Baby Intuitions Benchmark (BIB): Discerning the goals, preferences, and actions of others

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Abstract

To achieve human-like common sense about everyday life, machine learning systems must understand and reason about the goals, preferences, and actions of other agents in the environment. By the end of their first year of life, human infants intuitively achieve such common sense, and these cognitive achievements lay the foundation for humans' rich and complex understanding of the mental states of others. Can machines achieve generalizable, commonsense reasoning about other agents like human infants? The Baby Intuitions Benchmark (BIB) challenges machines to predict the plausibility of an agent's behavior based on the underlying causes of its actions. Because BIB’s content and paradigm are adopted from developmental cognitive science, BIB allows for direct comparison between human and machine performance. Nevertheless, recently proposed, deep-learning-based agency reasoning models fail to show infant-like reasoning, leaving BIB an open challenge.

1 Introduction

Humans have a rich capacity to infer the underlying intentions of others by observing their actions. For example, when we watch the animations from Heider and Simmel (1944) (see video and Figure 1), we attribute goals and preferences to simple 2D shapes moving in a flat world. Using behavioral experiments, developmental cognitive scientists have found that even young infants infer intentionality in the actions of other agents. Infants expect agents: to have object-based goals (Gergely et al., 1995; Luo 2011; Song et al., 2005; Woodward 1998, 1999; Woodward and Sommerville 2000); to have goals that reflect preferences (Repacholi and Gopnik 1997; Kuhlmeier et al., 2003; Buresh and Woodward, 2007); to engage in instrumental actions that bring about goals (Carpenter et al., 2005; Elsner et al., 2007; Hernik and Csibra, 2015; Gerson et al., 2015; Saxe et al., 2007; Woodward and Sommerville, 2000); and to act efficiently towards goals (Gergely et al., 1995; Gergely and Csibra, 1997, 2003; Liu et al., 2019, 2017; Colomer et al., 2020).

Machine-learning and AI systems, in contrast, are much more limited in their understanding of other agents. They typically aim only to predict outcomes of interest (e.g., churn, clicks, likes, etc.) rather than to learn about the goals and preferences that underlie such outcomes. This impoverished “machine theory of mind” may be a critical difference between human and machine intelligence more generally, and addressing it is crucial if machine learning aims to achieve the flexibility of human commonsense reasoning (Lake et al., 2017).

1The dataset and code are available here: https://kanishkgandhi.com/bib
2https://www.youtube.com/watch?v=VTNmLi7QX8E
Recent computational work has aimed to focus on such reasoning by adopting several approaches. Inverse reinforcement learning (Ng et al., 2000; Abbeel and Ng, 2004; Ziebart et al., 2008; Ho and Ermon, 2016; Xu et al., 2019) and Bayesian approaches (Ullman et al., 2009; Baker et al., 2009, 2011, 2017; Jara-Ettinger, 2019) have modeled other agents as rational, yet noisy, planners. In these models, rationality serves as the tool by which to infer the underlying intentions that best explain an agent’s observed behavior. Game theoretic models have aimed to capture an opponent’s thought processes in multi-agent interactive scenarios (see survey: Albrecht and Stone, 2018), and learning-based neural network approaches have focused on learning predictive models of other agents’ latent mental states, either through structured architectures that encourage mental-state representations (Rabinowitz et al., 2018) or through the explicit modeling of other agents’ mental states using a different agent’s forward model (Raileanu et al., 2018). Despite the increasing sophistication of models that focus on reasoning about agents, they have not been evaluated or compared using a comprehensive benchmark that captures the generalizability of human reasoning about agents. For example, some evaluations of machines’ reasoning about agents have provided fewer than 100 sample episodes (Baker et al., 2009, 2011, 2017), making it infeasible to evaluate learning-based approaches that require substantial training. Other evaluations have used the same distribution of episodes for both training and test (Rabinowitz et al., 2018), making it difficult to measure how abstract or flexible a model’s performance is. Moreover, existing evaluations have not been translatable to the behavioral paradigms that test infant cognition, and so their results cannot be analyzed in terms of the representations and processes that support successful human reasoning.

Our benchmark, the Baby Intuitions Benchmark (BIB), presents a comprehensive set of evaluations of commonsense reasoning about agents suitable for machines and infants alike. BIB adapts experimental stimuli from studies with infants that have captured the content and abstract nature of their knowledge (Baillargeon et al., 2016; Banaji and Gelman, 2013). It provides a substantial amount of training episodes in addition to out-of-distribution test episodes. Moreover, BIB adopts a “violation of expectation” (VOE) paradigm (similar to Ricochet et al., 2018; Smith et al., 2019), commonly used in infant research, which makes its direct validation with infants possible and its results interpretable in terms of human performance. The VOE paradigm, moreover, offers an additional advantage relative to other measures of machine performance like predictive accuracy, in that it reveals how an observer might fail: VOE directly contrasts one outcome, which requires a high-level, human-like understanding of an event, to another one, which instantiates some lower-level, heuristically, or perceptually based alternative. BIB thus presents both a general framework for designing any benchmark aiming to examine commonsense reasoning across domains as varied as agents, objects, and places, as well as a key step in bridging machines’ impoverished understanding of intentionality with humans’ rich one.

AGENT (Shu et al., 2021), a benchmark developed contemporaneously with BIB, is inspired by infants’ knowledge about agents and has been validated with behavioral data from adults. Similar to BIB, AGENT challenges machines to reason about the intentions of agents as the underlying cause of their actions. Both benchmarks test whether models can predict that agents have object-based goals and move efficiently to those goals. There are nevertheless key differences between BIB and AGENT. First, BIB evaluates whether models can reason about multiple agents, inaccessible goals, instrumental actions, and the differences between the intentions of rational and irrational agents; AGENT does not test these competencies. The advantage of including them is that they introduce additional elements—beyond a single rational agent and one or two possible goal objects—that models must flexibly account for in their reasoning. These competencies, moreover, extend the infant cognition literature, potentially allowing BIB to further inform tests for infants. Second, BIB and AGENT evaluate new models differently. AGENT involves training on many different leave-out splits, where those splits include relatively minor differences between the training and test sets. BIB, in contrast, presents a single canonical split designed to maximally evaluate the abstractness of a model’s reasoning: Models tested on BIB must flexibly combine learning from different types of training scenarios to solve a novel test scenario. We thus ultimately see BIB and AGENT as complementary and hope that new models focused on commonsense reasoning about agents will be evaluated on both.  

