Pragmatic Instruction Following and Goal Assistance via Cooperative Language-Guided Inverse Planning

Tan Zhi-Xuan*
Massachusetts Institute of Technology
xuan@mit.edu

Lance Ying*
Harvard University
lanceying@seas.harvard.edu

Vikash Mansinghka
Massachusetts Institute of Technology
vkm@mit.edu

Joshua B. Tenenbaum
Massachusetts Institute of Technology
jbt@mit.edu

ABSTRACT

People often give instructions whose meaning is ambiguous without further context, expecting that their actions or goals will disambiguate their intentions. How can we build assistive agents that follow such instructions in a flexible, context-sensitive manner? This paper introduces *cooperative language-guided inverse plan search* (CLIPS), a Bayesian agent architecture for pragmatic instruction following and goal assistance. Our agent assists a human by modeling them as a cooperative planner who communicates *joint plans* to the assistant, then performs *multimodal* Bayesian inference over the human's goal from actions and language, using large language models (LLMs) to evaluate the likelihood of an instruction given a hypothesized plan. Given this posterior, our assistant acts to minimize expected goal achievement cost, enabling it to pragmatically follow ambiguous instructions and provide effective assistance even when uncertain about the goal. We evaluate these capabilities in two cooperative planning domains (Doors, Keys & Gems and VirtualHome), finding that CLIPS significantly outperforms GPT-4V, LLM-based literal instruction following and unimodal inverse planning in both accuracy and helpfulness, while closely matching the inferences and assistive judgments provided by human raters.

KEYWORDS

Inverse Planning, Bayesian Theory-of-Mind, Instruction Following, Human-Robot Cooperation, Value Alignment

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1 INTRODUCTION

Humans act upon the world through our words. We make requests, give instructions, and communicate information, so that we can better coordinate with each other [4]. In doing so, we are often parsimonious, exploiting context to convey our intentions [20]. For example, if someone says "Can you hold that door?", it is typically obvious which door they mean, even though nothing in the sentence distinguishes the door they just walked past from the one they are heading towards. We understand these requests because we interpret them *pragmatically*, in light of the goals and actions of others. How might we build assistive machines that do the same?

In this paper, we introduce *cooperative language-guided inverse plan search* (CLIPS), a Bayesian architecture for pragmatic instruction following and goal assistance (Figure 1). Building upon prior work in inverse planning [7, 44], rational speech act theory [16, 19, 53], joint intentionality [52, 56, 63], assistance games [15, 21], and reward learning [25, 32, 43], CLIPS models humans as cooperative planners who communicate *joint plans* as instructions. Given this model, CLIPS performs *multimodal* goal inference from human actions and instructions, using a large language model (LLM) to score the likelihood of observed utterances [64], and computing a distribution over goals via sequential inverse planning [67]. This distribution then informs an assistive policy, which selects helpful actions under uncertainty about the human's goal.

We evaluate CLIPS on a suite of multi-step goal assistance problems in a doors-and-keys gridworld [67] and the VirtualHome domain [41, 42]. In these problems, the assistant must infer the human's goal from their actions and possibly ambiguous instructions, then decide how best to help. Even when leveraging LLMs, standard instruction following methods struggle with this setting because they disregard pragmatic context [2, 50, 60], while action-only goal inference [7, 42, 67] ignores linguistic information. Multimodal LLMs have access to all information, but they fail to ground it in a coherent theory-of-mind [11, 26]. In contrast, CLIPS is able to use observed actions and inferred goals to resolve *ambiguous language*, interpret *joint instructions*, and correct for *incomplete commands*, achieving much higher goal accuracy and cooperative efficiency than GPT-4V, LLM-based literal instruction following, and unimodal inverse planning, while correlating strongly with goal inference and assistance judgments provided by human raters.

2 COOPERATIVE LANGUAGE-GUIDED INVERSE PLAN SEARCH

We formulate the setting for CLIPS as a *language-augmented goal assistance game*, an extension of assistance games [15, 21] with linguistic utterances and uncertainty over goals (i.e. desired terminal states) [46]. We define this as a two-player Markov game between a human principal and an assistive agent, described by

*Equal contribution.

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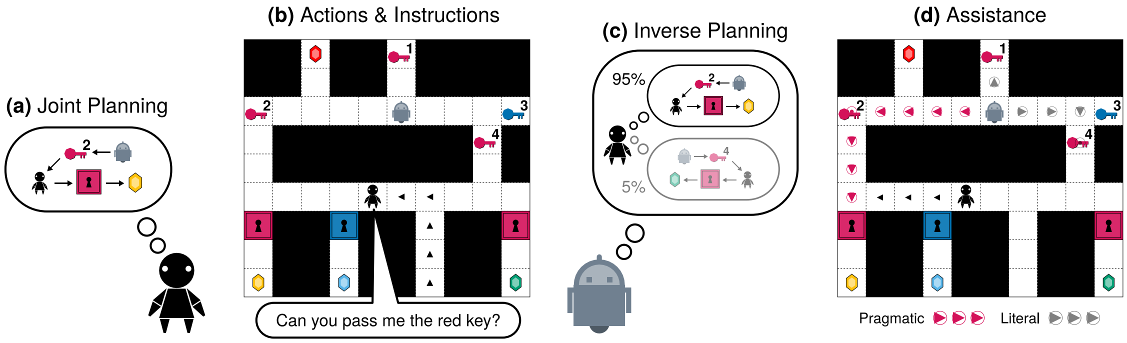


Figure 1: Overview of *cooperative language-guided inverse plan search* (CLIPS). We model a human principal as **(a)** cooperatively planning a joint policy for the human and the (robot) assistant. The human is **(b)** assumed to take actions from this joint policy while communicating planned actions as an instruction (*"Can you pass me the red key?"*). Observing this, **(c)** CLIPS infers the human's goal and policy via Bayesian inverse planning. CLIPS then **(d)** acts by minimizing expected goal achievement cost, pragmatically interpreting the ambiguous instruction by picking up *Key 2*. In contrast, a literal instruction follower might pick up *Key 1* or *Key 4*, which are also red in color.

the tuple $(\mathsf{S}, \mathsf{U}, \mathsf{A}^h, \mathsf{A}^r, \mathsf{C}, \mathsf{G}, H, P_s, P_i)$, where S is the set of environment states, U a space of utterances u that the human may use to communicate at any step, A^h the set of human actions a^h, A^r the set of assistant actions a^r, C a set of cost functions $C : \mathsf{S} \times \mathsf{U} \times \mathsf{A}^h \times \mathsf{A}^r \to \mathbb{R}$ that map state-action transitions to real numbers, $\mathsf{G} \subseteq \mathcal{P}(\mathsf{S})$ a set of possible goals g where each $g \subseteq S$ is a set of (terminal) states, H a horizon after which the game automatically terminates, $P_s(s'|s, a^r, a^h)$ the environment transition distribution, and $P_i(s_i, C, g)$ a distribution over initial states of the game. As in regular assistance games, the human knows (i.e. observes) the *true* cost function C and goal g sampled from P_i, but the assistant only observes the initial environment s_i. Thus, the assistant has to *infer* the true goal g.

Assistance games admit cooperative equilibria, but they are intractable to compute in general [15], and also assume more game-theoretic optimality from humans than may be warranted [37]. As such, our goal is to *approximately* solve the assistance game under reasonable modeling assumptions about how humans cooperate and communicate. By fixing a human model, the game becomes a partially observable Markov decision process (POMDP) from the assistant's perspective [14], which can be solved through approximate methods [35, 39]. We describe this human model, then show how an assistant can perform Bayesian inference over such a model, using the acquired information to better assist humans.

