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. Can machines achieve generalizable, common-sense 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[1] and Figure 1), we attribute goals and dispositions to simple 2D shapes moving in a flat world. Using behavioral experiments presenting both simple and complex visual displays, 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).

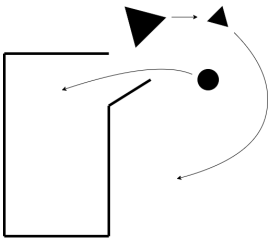

Figure 1: A still from Heider and Simmel (1944). Despite the simplicity of the visual display, we ascribe intentionality to the three shapes in the scene: The large triangle is chasing the small triangle and the circle whose goal is to avoid it.

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 underlying goals and preferences that underlie such outcomes. This impoverished "machine theory of mind"[2] may be a critical difference between human and machine intelligence more generally,

[1] https://www.youtube.com/watch?v=VTNmLt7QX8E

[2] Note that in the cognitive development literature, "theory of mind" typically refers to the attribution of mental states, such as phenomenological or epistemic states (e.g., perceptions or beliefs) to other intentional agents

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and addressing it is crucial if machine learning aims to approximate the flexibility of human commonsense reasoning (Lake et al., 2017).

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 focusing on reasoning about agents, they have not been evaluated or compared using a comprehensive benchmark that captures generalizable human competencies about agents. For example, some evaluations for agency reasoning 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 for both training and test episodes (Rabinowitz et al., 2018), making it difficult to measure how abstract or flexible a model's performance might be. Moreover, existing evaluations have not been translatable to the behavioral paradigms that test infant cognition. They therefore cannot be validated with infants nor can their results be analyzed in terms of the representations and processes that support successful human performance.

AGENT (Shu et al., 2021), a benchmark developed contemporaneously to the one presented here, is inspired by infants' knowledge about agents and has been validated with behavioral data from adults. Moreover, it challenges machines to reason about the intentions of agents as the underlying cause of their actions. In addition to probing different aspects of infants' knowledge, AGENT differs from our benchmark in the way that it evaluates new models. AGENT involves training on many different leave-out splits, where those splits include relatively minor differences between the training and test sets. Our benchmark, in contrast, presents a single canonical split designed to maximally evaluate the abstractness and flexibility of a model's reasoning. We ultimately see these benchmarks as complementary and hope that new models will be evaluated on both.

Our comprehensive benchmark, the Baby Intuitions Benchmark (BIB), derives from research on infant cognition. BIB adapts experimental stimuli from studies with infants that have captured the content and abstract nature of infants' reasoning about agents (Baillargeon et al., 2016; Banaji and Gelman, 2013). Moreover, BIB adopts a "violation of expectation" (VOE) paradigm (similar to Riochet 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. BIB thus serves as a key step in bridging machines' impoverished understanding of intentionality with humans' rich one.

2 Baby Intuitions Benchmark (BIB)

BIB presents a battery of agency-reasoning tasks, based on findings from developmental psychology and adopting its VOE paradigm, to evaluate computational models. We focus 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 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 predict 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

(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)

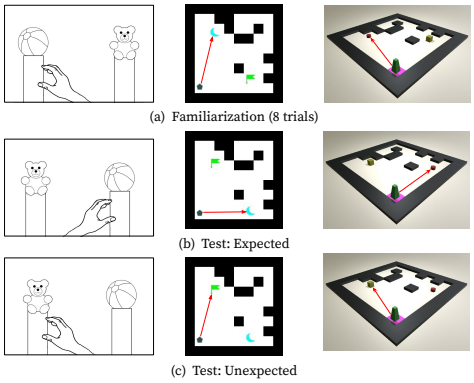


Figure 2: Can machines represent an agent's preferred goal object? Inspired by Woodward (1998)'s study with infants (left), BIB presents an agent navigating to their preferred object in approximately the same location across eight familiarization trials. At test, the location of the preferred object changes. The expected outcomes presents the agent moving to their preferred object in a new location, and the unexpected outcomes presents the agent moving to their nonpreferred object in the preferred object's old location. This evaluation has been rendered in 2D (middle) and 3D (right).