Note that in the psychology literature, “theory of mind” typically refers to the attribution of mental states, such as phenomenological or epistemic states (i.e., perceptions or beliefs) to other intentional agents (Premack and Woodruff, 1978). In this paper, we address on only one potential component of theory of mind, present from early infancy, which focuses on reasoning about the intentional states, not the phenomenological or epistemic states, of others (Spelke, 2016).
2 Baby Intuitions Benchmark (BIB)

BIB focuses on the following questions: 1) Can an AI system represent an agent as having a preferred goal object? 2) Can it bind specific preferences for goal objects to specific agents? 3) Can it understand that physical obstacles might restrict agents’ actions, and does it predict that an agent might approach a nonpreferred object when their preferred one is inaccessible? 4) Can it represent an agent’s sequence of actions as instrumental, directed towards a higher-order goal object? 5) Can it infer that a rational agent will move efficiently towards a goal object?

Following the VOE paradigm, each of BIB’s tasks includes a familiarization phase and a test phase, together referred to as an “episode.” The familiarization phase presents eight successive trials introducing the main elements of the visual displays used in the test phase and allows the observer to form expectations about the future behavior of those elements based on their prior knowledge or learning. The test phase includes an unexpected and expected outcome based on what was observed during familiarization. Typically, the unexpected outcome is perceptually similar to the familiarization trials but is conceptually implausible, while the expected outcome is more perceptually different but involves no conceptual violation. The unexpected outcome is thus unexpected only if the observer possesses an abstract understanding of the events, and the expected outcome reflects a lower-level, heuristically, or perceptually based alternative. When VOE is used with infants, their looking time to each outcome is measured, and infants tend to look longer at the unexpected outcome (Baillargeon et al., 1985; Turk-Browne et al., 2008; Oakes, 2010).

Inspired by Heider and Simmel (1944), the primary set of visual stimuli present a fully observable “grid world,” shown from an overhead perspective, and populated with simple geometric shapes that take on different roles (e.g. “agents,” “objects,” “tools”) and provide few cues to those roles. We chose this type of environment as particularly suitable for testing AI systems (e.g., Baker et al., 2017; Rabinowitz et al., 2015) because it allows for procedural generation of a large number of episodes, and the simple visuals focus the problem on reasoning about agents. This design will also allow infancy researchers to test new questions about infant’s understanding of agents in future work. While BIB and the baseline models tested here focus on this 2D grid-world environment, we have also instantiated the stimuli in 3D as a means of varying perceptual difficulty in future studies evaluating other models (appendix A).

2.1 Can an AI system represent an agent as having a preferred goal object?

Developmental Background. Infants infer that agents have preferences for goal objects, not goal locations (Gergely et al., 1995; Luo, 2011; Song et al., 2005; Woodward, 1998, 1999; Woodward and Sommerville, 2000). As illustrated in Figure 2a (left), Woodward’s seminal study showed that when 5- and 9-month-old infants saw a hand repeatedly reaching to a ball on the left over a bear on the right, they then looked longer when the hand reached to the left for the bear, even though the direction of the reach was more similar in that event to the events in the previous trials. These results suggest that the infants expected that the hand would reach consistently to a preferred goal object as opposed to a preferred goal location. Other studies have shown that infants’ interpretations are not restricted to reaching events. For example, infants attribute a preference for goal objects to a 3D box during a live puppet show when that box seemingly exhibits self-propelled motion. (Luo, 2011; Luo and Baillargeon, 2005; Shimizu and Johnson, 2004). When shown an agent repeatedly moving to the same object at approximately the same location, do machines infer that the agent’s goal is a preferred object, not location?

Familiarization Trials. The familiarization shows an agent repeatedly moving towards a specific object in a world with two objects (Figure 2a, center). The agent’s starting position is fixed, and the locations of the objects are correlated with their identities such that the preferred object and nonpreferred object appear in generally the same location across trials (appendix Figure 9 and 10).

Test Trials. The test uses two object locations that had been used during one familiarization trial, but the identity of the objects at those locations has been switched. In the expected outcome (Figure 2b), the agent moves to the object that had been their goal during the familiarization, i.e., their preferred object, but the trajectory of their motion and the location of that object is different from familiarization. In the unexpected outcome (Figure 2c), the agent moves to the nonpreferred object, but the trajectory of their motion and the location they move to is the same as familiarization. The model is successful if it expects the agent to go to the preferred object in a different location.
2.2 Can an AI system bind specific preferences for goal objects to specific agents?

Developmental Background. Infants are capable of attributing specific object preferences to specific agents (Repacholi and Gopnik, 1997; Kuhlmeier et al., 2003; Buresh and Woodward, 2007; Henderson and Woodward, 2012). For example, while 9- and 13-month-old infants looked longer at test when an actor reached for a toy that they did not prefer during a habituation phase, infants showed no expectations when the habituation and test trials featured different actors (Buresh and Woodward, 2007). When shown one agent repeatedly moving to the same object, do machines expect that that object is preferred by that specific agent?

Familiarization Trials. The familiarization shows an agent consistently choosing one object over the other, but objects appear at widely varying locations in the grid world.

Test Trials. The test includes four possible outcomes: the same agent moves to the preferred object (expected); a new agent moves to the object preferred by the first agent (no expectation) (appendix, Figure 12); the same agent moves to the nonpreferred object (unexpected); or the new agent moves to the nonpreferred object (no expectation) (appendix, Figure 13). The model is successful if it has the same relative expectations as listed above; that is, weak or no expectations about the preferences of the new agent compared to the familiar agent.

2.3 Can an AI system understand that physical obstacles might restrict agents’ actions, and does it predict that an agent might approach a nonpreferred object when the preferred one is inaccessible?