2.1 Modeling cooperative action and communication

When humans cooperate, we direct our actions towards a shared goal while expecting that others will do the same. This capacity for *joint intentionality* [58] allows us to cooperate rapidly and flexibly while avoiding nested reasoning about each other's minds [56, 63]. In CLIPS, we exploit this aspect of human cognition by modeling the human principal as a *cooperative planner*, who computes a *joint policy* π for both agents to achieve the goal g. The human follows π by taking an action a_t^h at each step t, and assumes the assistant will take an action a_t^r accordingly. These actions lead to a change in the state s_t. The human may also speak at any time t (with the decision denoted by d_t), issuing a command c_t that summarizes their intended policy π. This command is then rendered in natural language as an utterance u_t. The overall generative process is shown in Figures 2a–b, and can be summarized as follows:

$$\begin{aligned}
&\textit{Goal Prior:} && g \sim P(g) && (1)\\
&\textit{Joint Planning:} && \pi \sim P(\pi|g) && (2)\\
&\textit{Action Selection:} && a_t^h, a_t^r \sim P(a_t^h, a_t^r|s_t, \pi) && (3)\\
&\textit{Utterance Generation:} && u_t, c_t, d_t \sim P(u_t, c_t, d_t|s_t, \pi) && (4)\\
&\textit{State Transition:} && s_{t+1} \sim P(s_{t+1}|s_t, a_t^h, a_t^r) && (5)
\end{aligned}$$

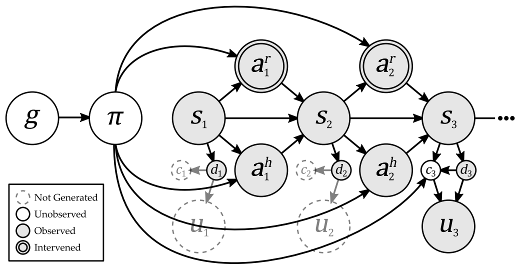
$P(g)$ is the assistant's prior over the human's goal $g \in \mathsf{G}$, which we take to be uniform. We can also fold in uncertainty over the human's cost function $C \in \mathsf{C}$ into this prior, treating g as a *specification* that includes both the goal condition and action costs.

To model joint planning, we assume that the human computes a Boltzmann policy π for goal g, which defines an approximately rational distribution over joint actions a_t^h, a_t^r:

$$\pi(a_t^h, a_t^r|s_t) = \frac{\exp(-\beta \hat{Q}_\pi(s_t, a_t^h, a_t^r))}{\sum_{\tilde{a}_t^h, \tilde{a}_t^r} \exp(-\beta \hat{Q}_\pi(s_t, \tilde{a}_t^h, \tilde{a}_t^r))} \quad (6)$$

Here, β is a rationality parameter controlling the optimality of the policy (higher β is more optimal), over which we may place a prior $P(\beta)$, and $\hat{Q}_\pi(s_t, a_t^h, a_t^r)$ is an estimate of the expected cost of reaching the goal g by taking actions a_t^h, a_t^r at state s_t. To estimate $\hat{Q}_\pi$ efficiently, we extend prior work in online goal inference [67], using model-based planning to compute policies on-the-fly. In particular, we use real-time heuristic search (RTHS) as an anytime planner [8, 27, 28], which estimates Q-values in a neighborhood around the current state s_t via search (RTHS-POLICY-UPDATE in Fig. 2b), while using previously estimated Q-values to guide future searches. Unlike earlier methods for inverse planning, this avoids the intractability of estimating Q for all states and actions [43, 68].[1]

[1] As an additional simplification, we assume that the human and the assistant take turns while acting (i.e. a_t^r is a no-op when a_t^h is not, and vice versa). This reduces the branching factor while planning, but preserves the optimal solution [9].



(a) One graphical realization of our Bayesian model.

model CLIPS-MODEL(s_1, G, T)
  $g \sim$ GOAL-PRIOR(G)
  $\pi \sim$ POLICY-INIT(g, s_1)
  for $t \in [1, T]$ **do**
    $\pi \leftarrow$ RTHS-POLICY-UPDATE(π, g, s_t)
    $a_t^h, a_t^r \sim$ BOLTZMANN-DIST(s_t, π)
    $u_t, c_t, d_t \sim$ UTTERANCE-MODEL(s_t, π)
    $s_{t+1} \sim$ TRANSITION(s_t, a_t^h, a_t^r)
  end for
end model

(b) CLIPS agent-environment model as a probabilistic program.

model UTTERANCE-MODEL(s_t, π)
  parameters: $p_{\text{speak}}, L, K, \mathcal{E}$
  $d_t \sim$ BERNOULLI(p_{speak})
  if d_t = TRUE **then**
    $a_{t:t+L} \leftarrow$ ROLLOUT-POLICY(s_t, π, H)
    $\alpha_{1:m} \leftarrow$ EXTRACT-SALIENT-ACTIONS($a_{t:t+H}$)
    $c_t \sim$ RAND-SUBSET($\alpha_{1:m}, K$)
    $u_t \sim$ LANGUAGE-MODEL($c_t, \mathcal{E}$)
  else
    $c_t, u_t \leftarrow \emptyset$, ""
  end if
end model

(c) Utterance model $P(u_t, c_t, d_t|\pi)$ as a probabilistic program.

Command:	(handover you me key2) where (iscolor key2 blue)
Utterance:	Hand me the blue key.
Command:	(unlock you key1 door1)
Utterance:	Can you unlock the door for me?
Command:	(pickup me key1) (unlock you key2 door1) where (iscolor key1 blue) (iscolor door1 green)
Utterance:	I'm getting the blue key, can you open the green door?
Command:	(handover you me key1) (handover you me key2) where (iscolor key1 green) (iscolor key2 red)
Utterance:	Can you pass me the green and red keys?

(d) Paired examples $\mathcal{E}$ of commands c_t and utterances u_t.

Figure 2: Model architecture. In CLIPS, we model the human as a cooperative planner who computes a joint policy π for a goal $g \in G$. The policy π dictates the human's and assistant's actions a_t^h, a_t^r at each state s_t, as well as the command c_t and utterance u_t that the human may decide d_t to communicate at step t. One realization of this process is depicted in **(a)**, showing a case where an utterance u_3 is only made at $t = 3$. We implement this process as probabilistic program, shown in **(b)**. Utterance generation is modeled by the subroutine in **(c)**, which summarizes salient actions from policy π as a command c_t, then samples an utterance u_t using a (large) language model prompted with c_t and **(d)** a list of few-shot examples $\mathcal{E}$ demonstrating how commands are translated into natural language.

Having computed the policy π, we model human communication as an approximately *pragmatic* process. Since the human wants to achieve their goal, they are likely to convey information about the policy they have in mind. However, long utterances are costly, and so the human is likely to convey only a salient summary of the policy, reducing the cost of communication. We capture these aspects of cooperative communication through a structured generation procedure that leverages the linguistic competence of LLMs:

(1) At each step t, the human decides whether to communicate (d_t) with probability p_{speak}. If d_t is true, we rollout the policy π for L steps, producing a series of planned actions $a_{t:t+H}$.
(2) The planned actions $a_{t:t+L}$ are filtered down to a domain-specific set of *salient* actions $\alpha_{1:m}$, and a random subset of up to K such actions are incorporated into a command c_t.
(3) Finally, the command c_t is translated into a natural language utterance u_t using an LLM prompted with few-shot examples (Figure 2d). This defines a likelihood function $P(u_t|c_t)$.

This procedure is implemented as the probabilistic program shown in Figure 2c. While it does not capture all ways in which a pragmatic speaker might prefer some utterances over others, key features of pragmatic speech are modeled: Utterances are about plans, and hence practically useful, but are also restricted to small ($\leq K$) but salient subsets of those plans, ensuring they are informative without being costly. Furthermore, using an LLM as an utterance model $P(u_t|c_t)$ provides broad coverage, enabling CLIPS to handle much richer utterances than traditional pragmatic models [19].

