



#### Introduction

- Intuitive psychology, the ability to reason about hidden mental variables that drive observable actions, comes naturally to people.
- Despite recent interest in machine agents that reason about other agents, it is unclear if such agents learn or hold core psychological principles that drive human reasoning. states and are willing to be trained towards the goal.
- · Inspired by cognitive development studies on intuitive psychology, we present a benchmark consisting of a large dataset of procedurally generated 3D animations, AGENT (Action, Goal, Efficiency, coNstraint, uTility), structured around four scenarios (see the figure on the right).

### **Dataset Structure and Evaluation**

- 9240 videos synthesized in ThreeDWorld (TDW).
- 3360 trials in total, divided into 1920 training trials, 480 validation trials, and 960 testing trials. All training and validation trials only contain expected test videos.
- We provide RGB-D frames, instance segmentation. camera parameters, and ground-truth 3D states.
- 7 object shapes and 6 types of obstacles:

# **Object Shapes** Obstacles

Following Riochet et al. (2018), we define a metric based on relative surprise ratings. For a paired set of  $N_{\perp}$  surprising test videos and  $N_{\perp}$  expected test videos (which share the same familiarization video(s)), we obtain two sets of surprise ratings,  $\{r_i^+\}_{i=1}^{N_+}$  and  $\{r_j^-\}_{i=1}^{N_-}$ respectively. Accuracy is then defined as the percentage of the correctly ordered pairs of ratings:

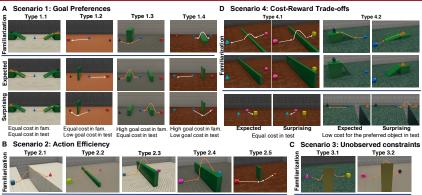
# $\frac{1}{N_i N_i} \sum_{i,j} \mathbf{1}(r_i^+ > r_j^+).$

# AGENT: A Benchmark for Core Psychological Reasoning

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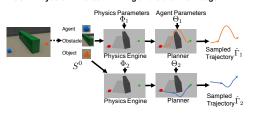


# Overview of Trial Types of Four Scenarios in AGENT

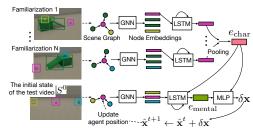


# **Baselines**

BIPaCK: Bayesian Inverse Planning and Core Knowledge



ToMnet-G: Theory of Mind Neural Network with Graphs



## **Experimental Results**

All: Trained on all types and scenarios: G1: Leave one type out: G2: leave one scenario out

Obstacle out of the A smaller obstacle in A different type of Path in the fam.

obstacle in test

violates solidity in test

surprising video

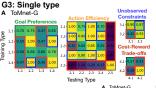
Condition	Method	Method Goal Preferences				Action Efficiency						Unobs.			Cost-Reward			All	
٠ ا		1.1	1.2	1.3	1.4	All	2.1	2.2	2.3	2.4	2.5	All	3.1	3.2	All	4.1	4.2	All	
	Human	.95	.95	.92	.97	.95	.87	.93	.86	.95	.94	.91	.88	.94	.92	.82	.91	.87	.91
=	ToMnet-G	.73	1.0	.53	1.0	.84	.95	1.0	.95	.88	1.0	.94	.95	.78	.85	.63	1.0	.82	.86
Ψ	BIPaCK	.97	1.0	1.0	1.0	.99	1.0	1.0	.85	1.0	1.0	.97	.93	.88	.90	.90	1.0	.95	.96
_	ToMnet-G	.63	.95	.53	1.0	.81	.95	.80	.45	.77	.05	.63	.45	.87	.70	.28	.42	.35	.63
G	BIPaCK	.93	1.0	1.0	1.0	.98	1.0	1.0	.80	1.0	1.0	.97	.93	.82	.86	.88	1.0	.94	.94
23	ToMnet-G	.50	.93	.50	.88	.73	.70	.60	.75	.75	1.0	.76	.60	.73	.68	.62	.98	.80	.74
5	BIPaCK	.93	1.0	1.0	1.0	.98	1.0	1.0	.75	1.0	.95	.95	.88	.85	.87	.83	1.0	.92	.94

G4: Single scenario

Inefficient path in the

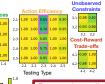
surprising situation

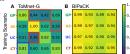
A ToMnet-G











Testing Scenario



Red: poor generalization (no better than chance); Blue: good generalization; Magenta: Failures of BIPaCK