Developmental Background. Infants understand the principle of solidity (e.g., that solid objects cannot pass through one another), and they apply this principle to both inanimate entities (Baillargeon, 1987; Baillargerion et al., 1992; Spelke et al., 1992) and animate entities, such as human hands (Saxe et al., 2006; Luo et al., 2009). Infants’ expectations about the objects agents might approach are also informed by object accessibility. Scott and Baillargeon (2013) demonstrate, for example, that 16-month-old infants expected an agent, facing two identical objects, to reach for the one in the container without a lid versus the one in the container with a lid. When shown an agent repeatedly moving to the same object, do machines recognize that the agent’s access to that object might change, and do they predict that an agent might then approach a nonpreferred object?
**Familiarization Trials.** The familiarization shows an agent consistently choosing one object over the other, as above, and objects appear at widely varying locations in the grid world (Figure 4).

**Test Trials.** The test presents two new object locations. In the no-expectation outcome, the preferred object is now blocked on all sides by fixed, black barriers, and the agent moves to the nonpreferred object. In the unexpected outcome, both of the objects remain accessible, and the agent moves to the nonpreferred object (Figure 4). The model is successful if it has the same relative expectations; that is, weak or no expectation about the agent’s moving to the nonpreferred object only when the preferred object is inaccessible.

2.4 Can an AI system represent an agent’s sequence of actions as instrumental, directed towards a higher-order goal object?

**Developmental Background.** Infants represent an agent’s sequence of actions as instrumental to achieving a higher-order goal (Carpenter et al., 2005; Elsner et al., 2007; Hernik and Csibra, 2015; Gerson et al., 2015; Saxe et al., 2007; Sommerville and Woodward, 2005; Woodward and Sommerville, 2000). For example, Sommerville and Woodward (2005) showed that 12-month-old infants understand an actor’s pulling a cloth as a means to getting the otherwise out-of-reach object placed on it. When shown an agent repeatedly taking the same action to effect a change in the environment that enables them to move towards an object, do machines expect that object is the goal, as opposed to the sequence of actions?

**Familiarization Trials.** The familiarization includes five main elements: an agent; a goal object; a key; a lock; and a green removable barrier (see Figure 5). The green barrier initially restricts the agent’s access to the object. And so, the agent removes the barrier by collecting and inserting the key into the lock. The agent then moves to the object.

**Test Trials.** The test phase presents three different scenarios for a total of six different outcomes. In the scenario with no green barrier: the agent moves directly to the object (expected); or to the key (unexpected) (Figure 5a). In the scenario with an inconsequential green barrier: the agent moves directly to the object (expected); or to the key (unexpected) (Figure 5b). In the scenario with variability in the presence/absence of the green barrier: the barrier blocks the agent’s access to the object, and the agent moves to the key (expected); or, the barrier does not block the object and the agent moves to the key (unexpected). The model is successful if it expects the agent to go to the key only when the green removable barrier is blocking the goal object (Figure 5c).
2.5 Can an AI system predict that a rational agent will move efficiently towards a goal object?

**Developmental Background.** Infants expect agents to move efficiently towards their goals (Gergely et al., 1995; Gergely and Csibra, 1997, 2003; Liu et al., 2017, 2019; Colomer et al., 2020). In a seminal study by Gergely et al. (1995), for example, 12-month-old infants repeatedly saw a small circle jumping over an obstacle to get to a big circle (see Figure 3 left). At test, the obstacle was removed, and the small circle either took the same, now inefficient, path to get to the big circle or took the straight, efficient path. Infants were surprised when the agent took the familiar, inefficient path. These findings have been replicated by instantiating the agent and object in different ways (as, e.g., humans, geometric shapes, or puppets) and by using different kinds of presentations (e.g., prerecorded or live) (Colomer et al., 2020; Phillips and Wellman, 2005; Sodian et al., 2004; Southgate et al., 2008; Liu et al., 2017). When infants see an irrational agent, i.e., one moving inefficiently to their goal from the start, however, they do not form any expectations about that agent’s actions at test (Gergely et al., 1995; Liu and Spelke, 2017). When shown a rational agent repeatedly taking an efficient path around an obstacle to its goal object, do machines expect that that agent will continue to take efficient paths, as opposed to similar-looking paths, relative to the obstacles in the environment?

**Familiarization Trials** The familiarization includes two different scenarios: a rational agent consistently moves along an efficient path to its goal object around a fixed black barrier in the grid world (Figure 3a); or, an irrational agent moves along these same paths as the rational agent, but there is no barrier in the way (appendix, Figure 14b).

**Test Trials.** The test includes two possible scenarios. One scenario shows only the rational agent, and it presents one of the familiarization trials but with the barrier between the agent and the goal object removed or changed in position (such that a curved path is still required). The agent either moves along an efficient path to its goal (expected) or the agent moves along one of two unexpected paths, either the exact same, but now inefficient, path that it had during familiarization (path control, Figure 3) or along a path that is inefficient but takes the same amount of time as the efficient path (in this latter case, the goal object starts off closer to the agent, appendix Figure 11). The second scenario shows either the rational or irrational agent taking an inefficient path towards its goal. This outcome should be unexpected in the case of the rational agent, but should yield no expectation in the case of the irrational agent (appendix, Figure 14). The model is successful if it expects only a rational agent to modify its path based on the location of barriers and move efficiently to its goal.

3 Background Training

While infants in the lab make meaningful inferences about novel stimuli and environments with only a brief familiarization phase, BIB includes tens of thousands of background episodes as a generous stand-in for this type of in-lab familiarization. Models should therefore not be surprised merely by BIB’s elements and dynamics. Just as infants may already have knowledge about agents, objects, and places prior to coming to the lab, moreover, we do not intend to limit models to just BIB’s background training prior to being tested. Although learning-centric approaches will learn something about agents if trained on the background set, either supplemental pretraining or additional prior knowledge can be enriched by the background training for a model to approach the benchmark successfully. The episodes in the background training are structured similarly to those in the evaluation, although the familiarization and test trials are drawn from the same distribution for the background training only. Similar to IntPhys (Riochet et al., 2018) and ADEPT (Smith et al., 2019), we only provide expected outcomes at test for the background training. There are four training tasks:

**Single-Object Task.** The agent navigates to an object at some varied location in the environment (Figure 5a). This task is different from the evaluation tasks, where there are two objects or the arrangement of the barriers in the environment changes. With this training, models can learn how agents start and end trials, how agents move, and how barriers influence agents’ motion. We provide 10,000 episodes of this type.