2.2 Goal inference via inverse planning from actions and instructions

Using this probabilistic model, our assistant can infer a posterior distribution over the human's goals g and policies π given a sequence of observed actions $a_{1:T}^h$, states $s_{1:T}$ utterance decisions $d_{1:T}$, and utterances $u_{1:T}$ (where u_t is the empty string whenever d_t = FALSE). Some care must be taken, however. Since the assistant is also taking actions $a_{1:T}^r$ alongside the human principal, it is tempting to infer the human's goal by conditioning on *both* agents' actions:

$$\begin{aligned} &P(g, \pi | s_{1:T}, d_{1:T}, u_{1:T}, a_{1:T}^h, a_{1:T}^r) \\ &\quad \propto P(g, \pi, s_{1:T}, d_{1:T}, u_{1:T}, a_{1:T}^h, a_{1:T}^r) \\ &\quad = P(g, \pi) \textstyle\prod_{t=1}^{T} P(s_t | s_{t-1}, a_{t-1}^{h,r}) P(u_t, d_t | s_t, \pi) \underline{P(a_t^h, a_t^r | s_t, \pi)} \end{aligned} \tag{7}$$

For an *external* observer, this is the appropriate distribution to compute [49, 64]. However, prior work on cooperative inference also computes Equation 7 when observers are *internal* to the environment [56, 63], which can lead to pathologies. For example, the assistant might condition on the fact that it has not moved so far ($a_{1:T}^r$ are no-ops), leading it to infer that the human is pursuing a goal g where the assistant's help is unnecessary. To address this, it is crucial to recognize that the assistant is *intervening* upon the environment through its actions (Figure 2a, double-lined nodes).[2]

[2]Alternatively, it is enough to note the assistant's actions are selected according to *different policy* π' than the inferred joint policy π computed by the human. Thus it is *safer* for the assistant not to update its beliefs as if its actions come from π.

As such, we should detach the evidential connection between the assistant's actions $a^r_{1:T}$ and any causal ancestors, which we denote using Pearl's **do**-operator [40]:

$$
\begin{aligned}
&P(g, \pi | s_{1:T}, d_{1:T}, u_{1:T}, a^h_{1:T}, \mathbf{do}(a^r_{1:T})) \\
&\quad \propto P(g, \pi, s_{1:T}, d_{1:T}, u_{1:T}, a^h_{1:T}, \mathbf{do}(a^r_{1:T})) \\
&\quad = P(g, \pi) \prod_{t=1}^{T} P(s_t | s_{t-1}, a^{h,r}_{t-1}) P(u_t, d_t | s_t, \pi) \underline{P(a^h_t | s_t, \pi)}
\end{aligned}
\tag{8}
$$

The difference between Equations 7 and 8 lies in the final underlined term: Whereas an external observer reweights its beliefs by incorporating the likelihood of both agents' actions $P(a^h_t, a^r_t | s_t, \pi)$, our assistive agent should only incorporate the likelihood of the human's action $P(a^h_t | s_t, \pi)$.

We compute the distribution in Equation 8 sequentially, as shown in Algorithm 1. An initial belief b_0 is returned by BELIEF-INIT, which generates a set of N weighted samples by either sampling or enumerating over the goal prior $P(g)$ and policy distribution $P(\pi|g)$ (accounting e.g. for uncertainty over the rationality parameter β). Then at each step t, the previous belief b_{t-1} is updated by adjusting the weight w^i associated with each goal g^i and policy π^i sample. To do this, BELIEF-UPDATE first refines the Q-value estimates that define the policy π^i by running more iterations of RTHS (RTHS-POLICY-UPDATE in L9). The weights are then updated to reflect the new state s_t and decision to speak d_t (L10-11). If d_t is true (i.e. u_t is observed), we also marginalize over all commands c_t that could have generated u_t from π, and update w^i with the resulting mixture likelihood (L13-14). Finally, we condition on the human's action a^h_t, and return the resulting sample collection (L16-18).

If we enumerate over all possible goals and policy configurations in BELIEF-INIT, this is an *exact* Bayesian inference algorithm. In environments where there are too many hypotheses for this to be efficient, Algorithm 1 can readily be extended to a sequential Monte Carlo algorithm [13, 30] in the style of sequential inverse plan search [67]. For our experiments, however, enumeration is feasible, and we opt for this approach to avoid variance from sampling.

2.3 Pragmatic instruction following as goal assistance under uncertainty

With Algorithm 1, our assistive agent is able to infer a distribution over the human's goal g and policy π at each step t. How should it use this information to act, especially if the goal g remains uncertain? In keeping with our Bayesian approach, we minimize *expected* cost, acting to help the human achieve their likely goal as quickly as possible [47]. Since each inferred policy π^i corresponds to a $\hat{Q}_{\pi^i}$-value function, the assistant can select actions by minimizing the expected $\hat{Q}_{\pi^i}$ value given its uncertainty over π^i:

$$
a^{r*}_t = \arg\min_{a^r_t} \mathbb{E}_{\pi^i} [\hat{Q}_{\pi^i}(s_t, a^h_t, a^r_t)] \tag{9}
$$

We implement this assistance policy with Algorithm 2, which effectively solves the Q_{MDP} approximation of the assistive POMDP [22, 33, 35]. At each step t, we assume the assistant has already updated its belief b_{t-1} from the previous step $t-1$, and also observes the human's action [3]. We then iterate over all samples (w^i, g^i, π^i), update the policies π^i if necessary, and perform a weighted sum of $\hat{Q}_{\pi^i}$-values for all assistant actions a^r_t according to their inferred weights w^i. This produces a vector of *assistive* Q-values, which we minimize over to compute the best assistive action a^{r*}_t.

[3] This assumption is natural in our turn-based setting. When actions are simultaneous the assistant can minimize expectation over both policies π^i and human actions a^h_t.

Algorithm 1 CLIPS belief initialization and update

1: **procedure** BELIEF-INIT(N)
2: $\quad w^i \leftarrow 0; \quad g^i \sim P(g); \quad \pi^i \sim P(\pi|g^i)$ **for** $i \in [1, N]$
3: $\quad b_0 \leftarrow \{(w^i, g^i, \pi^i)\}_{i=1}^N$; **return** b_0
4: **end procedure**
5:
6: **procedure** BELIEF-UPDATE($b_{t-1}, s_{t-1:t}, d_t, u_t, a^h_{t-1:t}, a^r_{t-1}$)
7: $\quad \{(w^i, g^i, \pi^i)\}_{i=1}^N \leftarrow b_{t-1}$
8: $\quad$ **for** $i \in [1, N]$ **do**
9: $\quad\quad \pi^i \leftarrow$ RTHS-POLICY-UPDATE(π^i, g^i, s_t)
10: $\quad\quad w^i \leftarrow w^i \cdot P(s_t | s_{t-1}, a^h_{t-1}, a^r_{t-1})$
11: $\quad\quad w^i \leftarrow w^i \cdot P(d_t | s_t, \pi)$
12: $\quad\quad$ **if** $d_t =$ TRUE **then**
13: $\quad\quad\quad P(u_t | s_t, \pi) \leftarrow \sum_{c_t} P(u_t | c_t) P(c_t | s_t, \pi)$
14: $\quad\quad\quad w^i \leftarrow w^i \cdot P(u_t | s_t, \pi)$
15: $\quad\quad$ **end if**
16: $\quad\quad w^i \leftarrow w^i \cdot P(a^h_t | s_t, \pi)$
17: $\quad$ **end for**
18: $\quad w^i \leftarrow w^i / \sum_{j=1}^N w_j$
19: $\quad b_t \leftarrow \{(w^i, g^i, \pi^i)\}_{i=1}^N$; **return** b_t
20: **end procedure**

Algorithm 2 CLIPS Q_{MDP} assistance policy

procedure ASSISTANCE-POLICY(b_{t-1}, s_t, a^h_t)
$\quad$ **for** $a^r_t \in \mathcal{A}^r(s_t)$ **do**
$\quad\quad \hat{Q}_{\text{assist}}(s_t, a^h_t, a^r_t) \leftarrow 0$
$\quad\quad$ **for** $(w^i, g^i, \pi^i) \in b_{t-1}$ **do**
$\quad\quad\quad \pi^i \leftarrow$ POLICY-UPDATE(π^i, g^i, s_t)
$\quad\quad\quad \hat{Q}_{\text{assist}}(s_t, a^h_t, a^r_t) \xleftarrow{+} w^i \cdot \hat{Q}_{\pi^i}(s_t, a^h_t, a^r_t)$
$\quad\quad$ **end for**
$\quad$ **end for**
$\quad a^{r*}_t \leftarrow \arg\min_{a^r_t} Q_{\text{assist}}(s_t, a^h_t, a^r_t)$
$\quad$ **return** a^{r*}_t
end procedure

