Human and Machine Cognition Lab

What makes humans so uniquely intelligent?
How do people make the best use of limited cognitive resources?
What are the unique algorithms we use to learn from other people?

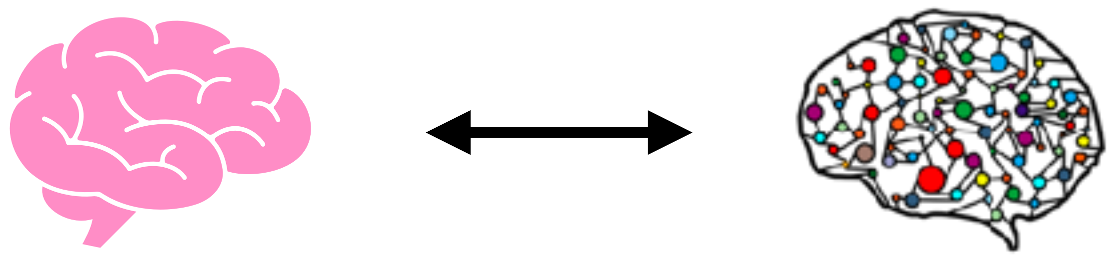
Lab Rotations and BSc/MSc Thesis Projects

[hmc-lab.com](hmc-lab.com)

Dr. Charley Wu
Group Leader
charley.wu@uni-tuebingen.de

About the HMC Lab

The HMC Lab is an Independent Research Group led by Dr. Charley Wu, with the goal of understanding the gap between human and machine learning.



Our research methods include:

- online experiments (commonly in the form of interactive games)
- lab-based virtual reality experiments
- computational modeling of behavior (e.g., decisions, search trajectories, and reaction times)
- evolutionary models and simulations
- developmental studies (comparing children and adults)
- neuroimaging using fMRI/EEG
- analyzing large scale real-world datasets

We also have a rich collaboration network of researchers from Harvard, MIT, Princeton, and multiple Max Planck Institutes around Germany. To find out more, visit the lab website at **www.hmc-lab.com**

Project 1: Pedagogy and Tool Discovery

Research Question

Tool use is a key signature of human intelligence (Rawlings & Legare, TICS 2020),
yet the cognitive mechanisms underlying how we develop and innovate upon tools is not well understood.

Here, we focus on the role of pedagogy in amplyifying individual innovations and unlocking cumulative cultural evolution

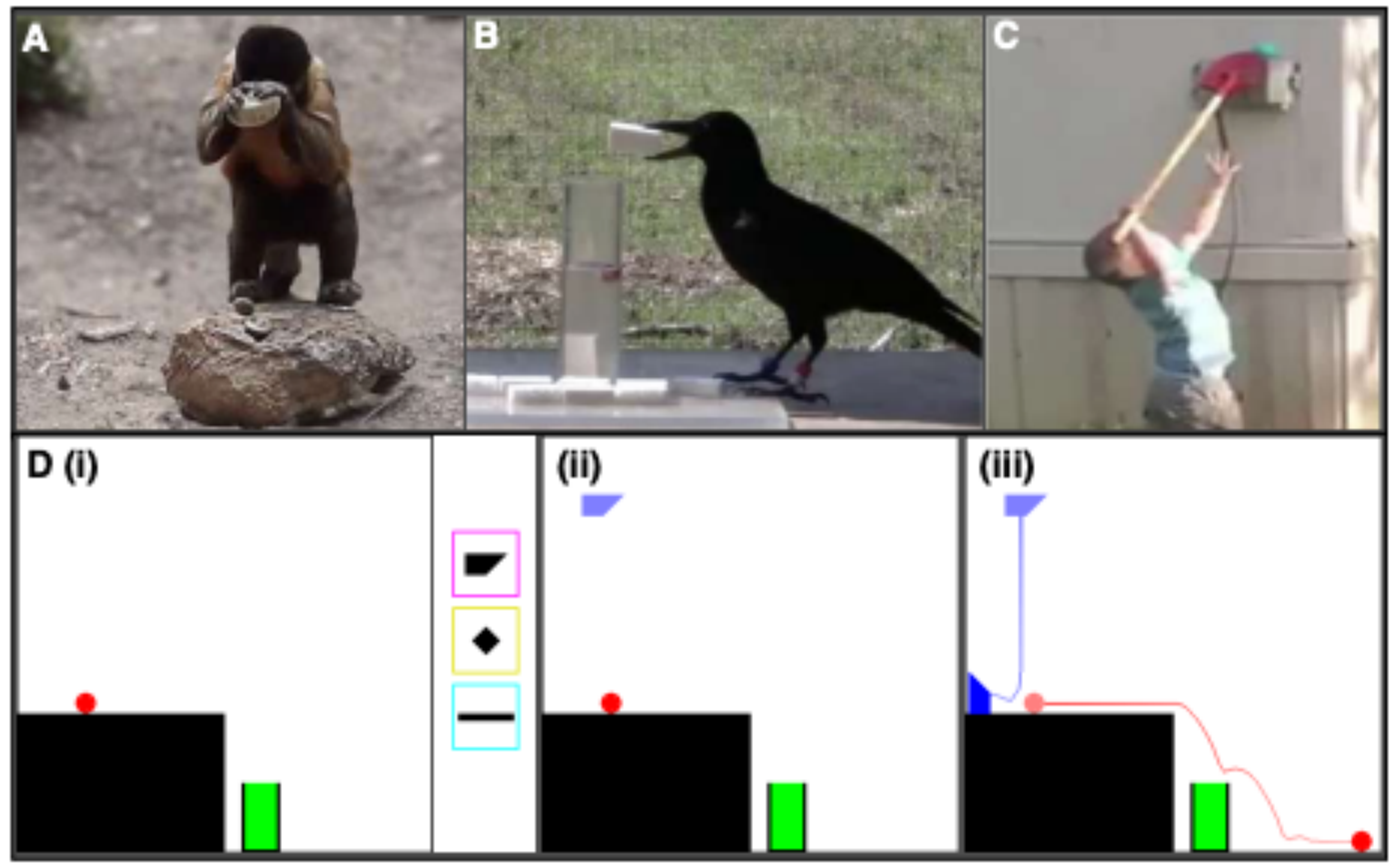
Approach

- Innovate upon a previous experiment (Allen*, Smith*, & Tenenbuam, PNAS 2020), where participants selected which tool they found most useful
- Here, we will allow people to develop their own tools and implement a transmission chain, where the solutions or instructions from one generation of participants will be passed along to the next
- Study the key ingredients for cumulative culture in tool use (e.g., observational learning vs. explicit pedagogy) and which task dimensions are most sensitive to pedagogy (e.g, opaque vs. transparent causal structure)

