General Principles of Human and Machine Learning

Lecture 1: Introduction

Dr. Charley Wu

https://hmc-lab.com/GPHML.html

Overview

- Organization
  - Contact information and office hours
  - Introductions
  - Course organization
  - Grading
  - Schedule
- What is learning?

Course & Contact Info

Instructor
Dr. Charley Wu (charley.wu@uni-tuebingen.de)
Office hours by appointment (email)

Charley

Teaching Assistants
Hanqi Zhou (hanqi.zhou@uni-tuebingen.de)
Turan Orujlu (turan.orujlu@tuebingen.mpg.de)
Alexandra Witt (alexandra.witt@gmx.net)

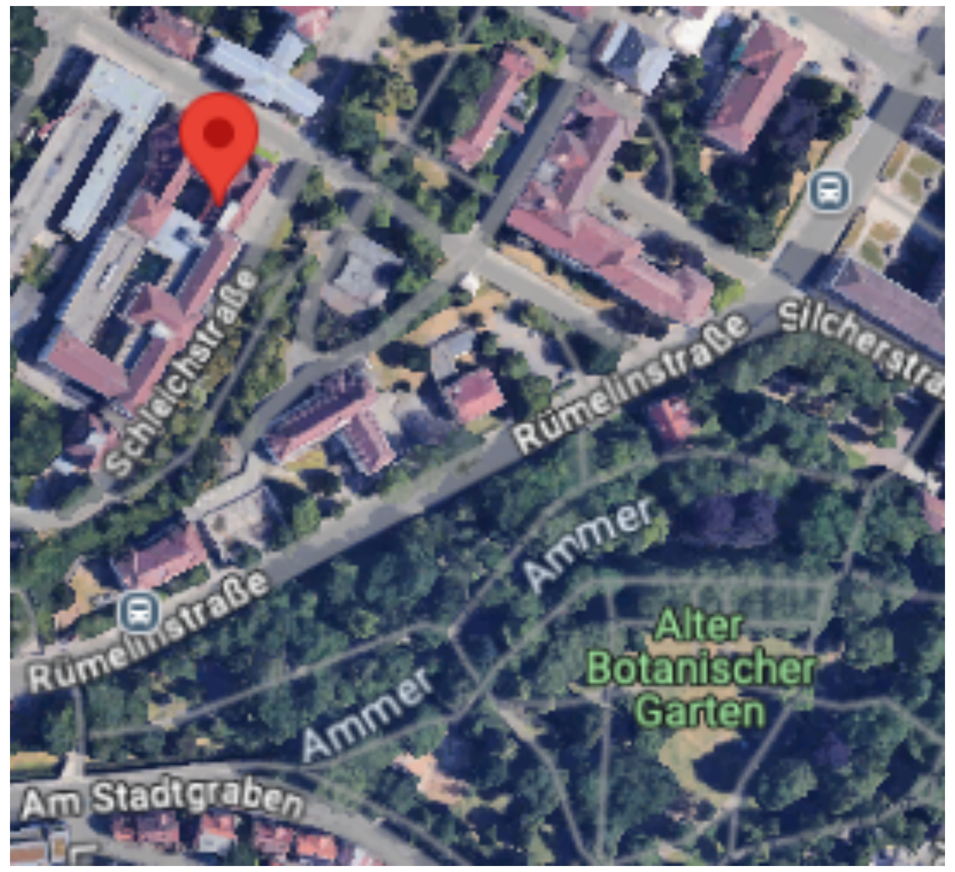
Hanqi

Turan

Alex

General information

Lectures: Tuesdays **12:15 - 13:45** @ Seminar Room 4332, Psychology Faculty (Alte Frauenklinik), Schleichstraße 4
Tutorials: Wednesdays **16:15 - 17:30** @ 3rd Floor Meeting Room, AI building, Maria-von-Linden-Str. 6



Course organization

Lectures

- Read assigned paper
- Show up to class, participate in discussion, and take notes

Tutorials

- Combination of hands-on exercises, (paper) discussions, programing challenges, and pop-quizzes (see Grading on next slide)
- Student responsibilities:
  - Keep up with material (complete assigned readings, re-visit lecture slides, visit office hours, ask TAs)
  - Show up and participate

Grading

- [**20% of grade**] Best 3 out of 4 pop-quizzes
  - They are designed to make sure you are following the material and are relatively easy marks
  - If you are unable to attend any tutorials, please email me and the assigned TA 24 hrs in advance (or as early as possible)
  - If you have well-documented absences, we may consider make-up quizzes or alternative solutions
- [**80% of grade**] Final exam
  - Tentative dates: Feb 21 (13:00-15:00) and April 11 (12:00-14:00)
  - Questions will be a combination of multiple choice and short answer questions

Discussion about tutorial scheduling

Some people have written me saying that the tutorial overlaps with other required courses

Alternative options given to me (location would still TBD, but likely SAND)

- Friday 8:00-10:00
- Friday 16:00-18:00

Should we keep the current slot or switch?

Introductions

- What is your name?
- What do you study?
- What do you hope to learn from this course?
- [Bonus] Name each of the people prior to you

Night sky for most of Earth’s history

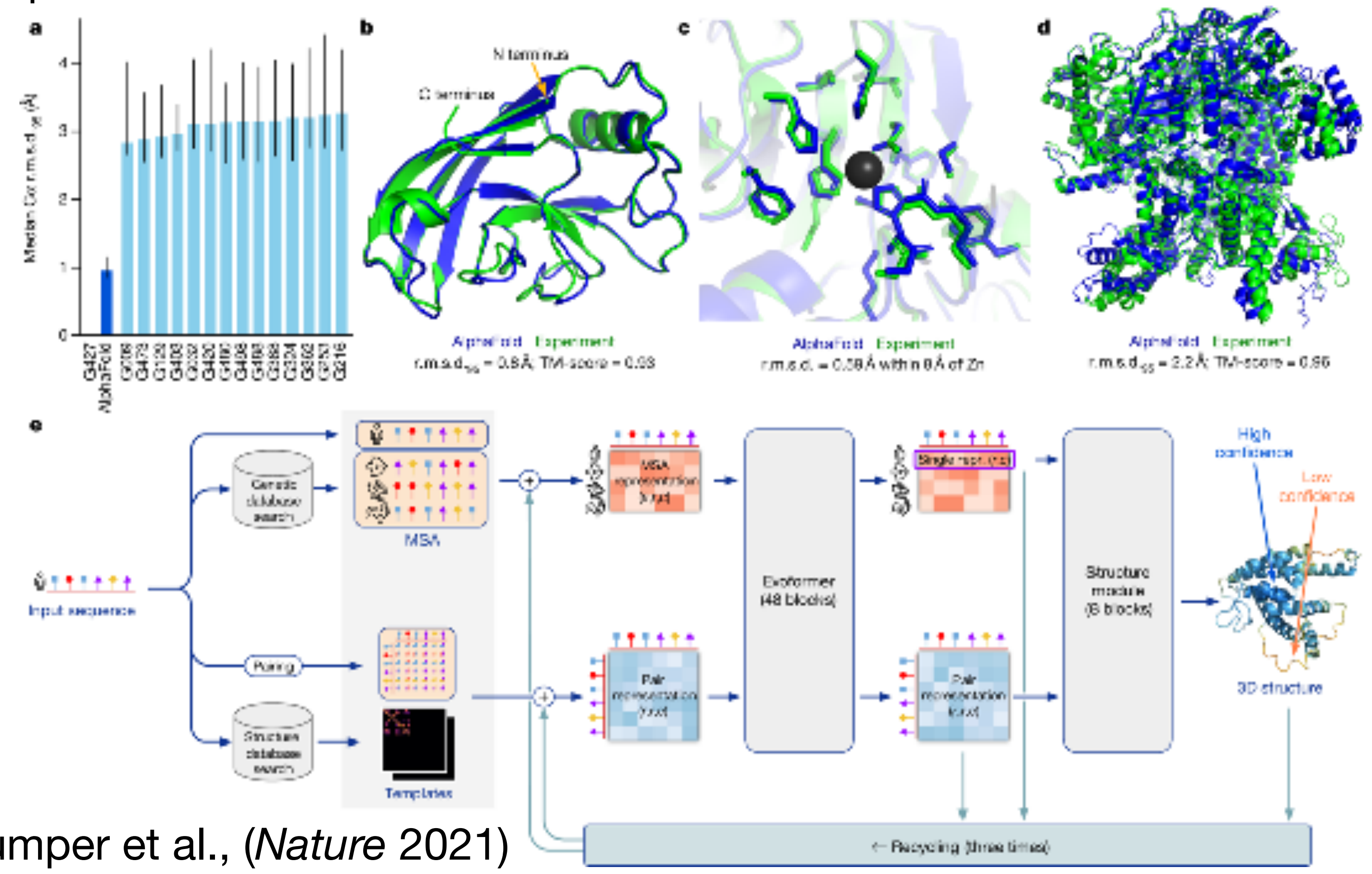
Night sky today

AI breakthroughs

AI breakthroughs

AI breakthroughs

AlphaFold



Jumper et al., (*Nature* 2021)

AI breakthroughs

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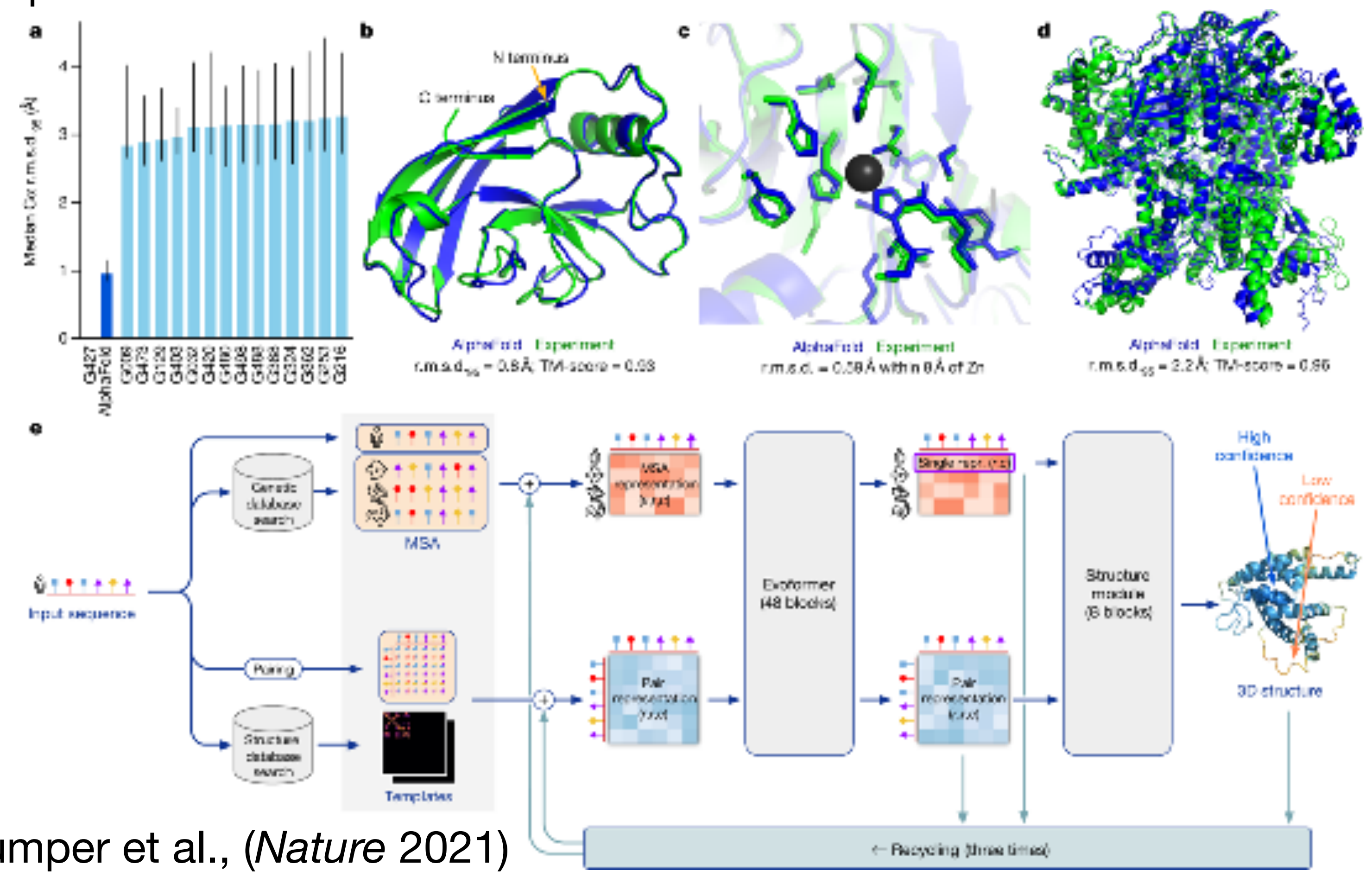