**No-Navigation Preference Task.** Two objects are located very close to the agent’s initial starting location but at varied locations, and the agent approaches one object consistently across trials (Figure 5b). The task allows the model to learn that agents display consistent preference-based behavior. Critically, the navigation in these trials is trivial compared to the evaluation trials, so navigation to a preferred goal object is not trained. We provide 10,000 episodes of this type.
Single-Object Multiple-Agent Task. One object is located very close to the agent’s initial starting location but at varied locations (Figure 6d). At some point during the episode, a new agent takes the initial agent’s place (for example, the initial agent could be replaced at the fourth trial, and all subsequent trials, including the test trial, would have the new agent). The task allows the model to learn that multiple agents can appear across trials. This task differs from the evaluation task, where there are two objects and a new agent appears only in the test trials. We provide 4,000 episodes of this type.

Agent-Blocked Instrumental Action Task. The trial starts with the agent confined to a small region of the grid world, blocked by a removable green barrier (Figure 6c). The agent collects the key and inserts it into the lock to make the barrier disappear. The agent then navigates to the object. This task allows the model to learn that the green barrier obstructs navigation and that inserting the key in the lock removes that barrier. These trials differ from the evaluation in that the removable barriers are around the agent instead of the object. We provide 4,000 episodes of this type.

To be successful at the evaluations, models must acquire or enrich their representations of agents for flexible and systematic generalization. For example, models have to combine acquired knowledge of navigation (Single-Object Task) and preferences (No-Navigation, Preference Task) to be successful at the evaluation testing their understanding that agents have preferences for goal objects, not goal locations (section 2.1).

4 Baseline Models

When being evaluated on BIB, a model cannot actively sample from the environment; it can only use the samples provided in the episodes themselves. We therefore did not test baseline models using traditional approaches in imitation learning (IL), inverse RL (IRL), and RL (Ng et al., 2000; Abbeel and Ng, 2004; Ziebart et al., 2008) because they require substantial privileged information, such as access to the environment to actively sample trajectories using the modelled policy, and, in the case of the RL algorithms, an observable reward. Moreover, these approaches often model one agent at a time, and BIB requires the same model to infer the behavior of different agents across different episodes (although recent approaches in deep RL and IRL try to mitigate this latter issue with work in meta-RL and meta-IRL (Xu et al., 2019; Yu et al., 2019; Rakelly et al., 2019) that allows for similar cross-episode adaptation). Although this feature of BIB makes it less suitable for testing RL models, it is essential to BIB’s design because it reflects infants’ reasoning. Infants rely on little to no active interaction with a particular environment to make meaningful inferences and predictions about the agents in that environment, and infants’ inferences are far more abstract than their particular observed or active experience (Skerry et al., 2013; Gergely et al., 2002; Liu et al., 2019; Zmyj et al., 2009).

We thus tested three baseline models spanning different approaches including video modeling, behavior cloning (BC), and offline RL (see appendix C for full model specifications). Models were trained passively and through observation only. An episode in BIB can be broken down into nine trials with trajectories, \( \{ \tau_i \}_{i=1}^{9} \), where \( \tau_i \forall i \in [1, 8] \) are the familiarization trials and \( \tau_9 \) is the test trial. Each trajectory \( \tau_i \) consists of a series of state (frames from the video) and action pairs \( \{ s_{ij}, a_{ij} \}_{j=1}^{T_i} \). The action space of the agents in BIB is of size eight; agents can move along the two axes or along the diagonals. Additionally, the transitions are deterministic.

Our baseline models either predict the next frame in the video (see Figure 7 for architecture) or the actions taken by the agent (see appendix C.2). To encode the context in the form of the familiarization trials, we use a sequence of frames (for the video model) and frame-action pairs (for the BC models). In terms of the architecture, the baseline models take inspiration from a state-of-the-art, neural-
Figure 7: Architecture of the video baseline model inspired by Rabinowitz et al. (2018). An agent-characteristic embedding is inferred from the familiarization trials using a recurrent net. This embedding, with a frame from the test trial, is used to predict the next frame of the video using a U-Net (Ronneberger et al., 2015).

(a) The model predicts that the brown agent will go to the green object instead of the gray object, its preferred goal object during familiarization.

(b) The model predicts that the blue agent will go to the inaccessible cyan object instead of an accessible object.

(c) The model predicts that the blue agent will go to the inaccessible orange object instead of performing the instrumental action to first collect the triangular key.

Figure 8: The most surprising frame (the frame with the highest prediction error) from the test trial for the video model taken from the evaluation tasks. Examples of failed expectations are shown here.

network-based approach to encode the characteristic of an agent: the theory of mind net (ToMnet) model in Rabinowitz et al. (2018). We encode the familiarization trials as context using either a bidirectional LSTM or an MLP. In addition to video modeling and BC, we also try an offline-RL baseline (Siegel et al., 2020). Offline-RL algorithms (Levine et al., 2020) are designed to learn a policy from demonstrations by using privileged information in the form of rewards received by the agent. We engineer a reward function based on the distance of the agent from the goal to train the RL policy (see appendix C.3).

During evaluation, the "expectedness" of a test trial, in the context of the previous familiarization trials, was inferred by a model’s error on the most ‘unexpected’ step (i.e., the step with the highest prediction error). The most ‘unexpected’ step was chosen for comparison as alternatives (like the mean expectedness of steps) consistently resulted in lower VOE scores. For each evaluation episode, we first calculated the model’s relative accuracy, i.e., whether the model found the expected video in each pair more expected than the unexpected video (chance is 50%).

5 Results

The models were trained on 80% of the background training episodes (training set), and the rest of the episodes were used for validation (validation set). A comparison of the MSE loss (on pixels for the video model and in the action space for the BC and RL models) on the training and validation sets indicated that the models had learned the training tasks successfully (see appendix C).