Scope

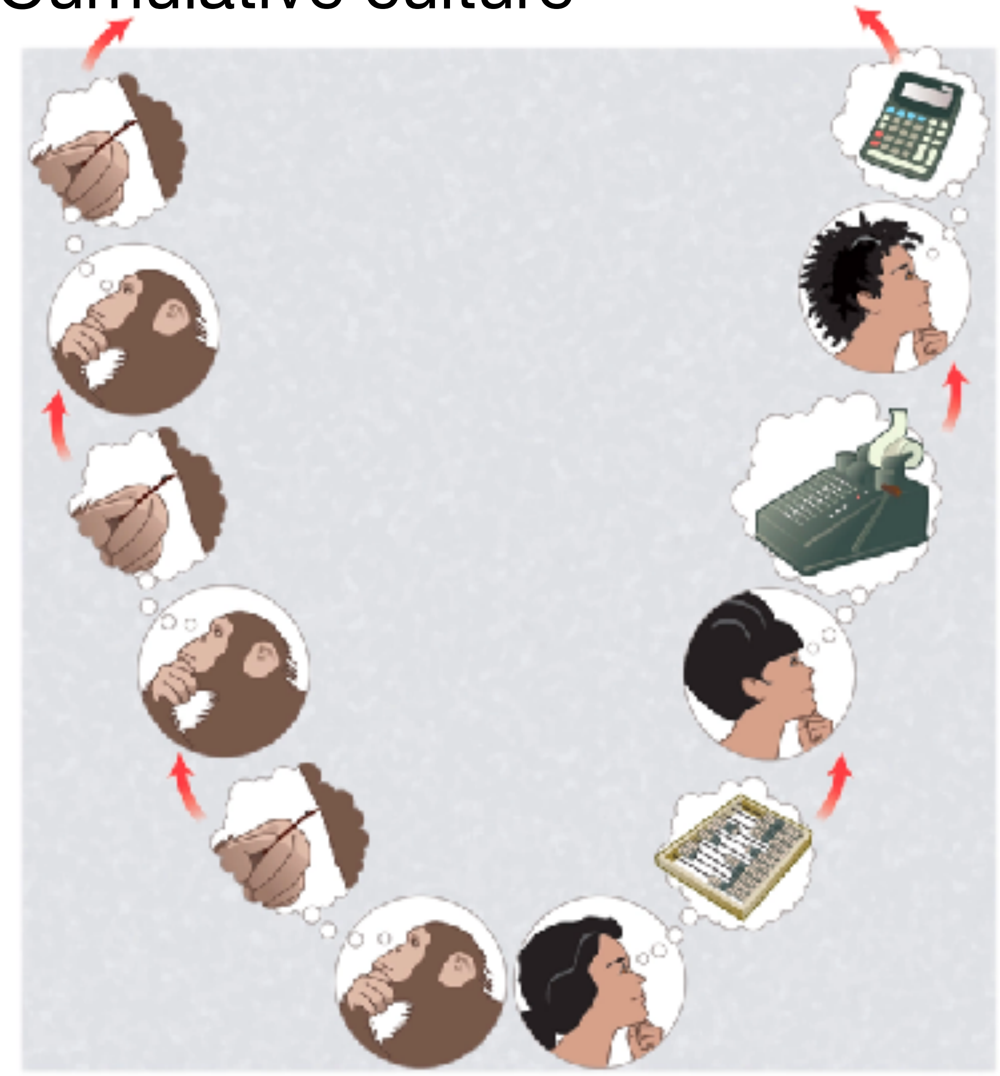
- Learn to design and implement an online experiment based on previous online experiment code (experience with Javascript/HTML/PHP highly recommended)
- Analyze data and perform statistical analyses (experience with Python/R encouraged)
- Collaboration with MIT and Deepmind

Tool use in animals and humans



Allen*, Smith*, & Tenenbuam (PNAS 2020)