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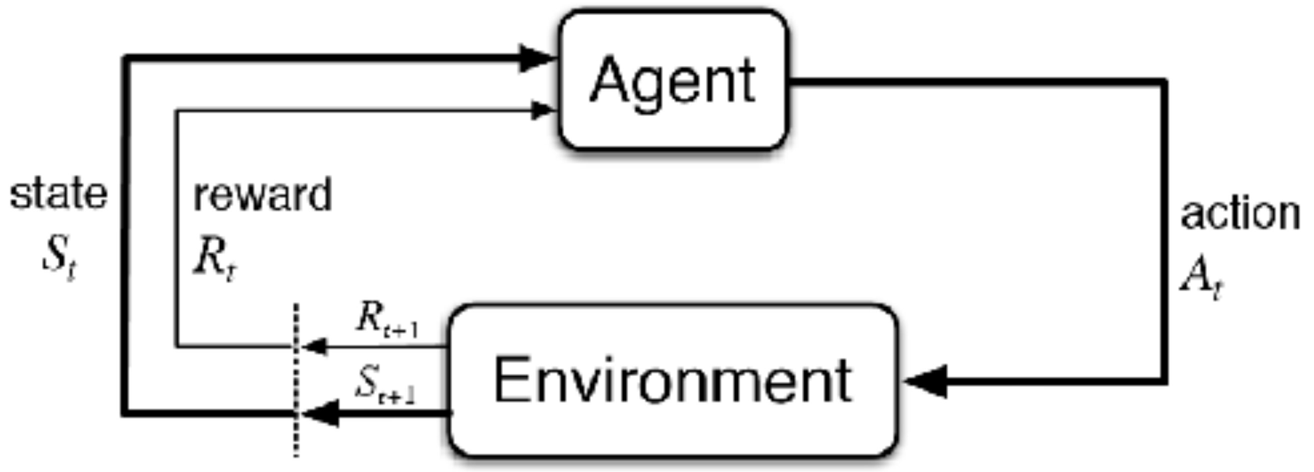
AI breakthroughs

Sutton & Barton (1998)



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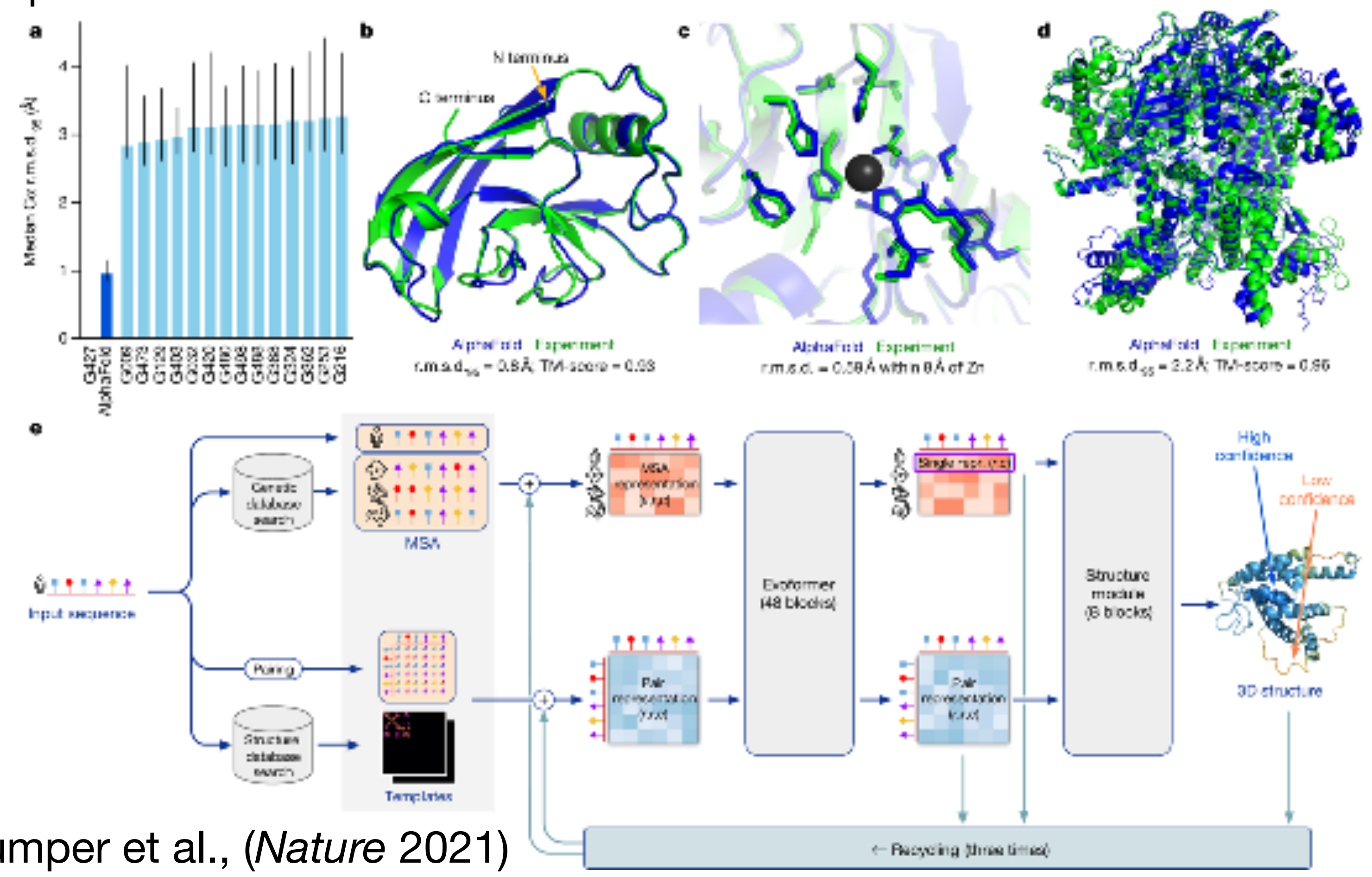

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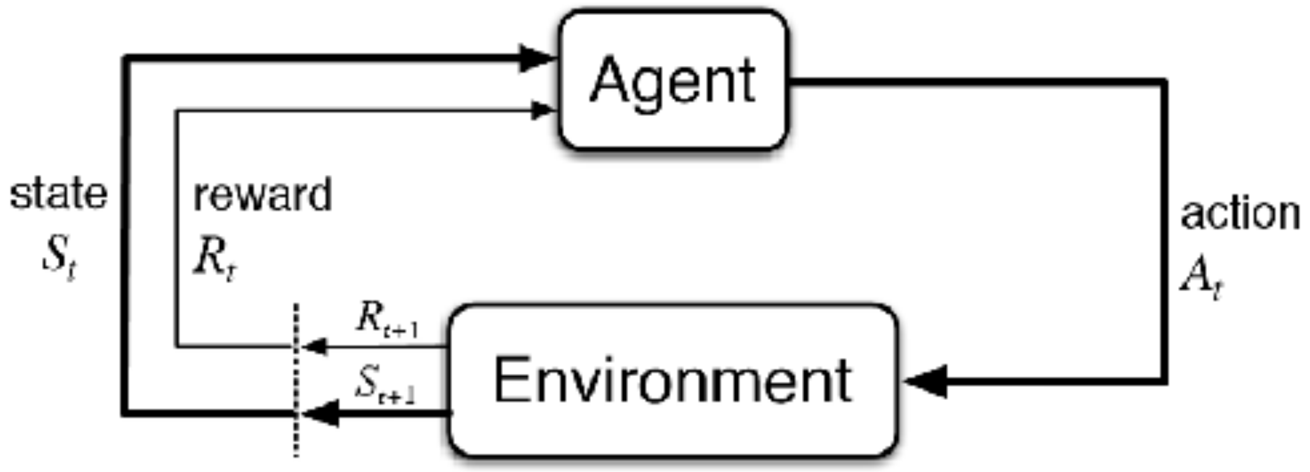