The results of our baselines are presented in Table 1. The offline RL model performs similarly to the BC approach (see appendix C.3 for details), so we do not consider the offline RL model further (offline RL is known to provide little improvement over BC when the demonstrations are not noisy (Siegel et al., 2020)). Comparing the performance of BC on BIB and AGENT (Shu et al., 2021), we see that BC performs worse on BIB. BC and offline-RL are known to perform poorly on out-of-distribution and systematically different scenarios from training to test (Siegel et al., 2020). Because systematic generalization is a primary feature of BIB but not AGENT, this is likely why BC performs worse on BIB.
The two models we tested with an RNN (Video-RNN; BC-RNN) perform at chance on the Preference Task (see Figure 8a for predictions made by the video model); they tend to predict that an agent will go to the closer object (this prediction is made in about 70% of trials). The models thus ignore the agent’s preference, established during familiarization. This finding is especially striking relative to the models’ success on the No-Navigation, Preference Task from the background training and could result from differences in the distance at which the objects are placed in the scene. In the background training, the objects are close to the agent, yielding short trial lengths during familiarization. The characteristic encoder RNN might find it difficult to generalize to the evaluation tasks’ longer sequences. The BC-MLP model is confused by how the object locations correlate with their identity, encoding an agent’s preference for a goal location instead of a goal object. This too is surprising, as the background training provides evidence that agents prefer object identities, not specific locations. None of these models, as a result, succeed in recognizing that agents have preferences and goals for specific objects.

The models also fail on the Multi-Agent Task, again tending to predict that an agent will go to the closer object regardless of any established preferences. Consistent with this failure, the models also fail to map specific preferences to specific agents. The models do slightly better than chance on the Inaccessible Goal Task. As seen in Figure 8b, the video model still, nevertheless, frequently predicts that the agent will go to the inaccessible goal. The models are proficient at finding the shortest path to the goal in the Efficiency Task (appendix Figure 16a), leading to high accuracy on both sub-evaluations that test for efficient action: Path Control and Time Control (Table 1). However, the two models with an RNN fail to modulate their predictions based on whether the agent was rational or irrational during familiarization (Table 1). The BC-MLP has a weak expectation of rationality from an irrational agent, scoring slightly higher that the two RNN models on this task. Finally, the models perform above chance on the Instrumental Action Task, but performance on the sub-evaluations (Table 1) indicate that they rely on the simple heuristic of directly going to the goal object rather than understanding the nature of the instrumental action (Figure 8c). This heuristic leads to higher scores on sub-evaluations with no barrier and an inconsequential barrier (Table 1) but lower scores on the sub-evaluation with a blocking barrier. This poor performance may be due to the difference in the relations between the agent and barrier in the background training (where the agent is confined; Figure 6c) and evaluation (where the object is confined; Figure 5).

### General Discussion

We introduced the Baby Intuitions Benchmark (BIB), which tests machines on their ability to reason about the underlying intentionality of other agents by only observing their actions. BIB is directly inspired by the abstract reasoning about agents that emerges early in human development, as revealed by behavioral studies with infants. BIB’s adoption of the VOE paradigm, moreover, means both that its results can be interpreted in terms of human performance and that low-level heuristics can be directly evaluated. While baseline, deep-learning models successfully generalize to BIB’s training tasks, they fail to systematically generalize to the evaluation tasks even though the models incorporate theory-of-mind-inspired architectures (Rabinowitz et al., 2018).
What kinds of models might succeed on BIB? Shu et al. (2021) proposes a Bayesian inverse planning model for success on AGENT’s agency-reasoning tasks. Extending this structured Bayesian approach to BIB is not straightforward, however, as it requires features that are not currently provided. Recent approaches in deep imitation learning and inverse RL, especially work in meta-IL and meta-IRL (Xu et al., 2019; Yu et al., 2019) that allows for test-time adaptation, also show promise and could ultimately lead to more human-like reasoning about other agents. Extending these approaches to BIB is nevertheless also non-trivial since they require active sampling of the environment, which is not something that BIB allows. We hope that BIB will catalyze future research in these directions.

While the comparison between human and machine performance will be bolstered by future behavioral studies with infants, the results from the baseline models already shed new light on critical differences between human and artificial intelligence (also see appendix D). For example, across tasks, the baseline models tended to predict that an agent would move to the closer of two objects, regardless of the agent’s previously demonstrated preference for only one of the objects. And, while models succeeded in predicting that an agent would move efficiently to an object, they over-generalized that efficiency principle to include agents who had previously demonstrated inefficient, irrational actions. For infants, object-based preferences and efficient, goal-directed action instead serve to enrich their understanding of the intentions of others. For example, when infants observe an agent going farther to a particular object or exerting more effort to reach it, they can attribute both a preference for that object to that agent and a value to that preference (Liu et al., 2017).

BIB also raises new questions about the foundations of common-sense reasoning about agents for both humans and machines alike. For example, the “extended familiarization” needed for training AI models (i.e., the background training) potentially reveals a striking difference between how BIB might challenge minds versus machines. While both infants and AI systems may have built-in knowledge and/or experience prior to participating in BIB, infants likely need only eight, as opposed to thousands, of videos of shapes moving around grid worlds to successfully apply their reasoning about agents to new, test events presented in that medium. Nevertheless, it remains unknown whether infants might also benefit from some kind of background training meant for machines; such designs have never been tested with infants. Relatedly, BIB challenges the generalizability of early emerging, human common-sense reasoning about agents. How well do humans recognize simple shapes with simple movements and minimal cues to animacy (e.g., no eyes/gaze direction, no distinctive sounds, and no emotional expressions) as agents with intentionality? Do navigation- versus reaching-contexts deferentially shift humans’ attention to locations versus objects as candidates for an agent’s goal? How does a comprehensive set of agency-reasoning abilities relate to one another within the same individual? Most of the existing infant literature on which BIB is based presents infants with richer cues to animacy (in the form of live-action or animated displays from frontal or three-quarters points of view), events with no or minimal navigation to establish preferences for goal objects, and individual tests of one competency or another, outside of a unified framework.

The origins and development of humans’ intuitive understanding of agents and their intentional actions have been studied extensively in developmental cognitive science. The representations and computations underlying such understanding, however, are not yet understood. BIB serves as a test for computational models with different priors and learning-based approaches to achieve common-sense reasoning about agents like human infants. A computational description of how we reason about agents could ultimately help us build machines that better understand us and that we better understand.

