

Theory-based Social Goal Inference

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Abstract

Everyday human interaction relies on making inferences about social goals: goals that an intentional agent adopts in relation to another agent, such as “chasing”, “fleeing”, “approaching”, “avoiding”, “helping” or “hindering”. We present a computational model of social goal inference that takes as input observations of multiple agents moving in some environmental context. The model infers a social goal for each agent that is most likely to have given rise to that agent’s observed actions, under an intuitive theory that expects agents to act approximately rationally. We provide evidence for our theory-based approach over a simpler bottom-up motion cue-based approach in a behavioral experiment designed to distinguish the two accounts.

Keywords: social cognition; theory of mind; action understanding; goal inference; inverse planning; Bayesian inference

Even the simplest everyday social interactions are supported by complex mental representations and processes. Contingent on the environment, our prior knowledge and our desires, we form goals, beliefs, intentions and other mental states with rich representational content. When we observe or participate in social interactions, we make joint inferences about the mental states of multiple interacting agents. For instance, watching a short film of two people moving inside a house, we might interpret it as follows: “X is trying to catch Y, and Y is trying to escape. X is sneaking up on Y in the bedroom but doesn’t realize that Y has already seen him and is preparing to escape out the back.” Inferring such intentional descriptions of social interactions is computationally challenging. Other agents’ mental states are not directly observable, and the space of possible beliefs and goals that one agent could have with respect to another is effectively infinite. Yet these inferences are remarkably quick and robust. Adults (Heider & Simmel, 1944) and even infants (Kuhlmeier, Wynn, & Bloom, 2003; Hamlin, Wynn, & Bloom, 2007; Gergely, Nádasdy, Csibra, & Biró, 1995) can infer relational goals such as “chasing”, “helping”, and “harming” from brief animations of simple shapes moving in a two-dimensional environment.

To account for inferences like these, it has been proposed that people draw on an intuitive theory of psychology, which may already be present in infancy in some simpler form as a rational agent schema (Gopnik & Wellman, 1992; Gopnik & Meltzoff, 1997; Gergely et al., 1995). This approach casts the interpretation of intentional action as a top-down process, drawing on a causal model of how agents’ beliefs, intentions and environmental and social context jointly influence their behavior. Agents’ mental states are inferred from observed social interactions through a process of “inference to the best explanation”, positing the goals and beliefs under which their observed actions are most plausible in the observed context.

A key challenge for theory-based accounts of action understanding is precisely specifying the nature of the causal relation between intentions, context and behavior. Several authors (Dennett, 1987; Gergely et al., 1995) have argued that this relation embodies the *principle of rationality*: the assumption that intentional agents should act to achieve their goals as efficiently as possible, given their beliefs about the world. The principle of rationality is appealing because it applies very generally across agents, intentions, and contexts, providing a way to dynamically build causal models of agents’ behavior in novel situations. However, the sense of rationality that people apply can be nuanced, particularly in the case of social interaction, where the rational strategy of an agent might depend on its expectations of others’ behavior, whose rational strategies depend on expectations of its behavior, and so on *ad infinitum*.

An alternative approach (Blythe, Todd, & Miller, 1999; Barrett, Todd, Miller, & Blythe, 2005; Zacks, 2004) to specifying the relation between mental states, context and behavior emphasizes simple visual cues that can be computed through bottom-up perceptual processes. Movements with a particular social intention, such as “chasing” or “fleeing”, are perceived as instances of categories defined by prototypical motion patterns. For example, by measuring the relative directions and velocities of two agents’ motions, we might be able to identify if one is trying to catch the other.

A simple cue-based approach appeals in part because it seems to be the kind of computation that can be done rapidly, robustly and in young infants without sophisticated cognitive capacities. It can also be formalized precisely in computational models (Blythe et al., 1999). However, it is unlikely to be sufficient to explain human social inference. The inferences of both adults and infants are highly sensitive to the environmental and task contexts in which actions take place, in ways that are hard to explain by a bottom-up motion analysis but suggest a deeper causal basis (Gelman, Durgin, & Kaufman, 1995). For instance, there are situations in which Y may be trying to avoid X, but Y’s best action is to head *toward* X rather than away from X; Y may be trapped in a corner with only one route of escape that runs directly past X.