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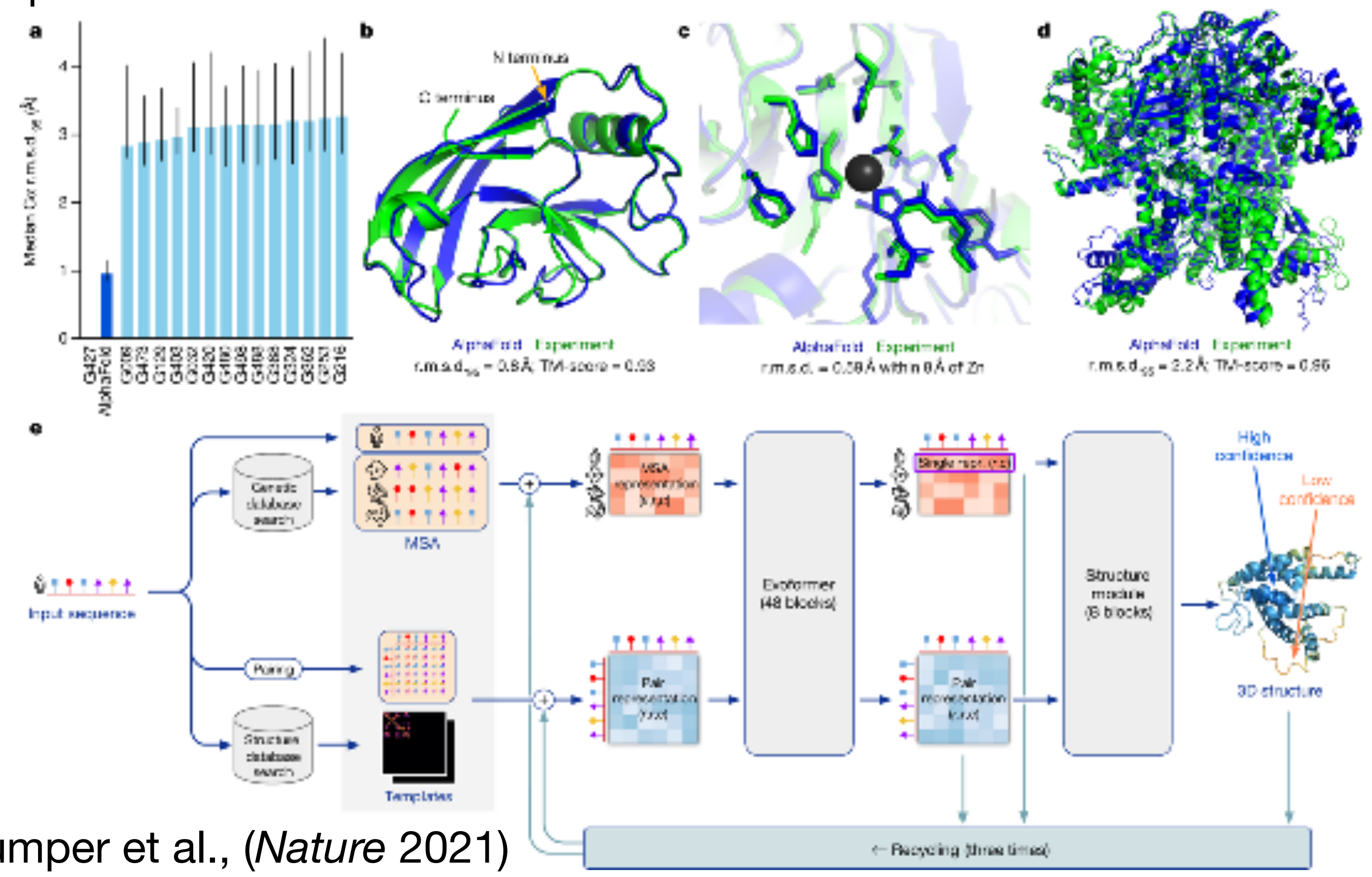

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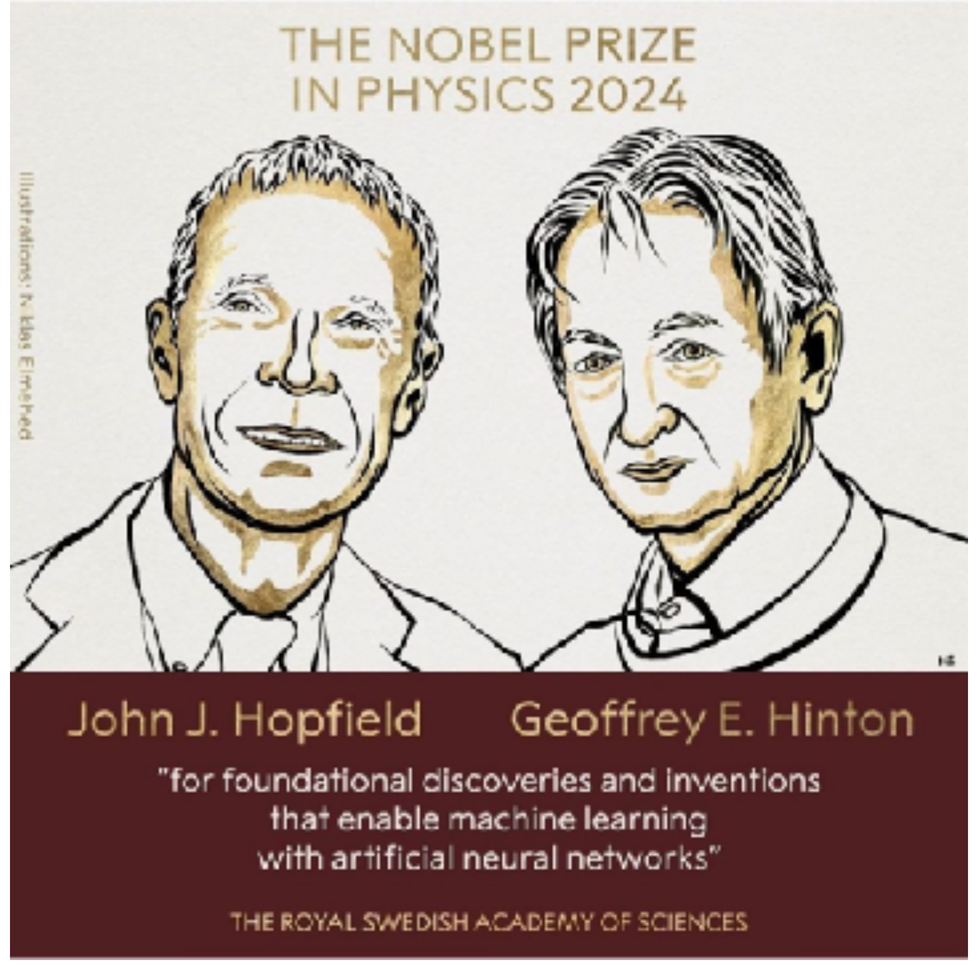

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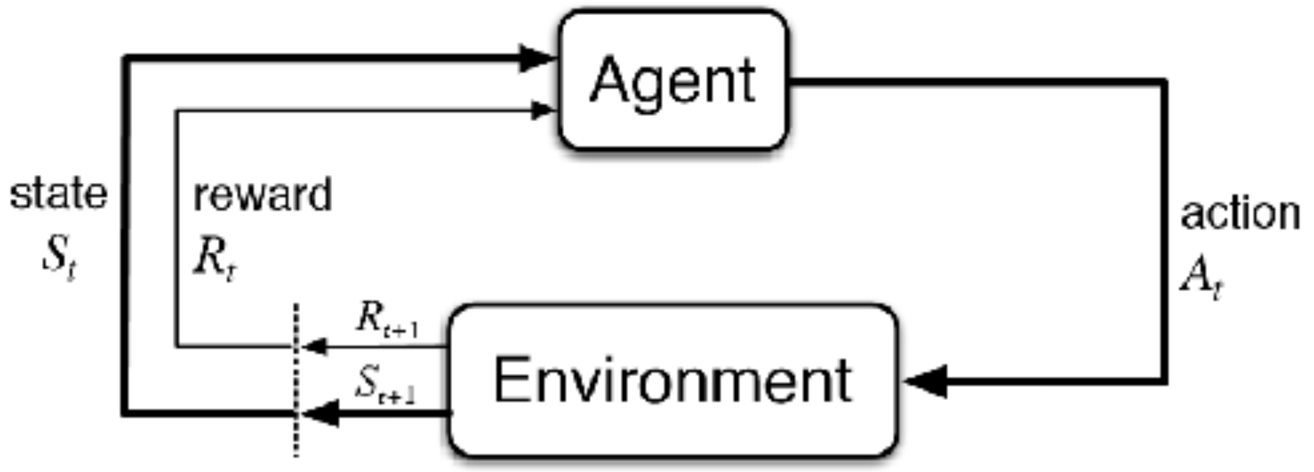

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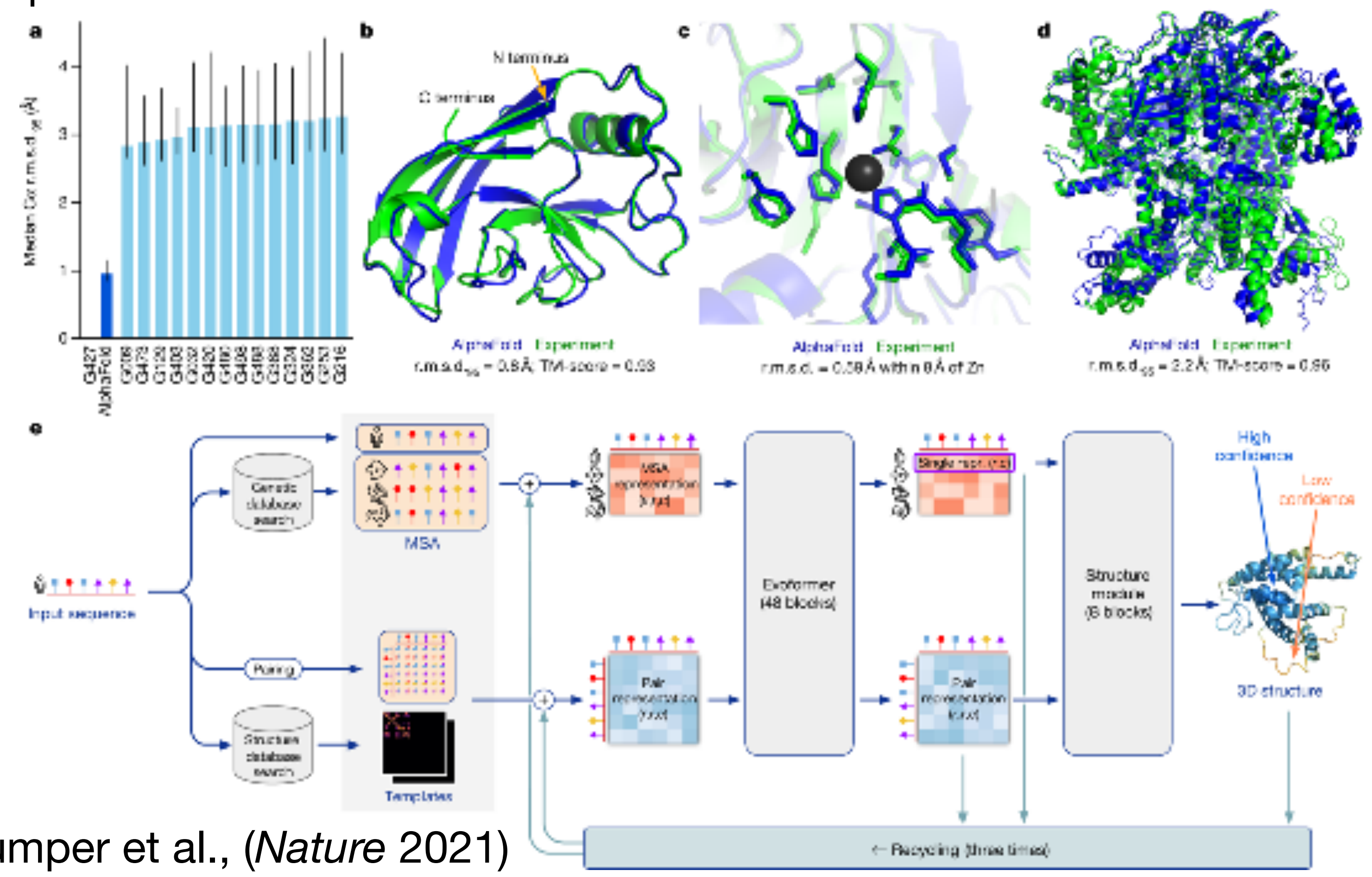