3 EXPERIMENTS

We evaluate our method against a variety of baselines in two domains: a cooperative gridworld puzzle called **multi-agent Doors, Keys & Gems** (mDKG) originally developed in [64, 67], and **VirtualHome** (VH), a virtual household simulator [41, 42]. In both domains, a human principal and a (robot) assistant cooperate on multi-step tasks to accomplish the human's goals. In mDKG, the goals are four colored gems which are often secured behind doors. Doors can be unlocked by keys of the same color, and the assistant can help by collecting keys or unlocking doors (Figure 1). In VirtualHome, the goals are 6–12 household tasks, including setting up tables and preparing ingredients (Figure 3). Both domains admit encodings in the Planning Domain Definition Language (PDDL)

Figure 3: Example goal assistance problem in VirtualHome, where the principal and assistant collaborate to set the dinner table. The principal places three plates on the table, then says *"Could you get the forks and knives?"*. A pragmatic assistant has to infer the number of forks and knives from context (in this case, three each).

[36] with some extensions [66], which we use as the environment representation for our planning and inverse planning algorithms.

To systematically test the ability of assistive agents to pragmatically follow a human's instructions and assist with their goals, we developed a dataset of *goal assistance problems* for each domain (30 problems in mDKG, 25 problems in VH). In each problem, the goal is initially unknown to the assistant. While taking a sequence of actions $a^h_{1:T}$, the human communicates one or more instructions $u_{1:T}$ to the assistant. The assistant then has to make an inference about the human's goal g, and chooses actions to best assist them. We designed our problems to cover a range of scenarios inspired by human communication we observed in exploratory studies, varying the information that can be deciphered from the human's actions or instructions (see Figure 4 and Supplementary Information). In mDKG, we restricted the human to only one instruction u_T, since more information would render goal inference trivial. In VH, however, the goal space was larger, allowing us to construct 10 problems with multiple utterances such as *"Can you get the plates?"* followed by *"Bring the bowls too!"*

3.1 Model configuration

In our experiments, we configured CLIPS to compute Q-values using the real-time adaptive A* variant of RTHS [27], and a Gamma prior over the rationality parameter β. For the utterance model, we used either OpenAI's 6.7B `curie` model [10] or the `davinci-002` as our LLMs, due to the more diffuse probabilities they provided as base models. For goal assistance, we ran Algorithm 2 in offline mode, fixing the inferred posterior after observing $a^h_{1:t}$ and u_t, then selecting actions by minimizing expected Q-values with respect to the fixed posterior. This was evaluated against a simulated human agent which followed a joint policy to the true goal, unless it was apparent that the assistant was not doing the same. While Algorithm 2 can also be run in online mode, we fixed the posterior to better match the information that our human raters were provided.

3.2 Baselines

To evaluate the benefit of pragmatic instruction following over either a literal interpretation of instructions, or goal inference from only one modality, we included the following baselines:

3.2.1 Unimodal Inverse Planning. We implemented action-only and language-only inverse planning (IP) baselines as ablations of CLIPS, where the action-only baseline is similar to sequential inverse plan search [67] for inference and Watch-and-Help [42] for assistance. In these baselines, the assistive agent uses the same belief update shown in Algorithm 1, except that it conditions on only actions $a^h_{1:t}$ or only the utterance u_t. In cases with no actions, CLIPS and the language-only baseline are equivalent.

3.2.2 LLM-Based Literal Listener. The literal listener baseline interprets the instruction u_t in state s_t without further information about the human's actions or goals. To implement this baseline, we adapt the utterance model in Figure 2c to sample from the space of all assistant-directed commands c_t that are possible in state s_t. In particular, we enumerate over all assistant actions $\mathcal{A}^r$, and select a subset of up to K salient actions to form a command c_t. This defines a distribution over commands $P(c_t|s_t)$ which *does not* depend the principal's policy π or goal g. Given the command c_t, we use an LLM (`text-davinci-002` for mDKG, `davinci-002` for VH) as an utterance likelihood $P(u_t|c_t)$. Assuming a uniform prior over commands, we can perform enumerative inference to compute the posterior $P(c_t|u_t, s_t)$ given an instruction u_t in state s_t.

Given a command c_t, the assistant still needs to generate an assistive plan. We did this in two ways: The *naive* literal assistant interprets a command c_t by randomly selecting one concrete grounding (e.g. *"Can you pick up the red key?"* could mean picking up the red key closest to the human or some other key), then planning to achieve that concrete goal. In contrast, the *efficient* literal assistant tries to directly satisfy the command c_t in the most efficient way[4] (e.g. *"Could you unlock the blue door?"* is satisfied by unlocking the blue door closest to the assistant). For both variants, the assistant can either satisfy the most likely command c^*_t, or sample a command from the full distribution $P(c_t|s_t)$. We report results for the latter after averaging over 10 samples, using systematic sampling to reduce variance.

3.2.3 Multimodal LLM (GPT-4V). For the mDKG domain, we used GPT-4 with Vision (GPT-4V) [1] as a purely neural baseline, prompting it with the same set of rules and instructions that we provided to our human raters, along with the final frame of each animated visual that we showed to humans (similar to Figure 1(b)). This allowed us to probe the degree to which multimodal LLMs are capable of intuitive pragmatic reasoning given spatially-grounded actions and verbal instructions [11]. Due to cost and rate limits, we report single-shot performance with a temperature of zero.

More details about our models and datasets can be found in the Supplementary Information (`https://osf.io/v8ru7/`). Source code is available at `https://github.com/probcomp/CLIPS.jl`.

3.3 Human judgments

As an additional standard for comparison, we conducted a study with 100 human participants from the US through Prolific (mean age = 39.8, 59 men, 38 women, 2 non-binary), presenting each of them with 15 goal assistance problems from the mDKG domain. In each problem, participants saw the actions taken by the human

[4]Note that the naive/efficient distinction was not meaningful in the VirtualHome problems, where utterance ambiguity was not due to grounding ambiguity.

Table 1: Performance of CLIPS vs. baseline methods, measured in terms accuracy (posterior probability of true goal, precision and recall for assistance options), helpfulness (plan length and human cost relative to CLIPS), and human similarity (correlation of goal inferences and assistance options with mean human ratings) Metrics are averaged across the dataset per domain, with standard errors reported in brackets.

