long thinking time (consistent with hard goals in our hypothesis) is observed, this shift is somewhat less pronounced (0.69 to 0.75). Additionally, we observed that this pattern remains consistent, irrespective of whether the hard goal is solvable or not.

We performed an identical log-likelihood ratio test using easiness to define *obs*, where short thinking time is consistent with easy goal A (assigned 1) and long thinking time is aligned with hard goal B (assigned -1). The results aligned with our initial intuition: Model M2 exhibits the most favorable fit ($\chi^2(1) = 45.425, p < 0.001$). This underscores the notion that thinking time is relevant for predicting the confidence level, while solvability's contribution remains negligible. The 95% confidence interval for the regression coefficient of the intercept spans from 0.26 to 0.34, indicating a strong tendency among participants to favor the easier target choice. Furthermore, the 95% confidence interval for the regression coefficient of *obs* (i.e. long/short thinking time) falls within the range of [0.04, 0.07]. This outcome emphasizes that the manipulation of thinking time can exert a notable influence on the confidence level, contributing to statistically significant variations in participants' goal inference processes.

5.2.3 Competing-path Pairs. Broadly speaking, the patterns observed within the *competing-path* pairs align closely with those of the *easy-goal* pairs. In particular, when participants observe the actions, their preferences shift towards the no-competing goals whether the actor spend more or less time. Unlike the *easy-goal* instances, the initial distribution of *competing-path* maps is nearly uniform (with confidence level to the no-competition goal of 0.5) as shown in Figure 3c. With consistent observations (i.e. short thinking time) favoring the no-competition goal, the confidence level to that goal increases to 0.58. Surprisingly, even with inconsistent observations (i.e. long thinking time), the confidence level still increases to 0.56. This result implies that our definition of consistency (long/short thinking time) may not be the primary factor observers take into account during goal inference.

We applied the same log-likelihood test using number of competing path as the standard to define *obs*, where short thinking time is consistent with no-competing goal A (assigned 1) and long thinking time is aligned with competing-path goal B (assigned -1). All three models yield significantly better fits than the baseline model. Model M1, which considers only solvability, achieves the optimal fit ($\chi^2(2) = 41.442, p < 0.001$) based on BIC scores. In the comprehensive Model M3, the 95% confidence interval for the regression coefficient of *soB* lies between [-0.07, -0.04], while the intervals for *soA* and *obs* are [0.00, 0.04] and [0.00, 0.03] respectively. These results indicate that in this context, the solvability of competing goal B presents a substantial impact on human inferences, while the solvability of the no-competing goal A and the influence of thinking time are comparatively more modest. Increased awareness of solvability of competing goals suggests individuals may allocate more time to plan for these goals, aligning with the assumption in A-LH [22, 23].

5.3 Model Comparison

We now evaluate a range of models by comparing them against human goal inference behavior. These models are formulated within the same Bayesian framework (Equation 1) but use 3 different priors $Prior(\cdot)$ (uniform prior, easiness prior model shown in Equation 2, and empirical prior from our problem solving data) and 5 different likelihoods $LL(\cdot, \cdot)$ (offline-planning likelihood, online-planning likelihood, online-planning likelihood with actions only, empirical likelihood, and empirical likelihood with actions only).

For offline-planning likelihood estimation, we adopt the PRP approach outlined by Ramírez and Geffner [17]. This approach is not designed to handle unsolvable goals, but as originally formulated it consistently prioritizes solvable goals ahead of unsolvable goals. All easy-goal and competing-path maps were intentionally designed so that actions would be uninformative about the goal, and in these cases the offline likelihood assigns equal weight to both targets.

The online likelihood is derived from 100 simulations conducted using the A-LH [22]. To minimize variance in our model predictions, we focus solely on the likelihood associated with the key step, as the other two steps are predetermined. Specifically, we need to calculate the action component LL_A and the timing component LL_T separately for each goal and then combine them. For the action component, the likelihood is estimated by dividing the number of action choices made in the simulations by the total number of simulations (i.e. 100). As illustrated by Figure 2a, we previously confirmed that A-LH aligns with human action choices in *action* instances. In the remaining two types of instances, we found that actions still provide valuable information for goal inference. In *action* instances, since the simulated times for both targets are the same, the timing likelihood LL_T effectively makes no contribution. In *easy-goal* and *competing-path* instances, the timing likelihood is computed under the assumption that $LL(\cdot, g)$ follows a Gaussian distribution with a mean determined by the average number of sampled iterations needed to achieve goal g. We further assume that long and short thinking times in the goal-recognition experiment correspond respectively to the average number of iterations generated by A-LH for hard and easy goals.

The empirical likelihood draws inspiration from the inverse planning approach introduced by Baker et al. [3]. We estimate the empirical action and timing likelihoods in the same way as the A-LH likelihoods except that the samples are based on human responses collected during the problem-solving phase instead of simulations from A-LH. For example, the mean and standard deviation for the Gaussian timing likelihood are based on the human responses provided during the problem-solving phase.