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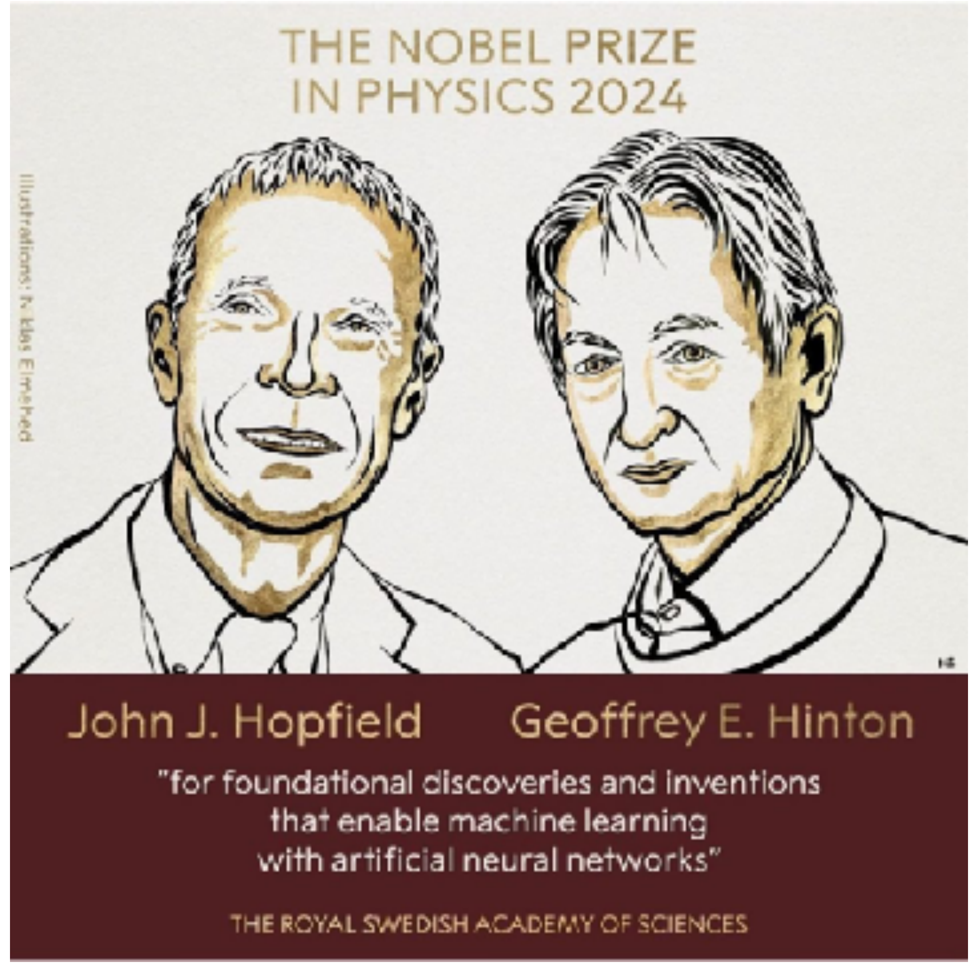

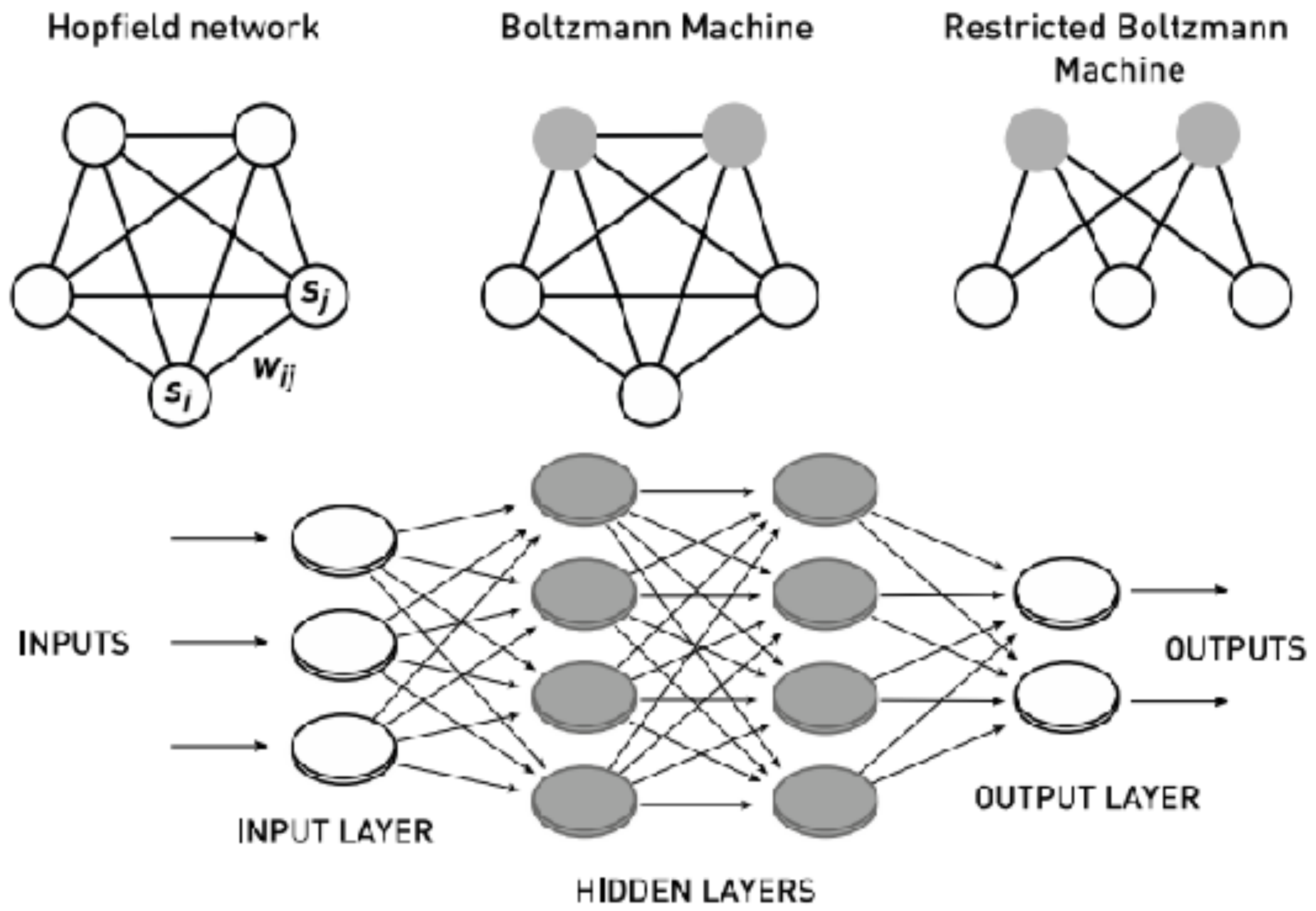

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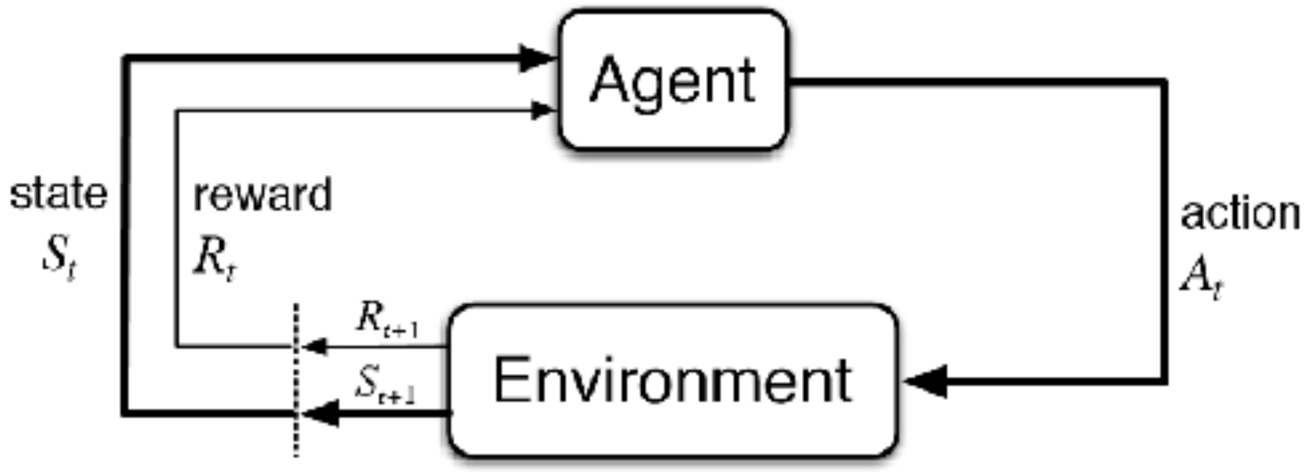

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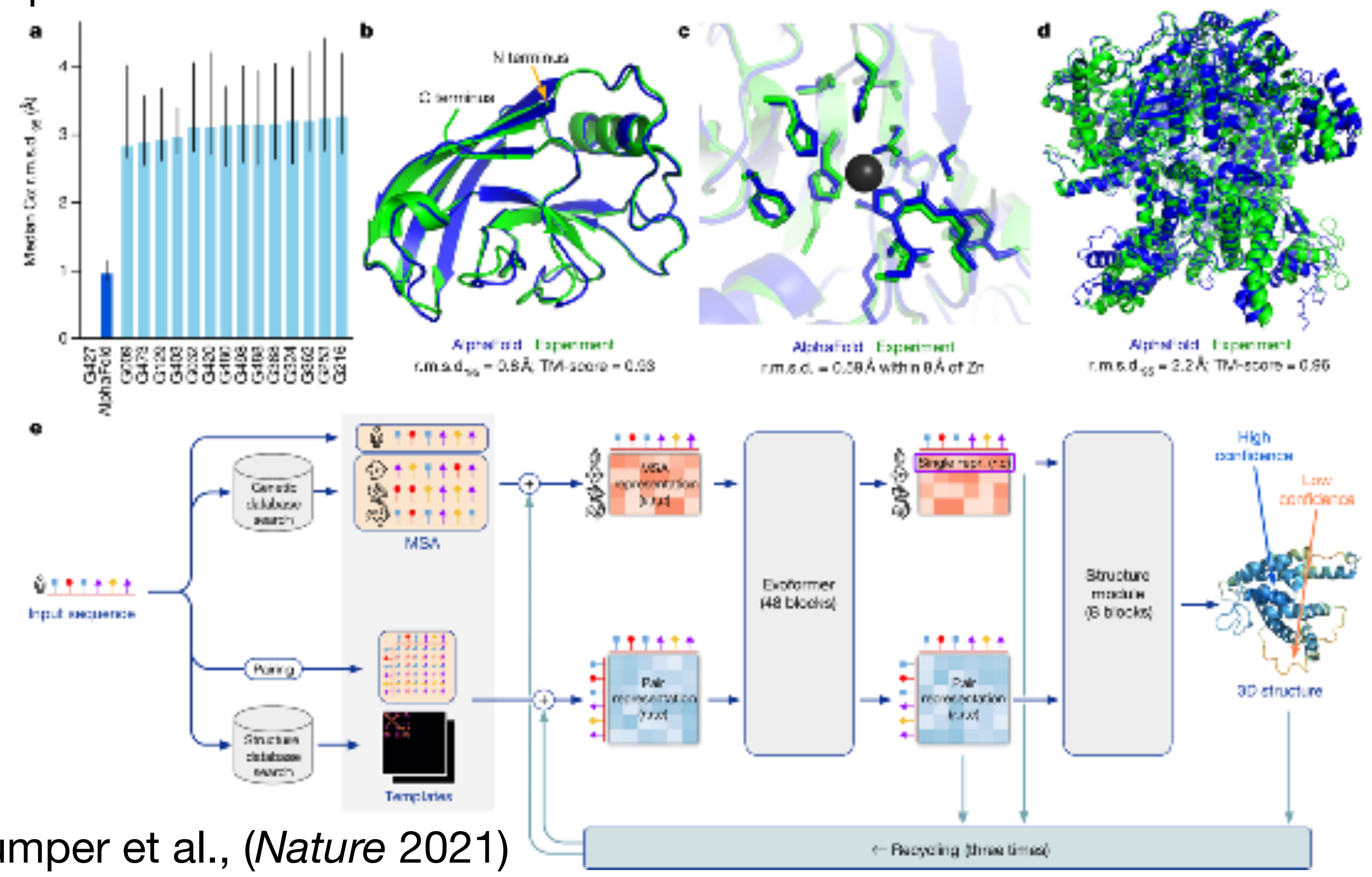