Cumulative culture

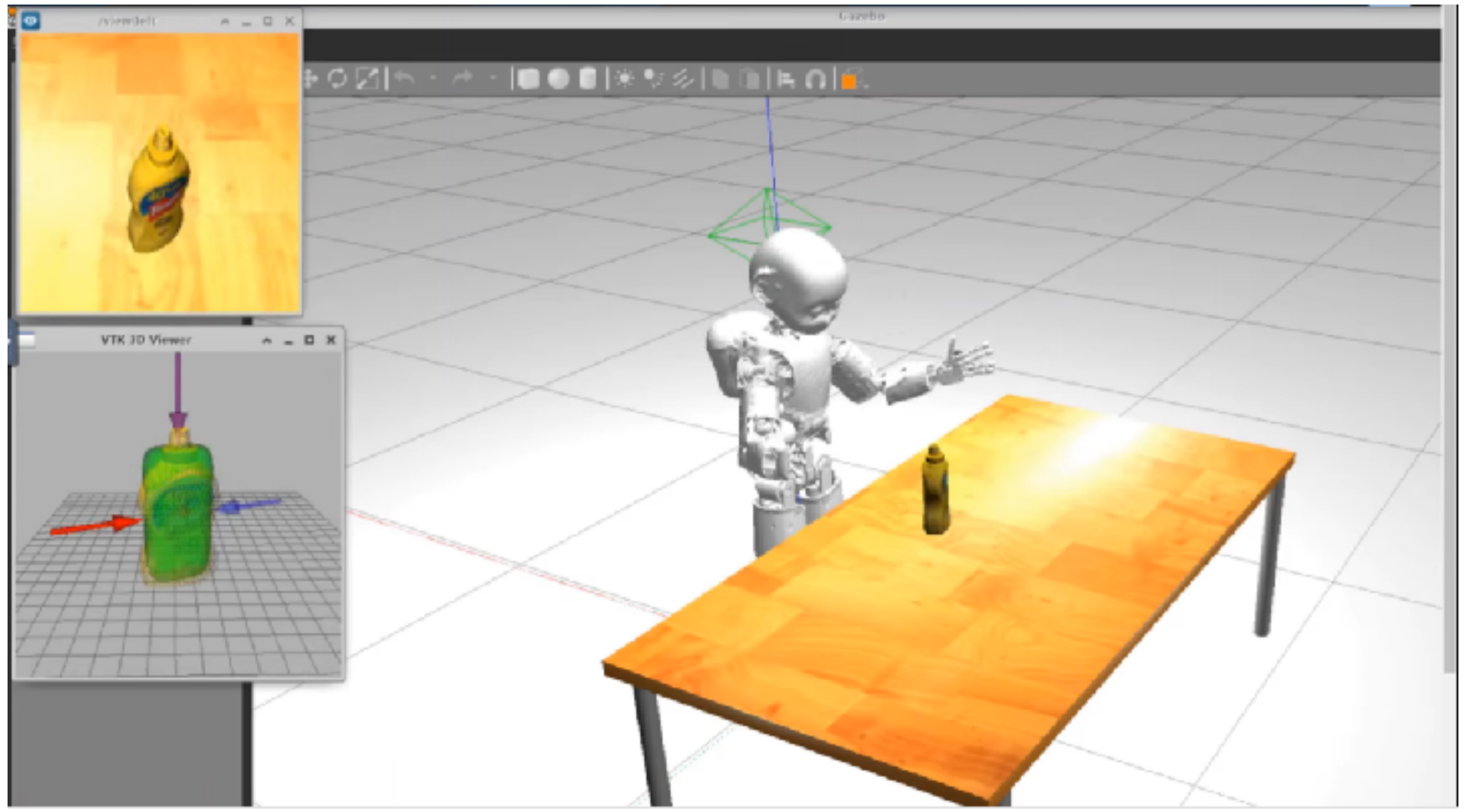


Kurzban & Barrett (Sci, 2012)

Project 2: Designing a MuJoCo environment for intuitive physical reasoning tasks

Research Question

According to Piaget, infants gradually learn to successfully search for hidden objects which points to the lack of *object permanence* as a cognitive concept in newborn's mind (Piaget, 1954). Other physical reasoning concepts like *continuity*, *solidity*, *gravity* and *inertia* also mature later during infant's cognitive development (Spelke et al., 1992). Smith and Gasser claim these reasoning abilities emerge in the interaction of an agent with an environment (Smith & Gasser, 2005). Taking inspiration from cognitive development literature, several attempts have been made to replicate intuitive physics reasoning in machines (Chang et al., 2017, Piloto et al., 2022, Agrawal et al., 2016, Smith et al., 2019). But none of these attempts have incorporated the idea from Smith and Gasser that intuitive physics understanding emerges from agent-environment interactions of the embodied agents. To implement this in practice, a simulated playground is necessary for the machine to interact in. The goal of this project is to build such an environment.



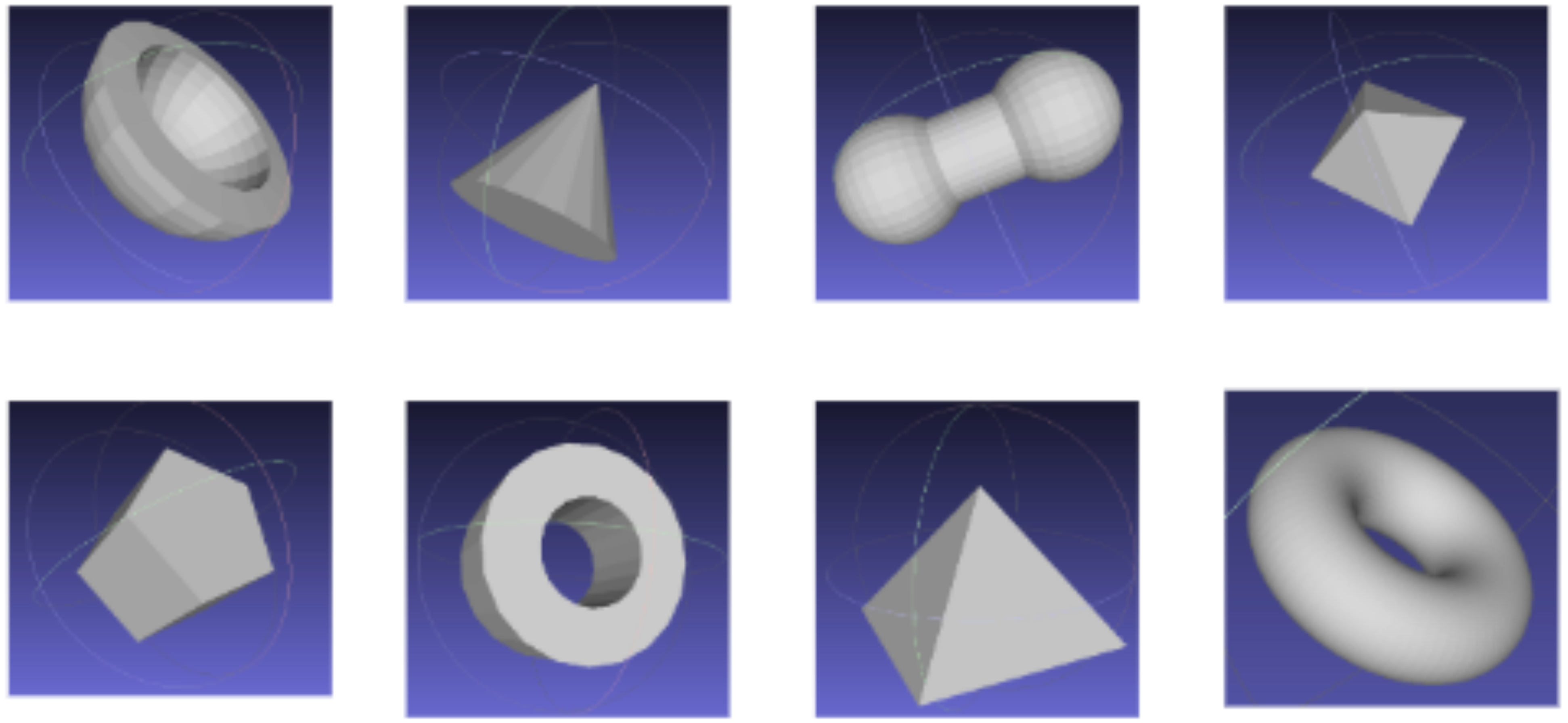
https://github.com/robotology/icub-gazebo-grasping-sandbox