	Accuracy			**Helpfulness**		**Human Similarity**	
Method	$P(g_{\text{true}})$	Assist. Prec.	Assist. Rec.	Rel. Plan Length	Rel. Human Cost	Goal Cor.	Assist. Cor.
			Doors, Keys & Gems				
Humans	0.67 (0.04)	0.83 (0.02)	0.85 (0.01)	–	–	–	–
CLIPS (Ours)	**0.74 (0.05)**	**0.97 (0.03)**	**0.97 (0.03)**	**1.00 (0.00)**	**1.00 (0.00)**	**0.93 (0.01)**	**0.96 (0.01)**
Lang. Only IP	0.55 (0.05)	0.90 (0.06)	0.83 (0.06)	1.26 (0.10)	1.18 (0.07)	0.74 (0.01)	0.83 (0.01)
Action Only IP	0.31 (0.04)	0.43 (0.09)	0.40 (0.09)	1.68 (0.15)	1.46 (0.08)	0.15 (0.01)	0.45 (0.01)
Literal Efficient	–	0.65 (0.08)	0.54 (0.07)	1.55 (0.11)	1.58 (0.10)	–	0.47 (0.01)
Literal Naive	–	0.58 (0.04)	0.47 (0.02)	1.54 (0.07)	1.52 (0.05)	–	0.54 (0.01)
GPT-4V	0.29 (0.08)	0.39 (0.08)	0.26 (0.06)	–	–	0.10 (0.01)	0.11 (0.01)
			VirtualHome				
CLIPS (Ours)	**0.63 (0.04)**	**0.87 (0.04)**	**1.00 (0.00)**	**1.00 (0.00)**	**1.00 (0.00)**	**–**	**–**
Lang. Only IP	0.37 (0.05)	0.59 (0.05)	0.96 (0.03)	1.33 (0.07)	1.35 (0.08)	–	–
Action Only IP	0.25 (0.03)	0.61 (0.07)	0.84 (0.07)	1.30 (0.07)	1.33 (0.07)	–	–
Literal Listener	–	0.64 (0.06)	0.70 (0.07)	1.48 (0.08)	1.54 (0.09)	–	–

principal and observed the instruction at the end. Participants were then asked to select the set of gems that they thought were likely to be principal's goal, and then indicate how the robot agent should best assist the principal. This gave 50 goal and assistance ratings for each problem (93% power for Cohen's d=0.5 at α=0.05).

For the assistance question, we presented each participant with a set of *assistance options*, corresponding to either picking up keys or unlocking doors. This allowed us to query participants' understanding of how to provide assistance without having them solve the entire problem. To compare these human-provided assistance options with CLIPS and our baselines, we extracted the corresponding actions from the assistive plans generated by each method, and (where applicable) estimated the marginal probability of a particular assistance option occurring in the assistive plan via sampling.

3.4 Performance metrics

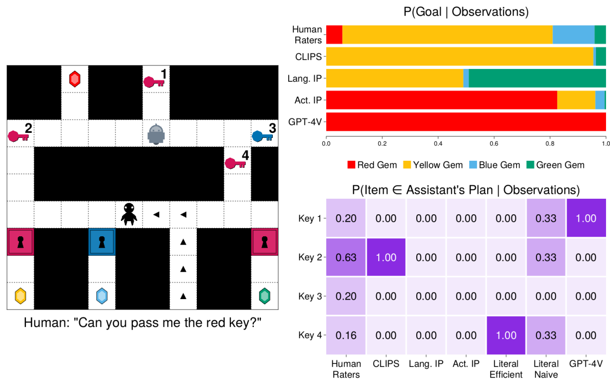
We evaluated CLIPS and the baseline methods in terms of their goal and assistance accuracy, the helpfulness and efficiency of the generated plans, and their similarity to human judgments. To evaluate accuracy, we calculated the probability $P(g_{\text{true}})$ assigned to the true goal for the non-literal methods, as well as precision and recall for selecting the optimal assistance options that were consistent with the instruction. To evaluate helpfulness and efficiency, we computed the length of the generated plan and the total action cost incurred by the human principal, relativized to CLIPS. Finally, to evaluate human similarity in mDKG, we calculated the correlation between each method's outputs with the average ratings provided by our participants. We calculated Pearson's r as well its variability from 1000 bootstrapped samples of the human dataset.

3.5 Results

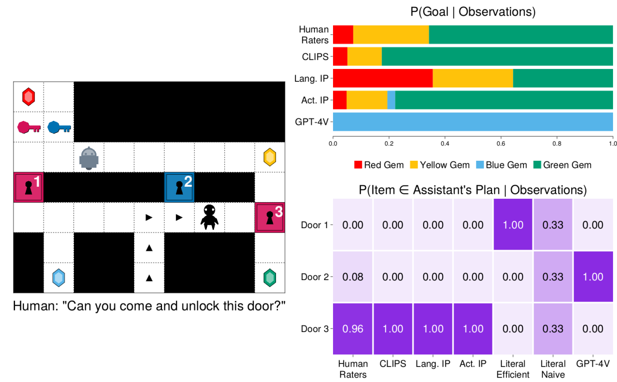
The results of our experiments are presented in Table 1. In terms of accuracy, CLIPS assigned higher probability to the true goal than the baselines (note that 100% is not possible since goals cannot always be distinguished, as in Fig. 4d), while achieving close to perfect precision and recall in selecting the optimal assistance options. Indeed, CLIPS outperformed the average human in this regard. In contrast, unimodal inverse planning was much less accurate at inferring the true goal, and all baselines selected the correct assistance options at significantly lower rates. This affected the efficiency of assistance: CLIPS was 1.26 to 1.68 times faster in achieving the human's goal than the baselines, and produced plans that were 1.18 to 1.58 times less costly for the human.

For human similarity in the mDKG domain, we found that both the goal inferences and the assistance options produced by CLIPS correlated highly with human ratings, achieving Pearson's r of 0.93 (95% CI: 0.91–0.94) and 0.96 (95% CI: 0.95–0.96) respectively. In contrast, unimodal inverse planning produced goal inferences that were highly dissimilar from humans. Correlation with human-selected assistance options was also poor. These results demonstrate the importance of accounting for pragmatic context. Out of all methods, GPT-4V performed the worst, possibly because of the spatial reasoning and multi-step planning required for coherent goal inference in mDKG. Among participants themselves, we found that the median Pearson's r of each participant's ratings with the mean rating was 0.85 (IQR: 0.71–0.94) for goal inferences and 0.87 (IQR: 0.65–0.95) for assistance options, indicating that our dataset of human judgments is a reliable measure of average human performance.

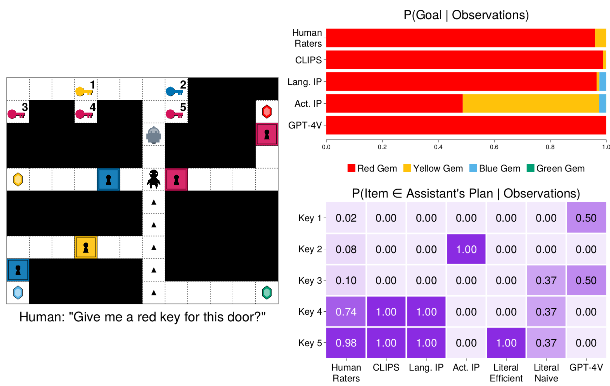
In Figure 4, we compare the results of CLIPS against human judgements and baselines on six illustrative goal assistance problems, providing qualitative observations in the captions. The results show how CLIPS closely mirrors human judgements for both goal inference and assistance, resolving ambiguity in predicates (Fig. 4a) and indexicals (Fig. 4b) while successfully completing partial instructions (Fig. 4c) and interpreting joint instructions (Fig. 4e). In comparison, the unimodal and literal baselines make less confident inferences or fail to assist appropriately, while GPT-4V provides incoherent answers. We also find that both humans and CLIPS are able to assist appropriately when there is significant goal uncertainty (Fig. 4d), and even when the optimal assistive plans for each goal make diverging recommendations (Fig. 4f), illustrating the importance of uncertainty-aware assistance.



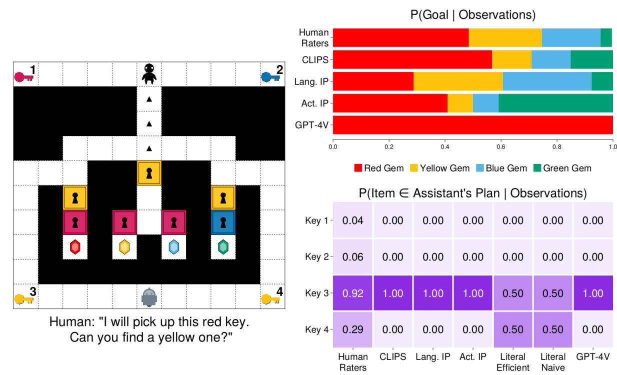
(a) Ambiguous Predicates. The human player asks for a red key when three are available. CLIPS resolves this ambiguity, inferring that the human wants *Key 2* to reach the yellow gem.