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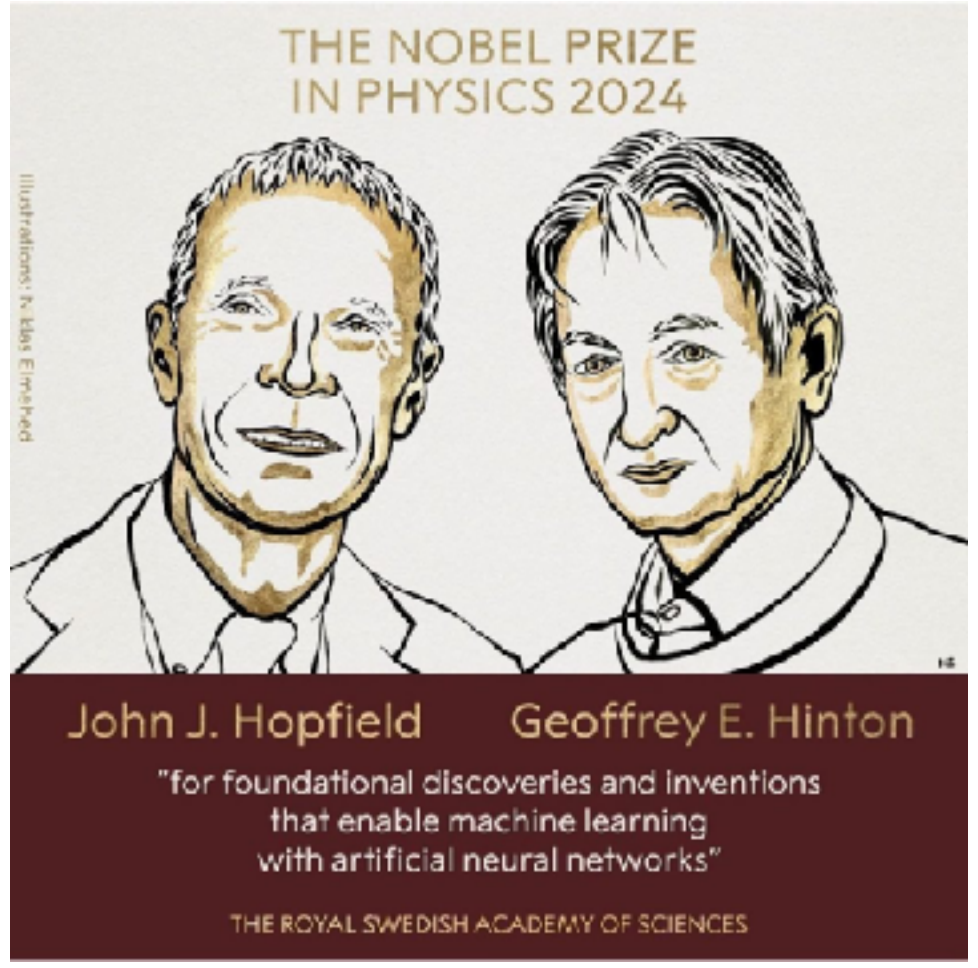
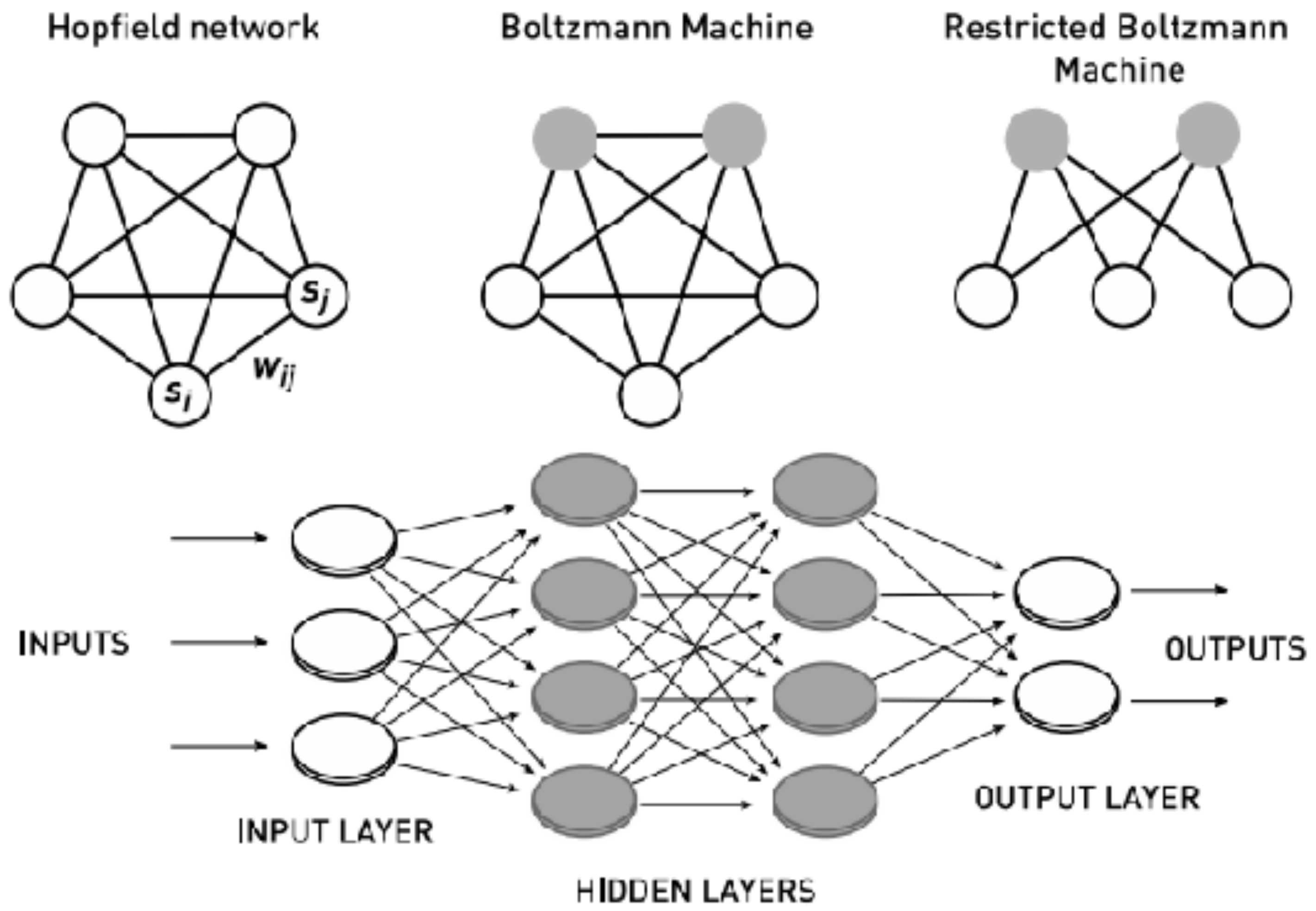




Alexnet (Krizhevsky et al., 2017)

ChatGPT

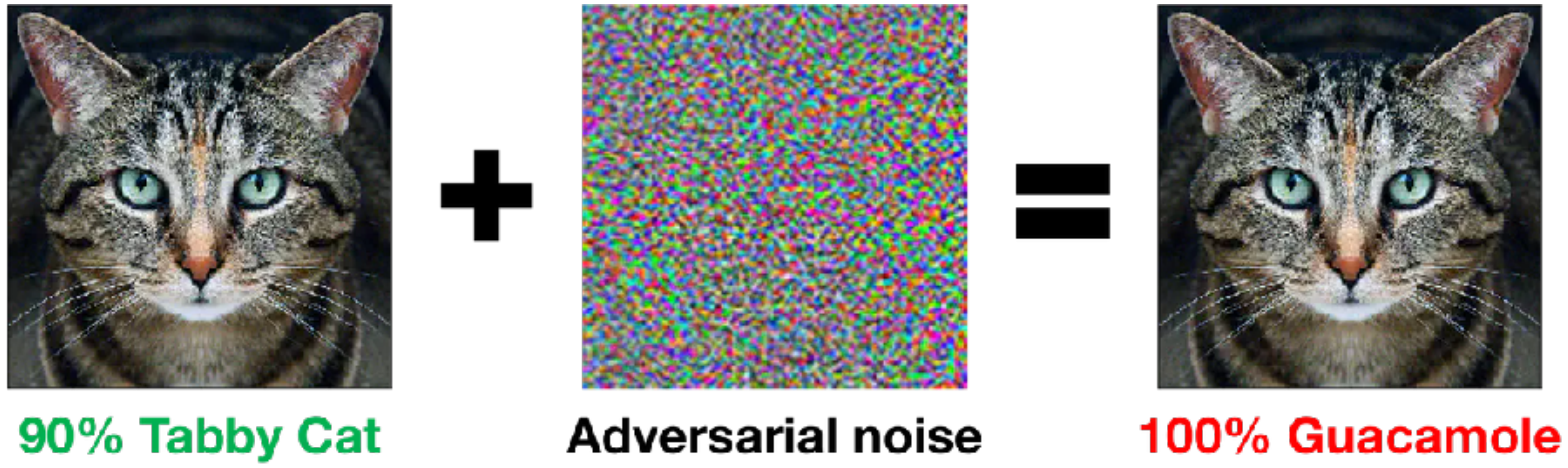
Prompt: A gorgeously rendered papercraft world of a coral reef, rife with colorful fish and sea creatures.