Approach

- Improve upon the existing MuJoCo environment
- Add a curriculum of tasks with different objects for the iCub robot to interact with in the simulation
- Create an OpenAI gym environment from the MuJoCo environment

Scope

- This is meant as a lab rotation project
- Learn to code MuJoCo environments and turn them into an OpenAI gym environment
- Time permitting, the environments can be tested with existing neural network architectures



Kachergis et al. (2021)

Project 3: Neuro-Computational Cultural Evolution

Research Question

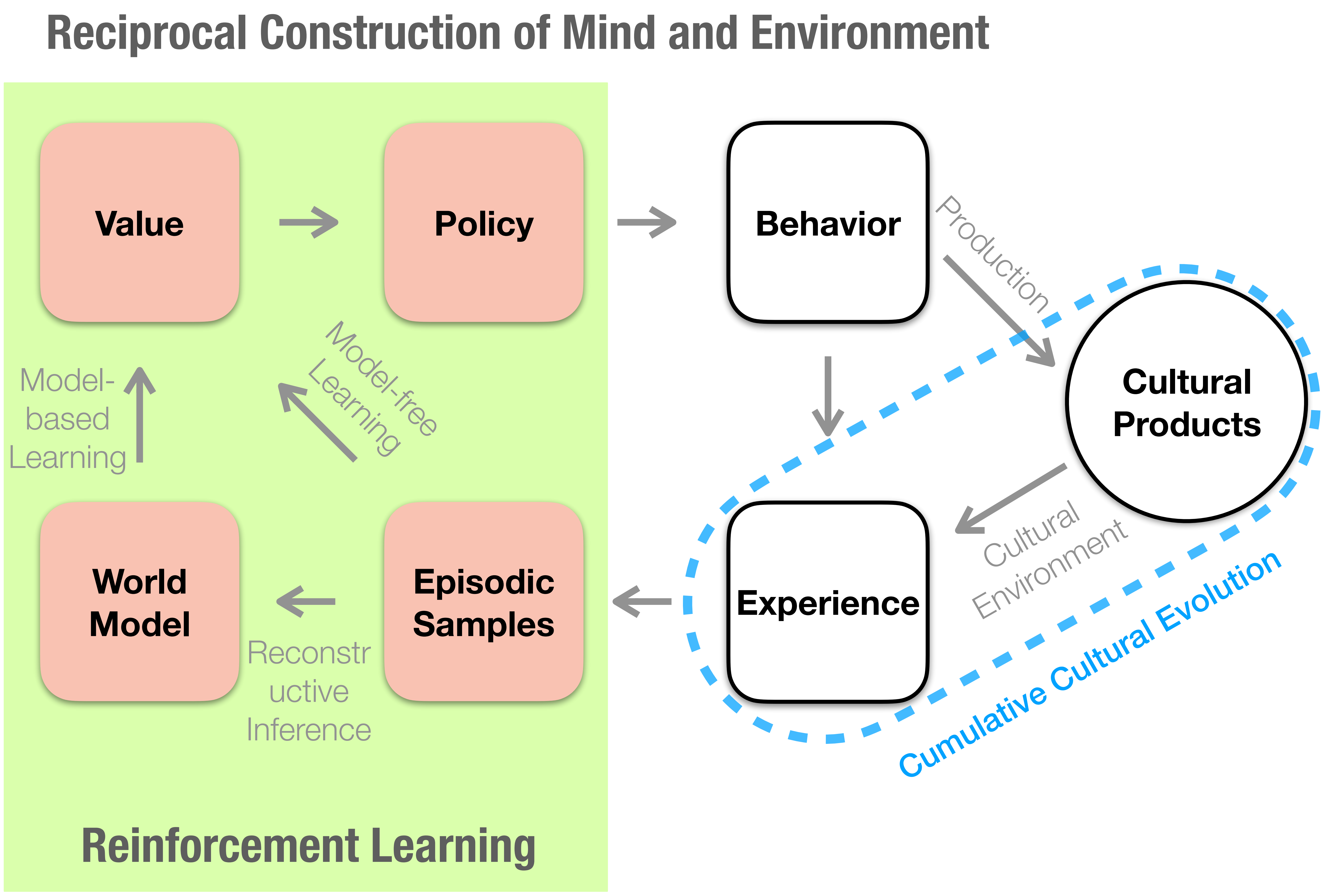
Originating from mathematical anthropology, the framework of cultural evolution has greatly advanced our understanding of cultural inheritance as an evolutionary dynamic akin to genetic evolution. It is currently the best explanation for human uniqueness, but it focuses largely on overt behavior. Here we aim to develop an understanding of how cultural evolution can shape representations in the mind (e.g., world models).