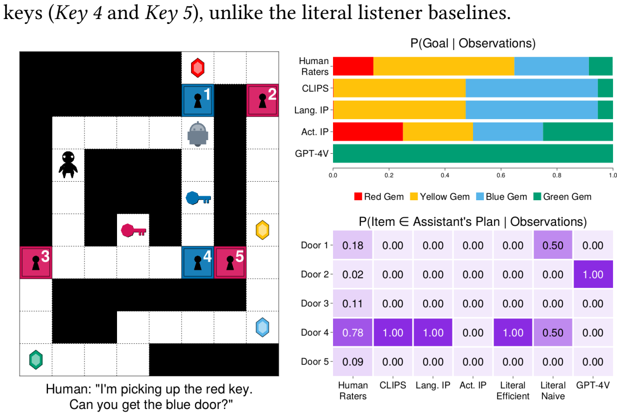
(b) Ambiguous Indexicals. The human player refers to a door using the indexical "this". CLIPS interprets this pragmatically, inferring that *Door 3* is intended even though *Door 2* is equally close to the human.



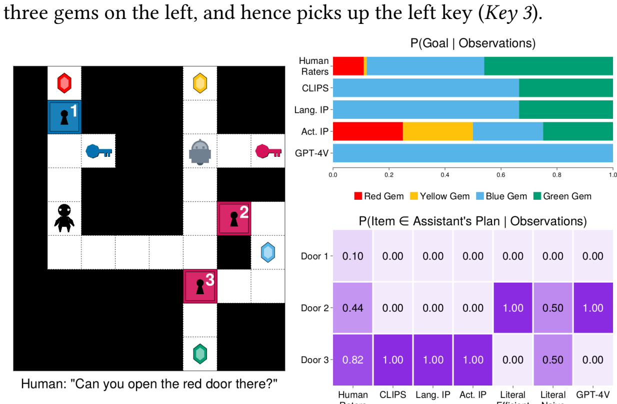
(c) Partial Instructions. The human player asks for a single red key, but requires two to reach the red gem. CLIPS infers this and picks up both keys (*Key 4* and *Key 5*), unlike the literal listener baselines.



(d) Uncertain Goals. The human player asks for a yellow key while going to pick up a red key. CLIPS pragmatically infers their goal to be one of the three gems on the left, and hence picks up the left key (*Key 3*).



(e) Joint Instructions. The human player asks for a blue door to be unlocked while indicating that they will pick up a red key. The CLIPS assistant infers that it should unlock *Door 4* so that the human can unlock *Door 5*.



(f) Safe Assistance. The human player asks the robot to unlock a red door when there are two such doors. The CLIPS assistant reasons that unlocking *Door 3* is safer as it leads to *both* blue and green gems, unlike *Door 2*.

Figure 4: Goal assistance problems in Doors, Keys & Gems. Each sub-figure contains a visual (*left*), instruction (*bottom left*), goal posteriors produced by each method (*top right*), and the probability of a key or door appearing in the assistive plans generated by each method (*bottom right*). Our pragmatic goal assistance method, CLIPS, best matches the goal inferences and assistance options produced by human raters (averaged across raters). In contrast, language and action-only inverse planning (Lang. IP & Act. IP) have higher goal uncertainty, the literal baselines fail to resolve instruction ambiguity, and GPT-4V often produces incoherent responses.

4 RELATED WORK

Theory of Mind as Bayesian Inverse Planning. Bayesian Theory of Mind (BToM) posits that humans reason about the actions and mental states of others through (approximately) Bayesian inference [5, 6]. In particular, Bayesian inverse planning can model how humans infer the goals of others by assuming that agents act rationally to achieve their goals [7, 18, 24, 49]. To efficiently solve these inference problems, prior work uses sequential Monte Carlo methods [13, 30] to perform online goal inference over model-based planning agents [3, 67]. CLIPS builds upon this paradigm, extending recent work by Ying et al. [64] on multi-agent inverse planning.

Rational Speech Acts. Rational Speech Act (RSA) theory frames communication as a recursive process, where speakers make pragmatic utterances that optimize relevance to listeners, and listeners interpret speaker utterances in light of the pragmatic goals that underlie those utterances [16, 19, 53]. CLIPS instantiates the RSA framework in the context of cooperative planning.

Multimodal Goal Inference and Reward Learning. Goal inference can be framed as online inverse reinforcement learning (IRL), where the aim is to to learn a reward or cost function explaining the agent's behavior in a single episode [23]. CLIPS can thus be viewed as a language-informed IRL method, though IRL is primarily applied offline given a dataset of expert demonstrations [17, 59, 62]. Particularly relevant is *reward-rational implicit choice* [25], a framework for multimodal Bayesian reward learning from heterogeneous human feedback. CLIPS can be seen as an application of this framework for specific modalities, but extended to the cooperative setting.

Decentralized Cooperation and Joint Intentionality. When multiple agents cooperate on a task, they usually need to track each other's mental states to make decisions. Common approaches to this involve recursive reasoning over each other's goals and plans, which can quickly grow intractable [12, 14]. To address this challenge, computational cognitive scientists have developed models of *joint intentionality* [58], where cooperating agents conceive of themselves as a *group agent* with a common goal in mind [52, 55]. This approach allows groups of agents to converge on shared goals [56] and efficient task decompositions [63] in a decentralized manner with limited recursion. CLIPS uses this insight to model joint planning and pragmatic instruction generation in humans.

Value Alignment and Assistance Games. CLIPS is a solution strategy for language-augmented goal assistance games, an extension of the assistance game formalism for human-AI value alignment [21, 45]. In contrast to prior work, our framework leverages joint intentionality when modeling human principals, thereby requiring less recursion than iterated best-response [21], while avoiding the intractability of equilibrium solutions [15, 37].

Instruction Following with Language Models. CLIPS is a form of grounded instruction following from natural language [38, 51, 57], using LLMs to score the likelihood of an utterance given a grounded command. While many recent studies have employed LLMs for translating language into actions [2, 50] or task specifications [29, 34, 65], we opt for an explicitly Bayesian approach, allowing our method to integrate information from both actions and instructions in a principled, reliable, and modular manner.

5 DISCUSSION AND FUTURE WORK

In this paper, we introduced cooperative language-guided inverse plan search (CLIPS) as a Bayesian architecture for pragmatic instruction following and goal assistance. By using a structured cognitive model of how speakers produce both actions and utterances given their goals, CLIPS is able to integrate information from observed actions and ambiguous instruction, inferring a distribution over speaker's goals and intentions. Using this distribution, a CLIPS assistant is then able to assist the speaker in achieving their goal through expected cost minimization. Through our experiments, we show that the proposed architecture produces human-like outputs on goal inference and assistance tasks. Compared with the baselines, CLIPS also makes more accurate goal inferences, and chooses actions that result in more efficient plans.

While CLIPS demonstrates compelling theoretical properties and strong empirical performance, a number of challenges remain before it can be applied to scenarios with a larger number of goals and assistance options. As noted in Section 2.2, the Bayesian inference strategy we adopt is fully enumerative, but this approach breaks down once the space of possible goals, plans, and commands grows sufficiently large. Recent advances in probabilistic programming could overcome these bottlenecks. For example, more sophisticated sequential Monte Carlo strategies could be used to flexibly propose and update hypotheses, focusing computation on only the most likely sets of latent variables [30, 67]. These strategies can be applied to perform *constrained decoding* from large language models [31, 61], thereby allowing LLMs to be used as sound proposal distributions over a grammar for commands. This would benefit from LLMs' performance at few-shot semantic parsing and translation [48], while preserving the Bayesian nature of our framework.

The assistance policy we introduced in Algorithm 2 could also be extended in a number of ways. In many assistive settings, uncertainty is sufficiently high that it makes sense for the assistant to take *information gathering actions.* Indeed, this is what people typically do when we are confused: we ask questions. To enable this ability, assistants should perform *belief-space planning* over the set of possible goal beliefs [35, 54], thinking ahead about which actions reveal more information about the principal's goals. Such planning would alleviate issues that can arise due to the Q_{MDP} approximation [22, 33] used by Algorithm 2. In the longer run, assistants could be augmented with natural language outputs, enabling them to ask clarifying questions by planning ahead in a white-box, interpretable manner. If successful, this would constitute a considerable step towards trustworthy assistive AI that effectively collaborates and communicates with humans.