Sora

AI limitations

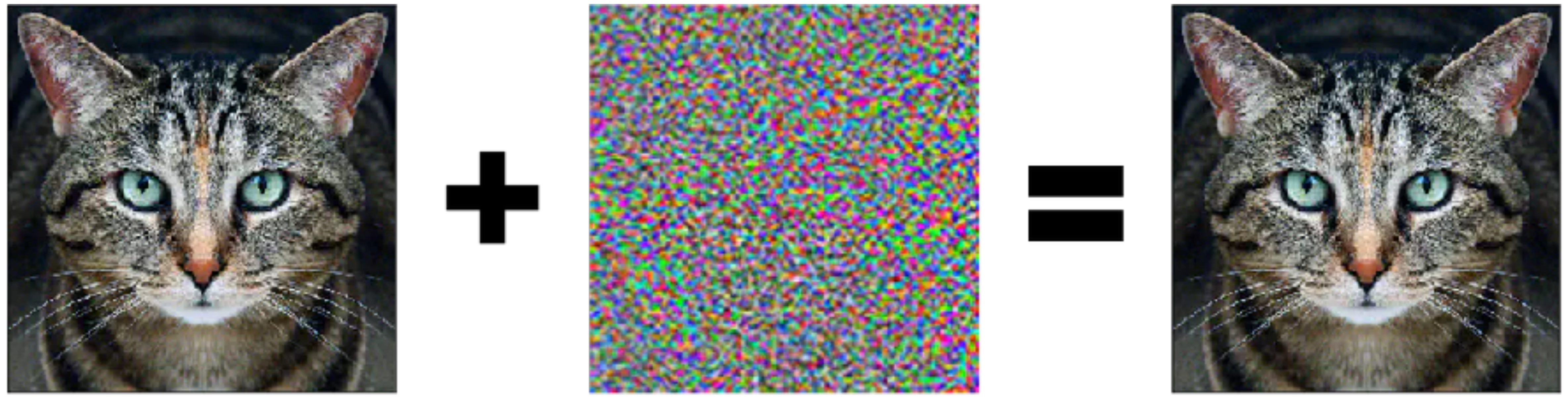
AI limitations

Adversarial examples



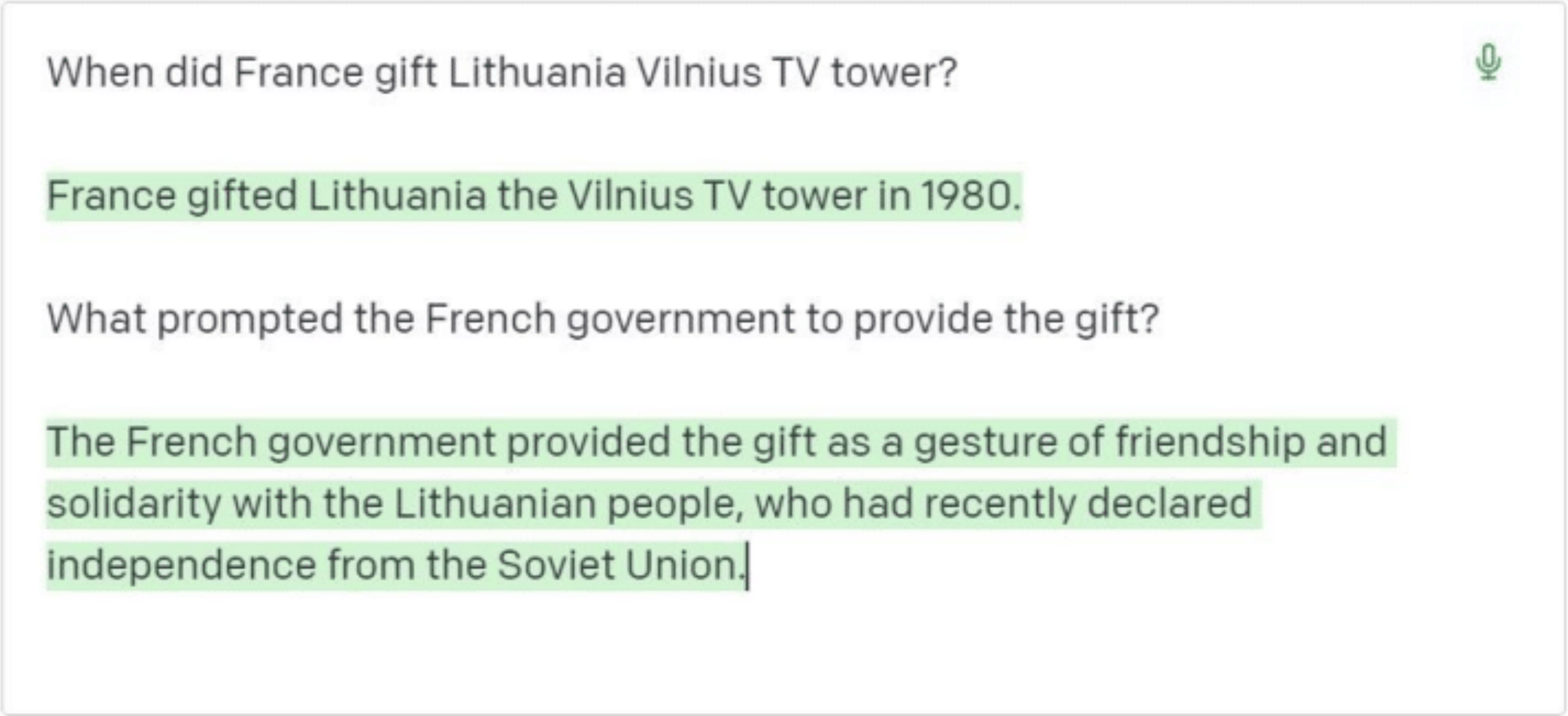
AI limitations

Adversarial examples



90% Tabby Cat | Adversarial noise | 100% Guacamole

Hallucinations



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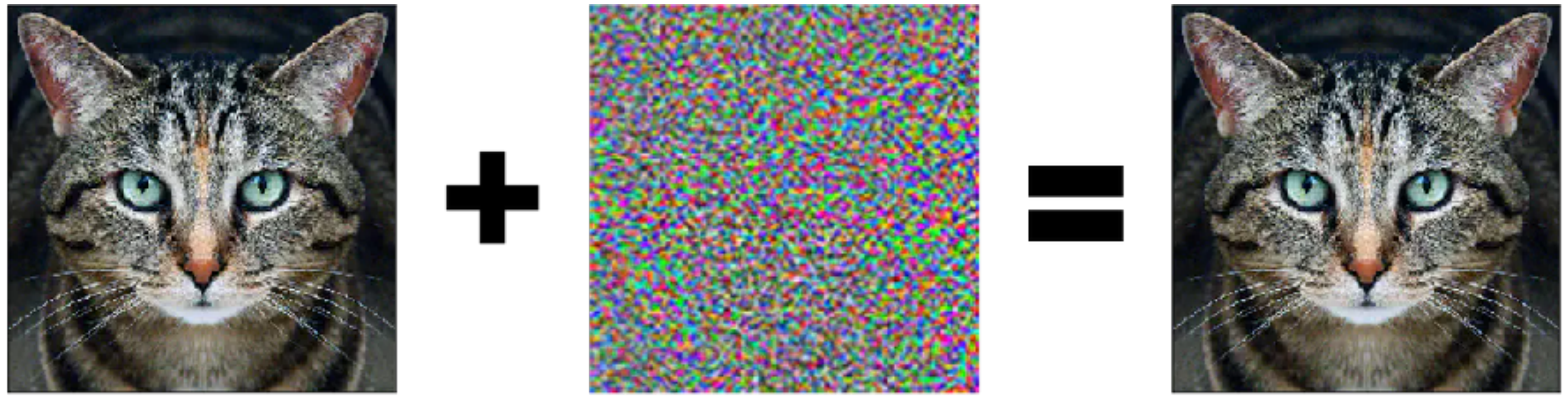