Approach

- Model the cultural evolution of the human mind by combining reinforcement learning and other AI systems (e.g., VAE, RNNs) with cultural evolutionary models of population dynamics
- Use the model to simulate the evolutionary divergence in cognitive abilities between humans and chimpanzees, in collaboration with primatologist Dr. Claudio Tennie

Scope

- We will build a computational simulation of the proposed process (figure on the right) using e.g., Python or R
- You will learn how to use such models to test evolutionary scenarios, comparing results with findings from animal behavior



Project 4: Episodic and model based control

Research question

Humans construct internal models to predict the consequences of possible actions. However in a newly encountered environment, limited experience can make it unfeasible to fit a parametric model. Therefore in the early stages of learning, relying on experiences directly may be more efficient (Lengyel & Dayan, 2009). It has been hypothesised that this constitutes a normative rationale for two complementary learning systems, one that constructs a parametric model (typically associated with the neocortex) and a non-parametric one (typically associated with episodic memory and hippocampal regions) (Kumaran et al, 2016, Nagy & Orban, 2006). We are interested in how the brain arbitrates between these two controllers as well as better understanding the computational trade-offs that they make.

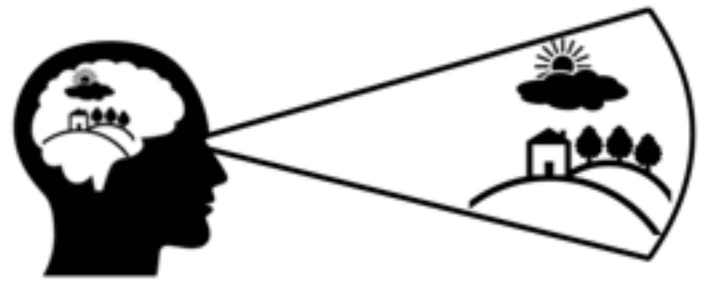
Approach

- Explore the interaction between parametric and non-parametric learning systems in a behavioural experiment, building on the setting of Xiong, Moneta, Banyai, & Wu, 2023
- Investigate how the contents of episodic memory are selected, specifically whether they are optimised to support the construction of the model
- We use a reinforcement learning framework and bayesian methods for computational modelling

Scope

- Implement an online experiment (experience with Javascript/HTML/PHP will be required)
- Option to construct computational models and analyse data (Python knowledge useful)
- Project in collaboration with MPI for Biological Cybernetics

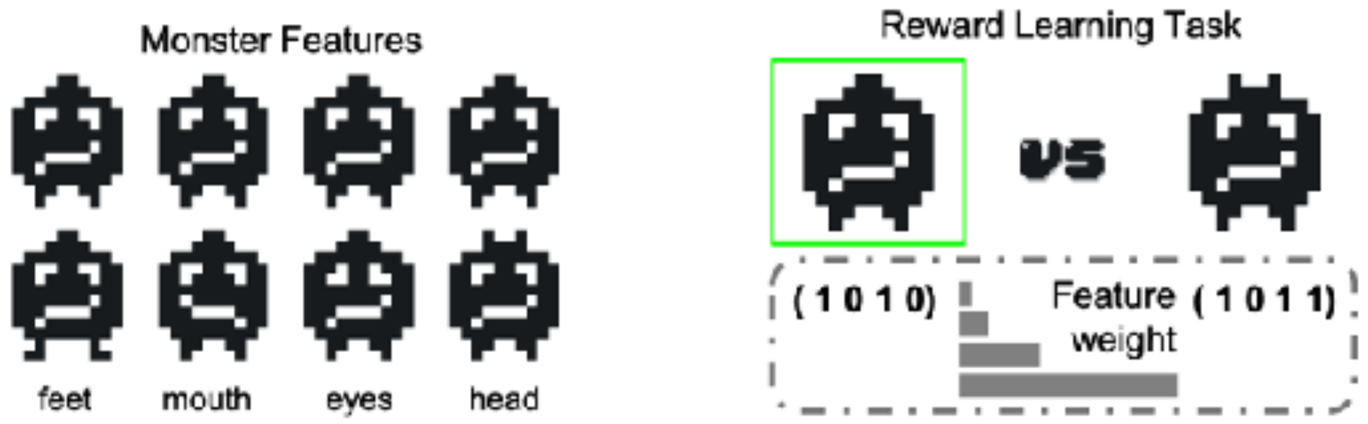
semantic model



$$p(x, z, \theta \mid \mathcal{D})$$

episodic memory

$$\{x_t\} \subset \mathcal{D}$$



Xiong, Moneta, Banyai, & Wu (CCN 2023)

Project 5: Neural correlates of reward generalization and exploration

Research Question

How do people integrate observations of reward when they also generalize to similar options?