Theory-based approaches seem to offer a deeper account of social goal inference, but unlike bottom-up cue-based models, they have not been worked out computationally or tested rigorously. These are the goals of our present paper. We give a Bayesian formulation of the theory-based approach to inferring social goals from observed action sequences. Our framework can capture a range of theory-based models, differing in how richly they model agents’ mental states. We show how

different theory-based approaches can be tested against each other and against simpler cue-based approaches.

Previously (Baker, Tenenbaum, & Saxe, 2006, 2007) we showed how to model action understanding as *inverse planning*: Bayesian inference about the structure of a goal-based Markov Decision Problem (MDP), a rational model for probabilistic planning. Here, we extend this work to model people’s inferences about social goals, such as approaching and avoiding, from observations of multiple agents interacting in simple environments.

People’s representations of other minds might include not just first-order content, such as agents’ intentions or beliefs about the state of the world, but also second-order content: representing agents’ strategies, contingent on *their* representation of other agents. Second-order mentalizing is particularly important in social interaction, where understanding social relations between agents such as helping, loving, loathing, and empathizing require the ability to represent a mind representing another mind. We show how to represent both first- and second-order content in our framework.

The plan of the paper is as follows. We first introduce our computational framework for theory-based social goal inference, and then describe several alternative heuristic motion cue-based models which we consider. Next, we compare the accuracy of both theory-based models and cue-based models in predicting how people categorize pairs of interacting agents moving in simple environments. We close by discussing the insights gained into the representations and principles underlying people’s social goal inferences.

Computational framework

Our theory-based framework represents the structure of the causal relation between agents’ environmental and social context, their mental states, and their behavior. Fig. 1 illustrates how models of rational planning allow observers to dynamically generate a conditional probability distribution over agents’ actions (A_i), given their goals (G_i), their beliefs about other agents’ goals ($B_i(G_j)$; “social context”) and the state of the world (W). For simplicity, we consider situations with two agents, who both have complete knowledge of the world state $W = \langle S_1, S_2, E \rangle$, which includes both agent states S_1, S_2 and the environment E . The environment is assumed to be static, while agent states are dynamic. In Fig. 1, agents choose their actions independently of each other, so the conditional joint probability over actions factors into the product of the conditional probability of each agent’s action:

$$P(A_1, A_2 | G_1, G_2, B_1(G_2), B_2(G_1), W) = P(A_1 | G_1, B_1(G_2), W) \cdot P(A_2 | G_2, B_2(G_1), W). \quad (1)$$

Inferring mental states given observed actions and the world state is done by inverting this model using Bayes’ rule:

$$P(G_1, G_2, B_1(G_2), B_2(G_1) | A_1, A_2, W) \propto P(A_1 | G_1, B_1(G_2), W) \cdot P(A_2 | G_2, B_2(G_1), W) \cdot P(G_1, B_1(G_2)) \cdot P(G_2, B_2(G_1)), \quad (2)$$

called inverse planning. Equation 2 describes a kind of “interaction parse”, assigning social goals and beliefs about others’ goals to all agents by integrating bottom-up information from observed actions with top-down information from the context and the prior over agents’ mental states, $P(G_i, B_i(G_j))$.

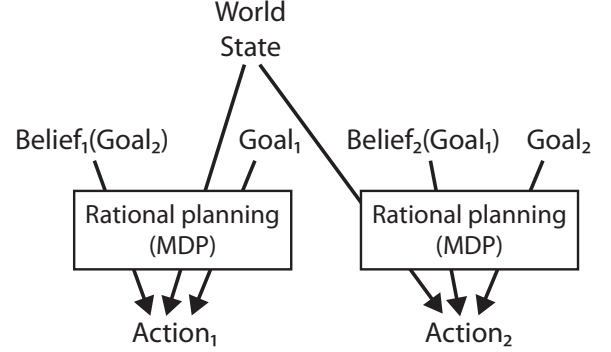


Figure 1: Causal schema for an intuitive theory of social interaction, specialized to two agents for simplicity.

We model first- and second-order content in people’s theories with agents of type L1 and L2, respectively. Agents of both types have social goals. We assume that L1 agents do not represent other agents’ goals, and thus cannot anticipate others’ actions. We model L1 agents’ predictions as being maximally uncertain about other agents’ behavior, predicting they will follow a random walk. L2 agents are assumed to represent other agents’ social goals, and to model others’ planning processes to predict their future behavior, allowing L2 agents to pursue their own goals more efficiently.