For both the online and empirical likelihoods, we consider variants that incorporate only the action component LL_A. These variants are useful for establishing whether timing information is needed to account for our human goal-recognition data. For all log-likelihood calculations, we add a small value of 0.025 to both options to prevent the occurrence of zero probabilities.

5.3.1 *Results and Discussion.* As shown in Fig 4, the Easiness prior with online likelihood (actions only) achieves the best overall performance as measured by the log-likelihood assigned to the entire data set. Comparing the rows of Fig 4 suggests that the contribution of the prior is important but small. In contrast, comparing the columns reveals that changing the likelihood can have a dramatic effect on model performance.

It is striking that the online likelihoods seems comparable or superior to the empirical likelihoods even though the empirical likelihoods were directly fit to human behavioral data. The online likelihoods are based on the A-LH planner, and the strong performance of these likelihoods suggests that the A-LH planner provides a robust and reliable account of human behavior. In contrast, the offline likelihood performs substantially worse than the online and empirical likelihoods, suggesting that our participants implicitly assumed that the actor in the goal-recognition task relied on an online planning strategy.

Comparing results for likelihoods with and without timing information suggests that timing information is not needed to account for our behavioral data, and that incorporating this information may slightly impair model performance. Although the online likelihoods with and without timing information yield similar levels of performance, the two show distinct patterns across the three map types. Of the two online likelihoods, the action-only version performs worse across easy-goal maps, but better across the other two map types. This finding suggests that timing information may be beneficial in specific scenarios even though it provided no overall boost in performance across our entire data set.

Although varying the prior does not affect model performance as much as varying the likelihood, it is notable that the Easiness prior model and the empirical prior achieve similar levels of performance. This finding provides additional support for our previous finding (see Fig 3b) that the Easiness model is well-aligned with human judgments.

6 RELATED WORK

Ramírez and Geffner [17], along with subsequent researchers such as Vered et al. [21] and Masters and Sardina [13], introduced the Plan Recognition as Planning (PRP) approach that uses planning to estimate the likelihood. We evaluated this approach (referred to as the offline likelihood) as a baseline. This approach assumes agent rationality and focuses exclusively on actions, leaving unaddressed the explicit treatment of unsolvable goals.

Zhang et al. [22] introduced the Adaptive Lookahead Planner, which was designed to generate human-like response times. We have adapted their planner to incorporate awareness of solvability, and it serves as the online likelihood component in our experiment. While their work explores the impact of timing and how individuals handle timing information within the Sokoban domain, it does not consider the influence of actions and solvability, nor does it provide an explicit and systematic evaluation of the Bayesian approach to goal recognition. Berke et al. [4] have explored the influence of timing information on human understanding of others. Their study, however, is not anchored in the domain of goal recognition, and they rely on a domain-specific algorithm for likelihood estimation.

Baker et al. [2] introduced a Bayesian framework for human goal inference and conducted a systematic human experiment demonstrating their model's ability to achieve human-like inference, but did not consider the influence of timing and solvability. They acknowledged the possibility of a non-uniform prior in humans, but did not explore this idea experimentally.

Some recent research has considered non-uniform priors in goal recognition [8, 12]. These approaches, however, focus mainly on incorporating past information into the prior within the context of sequential Bayesian updating. We depart from this approach by investigating how domain-independent factors (i.e solvability and easiness) influence human priors.

7 CONCLUSION

In this study we used a Bayesian framework to systematically investigate the influence of actions, timing, and goal solvability on goal recognition. Through an in-depth analysis of human responses in the Sokoban domain, we found that while actions are typically