Approach

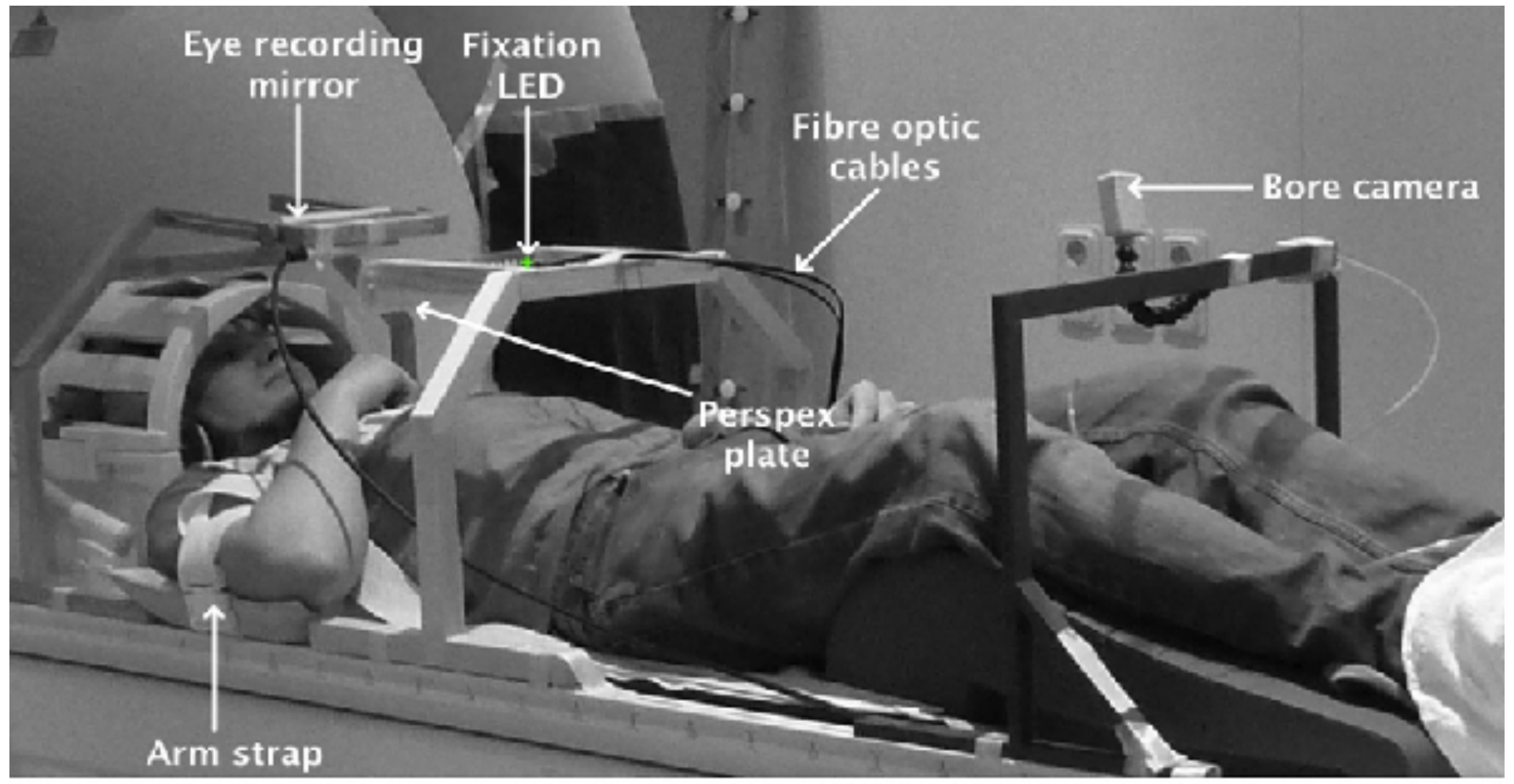
- Simultaneous fMRI and eye-tracking study planned for early 2023, using a modified version of the Spatially correlated bandit task
- Use eye-tracking to improve our process-level understanding of previous computational models (**Wu et al., 2018**; **Wu et al., 2020**)
- Relate model predictions and parameters to understand the neural mechanism underlying reward generalization and exploration

Scope

- Learn to design and implement an fMRI experiment based on previous online experiment code (Javascript/HTML)
- Learn to work with the analysis of eye-tracking data
- Collaboration with MPI Berlin and University of Hamburg

Spatially correlated bandit

7	5	10	22	32	32	28	24	22	26	33
6	11	19	29	38	41	42	40	37	36	40
22	27	30	35	43	50	53	53	51	49	46
45	44	38	36	40	46	47	49	54	55	48
61	55	46	40	37	32	27	31	44	52	44
62	59	57	54	44	27	14	17	33	46	45
53	59	68	71	59	36	17	15	28	45	51
46	57	71	77	67	47	26	18	27	45	56
45	56	65	67	60	46	29	20	27	42	55
51	57	58	53	47	40	30	23	28	40	49
60	62	58	47	39	38	35	31	35	41	46



Project 6: Experiments in Virtual Reality (VR)

Research Question

VR provides naturalistic and immersive setting for human experiments, combined with total control over environmental factors (ICON). This allows us to effectively study several cognitive processes like navigation (Kuhrt et al., 2022), cognitive load (Albus et al., 2021), and memory (Plancher et al., 2018), in social and individual settings.

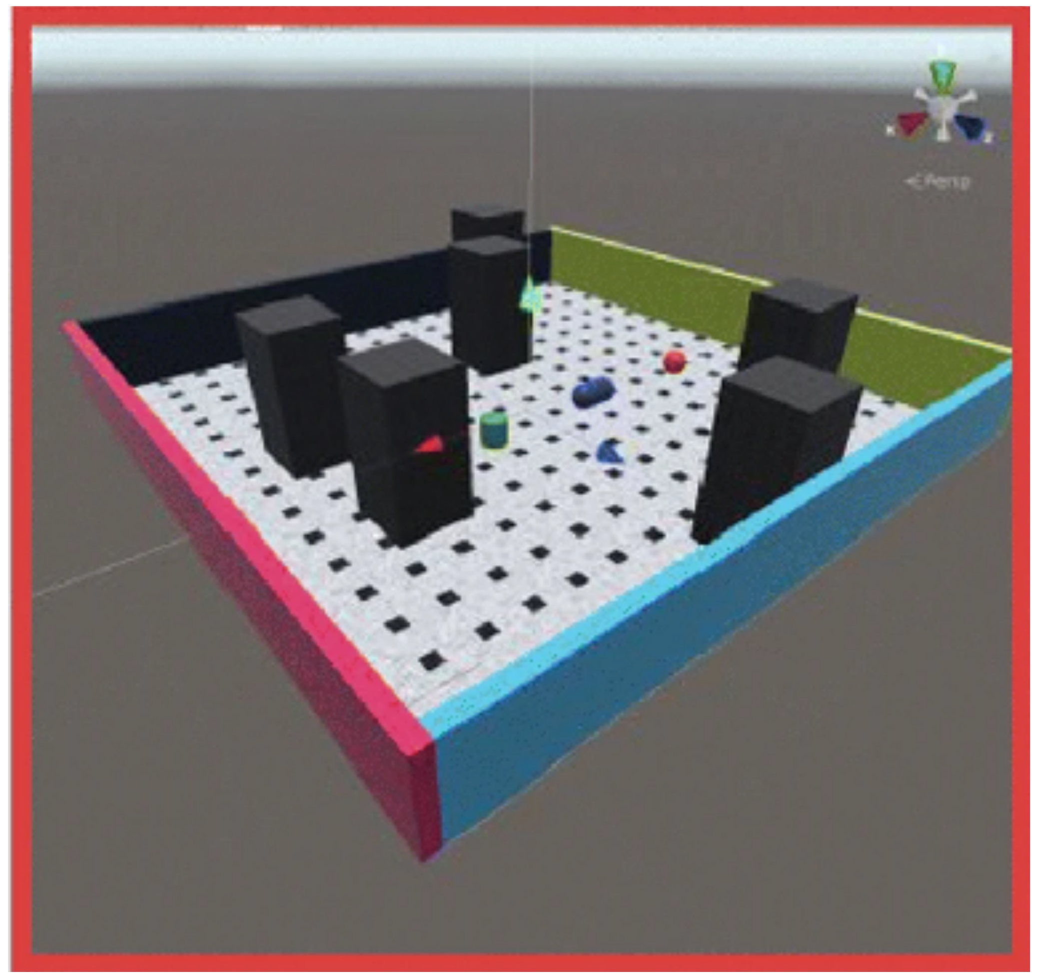
We are currently interested in understanding the role of social learning in competitive settings like Hide and Seek (Shen et al., 2019, Crawford et al., 2007, Wang et al., 2019).