For concreteness, we consider two kinds of social goals for L1 and L2 agents: *Approach* and *Avoid*. The meaning of these goals roughly corresponds to the meaning of their words in English; however, their precise semantics is defined by their role in our theory-based models of social interaction. We assume a uniform prior over goals, so that cooperation and competition are equally likely. Next, we describe how Equation 1 is computed for these social goals.

(Inverse) planning with social goals

The principle of rationality states that agents will take efficient means to achieve their goals, given their beliefs about the world. We assume that agents receive rewards that depend on their goals, their own states and the states of their conspecifics, and that agents plan to maximize their expected future rewards minus the costs they incur, potentially using a predictive model of the other agent’s behavior.

Let $\mathcal{R}(W, G_i)$ be an agent’s real-valued reward function, defined over the state of the world and the agent’s goal. We assume the reward function for each goal is a linear function of the geodesic (shortest-path) distance $\text{geo_dist}(S_i, S_j)$ between agent i and agent j :

$$\mathcal{R}(W, \text{Approach}) = -\alpha \cdot \text{geo_dist}(S_i, S_j), \quad (3)$$

$$\mathcal{R}(W, \text{Avoid}) = \alpha \cdot \text{geo_dist}(S_i, S_j). \quad (4)$$

Let $C(S_i^t, a_i^t, E)$ be the cost of taking action a_i^t from state S_i^t in environment E , defined to be the Euclidean distance of the resulting movement. The rational behavior (or optimal policy) π_i^* for an agent is defined to be the rule of action that maximizes the expected sum of future rewards, while minimizing the sum of incurred costs. The value function of π_i^* , defined over the world state W , agent i 's goal G_i , and agent i 's belief about agent j 's goal $B_i(G_j)$ is:

$$\mathcal{V}^{\pi_i^*}(W, G_i, B_i(G_j)) = \mathbb{E}_{\pi_i^*} \left[\sum_{t=0}^{\infty} \gamma^t \left(\mathcal{R}(W^t, G_i) - C(S_i^t, a_i^t, E) \right) \middle| W^0 = W \right], \quad (5)$$

where the *discount rate* γ determines how much the agent values immediate rewards over future rewards.

To maximize their expected future rewards, agents must choose actions that incur a low cost and lead to states with high value. The value of action a_i^t in world W^t , given G_i and $B_i(G_j)$ is defined as the reward of the current state, minus the cost of the action, plus the expected discounted sum of future rewards after the action:

$$Q^{\pi_i^*}(a_i^t, W^t, G_i, B_i(G_j)) = \mathcal{R}(W^t, G_i) - C(S_i^t, a_i^t, E) + \gamma \cdot \mathbb{E}_{P(W^{t+1}|W^t, a_i^t)} [\mathcal{V}^{\pi_i^*}(W^{t+1}, G_i, B_i(G_j))]. \quad (6)$$

We assume that agents maximize rewards probabilistically, and sometimes only approximate the optimal sequence of actions. The probability that agent i will take action a_i^t from world state W^t , given G_i and $B_i(G_j)$ is:

$$P(a_i^t | G_i, B_i(G_j), W^t) \propto \exp(\beta \cdot Q^{\pi_i^*}(a_i^t, W^t, G_i, B_i(G_j))). \quad (7)$$

Given Equation 7, Equation 1 is computed as the product of the probability of each agent's actions over all time steps.

Computing the expectation involved in Equation 5 requires averaging over all future state sequences, conditioned on W^t , G_i and $B_i(G_j)$. For L1 agents, $B_i(G_j) \equiv \text{Null}$, and we assume their model of other agents is given by a uniform distribution over available actions, predicting a random walk through the state space. For L2 agents, representing other agents' goals allows anticipation of their future actions. We assume that L2 agents represent the other agent as having type L1, and first compute the optimal policy π_j^* for this agent given $B_i(G_j)$. L2 agents then predict other agents' behavior using Equation 7, and plan their own actions contingent on these predictions. For both L1 and L2 agents, Equation 5 can be efficiently approximated using dynamic programming algorithms (Bertsekas, 2001).