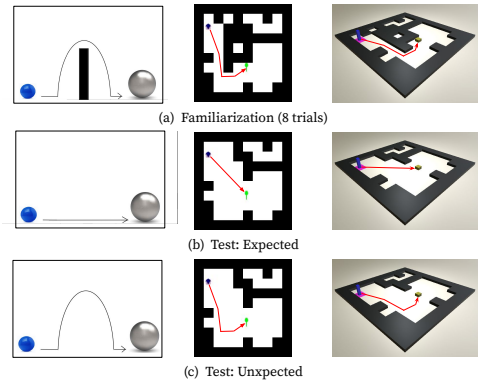


Figure 3: Can machines predict that rational agents move efficiently towards their goals? Inspired by Gergely et al. (1995) (left), BIB presents either a rational agent navigating around an obstacle to its goal or an irrational agent moving inefficiently to its goal. At test in both cases, there are no obstacles, and following an inefficient path is unexpected for the rational agent but yields no expectation for the irrational agent.

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 events while the expected outcome is more perceptually different. When VOE is used with infants, their looking time to each outcome is measured, and infants tend to look longer at unexpected outcomes, which "violate their expectations" (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 geometric shapes that take on different roles (e.g. "agents", "objects", "tools"). We chose this type of environment as particularly suitable for testing AIs (e.g., Baker et al., 2017; Rabinowitz et al., 2018) because it allows for procedural generation of a large number of episodes, and the simple visuals focus the problem on reasoning about agents. This environment 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 the 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 2 (left), Woodward (1998, 1999)'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 object 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 AIs, like infants, 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 contrast, 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 an one agent repeatedly moving to the same object, do AIs, like infants, expect that that object is preferred to 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 13; the same agent moves to the nonpreferred object (unexpected); or the new agent moves to the nonpreferred object (no expectation) (appendix, Figure 12). The model is successful if it has weak or no expectations about the preferences of the new agent.

2.3 Can an AI system understand that physical obstacles might restrict agents' actions and 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; Baillargeon et al., 1992; Spelke et al., 1992) and also 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.

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 6).

Test Trials. The test presents two new object locations. In the expected 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 6). The model is successful if it expects the agent to move 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

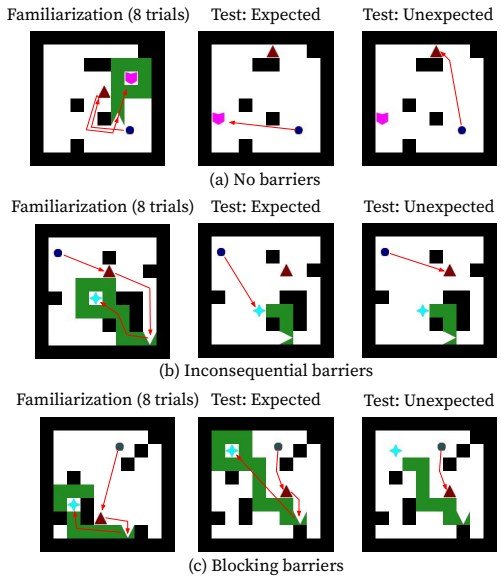


Figure 4: Can machines recognize instrumental actions towards higher-order goals? BIB's three types of trials test machines' understanding of instrumental actions. The agent's goal is initially inaccessible (blocked by a green removable barrier). During familiarization, the agent removes the barrier by retrieving the key (triangle) and inserting it into the lock. At test, the green barrier is not blocking the agent's goal, and so the agent's moving directly to the goal is expected, and its moving to the key is unexpected.

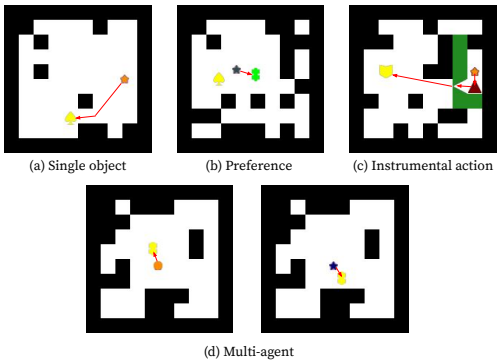


Figure 5: The four tasks from the background training set. Only the test trials are shown here.