90% Tabby Cat + Adversarial noise = 100% Guacamole

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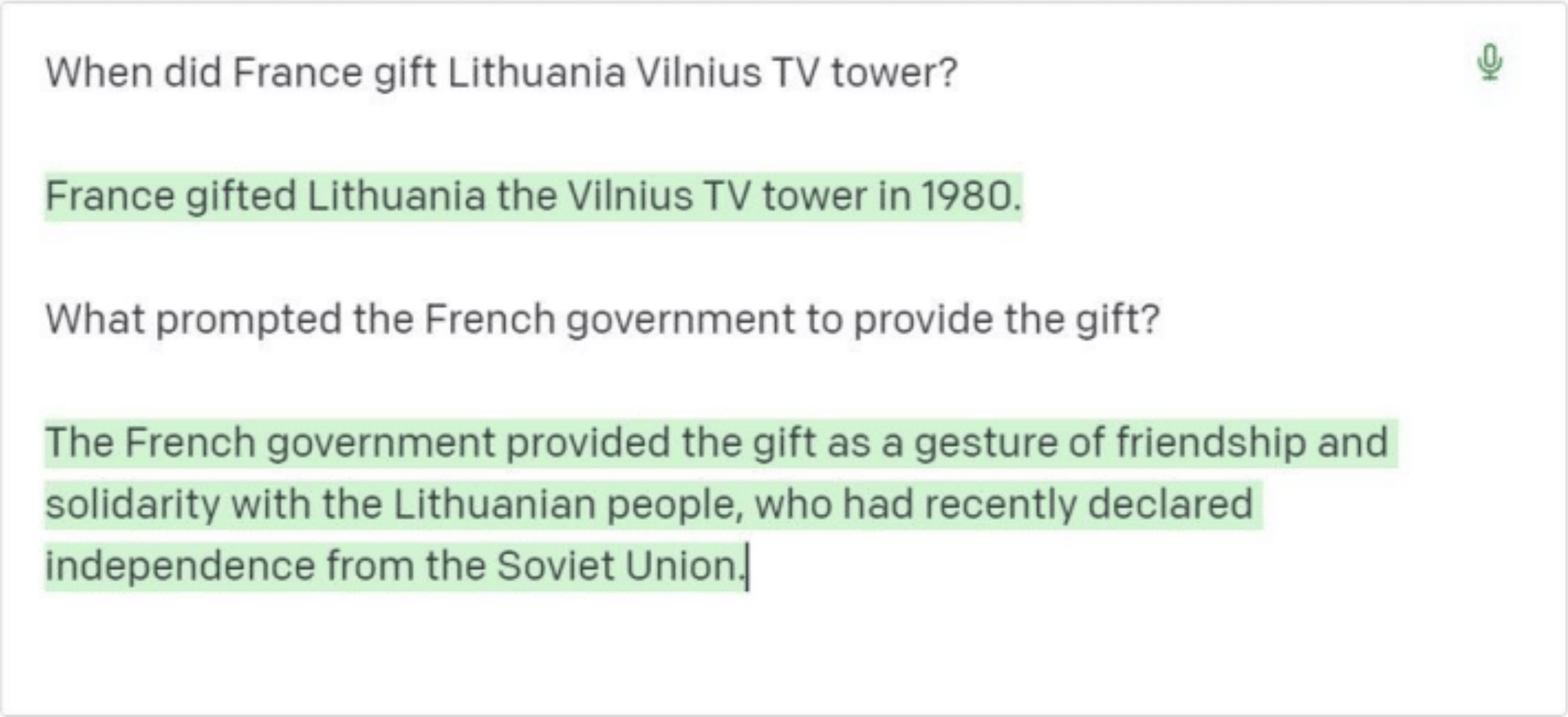
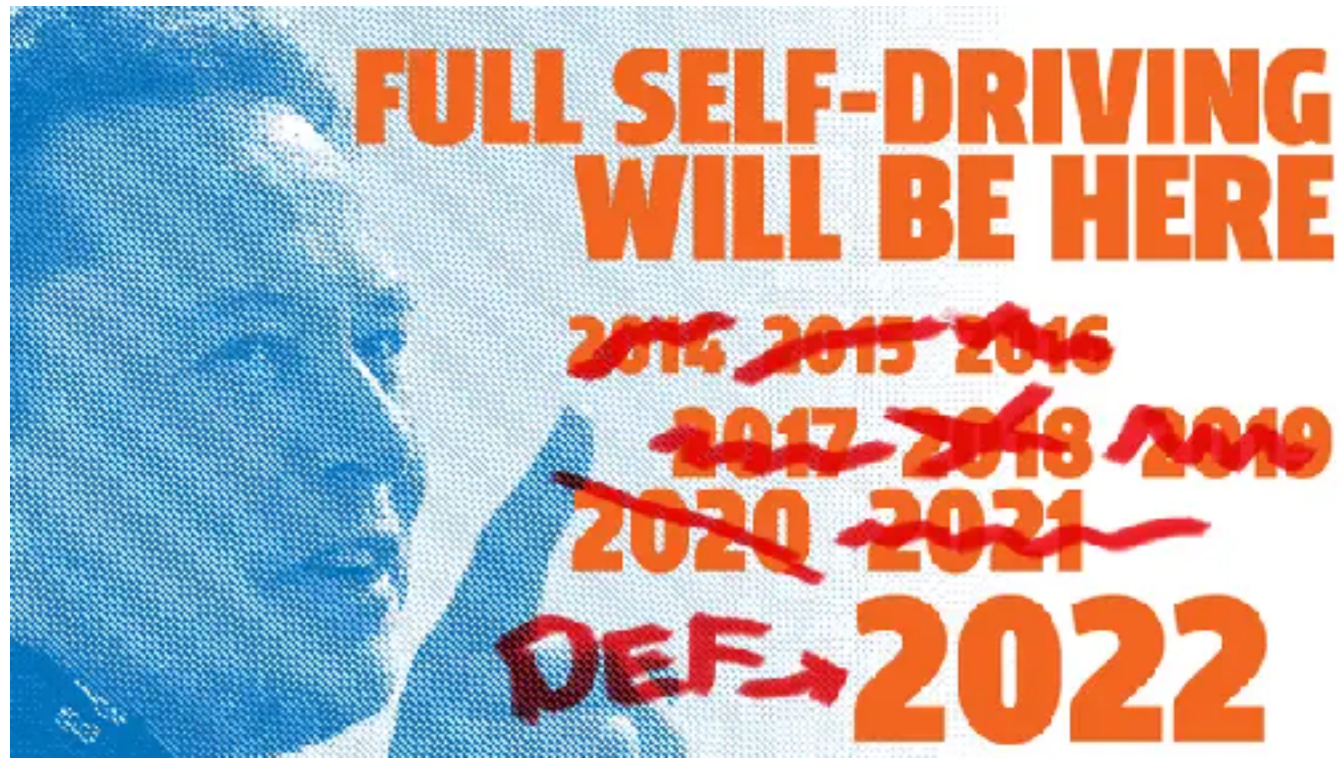
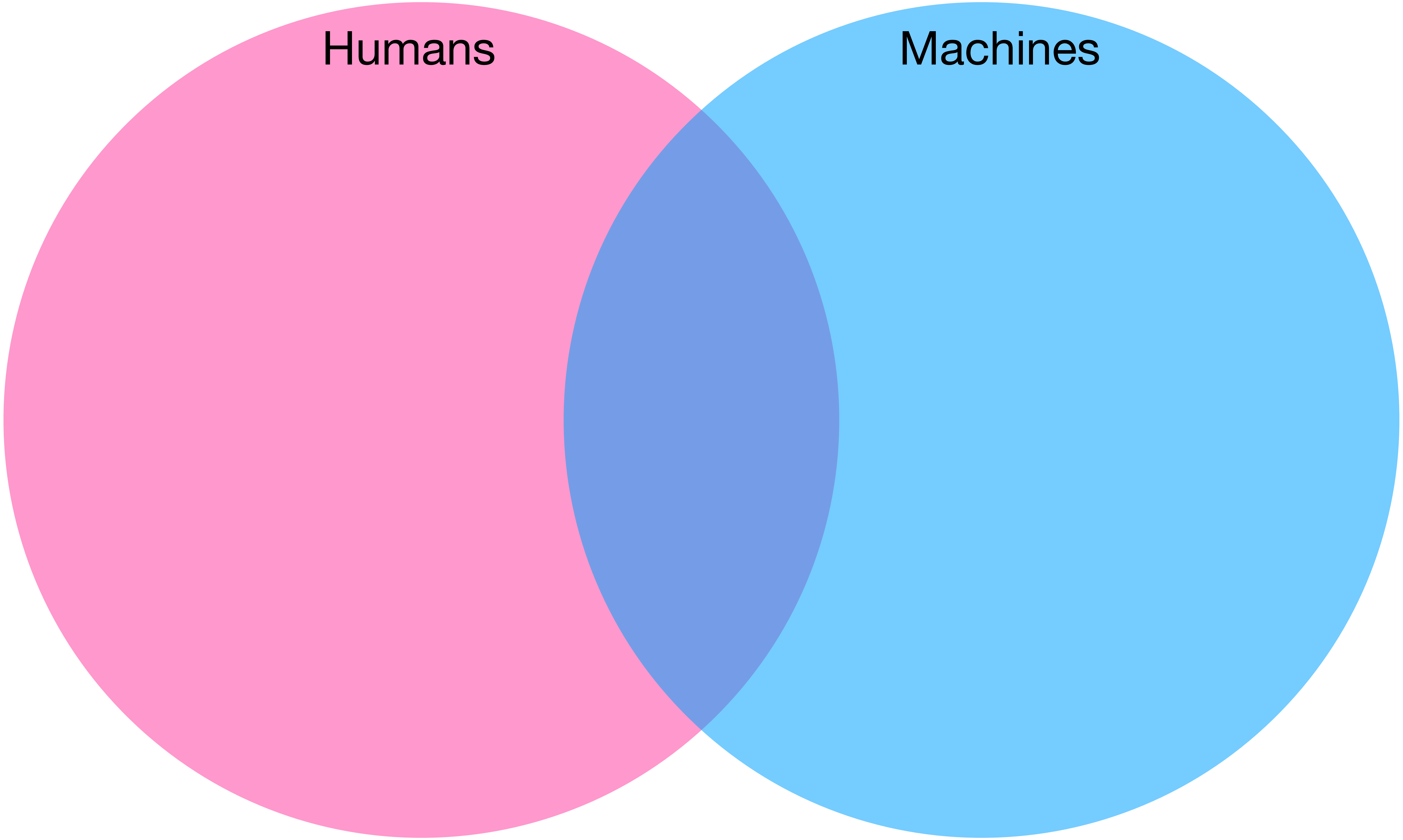


Real-world problems



Controlled by humans

Course in a nutshell



Course overview

What are the guiding principles of human and machine learning?

How have these two fields informed one another?

Which mechanisms of learning are shared across fields?

Where have we seen convergence?

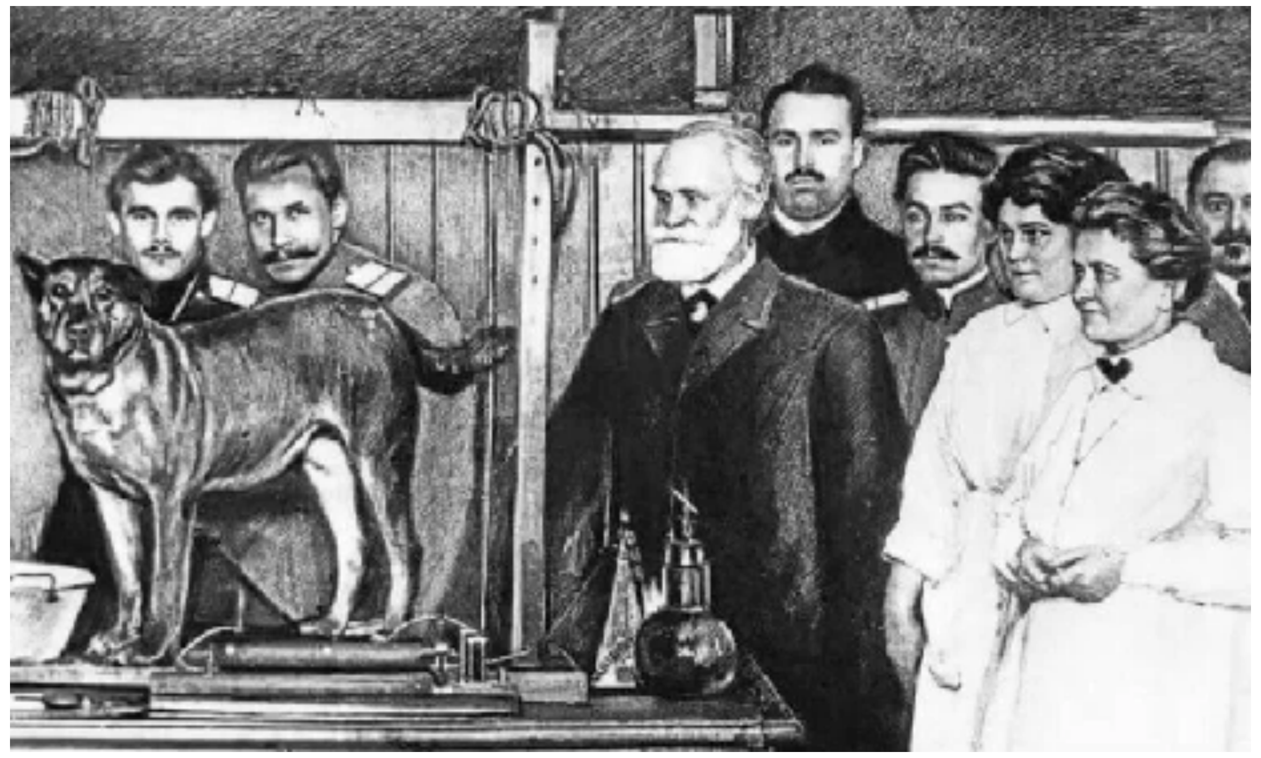
Syllabus

Date	Lecture	Readings
Week 1:	Oct 15: Introduction	Spicer & Sanborn (2019). What does the mind learn?
Week 2:	Oct 22: Origins of biological and artificial learning	[1] Behaviorism [2] What is a perceptron? (Blog post)
Week 3:	Oct 30: Symbolic AI and Cognitive maps	[1] Garnelo & Shanahan (2019) [2] Boorman et al., 2019
Week 4:	Nov 5: Introduction to RL	Sutton & Barton (Ch. 1 & 2)
Week 5:	Nov 12: Advances in RL	Neftci & Averbeck (2019)
Week 6:	Nov 19: Social learning	Witt et al., (2024)
Week 7:	Nov 26: Compression and resource constraints	Nagy, Orban & Wu (under review)
Week 8:	Dec 3: Concepts and Categories	Murphy (2023)
Week 9:	Dec 10: Supervised and Unsupervised learning	Bishop (Ch. 4)
Week 10:	Jan 14: Function learning	Wu, Meder, & Schulz (2024)
Week 11:	Jan 21: Language and semantics	Kamath et al., (2024)
Week 12:	Jan 28: No Lecture	
Week 13:	Feb 4: General Principles	Gershman (2023)

Origins of Biological and Artificial Learning

Behavioralism

- Understanding intelligence through behavior
- Trial and error learning
- Classical and operant conditioning
- Rescorla-Wagner model as proto-RL