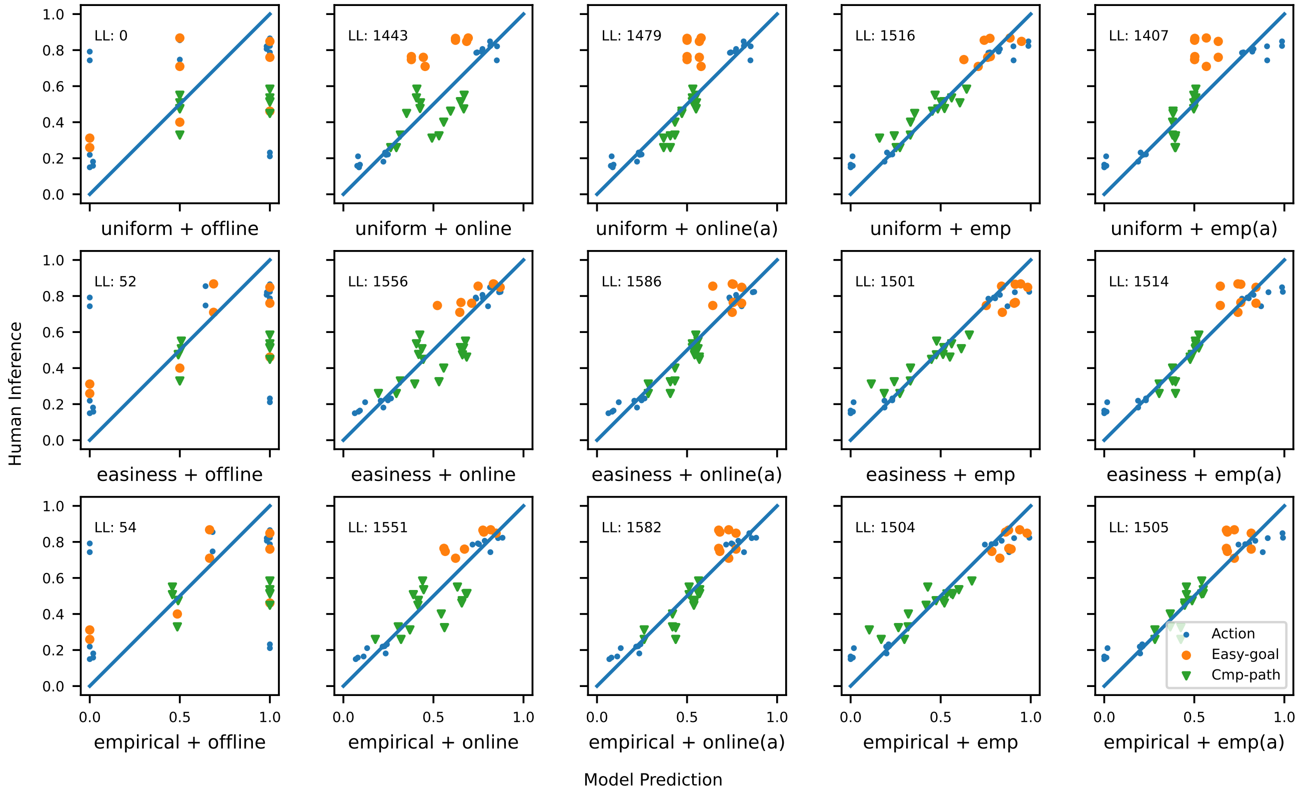


Figure 4: Comparison between model predictions and human inferences. All model labels show the prior followed by the likelihood: for example, *uniform + emp* is the model with uniform Prior and the empirical likelihood. *emp(a)* and *online(a)* are likelihoods that incorporate actions but not timing information. For readability, log likelihoods (higher is better) are shown as offsets relative to the log likelihood of the *uniform+offline* model.

attributed the highest importance, timing and goal solvability also influence goal recognition, particularly in scenarios where actions offer limited information. Leveraging these insights, we developed a goal recognition model that closely aligns with human inferences, surpassing the performance of existing algorithms.

Our work departed from the conventional assumption of a uniform prior, and our results suggest that humans rely on a prior that incorporates factors such as solvability and perceived goal difficulty. We formulated a model of the prior (the Easiness model) that proved successful in accounting for human responses, both before and after any actions had been observed.

We extended the Adaptive Lookahead Planner to capture human behavior in the presence of unsolvable goals, and our model comparison suggests that this extended model is useful for estimating the likelihood term in the Bayesian goal recognition framework. This planner, however, departs from human behavior in some respects (e.g. by taking more steps before recognizing a goal as unsolvable). This could impact the generalization of our results to real word interactions, and future work should aim to improve it further.

Our evaluation of the influence of actions, timing, and solvability suggested that actions (when available) have a dominant influence on people's choices. This finding provides some justification for the standard emphasis on actions within the goal-recognition literature. Nevertheless, our observations also revealed the influence of solvability and timing, particularly in situations where actions are uninformative. Our results seem broadly compatible with an information-seeking approach [5] to goal-recognition in which humans focus initially on actions but turn to other factors such as timing and solvability if actions prove uninformative. Future work can explore this information-seeking approach in more detail and compare it with the traditional Bayesian approach.

Finally, we conducted a thorough examination of Bayesian inference and the commonly used mirroring approach (i.e. planning for likelihood estimation) discussed in previous work [2, 3, 17, 21]. Our empirical model, which relies on problem-solving data, exhibits a strong alignment with human goal inference. This finding suggests that humans may indeed rely on Bayesian inference and mirroring to carry out goal-recognition. We also introduced a goal recognition model (the model that combines the easiness prior with the online likelihood) that can be implemented independently of human problem-solving data while generating human-like goal inferences. We expect that this model may prove to be useful in a range of downstream applications, including explainable goal recognition [1] and transparent planning, a process focused on selecting actions that effectively convey the actor's intentions to observers [11]. Researchers in these domains may be able to leverage this model to advance the development of more interpretable AI behavior.

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