Finally, BIB serves as a key step in bridging machines’ impoverished understanding of others’ mental states with humans’ rich one. To achieve a human-like theory of mind, a model would not only have to understand intentionality, which is tested in BIB, it would also have to understand the perceptions and beliefs of other agents. A combined, comprehensive understanding may underlie human theory of mind and lead to, for example, success in a false belief task, in which humans have expectations about where an agent would search for a goal object based on where that agent last saw it (Baron-Cohen et al., 1985; Spelke, 2016). A benchmark that focuses on reasoning about agents’ phenomenological and epistemic states is thus a natural extension of BIB and could further advance our understanding of both human and artificial intelligence.
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Figure 9: Evaluation to test if machines can represent an agent’s preference for a goal object not a goal location. 2D versions of the stimuli are shown here.

Figure 10: Evaluation to test if machines can represent an agent’s preference for a goal object not a goal location. 3D versions of the stimuli are shown here.

Figure 11: We draw inspiration from Gergely et al. (1995) to ask whether machines can understand that rational agents move efficiently towards their goals. In this task, the time taken by the agent to reach the goal in the expected and unexpected outcomes is the same (time control).

A Generating the Evaluations

For each of the five evaluation tasks, we generated 1000 episodes, each with one expected and one unexpected outcome (2000 videos), by sampling the locations of barriers, agents, and objects in the $10 \times 10$ grid. The locations were controlled to account for the distances and obstacles between the agent and the objects so that, e.g., preferred objects were not consistently closer or farther from agents. We provide two evaluation sets, one with objects and agents seen during the background training and the other with new objects and agents. Finally, as a means of varying the perceptual difficulty of
Figure 12: Evaluation to test if machines can bind specific preferences to specific agents. The gray agent consistently chooses the cyan object over the yellow object (a). The same gray agent moves to the preferred cyan object (b). The new agent moves to the preferred (by the first agent) cyan object (c).

Figure 13: Evaluation to test if machines can bind specific preferences to specific agents. The orange agent consistently chooses the pink object over the green object (a). A new blue agent moves to the nonpreferred (by the first agent) green object (b). The same orange agent moves to the nonpreferred green object (c).

Figure 14: Inspired by Gergely et al. (1995), we ask whether machines can differentiate between rational or irrational agents in terms of their efficient action.

In the benchmark, we also include 3D versions of the stimuli rendered to match the 2D versions and presented at a three-quarters point of view (Figure 2). The 2D stimuli (except for the instrumental action tasks) are directly translated to 3D using the AI2THOR framework. For both 2D and 3D videos, we provide scene configuration files describing the objects and agents present in the scene.

B Data Specifications

Each video has a resolution of 200 x 200 at 25 fps (the videos can be converted to a higher resolution if required). In addition to the videos, we provide metadata in the form of json files describing every frame in the video. This description contains information about the layout of the scene and the elements present. Each video has a json file associated with it. A video has nine trials which correspond to the nine items in the json file. These nine trials have a variable number of frames. Each frame is described by the elements contained in it.

These include:

- The ‘size’ attribute specifies the resolution of the frame.
• The ‘walls’ attribute has a list of [bottom-left, extent] attributes describing the barriers. The bottom-left attribute is 2-dimensional and is defined by an x and y coordinate. Similarly, the extent for each wall is 2-dimensional and describes the width and height of the wall.

• The ‘objects’ attribute is defined as a list of attributes [bottom-left, size, image, color]. The bottom-left attribute is 2-dimensional and is defined by an x and y coordinate. The size is the half of the side of the square shape that the image of the object would be resized to. So, if the size is 10, an object image of size 100x100 would be resized to 20x20. The image attribute gives the path of the object image. The color attribute gives the color of the object in RGB format in the range [0, 255].

• The ‘home’, ‘agents’, ‘key’ and ‘lock’ attributes have a similar structure to the objects attribute.

• The ‘fuse’ attribute corresponds to the removable barrier and has a similar structure to the ‘walls’ attribute.

C Baseline Details

C.1 Video Model

Model Description. The models (see Figure 7) operate on videos sampled at 3 fps and resized to 64 × 64. Each frame in each familiarization trial is encoded using a convolutional neural network. The frame embeddings in a trial are passed to a bidirectional LSTM. The last output embedding of the LSTM represents the characteristic of the agent in the trial. These embeddings are averaged across familiarization to obtain a characteristic embedding for an agent. The characteristic embedding is tiled to a 64 × 64 spatial resolution, concatenated to a frame from the test trial, and passed through a U-net to predict the next frame in the trial. A mean squared error loss is used to train the network.

In the video model, the frames of a familiarization trial are encoded using a residual convolutional network with four blocks, each with two 3 × 3 convolutional operations with 16 feature maps. This is followed by a 1 × 1 convolutional layer to map the 16 feature maps to one map. This representation is flattened and passed sequentially to a bi-directional LSTM. The output from the last timestep is used as the agent characteristic representation of size 1 × 16 for the trial (see Figure 7). The characteristic embedding across the eight familiarization trials is averaged to get a final agent characteristic embedding. This embedding is tiled to get a vector of size 64 × 64 × 16 and concatenated to the current frame from the test trial. This vector of size 64 × 64 × 19 is passed to a U-Net (Ronneberger et al., 2015) to predict the next frame. We use an MSE loss in the pixel space to train the model and an Adam optimizer with a learning rate of 1e-4 (betas=(0.9, 0.999)). We train the 2D video model for 11 epochs and the 3D model for ten epochs.

Background Training. The errors on the validation set for the model are shown in appendix Table 2. Some of the predictions made by the model can be seen in Figure 15. Only the Preference Task requires the model to take the familiarization phase into consideration.

| BIB TASK       | MSE          |
|----------------|--------------|
| SINGLE OBJECT  | 3.3 × 10^{-4}|
| PREFERENCE     | 5.4 × 10^{-4}|
| MULTI-AGENT    | 2.4 × 10^{-4}|
| INSTRUMENTAL ACTION | 9 × 10^{-4} |

Table 2: The performance of the video model on the 2D background training tasks.