Motion cue-based models

In addition to the theory-based models L1 and L2, we consider two models based on low-level motion cues, inspired by a "simple heuristics" account of human social goal inference (Blythe et al., 1999; Zacks, 2004). Unlike theory-based models, cue-based models do not represent other agents'

mental states or use a model of rational planning to reason about how other agents' behavior depends on the context. Instead, these models directly associate social goals such as chasing or fleeing with typical movement patterns that can be computed efficiently from local information, like changes in direction or velocity.

We denote our motion cue-based alternatives H1 and H2. Both models assume that movements which decrease the distance to the other agent suggest the goal of approaching the other agent, while movements that increase the distance from the other agent suggest the goal to avoid. In H1, social goal inferences are assumed to be independent of the environment, and are computed solely based on movement relative to the location of the other agent. In H2, the environment is assumed to influence agents' behavior in a local way: H2 is expected to move closer to or farther from the other agent along the geodesic path, given its goal and subject to the constraints of the environment, but without planning ways in which locally moving closer to or farther from the other agent may be a rational strategy.

For the sake of comparison with L1 and L2, we implement H1 and H2 as degenerate cases of theory-based models with no planning capacity. Let $\mathcal{R}(W^t, G_i)$ and $C(S_i^t, a_i^t, E)$ be defined as above. The probability of action a_i^t , given the world state and goal G_i for an H1 or H2 agent is:

$$P(a_i^t | G_i, B_i(G_j), W^t) \propto \exp\left(\beta \left(\mathbb{E}_{P(W^{t+1}|W^t, a_i^t)} [\mathcal{R}(W^{t+1}, G_i)] - C(S_i^t, a_i^t, E) \right)\right). \quad (8)$$

Compared with L1 and L2, H1 and H2 could be considered to have "zero-th order representational content". Next, we describe an experiment designed to distinguish the predictions of these models and provide evidence for higher-order representational content in human social goal inference.

Experiment

Our experiment was designed to distinguish the predictions of theory-based models L1 and L2 from motion cue-based models H1 and H2. We collected people's judgments in a task of inferring two agents' social goals toward one another given short observations of their interactions in a simple, two-dimensional maze-like environment. Subjects were told that the agents could have a variety of social goals, such as catching or meeting up with the other agent, or trying to flee, escape or avoid it. They were then asked to categorize each agent in terms of its social goal.

Our experimental design varied the environmental and social context and the relative motion patterns of the two agents to assess our models' accuracy in predicting people's judgments. We hypothesized that only theory-based models would be able to explain the interaction between people's sensitivity to subtle environmental changes and the highly salient motion cues provided by agents' action sequences. In particular, by holding agents' relative motion fixed while changing the context in ways that affected the relative value of differ-

ent actions for theory-based models, but not for motion cue-based models, we hypothesized that cue-based models would fail to account for people’s social goal inferences across all conditions.

Method

Participants Participants were 20 members of the MIT community, 13 female and 7 male.

Stimuli Our stimuli were designed following previous research showing that simple two-dimensional animations of moving shapes evoke strong impressions of animacy and inferences of mental states (Tremoulet & Feldman, 2000). All experimental stimuli are shown in Fig. 2. Each stimulus displayed two agents, represented by red and green dots respectively. As agents moved along their trajectories, smaller dots of the same color trailed behind them, recording their path history. Agents’ paths were either 4 steps or 6 steps long. The environment was a discrete grid of 23 squares wide by 23 squares high, with walls represented as solid black lines. Agents’ movements were restricted to adjacent squares, with directions {N,S,E,W,NE,NW,SE,SW}. Up-down orientation of the display was counterbalanced within subjects, yielding 56 stimuli in total. The side on which red and green agents appeared, and the order of the “Avoiding/Approaching” options were randomized between subjects (but constant throughout the experiment for individual subjects). Stimuli were presented in random order.

Our experimental design combined four different relative movement conditions with 7 different environmental and social contexts. The four relative movement conditions were: $\rightarrow\leftarrow$, $\rightarrow\rightarrow$, $\leftarrow\leftarrow$, and $\leftarrow\rightarrow$. These movement conditions are shown across the rows of Fig. 2.