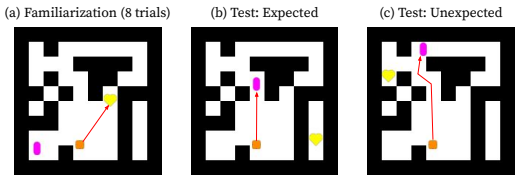


Figure 6: Evaluation of whether machines can understand that obstacles restrict actions. The familiarization trials establish the preference of the agent.

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 AIs, like infants, expect that 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 4). The green barrier initially restricts the agent's access to the object. And so, the agent removes the barrier by collecting and then 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 4a). In the scenario with an inconsequential green barrier: the agent moves directly to the object (expected); or to the key (unexpected) (Figure 4b). 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 goes 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 that object (Figure 4c).

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 (Baillargeon et al., 2015; 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 performed the same, now inefficient, action to get to the big circle or performed the straight, now efficient action. Infants were surprised when the agent performed the familiar but inefficient action. 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 efficient action at test (Gergely et al., 1995; Liu and Spelke, 2017). When shown a rational agent repeatedly taking an efficient path around a barrier to its goal object, do AIs, like infants, expect that that agent will continue to take efficient paths as opposed to similar-looking paths, once that barrier is removed?

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 gird 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. The agent either moves along an efficient path to its goal (expected) or the agent moves along 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 presence or absence of barriers and move efficiently to its goal.

3 Background Training

While infants in the lab make meaningful inferences about novel stimuli/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 the various elements and dynamics used in BIB's evaluation tasks. Just as infants get varied experience with agents, objects, and places in the real world, 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 now drawn from the same distribution within each episode. Similar to IntPhys (Riochet et al., 2018) and ADEPT (Smith et al., 2019), we only provide expected outcomes, predictable by human reasoning about agents, during training. There are four training tasks:

Single Object Task. The agent navigates to an object at some varied location in the scene (Figure 5a). This task is different from the evaluation task in that it presents only a single object. 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 but at varying locations relative to the agent's starting location, 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 preferred goal objects is not trained. We provide 10,000 episodes of this type.

No-Preference, Multiple-Agent Task. One object is located very close to the agent's initial starting location (Figure 5d). 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 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 trials, where the 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 5c). 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

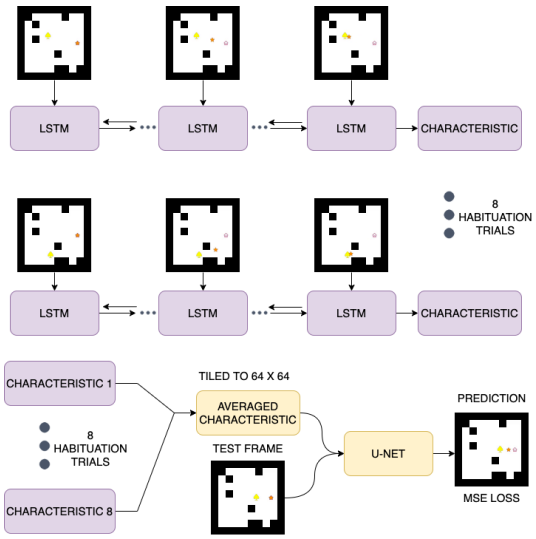
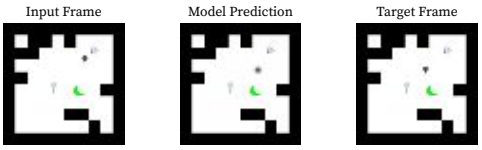
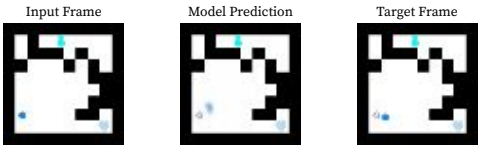


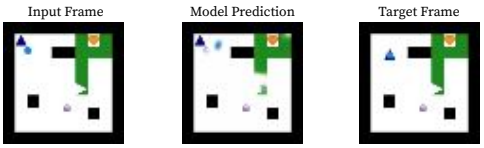
Figure 7: Architecture of the video baseline model inspired by Rabinowitz et al. (2018). An agent-characteristic embedding is inferred from the familiarization trials using a recurrent net. This embedding, with the state at test, is used to predict the next frame of the video using a U-Net (Ronneberger et al., 2015).