The model fails to reliably understand the agent’s preference. This could be a result of differences in the distance at which the objects are placed in the scene. In the background training, the objects are placed close (section 3) to the agent, making the length of the familiarization trials short. The characteristic encoder LSTM might find it difficult to extract characteristics from the longer sequences in the evaluation tasks.
The model learns the simple heuristic of always going to the object in the Instrumental Action Task. This result could be due to a difference in the distribution of the background training and evaluation tasks. In the background training (Figure 6c), the agent is confined to a small space, blocked by the green removable barrier. The number of samples that the model has to predict for the agent’s movement to the key or the lock is relatively small compared to the number of samples for the barriers disappearing and the agent’s moving towards the object goal. In the evaluation tasks (Figure 5c), the agent’s movement to the key and the lock are significantly greater (as the object goal is now blocked by the removable barrier). The model thus has trouble generalizing to this case (Table 1 Instrumental: Blocking barriers task).

When we replace the elements in the evaluation set with new ones, moreover, the video model scores fall slightly, but the trends remain the same (Table 3). Finally, the video model performs similarly on the 3D videos of the tasks, although performance is generally worse overall with 3D videos. This is likely because perceiving the trajectories of agents in 3D is more difficult for a predictive model in pixel space. The predictive networks trained with MSE find it challenging to model trajectories in depth.

| BIB AGENCY TASK         | NEW OBJECTS | 3D VIDEOS |
|-------------------------|-------------|-----------|
| PREFERENCE              | 47.4        | 49.2      |
| MULTI-AGENT             | 50.0        | 50.0      |
| INACCESSIBLE GOAL       | 61.7        | 40.0      |
| EFFICIENCY: PATH CONTROL| 98.5        | 66.3      |
| EFFICIENCY: TIME CONTROL| 96.9        | 75.4      |
| EFFICIENCY: IRRATIONAL AGENT | 47.8    | 50.0      |
| EFFICIENT ACTION AVERAGE| 72.7        | 62.9      |
| INSTRUMENTAL: NO BARRIER| 93.0        | -         |
| INSTRUMENTAL: INCONSEQUENTIAL BARRIER | 66.0 | -         |
| INSTRUMENTAL: BLOCKING BARRIER | 59.7 | -         |
| INSTRUMENTAL ACTION AVERAGE | 69.6  | -         |

Table 3: Performance of the video model on BIB with new objects and on the 3D videos. The scores quantify pairwise VOE judgements.

C.2 Behavior Cloning

In behavior cloning, we try to predict the actions of an agent given the current state and context (in the form of familiarization trials). We sample the videos (originally at 30fps) at 3fps and resize the frames (originally 200 × 200) to 84 × 84. We define the action that an agent takes from one state to another as the change in its location. This results in a 2-dimensional continuous action space where values are in the range from [−20, 20]. We normalize the values so that they are in the range [−1, 1].

Model Description. There are three components to the behavior cloning model: the state encoder; the context encoder; and the policy network. The architecture is similar to that of Yu et al. (2019); Rakelly et al. (2019); Rabinowitz et al. (2018). First, the states (frames) are encoded with a CNN (state encoder). We pretrain the state encoder using Augmented Temporal Contrast (ATC) (Stooke et al., 2021), which uses a contrastive loss to predict future state embeddings with random shift augmentations. We train the encoder on videos from the background training set for 350K iterations using ADAM with a learning rate of $1e^{-4}$ and default parameters. See Table 4 for specifications.

The second part of the BC model is the context encoder. States from the familiarization trials are encoded using the context encoder and these embeddings are concatenated to the actions. We either use a bidirectional LSTM or an MLP to encode the context. When using a bidirectional LSTM, we sample a sequence from each familiarization trial (with a max length of 30) to extract a trial embedding. This is averaged across the eight trials to get the characteristic embedding (similar to the video model). When using an MLP, we randomly sample 30 state-action pairs (state embedding concatenated with action). Each of these pairs is encoded using an MLP to get a transition embedding. The 30 transition embeddings are averaged to get a characteristic embedding.
(a) A trial from the training set where the model predicts that the brown agent will go to the preferred gray object.

(b) A trial from the training set where the model predicts that the blue agent will go to the preferred magenta object. We see that there is blurred blue prediction close to the yellow object but the model thinks that it is more likely that the agent will go to the magenta one.

(c) The model correctly predicts that the agent will take the shortest path to go to the goal object.

(d) The model correctly predicts that in the Instrumental Action Task, when the key is inserted into the lock, the removable barriers will slowly disappear.

Figure 15: Predictions of the video model on the background training tasks. (a) and (b) show model predictions for two preference trials where the model splits its predictions between the two objects but thinks that going to the preferred object is more likely. (c) shows model predictions for the Single Object Task where the model predicts that the agent will take the shortest path to the object. (d) shows the Instrumental Action Task where the model predicts the disappearance of the removable barriers. Test trials are shown here.
Figure 16: The most unexpected frame (the frame with the highest prediction error) from the test trial for the video model taken from the evaluation tasks. Successful examples are shown here.

| PARAMETER                  | VALUE |
|----------------------------|-------|
| # OF CONV LAYERS           | 4     |
| # OF FILTERS               | 32    |
| KERNEL SIZE                | $3 \times 3$ |
| EMBEDDING SIZE             | 256   |
| TARGET UPDATE INTERVAL     | 1     |
| TARGET UPDATE WEIGHT       | 0.01  |
| RANDOM SHIFT PROBABILITY   | 1     |

Table 4: Specifications of the state encoder model and parameters used to train it using augmented temporal contrast (ATC) (Stooke et al., 2021).

The final part of the BC model is the policy network. The current state (frame) is encoded using the state encoder. The state embedding is concatenated with the characteristic embedding. This state-context vector is passed through an MLP to predict the action of the agent. See Table 5 for specifications.

| PARAMETER                  | VALUE                  |
|----------------------------|------------------------|
| CONTEXT LSTM LAYERS        | 2                      |
| CONTEXT LSTM HIDDEN SIZE   | 32                     |
| CONTEXT MLP HIDDEN SIZES   | [64, 64]               |
| CONTEXT EMBEDDING SIZE     | 32                     |
| POLICY MLP HIDDEN SIZES    | [256, 128, 256]        |

Table 5: Specifications of the BC model.