The 7 different contexts are shown across the columns of Fig. 2. Conditions 2-6 varied the environmental context by modifying the pattern of gaps in the wall of the maze, and contexts 3-5, marked with a star above in Fig. 2, displayed identical motion patterns in all contexts to isolate the effect of the different contexts on people’s inferences. Conditions 1 and 7 varied the length of the agents’ paths, displaying two more steps than the other conditions.

Procedure Subjects were first presented with a cover story about intelligent aliens interacting in their natural environment. They were told that the aliens could not move through walls in the environment but that they could move through gaps in walls, and that they could see past walls and knew the complete state of the world at all times. Several possible social goals, such as “trying to catch, ..., approach, ..., meet up with, ..., and engage with” were given as reasons for trying to get closer to the other alien, and “trying to flee, ..., escape, ..., avoid, ..., or disengage” were given as reasons for trying to get farther away. They were then told that each of the four combinations of social goals was equally likely. During the experiment, subjects viewed short animations of agents’ interactions and made forced-choice decisions between the op-

tions “Approaching”, “Avoiding” and “Can’t tell” for both agents in each stimulus.

Modeling We applied Equation 2 to model people’s judgments. For L2 agents, computing the posterior marginal over goals was done by marginalizing over the agent’s beliefs about the other agent’s goal, assuming a uniform prior over Approaching and Avoiding.

For each stimulus, the model provided the posterior probability that each agent had goal Approaching (the probability that an agent had goal Avoiding was the complement of this). To compare people’s judgments to these model predictions, we first coded the Approaching rating as 1, the Avoiding rating as 0, and the “Can’t tell” rating as 0.5. We then averaged over the counterbalanced orientation conditions within subjects, and averaged over ratings between subjects and computed the standard errors of these means.

For L1 and L2, we used $\alpha = .5$, $\beta = 1$, and $\gamma = .9$. α was set by hand to yield Q values that were of comparable magnitude to action costs, and β was set to 1 by default. We explored a range of γ values, with $\gamma = .9$ providing the best fit to people’s judgments, although nearby values yielded comparable results. For H1 and H2, we used β and α values of 1. L1 and L2 made similar predictions for our stimuli at the chosen parameter values; we only display L2. H1 and H2 yielded similar predictions as well; only H2 is shown.

Results

Results of the experiment are shown in Fig. 3. People’s judgments are shown in column 1, demonstrating significant sensitivity to environmental factors. For instance, in contexts 3-5, people’s ratings showed significant variability within the $\rightarrow\leftarrow$, $\rightarrow\rightarrow$, and $\leftarrow\leftarrow$ movement conditions, despite the fact that the paths were identical across the three environments. L2 predicted this variability, while H2 predicted no variability in any of the contexts, basing its predictions on superficial motion features every time.

In addition to predicting the sensitivity of people’s judgments to environmental factors very accurately across contexts 3-5, there are several specific phenomena that confirm L2’s predictions as well. Consider L2’s predictions for contexts 3 and 5 for movement $\rightarrow\leftarrow$: in context 3, L2 rates Red’s movement as being very ambiguous, as do people. However, in context 5, where the gap is located on the other side of the environment, L2 predicts that Red is probably trying to approach Green, in accord with people’s judgments again. A replication of this effect occurs for Red between contexts 3 and 5 for the $\rightarrow\rightarrow$ movement as well.

Another example of a dramatic shift in judgments occurs between contexts 2 and 3 for movements $\rightarrow\leftarrow$ and $\rightarrow\rightarrow$. In these cases, in context 2, people rate the probability of Red trying to approach Green very highly, presumably because if it were trying to escape, it would have gone through the exit behind it. However, in context 3, when this exit is eliminated, people are now uncertain about whether Red is approaching or avoiding. L2 predicts this effect very accurately.

