

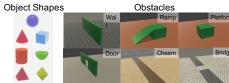


#### Introduction

- 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.
- 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:



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

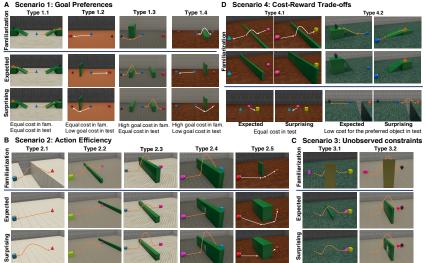
# AGENT: A Benchmark for Core Psychological Reasoning

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<sup>1</sup>MIT <sup>2</sup>MIT-IBM Watson Al Lab <sup>3</sup>Harvard Website: https://www.tshu.io/AGENT



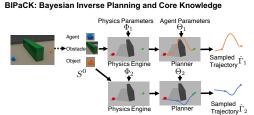
# Overview of Trial Types of Four Scenarios in AGENT



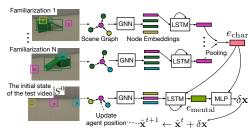
## Baselines

Inefficient path in the

surprising situation



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.

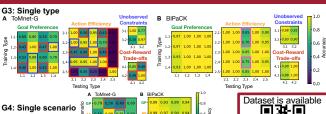
obstacle in test

.E	Method	Goal Preferences					Action Efficiency						Unobs.			Cost-Reward			All
Condition											$\odot$ $\Lambda$ $\triangle$			A@/					
_		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
W	ToMnet-G	.57	1.0	.67	1.0	.84	.95	1.0	.95	1.0	1.0	.98	.93	.87	.89	.82	.97	.89	.90
	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	.50	.90	.63	.88	.75	.90	.75	.45	.90	.05	.66	.58	.77	.69	.48	.48	.48	.65
5	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
-7	ToMnet-G	.37	.95	.63	.88	.71	.35	.60	.75	.68	.85	.65	.63	.80	.73	.55	.95	.75	.71
C5	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

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

violates solidity in test

surprising video



Testing Scenario