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REFERENCES

[1] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal

Anadkat, et al. 2023. GPT-4 Technical Report. *arXiv preprint arXiv:2303.08774* (2023).
[2] Michael Ahn, Anthony Brohan, Noah Brown, Yevgen Chebotar, Omar Cortes, Byron David, Chelsea Finn, Chuyuan Fu, Keerthana Gopalakrishnan, Karol Hausman, et al. 2022. Do as I can, not as I say: Grounding language in robotic affordances. *arXiv preprint arXiv:2204.01691* (2022).
[3] Arwa Alanqary, Gloria Z Lin, Joie Le, Tan Zhi-Xuan, Vikash K Mansinghka, and Joshua B Tenenbaum. 2021. Modeling the mistakes of boundedly rational agents within a Bayesian theory of mind. *arXiv preprint arXiv:2106.13249* (2021).
[4] John Langshaw Austin. 1975. *How to do things with words*. Vol. 88. Oxford University Press.
[5] Chris Baker, Rebecca Saxe, and Joshua Tenenbaum. 2011. Bayesian Theory of Mind: Modeling Joint Belief-Desire Attribution. In *Proceedings of the Annual Meeting of the Cognitive Science Society, 33 (33)*.
[6] Chris L Baker, Julian Jara-Ettinger, Rebecca Saxe, and Joshua B Tenenbaum. 2017. Rational quantitative attribution of beliefs, desires and percepts in human mentalizing. *Nature Human Behaviour* 1, 4 (2017), 1–10.
[7] Chris L Baker, Rebecca Saxe, and Joshua B Tenenbaum. 2009. Action understanding as inverse planning. *Cognition* 113, 3 (2009), 329–349.
[8] Andrew G Barto, Steven J Bradtke, and Satinder P Singh. 1995. Learning to act using real-time dynamic programming. *Artificial intelligence* 72, 1-2 (1995), 81–138.
[9] Craig Boutilier. 1996. Planning, learning and coordination in multiagent decision processes. In *TARK*, Vol. 96. Citeseer, 195–210.
[10] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.
[11] Luca M. Schulze Buschoff, Elif Akata, Matthias Bethge, and Eric Schulz. 2024. Visual cognition in multimodal large language models. arXiv:2311.16093 [cs.LG]
[12] Colin F Camerer, Teck-Hua Ho, and Juin-Kuan Chong. 2004. A cognitive hierarchy model of games. *The Quarterly Journal of Economics* 119, 3 (2004), 861–898.
[13] Pierre Del Moral, Arnaud Doucet, and Ajay Jasra. 2006. Sequential Monte Carlo samplers. *Journal of the Royal Statistical Society Series B: Statistical Methodology* 68, 3 (2006), 411–436.
[14] Prashant Doshi and Piotr J Gmytrasiewicz. 2009. Monte Carlo sampling methods for approximating interactive POMDPs. *Journal of Artificial Intelligence Research* 34 (2009), 297–337.
[15] Jaime F Fisac, Monica A Gates, Jessica B Hamrick, Chang Liu, Dylan Hadfield-Menell, Malayandi Palaniappan, Dhruv Malik, S Shankar Sastry, Thomas L Griffiths, and Anca D Dragan. 2017. Pragmatic-Pedagogic Value Alignment. *arXiv preprint arXiv:1707.06354* (2017).
[16] Daniel Fried, Jacob Andreas, and Dan Klein. 2018. Unified Pragmatic Models for Generating and Following Instructions. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, Marilyn Walker, Heng Ji, and Amanda Stent (Eds.). Association for Computational Linguistics, New Orleans, Louisiana, 1951–1963. https://doi.org/10.18653/v1/N18-1177
[17] Justin Fu, Anoop Korattikara, Sergey Levine, and Sergio Guadarrama. 2019. From language to goals: Inverse reinforcement learning for vision-based instruction following. *arXiv preprint arXiv:1902.07742* (2019).
[18] György Gergely and Gergely Csibra. 2003. Teleological reasoning in infancy: The naıve theory of rational action. *Trends in cognitive sciences* 7, 7 (2003), 287–292.
[19] Noah D Goodman and Michael C Frank. 2016. Pragmatic language interpretation as probabilistic inference. *Trends in cognitive sciences* 20, 11 (2016), 818–829.
[20] Herbert P Grice. 1975. Logic and Conversation. In *Speech Acts*. Brill, 41–58.
[21] Dylan Hadfield-Menell, Stuart J Russell, Pieter Abbeel, and Anca Dragan. 2016. Cooperative inverse reinforcement learning. In *Advances in neural information processing systems*. 3909–3917.
[22] Milos Hauskrecht. 2000. Value-function approximations for partially observable Markov decision processes. *Journal of artificial intelligence research* 13 (2000), 33–94.
[23] Julian Jara-Ettinger. 2019. Theory of mind as inverse reinforcement learning. *Current Opinion in Behavioral Sciences* 29 (2019), 105–110.
[24] Julian Jara-Ettinger, Laura Schulz, and Josh Tenenbaum. 2019. The Naive Utility Calculus as a unified, quantitative framework for action understanding. *PsyArXiv* (2019).
[25] Hong Jun Jeon, Smitha Milli, and Anca Dragan. 2020. Reward-rational (implicit) choice: A unifying formalism for reward learning. *Advances in Neural Information Processing Systems* 33 (2020), 4415–4426.
[26] Chuanyang Jin, Yutong Wu, Jing Cao, Jiannan Xiang, Yen-Ling Kuo, Zhiting Hu, Tomer Ullman, Antonio Torralba, Joshua B Tenenbaum, and Tianmin Shu. 2024. MMToM-QA: Multimodal Theory of Mind Question Answering. *arXiv preprint arXiv:2401.08743* (2024).
[27] Sven Koenig and Maxim Likhachev. 2006. Real-Time Adaptive A*. In *Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems*. 281–288.
[28] Richard E Korf. 1990. Real-time heuristic search. *Artificial intelligence* 42, 2-3 (1990), 189–211.
[29] Minae Kwon, Sang Michael Xie, Kalesha Bullard, and Dorsa Sadigh. 2023. Reward Design with Language Models. In *The Eleventh International Conference on Learning Representations*. https://openreview.net/forum?id=10uNUgI5Kl
[30] Alexander K Lew, George Matheos, Tan Zhi-Xuan, Matin Ghavamizadeh, Nishad Gothoskar, Stuart Russell, and Vikash K Mansinghka. 2023. SMCP3: Sequential Monte Carlo with probabilistic program proposals. In *International Conference on Artificial Intelligence and Statistics*. PMLR, 7061–7088.
[31] Alexander K Lew, Tan Zhi-Xuan, Gabriel Grand, and Vikash K Mansinghka. 2023. Sequential Monte Carlo Steering of Large Language Models using Probabilistic Programs. *arXiv preprint arXiv:2306.03081* (2023).
[32] Jessy Lin, Daniel Fried, Dan Klein, and Anca Dragan. 2022. Inferring rewards from language in context. *arXiv preprint arXiv:2204.02515* (2022).
[33] Michael L Littman, Anthony R Cassandra, and Leslie Pack Kaelbling. 1995. Learning policies for partially observable environments: Scaling up. In *Machine Learning Proceedings 1995*. Elsevier, 362–370.
[34] Jason Xinyu Liu, Ziyi Yang, Benjamin Schornstein, Sam Liang, Ifrah Idrees, Stefanie Tellex, and Ankit Shah. 2022. Lang2LTL: Translating Natural Language Commands to Temporal Specification with Large Language Models. In *Workshop on Language and Robotics at CoRL 2022*.
[35] Owen Macindoe, Leslie Pack Kaelbling, and Tomás Lozano-Pérez. 2012. POMCoP: Belief Space Planning for Sidekicks in Cooperative Games.. In *AIIDE*.
[36] Drew McDermott, Malik Ghallab, Adele Howe, Craig Knoblock, Ashwin Ram, Manuela Veloso, Daniel Weld, and David Wilkins. 1998. PDDL - The Planning Domain Definition Language.
[37] Smitha Milli and Anca D Dragan. 2020. Literal or pedagogic human? analyzing human model misspecification in objective learning. In *Uncertainty in artificial intelligence*. PMLR, 925–934.
[38] Dipendra K Misra, Jaeyong Sung, Kevin Lee, and Ashutosh Saxena. 2016. Tell me Dave: Context-sensitive grounding of natural language to manipulation instructions. *The International Journal of Robotics Research* 35, 1-3 (2016), 281–300.
[39] Truong-Huy Nguyen, David Hsu, Wee-Sun Lee, Tze-Yun Leong, Leslie Kaelbling, Tomas Lozano-Perez, and Andrew Grant. 2011. Capir: Collaborative action planning with intention recognition. In *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, Vol. 7. 61–66.
[40] Judea Pearl. 2012. The do-calculus revisited. In *Proceedings of the Twenty-Eighth Conference on Uncertainty in Artificial Intelligence*. 3–11.
[41] Xavier Puig, Kevin Ra, Marko Boben, Jiaman Li, Tingwu Wang, Sanja Fidler, and Antonio Torralba. 2018. Virtualhome: Simulating household activities via programs. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 8494–8502.
[42] Xavier Puig, Tianmin Shu, Shuang Li, Zilin Wang, Yuan-Hong Liao, Joshua B Tenenbaum, Sanja Fidler, and Antonio Torralba. 2020. Watch-and-help: A challenge for social perception and human-ai collaboration. *arXiv preprint arXiv:2010.09890* (2020).
[43] Deepak Ramachandran and Eyal Amir. 2007. Bayesian Inverse Reinforcement Learning.. In *IJCAI*, Vol. 7. 2586–2591.
[44] Miguel Ramírez and Hector Geffner. 2010. Probabilistic plan recognition using off-the-shelf classical planners. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 24.
[45] Stuart Russell. 2021. Human-Compatible Artificial Intelligence. *Human-like machine intelligence* (2021), 3–23.
[46] Sandhya Saisubramanian, Kyle Hollins Wray, Luis Pineda, and Shlomo Zilberstein. 2019. Planning in stochastic environments with goal uncertainty. In *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 1649–1654.
[47] Ankit Shah, Shen Li, and Julie Shah. 2020. Planning with uncertain specifications (puns). *IEEE Robotics and Automation Letters* 5, 2 (2020), 3414–3421.
[48] Richard Shin, Christopher H Lin, Sam Thomson, Charles Chen, Subhro Roy, Emmanouil Antonios Platanios, Adam Pauls, Dan Klein, Jason Eisner, and Benjamin Van Durme. 2021. Constrained language models yield few-shot semantic parsers. *arXiv preprint arXiv:2104.08768* (2021).
[49] Michael Shum, Max Kleiman-Weiner, Michael L Littman, and Joshua B Tenenbaum. 2019. Theory of minds: Understanding behavior in groups through inverse planning. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 33. 6163–6170.
[50] Ishika Singh, Valts Blukis, Arsalan Mousavian, Ankit Goyal, Danfei Xu, Jonathan Tremblay, Dieter Fox, Jesse Thomason, and Animesh Garg. 2023. Progprompt: Generating situated robot task plans using large language models. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 11523–11530.
[51] Shawn Squire, Stefanie Tellex, Dilip Arumugam, and Lei Yang. 2015. Grounding English commands to reward functions. In *Robotics: Science and Systems*.
[52] Stephanie Stacy, Chenfei Li, Minglu Zhao, Yiling Yun, Qingyi Zhao, Max Kleiman-Weiner, and Tao Gao. 2021. Modeling communication to coordinate perspectives in cooperation. *arXiv preprint arXiv:2106.02164* (2021).