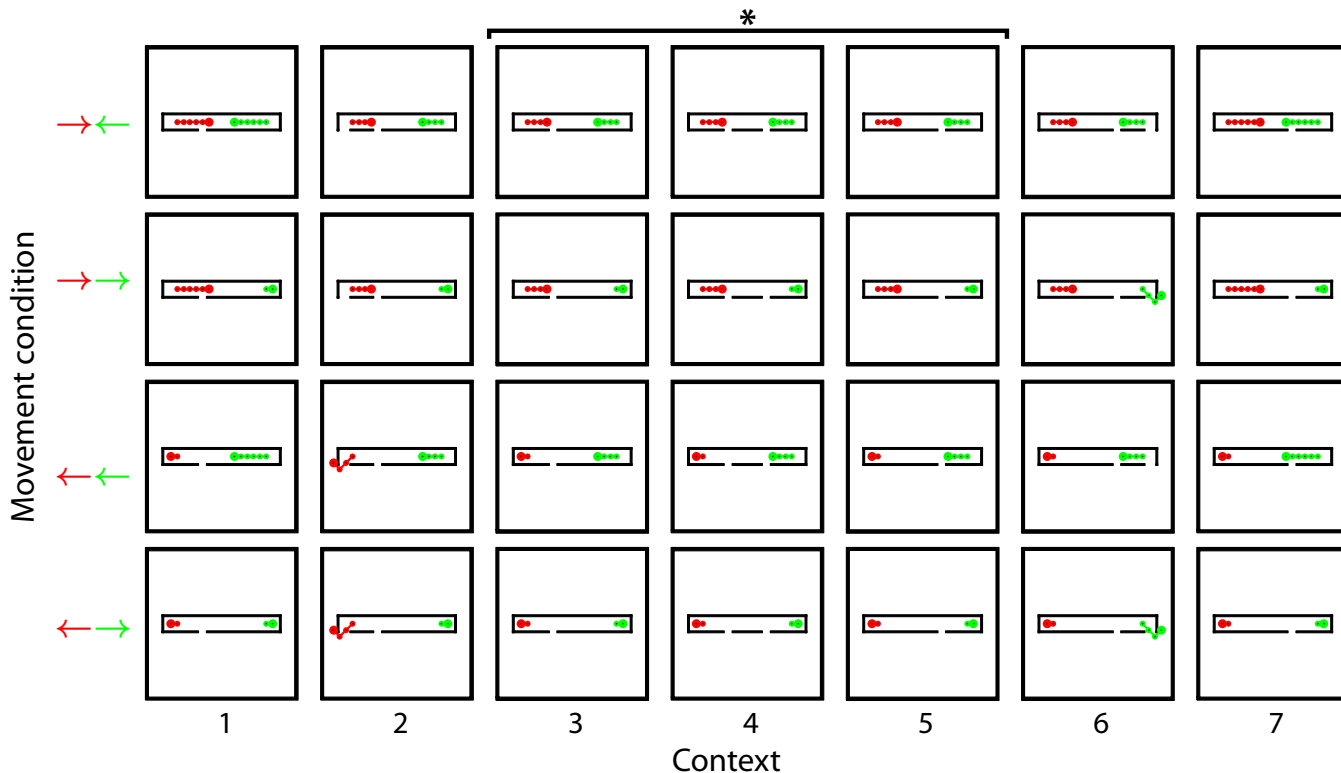


Figure 2: Experimental stimuli. The experimental design combined four different relative movement conditions with 7 different contextual conditions. In contexts 3-5, marked above by an “*”, contexts and movement patterns varied independently, allowing the effect of the different contexts to be isolated.

The L2 model also provides a plausible explanation for why people make the inferences they do. For instance, for movement $\rightarrow\leftarrow$ in context 3, Red’s action appears to be an equally sensible option whether it is approaching or avoiding, which the model confirms. In the cases where L2 strongly favors one interpretation over the other, both people and the model see the agent’s actions as unambiguously supporting this interpretation.

In contrast, because H2 does not incorporate planning into its predictions, it assumes that agents with the avoid goal will head directly away from the other agent, and that agents with the approach goal will head directly for the other agent. Because of this, H2 makes the same predictions in every context for the movement condition, failing to account for the effect of context on people’s judgments, as originally hypothesized.

Conclusion

How can we reason about the social goals of other people, effortlessly inferring that “she’s chasing him” and “he wants her to notice him”? On one side, bottom-up approaches focus on simple, easily computed cues such as the relative motion between two agents. On the other side, theory-based approaches cast these inferences as top-down processes drawing on abstract knowledge and sensitive to context and background knowledge. The theory-based approach is attractive for its promise of capturing more realistic interactions across

a very general set of contexts, but can be quite difficult to interpret in a precise, computational way.