Approach

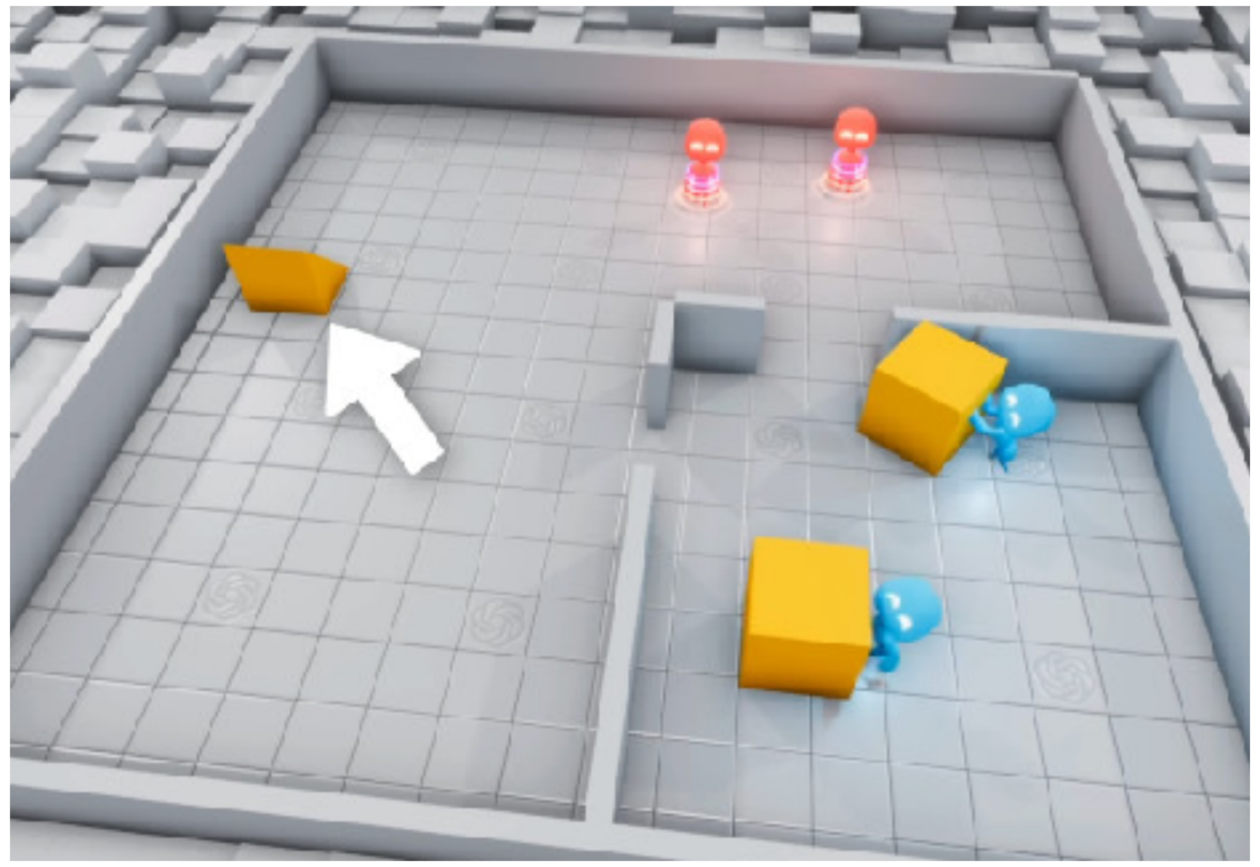
- Develop experiments in Virtual Reality using Unity. You can build off of an existing multiplayer hide and seek environment
- Collect data from players in Virtual Reality setting.
- Study the cognitive process in question using the collected data.

Scope

- Formulate research question to study relevant cognitive process (theory of mind, navigation, memory, etc.)
- Learn to develop environment using Unity or other VR toolboxes. Collect and analyze data using Python or R.



Landmarks: A solution for spatial navigation and memory experiments in virtual reality



OpenAI: Multi-Agent Hide and Seek

Project 7: Propose your own project!