[53] Theodore R Sumers, Mark K Ho, Thomas L Griffiths, and Robert D Hawkins. 2023. Reconciling truthfulness and relevance as epistemic and decision-theoretic utility. *Psychological Review* (2023).

[54] Zachary Sunberg and Mykel Kochenderfer. 2018. Online algorithms for POMDPs with continuous state, action, and observation spaces. In *Proceedings of the International Conference on Automated Planning and Scheduling*, Vol. 28. 259–263.

[55] Ning Tang, Siyi Gong, Minglu Zhao, Chenya Gu, Jifan Zhou, Mowei Shen, and Tao Gao. 2022. Exploring an Imagined "We" in human collective hunting: Joint commitment within shared intentionality. In *Proceedings of the annual meeting of the cognitive science society*, Vol. 44.

[56] Ning Tang, Stephanie Stacy, Minglu Zhao, Gabriel Marquez, and Tao Gao. 2020. Bootstrapping an Imagined We for Cooperation.. In *CogSci*.

[57] Stefanie Tellex, Thomas Kollar, Steven Dickerson, Matthew Walter, Ashis Banerjee, Seth Teller, and Nicholas Roy. 2011. Understanding natural language commands for robotic navigation and mobile manipulation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 25. 1507–1514.

[58] Michael Tomasello and Malinda Carpenter. 2007. Shared intentionality. *Developmental science* 10, 1 (2007), 121–125.

[59] Hsiao-Yu Tung, Adam W Harley, Liang-Kang Huang, and Katerina Fragkiadaki. 2018. Reward learning from narrated demonstrations. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 7004–7013.

[60] Yanming Wan, Jiayuan Mao, and Josh Tenenbaum. 2022. HandMeThat: Human-Robot Communication in Physical and Social Environments. *Advances in Neural Information Processing Systems* 35 (2022), 12014–12026.

[61] Brandon T Willard and Rémi Louf. 2023. Efficient Guided Generation for LLMs. *arXiv preprint arXiv:2307.09702* (2023).

[62] Edward C Williams, Nakul Gopalan, Mine Rhee, and Stefanie Tellex. 2018. Learning to parse natural language to grounded reward functions with weak supervision. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 4430–4436.

[63] Sarah A Wu, Rose E Wang, James A Evans, Joshua B Tenenbaum, David C Parkes, and Max Kleiman-Weiner. 2021. Too Many Cooks: Bayesian Inference for Coordinating Multi-Agent Collaboration. *Topics in Cognitive Science* 13, 2 (2021), 414–432.

[64] Lance Ying, Tan Zhi-Xuan, Vikash Mansinghka, and Joshua B Tenenbaum. 2023. Inferring the Goals of Communicating Agents from Actions and Instructions. In *First Workshop on Theory of Mind in Communicating Agents*.

[65] Wenhao Yu, Nimrod Gileadi, Chuyuan Fu, Sean Kirmani, Kuang-Huei Lee, Montse Gonzalez Arenas, Hao-Tien Lewis Chiang, Tom Erez, Leonard Hasenclever, Jan Humplik, et al. 2023. Language to Rewards for Robotic Skill Synthesis. *arXiv preprint arXiv:2306.08647* (2023).

[66] Tan Zhi-Xuan. 2022. *PDDL. jl: An Extensible Interpreter and Compiler Interface for Fast and Flexible AI Planning*. Ph.D. Dissertation. Massachusetts Institute of Technology.

[67] Tan Zhi-Xuan, Jordyn Mann, Tom Silver, Josh Tenenbaum, and Vikash Mansinghka. 2020. Online Bayesian Goal Inference for Boundedly Rational Planning Agents. *Advances in Neural Information Processing Systems* 33 (2020).

[68] Brian D Ziebart, Andrew L Maas, J Andrew Bagnell, and Anind K Dey. 2008. Maximum entropy inverse reinforcement learning.. In *AAAI*, Vol. 8. Chicago, IL, USA, 1433–1438.