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



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



(c) The model predicts that the blue agent will directly 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. Failure cases are shown here.

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 trials 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 dataset. 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 an observable reward for RL algorithms. 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' understanding and 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. 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-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 either using 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).

5 Results

BIB Agency Task	BC-MLP	BC-RNN	Video-RNN
Preference	26.3	48.3	47.6
Multi-Agent	48.7	48.2	50.3
Inaccessible Goal	53.1	46.6	66.0
Efficiency: Path control	96.0	95.8	99.8
Efficiency: Time control	99.1	99.1	99.9
Efficiency: Irrational agent	73.4	48.8	50.0
Efficient Action Average	85.5	73.1	74.9
Instrumental: No barrier	98.8	98.8	99.7
Instrumental: Inconsequential barrier	56.7	78.2	76.7
Instrumental: Blocking barrier	48.2	55.9	58.2
Instrumental Action Average	67.9	77.6	78.2

Table 1: Performance of the baseline models on BIB. The scores quantify pairwise VOE judgements.

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). During evaluation, the expectedness of a test trial, in the context of the previous familiarization trials, is inferred by its error on the most 'unexpected' step (step with the highest prediction error). The most 'unexpected' step was chosen for comparison as alternatives (like the mean expectedness of steps) were empirically found to be inferior. 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%).

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)). The models with an 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 model thus neglects the agent's preference, established during familiarization. This is striking because the model does take into account the familiarization phase when succeeding in the No-Navigation Preference Task in the background training. This 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, making the familiarisation trials' length short. The characteristic encoder RNN might find it difficult to generalize to longer sequences seen in the evaluation tasks. The BC-MLP model is confused by how the object locations correlate with their identity, encoding an agent's preference for location instead of objects. This is surprising as the background training provides evidence that agents prefer object identities, not specific locations.

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 RNN-based-models fail to modulate their predictions based on whether the agent was rational or irrational during familiarization (Table 1). In contrast, BC-MLP has a weaker expectation of rationality from an irrational agent, scoring 73.4% 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 leads to higher scores on sub-evaluations with no barrier and an inconsequential barrier (Table 1) but lower ones on the sub-evaluation with a blocking barrier. This poor performance may be due to the difference between the agent and barrier conditions in the background training (where the agent is confined; Figure 5c) and evaluation (where the object is confined; Figure 4).

6 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 its results can be interpreted in terms of human performance. 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).

While the comparison between human and machine performance will be bolstered by future behavioral validation with infants, the results from the baseline models already shed new light on critical differences between human and artificial intelligence. 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 object. 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. Unlike infants, models thus seem to learn that efficiency, itself, is a goal. For infants, efficiency instead serves to inform their understanding of intentional actions. For example, when infants observe an agent going farther to a goal or exerting more effort to achieve it, they attribute both a preference for that particular goal to that agent and also 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 AIs may have built-in knowledge and/or pretraining, infants may need to watch 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. Relatedly, BIB's use of such simple visual displays raises new questions about the generalizibility of reasoning about agents. How is it that humans or machines might 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? Most of the existing infant literature off of which BIB is based presents infants with richer cues to animacy and in the form of live-action or animated displays from frontal or three-quarters points of view.

The origins and development of human, 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 intentionality with humans' rich one, since intentionality is one key component to understanding and reasoning about others in terms of their underlying mental states, including their beliefs and desires. A benchmark that focuses on reasoning about agents' intentional states, as well as their phenomenological and epistemic states, such as false-beliefs (a litmus test of human theory of mind (e.g. Baron-Cohen et al. (1985); Leslie (1987)), is thus a natural extension of BIB and could further advance our understanding of both human and artificial intelligence.

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1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See general discussion
   (c) Did you discuss any potential negative societal impacts of your work? [No]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
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