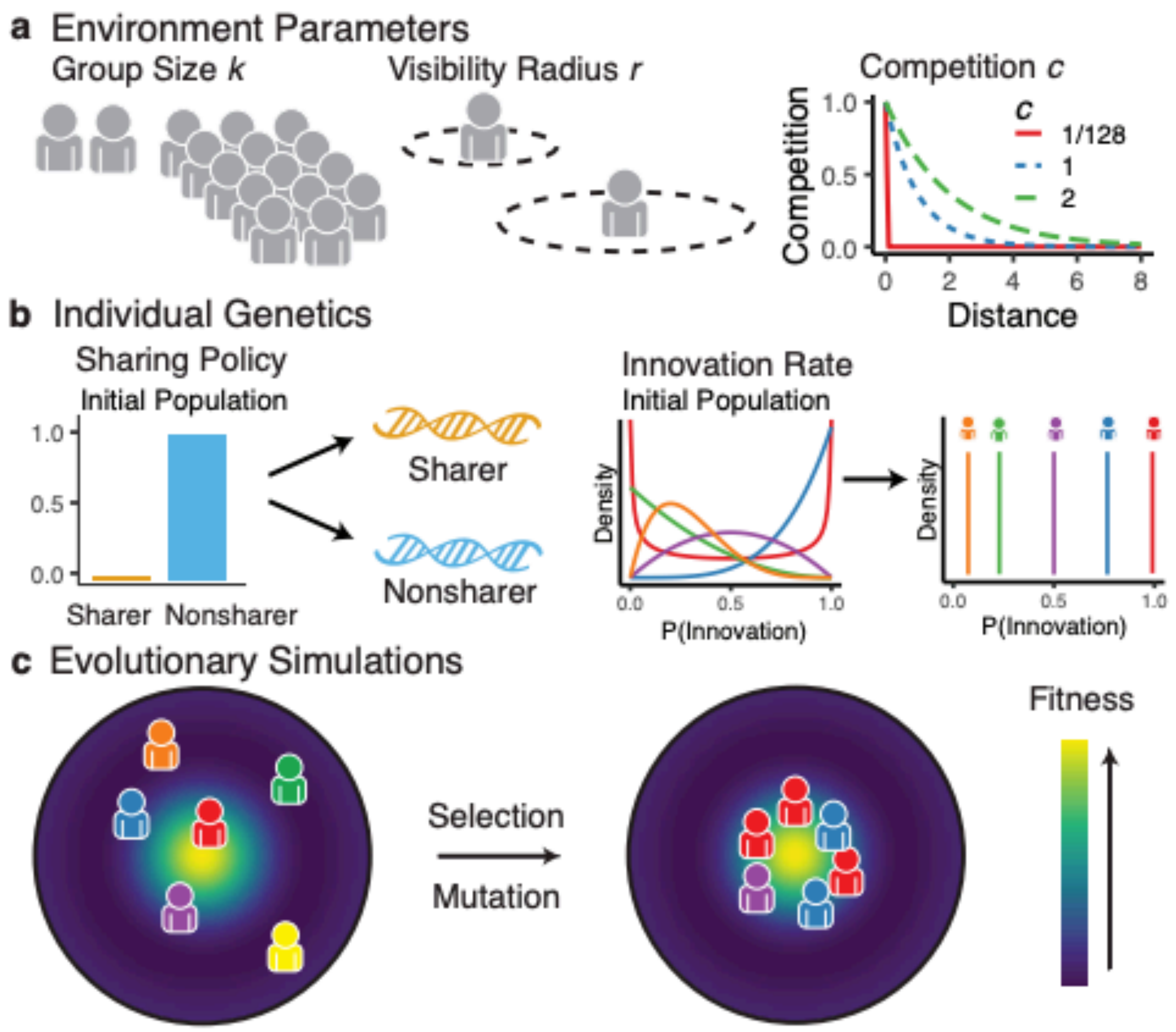
- Take the reigns and propose your own research project! To make things feasible within the rotation period or for a thesis, here are some suggestions of projects with existing data/code that could be built upon:

- **How does cooperation arise in competitive environments?** Through a series of agent-based and evolutionary simulations, we found that unconditional sharing of information can be beneficial, even in the absence of traditional reciprocity or reputation-based mechanisms. Many open questions, new environments, and learning mechanisms that can be tested

- **Why do people systematically under-generalize? Why are people systematically biased towards performing local search?** These are unexplained questions from a series of previous papers studying the search for rewards in spatially structured (Wu et al., 2018) and conceptually structured (Wu et al., 2020), and graph-structured environments (Wu et al., 2021). All the code and data are publicly available (1, 2, 3)

- **Note**: proposing your own project requires a high level of independent thinking and ability to craft an interesting and obtainable research question

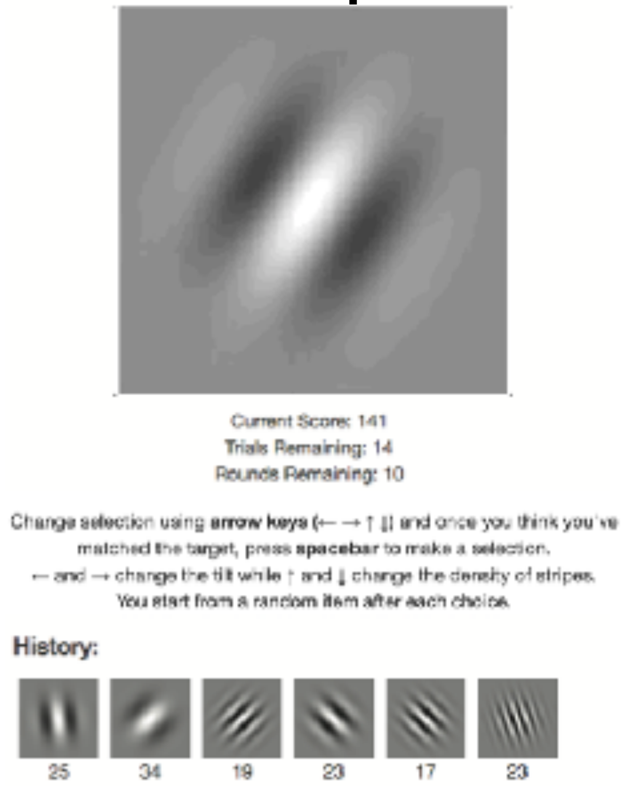
Evolutionary simulations



Spatial

7	5	10	22	32	32	28	24	22	26	33
6	11	19	29	38	41	42	40	37	36	40
22	27	30	35	43	50	53	53	51	49	46
45	44	38	36	40	46	47	49	54	55	48
61	55	46	40	37	32	27	31	44	52	44
62	59	57	54	44	27	14	17	33	46	45
53	59	68	71	59	36	17	15	28	45	51
46	57	71	77	67	47	26	18	27	45	56
45	56	65	67	60	46	29	20	27	42	55
51	57	58	53	47	40	30	23	28	40	49
60	62	58	47	39	38	35	31	35	41	46

Conceptual



Graph-structured