Background Training. We use an MSE loss in the action space to train the network. We train the models to convergence using ADAM with a learning rate of $5e^{-4}$. The model is successful on the background tasks (see Table 6).
Evaluation Tasks. At test, we increase the number of samples passed as context to the BC-MLP model to 100. The expectedness of a transition is measured by the MSE error of predicting an action. The expectedness of an episode is formulated as the most ‘unexpected’ action in the test trial (we can use the average expectedness of the test trial as an alternate measure, but using the max was empirically found to perform better).

C.3 Offline RL

There are several ways to learn from demonstrations using Offline RL/ Batch RL (Levine et al., 2020). We use a method defined in Siegel et al. (2020) that relies on constraining the policy using a policy prior. This policy prior is simply a policy model that maximizes the likelihood of the observed data. Siegel et al. (2020) use either a simple Behavior Model (BM) (maximizes the likelihood of data similar to behavior cloning) an Advantage Weighted Behavior Model (ABM) (maximizes the likelihood of observed actions weighted by a learned advantage function). In addition to learning the prior, a Q-value estimator is learned to evaluate a policy. An RL policy is learned with the Q-value estimates and the behavioral prior using Maximum a posteriori policy optimization (Abdolmaleki et al., 2018). See Siegel et al. (2020) for details.

Siegel et al. (2020) show that when the demonstrations are not noisy and come from a reliable expert, the Q-network can be learned using the prior policy. The RL policy improvement step can be performed independently from the prior learning and Q-value estimation step. Since the data in the BIB background training set comes from a reliable expert and the prior policies can solve the task, we use this formulation for offline RL.

We use (state, action, next-state, reward) tuples to provide context to the model. These tuples are sampled from the familiarization trials in the episode. We engineer an artificial reward function based on the distance of the agent from the goal. For a state $s$, if the location of the agent is $x_a$, the location of the goal is $x_g$, then the reward $r$ is defined as:

$$r(s) = \begin{cases} 
-\|x_a - x_g\|^2 & \text{if } \|x_a - x_g\|^2 < 20 \\
-100 & \text{if } \|x_a - x_g\|^2 \geq 20
\end{cases}$$ (1)

Model Description The model has five components: state encoder; context encoder; Q-network (and the target Q-network); the policy network; and the prior policy network. The state encoder is pretrained similarly to the BC Model.

The context encoder is an MLP which takes (state, action, next-state, reward) tuples as input to produce a context embedding. The Q-network is an MLP that outputs the Q-value given the state, context, and action. The prior policy network and the RL policy network are identical MLPs that predict a 2-d Gaussian distribution in the action space. See table 7 for model specifications.

Background Training. The model is trained using ADAM optimizers with a learning rate of $5e^{-4}$ and default parameters. The model is successful on the background training tasks, but it is slightly worse than the BC models on the background tasks.

Evaluation Tasks. At test, we increase the number of transition context tuples used to infer the context to 100 (as opposed to 30 during training). The expectedness of an episode is measured by the likelihood of the observed actions in the test trial (see Table 8). The model does not improve on the behavior cloning model (similar to the effect observed in Siegel et al. (2020); the BM+MPO model is close to the BM prior when the demonstrations come from a reliable expert). Alternate

| BIB Task                                | BC-MLP | BC-RNN | OFFLINE RL |
|-----------------------------------------|--------|--------|------------|
| SINGLE OBJECT TASK                      | 0.05   | 0.05   | 0.09       |
| NO-Navigation Preference Task           | 0.02   | 0.02   | 0.03       |
| NO-PREFERENCE Multi-Agent Task           | 0.05   | 0.03   | 0.05       |
| AGENT-BLOCKED Instrumental Action Task  | 0.04   | 0.03   | 0.07       |

Table 6: Performance of the BC models and the Offline RL model on the validation set. MSE values of the predicted actions are shown above. An MSE value of 0.01 corresponds to the predicted action being off by two pixels, when the video frame is $200 \times 200$. 

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Table 7: Specifications of the Offline RL model.

| PARAMETER                        | VALUE               |
|----------------------------------|---------------------|
| CONTEXT MLP HIDDEN SIZES         | [64, 64]            |
| CONTEXT EMBEDDING SIZE           | 32                  |
| Q-NET MLP HIDDEN SIZES           | [256, 128, 256]     |
| POLICY MLP HIDDEN SIZES          | [256, 128, 256]     |
| PRIOR POLICY MLP HIDDEN SIZES    | [256, 128, 256]     |
| TARGET Q-NET UPDATE INTERVAL     | 200                 |
| GAMMA                            | 0.995               |

offline-RL models might be able to improve on this model and use privileged reward information more effectively.

| BIB AGENCY TASK          | OFFLINE RL |
|--------------------------|------------|
| PREFERENCE               | 45.7       |
| MULTI-AGENT              | 52.2       |
| INACCESSIBLE GOAL        | 42.8       |
| EFFICIENCY: PATH CONTROL | 90.3       |
| EFFICIENCY: TIME CONTROL | 45.1       |
| EFFICIENCY: IRRATIONAL AGENT | 43.2   |
| EFFICIENT ACTION AVERAGE | 55.5       |
| INSTRUMENTAL: NO BARRIER | 92.4       |
| INSTRUMENTAL: INCONSEQUENTIAL BARRIER | 74.7 |
| INSTRUMENTAL: BLOCKING BARRIER | 37.9    |
| INSTRUMENTAL ACTION AVERAGE | 68.3     |

Table 8: Performance of the baseline Offline-RL model on BIB. The scores quantify pairwise VOE judgements.

*These results are from an older version of the task in which the expected and unexpected test trials were not perfectly matched (the location of the preferred and the nonpreferred objects was not matched). We predict that the Offline RL model’s score would be higher on the current version but still lower than the BC model’s score on this task.

D Comparing the performance of infants and AI systems

A potential challenge in comparing the performance of infants and AI systems on tests like BIB is that there is no metric that could suggest that infants’ performance is 100%. So, what would it mean for an AI system to be as successful as infants on these tasks? Studies with infants focus on group-wise performance comparing looking times for expected and unexpected outcomes. When group-wise looking times are statistically different across outcomes, researchers infer that infants, in general, have certain expectations that reflect their knowledge about the world. When we designed BIB, we focused both on developmental findings that were well established in the field through multiple experiments and replications as well as on extensions of those findings, which would potentially inform new tests for infants.