This paper presented a family of theory-based models of social goal inference. These models all embody the principle of rationality and use inverse planning as their core inferential engine, but vary in the sophistication of representations required. At one end, the simplest of these models (L1) allows agents to represent only the properties of other agents (such as location), but not their goals. The most sophisticated of these models (L2) realizes second-order social goal inference: reasoning about agents’ representations of other agents’ goals. We distinguished simple cue-based models from our theory-based models using an experiment based on simple motion patterns of pairs of agents, but both first-order and second-order models accounted for people’s judgments.

Further work is needed to better distinguish between first- and second-order content in social goal inference, and to understand the factors that affect people’s use of these various representational abilities. More generally, the inverse planning approach can be applied to a much wider range of social goals than we have considered here. We are particularly interested to model goals such as “helping” or “hindering”, in which agents take as their reward function some function of another agent’s reward. Inference to these goals has recently been shown to be within the reach of human infants. Though

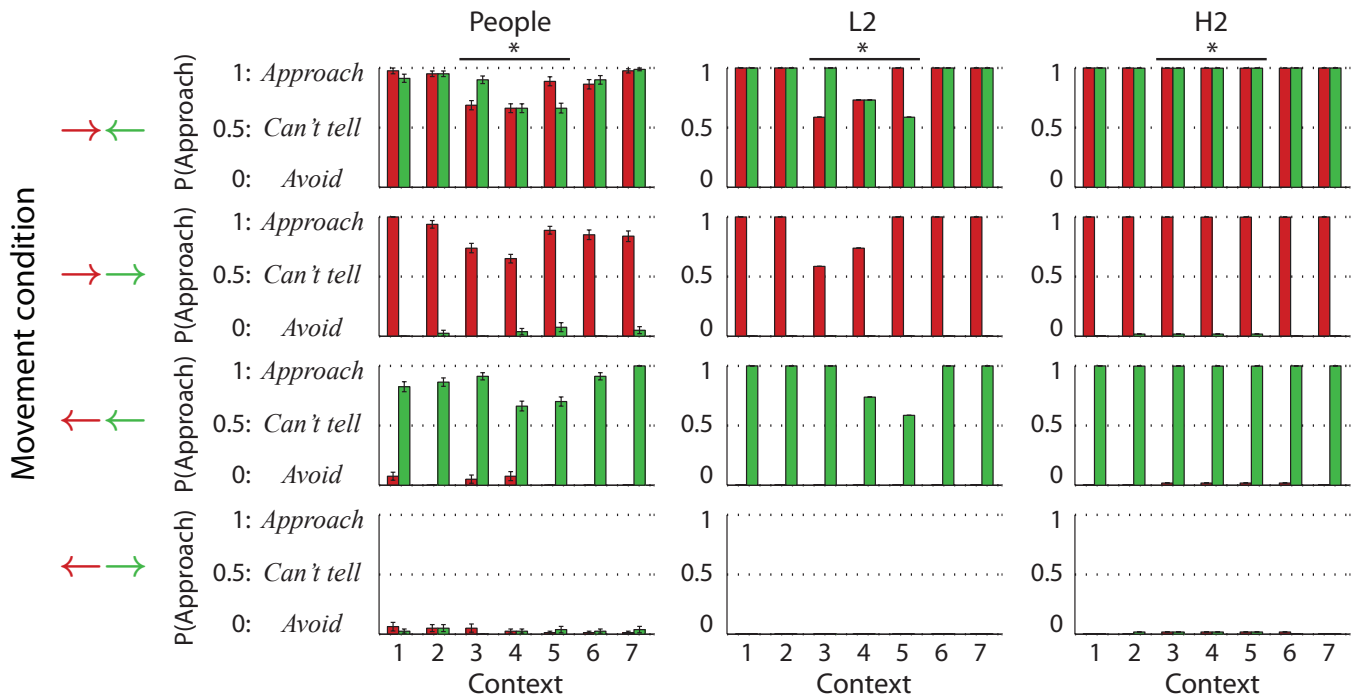


Figure 3: Experimental results. Column 1: average subject ratings with standard error bars for all stimulus conditions. Column 2: predictions of L2 for all stimuli. L2 closely matches the trends of people’s judgments. Column 3: Predictions of H2 for all stimuli. H2 makes the same predictions for every context, failing to account for the differences in people’s judgments due to changes in the environment.

computationally challenging, inferring these goals still falls under the scope of our inverse planning framework, and is an exciting direction for future research.

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