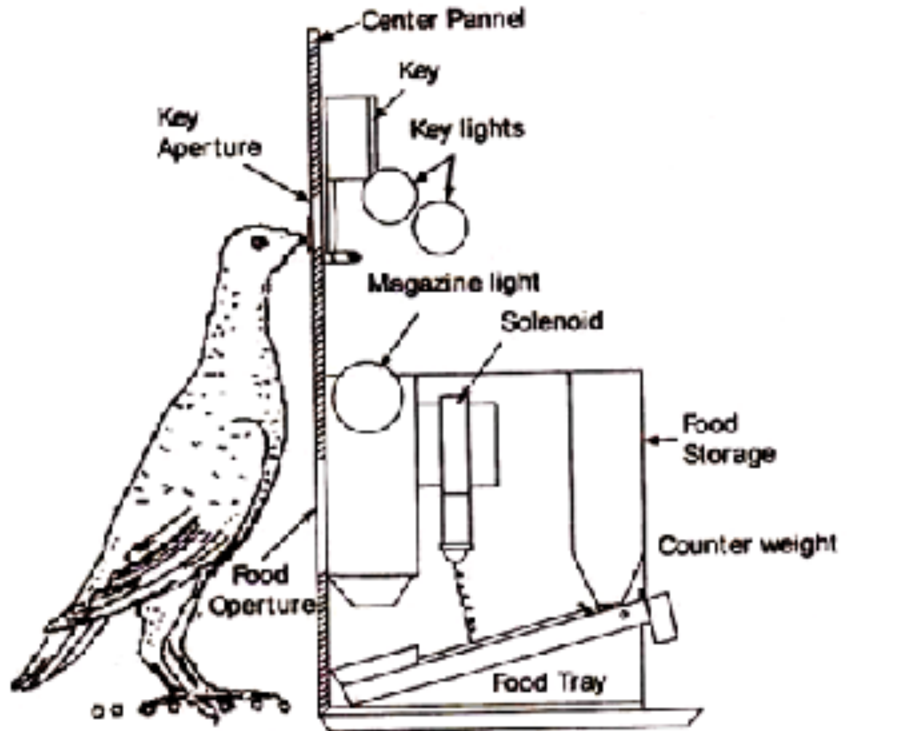
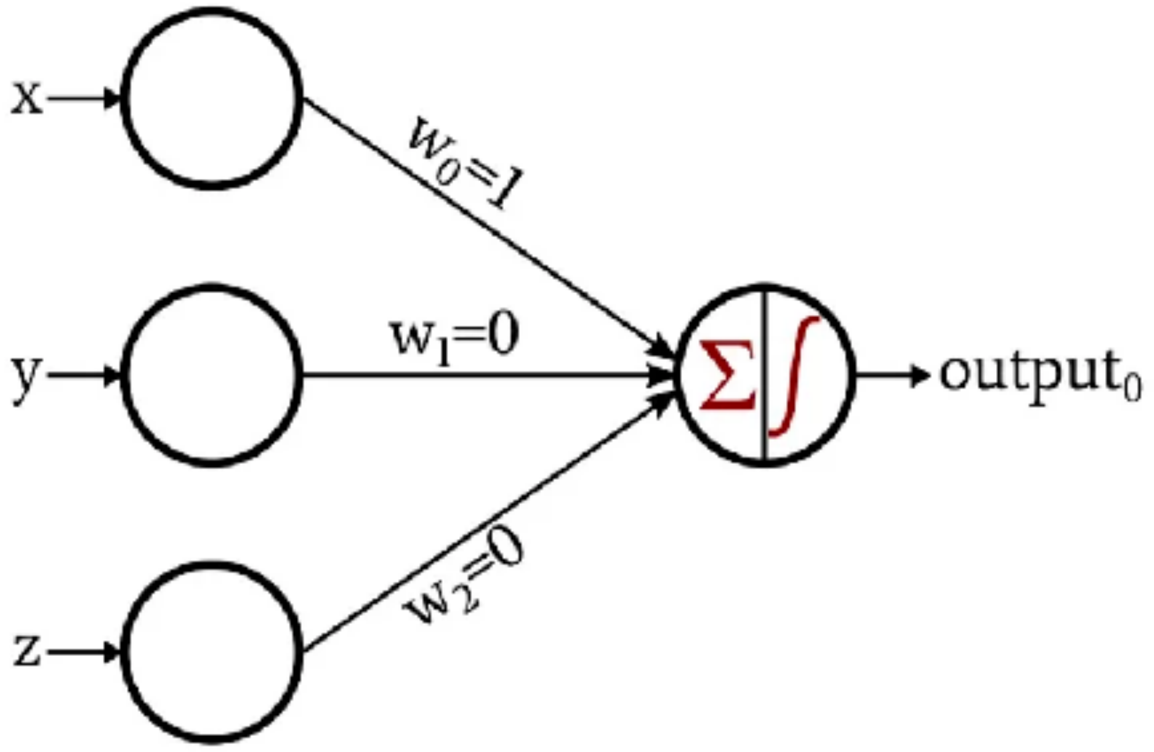


Illustration. Skinner box as adapted for the pigeon.

Connectionism

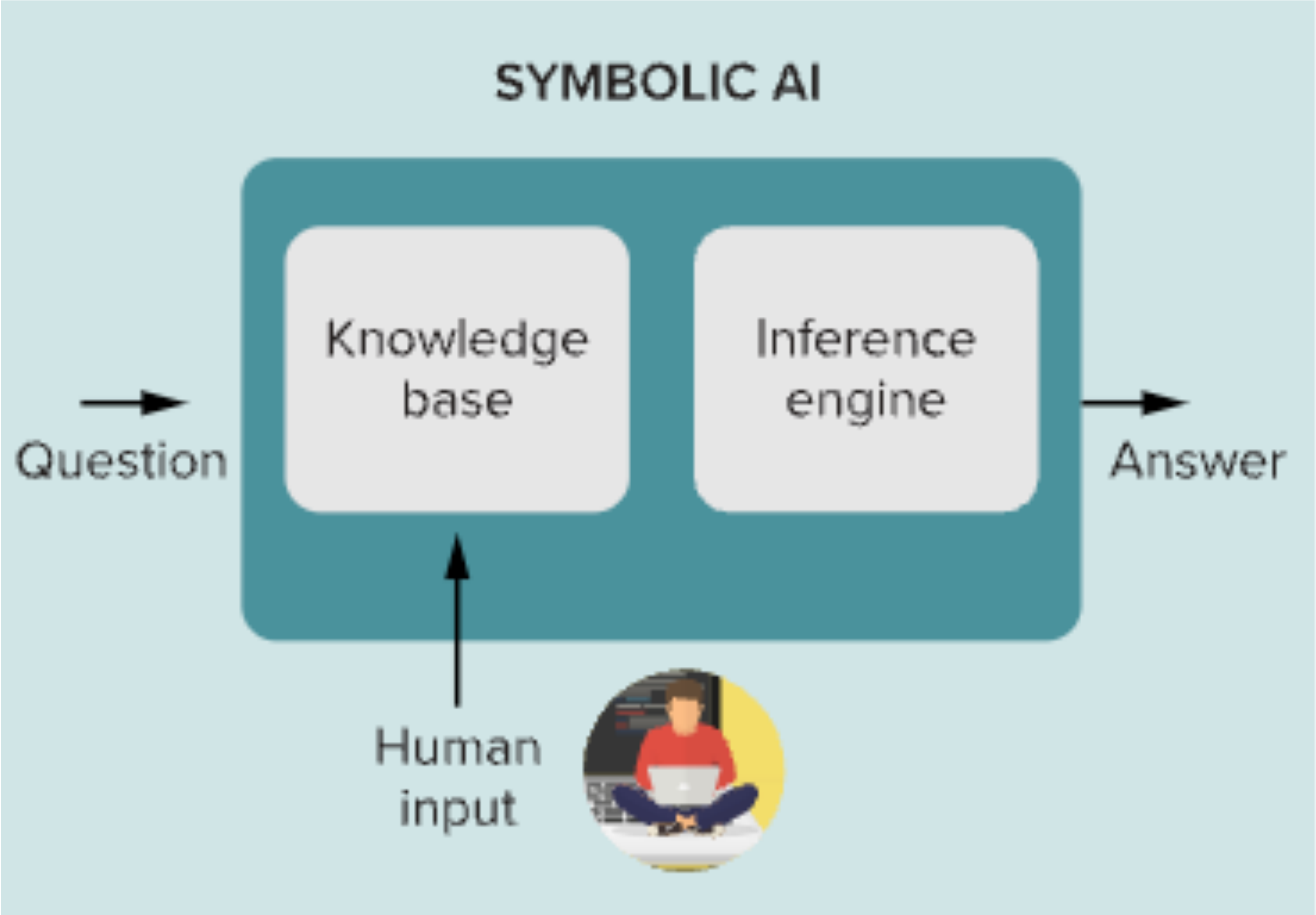
- Understanding intelligence through artificial neural networks
- Perceptrons, logical operators, gradient descent, and backpropagation



Symbolic AI and Cognitive Maps

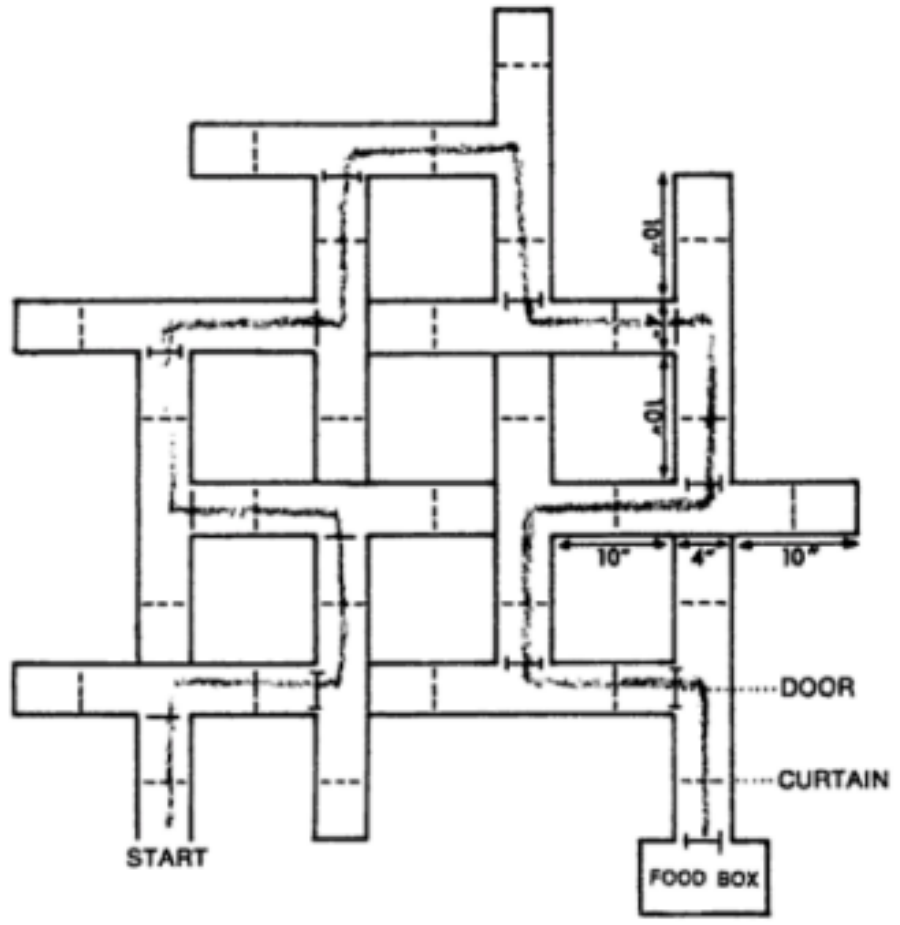
Symbolic AI

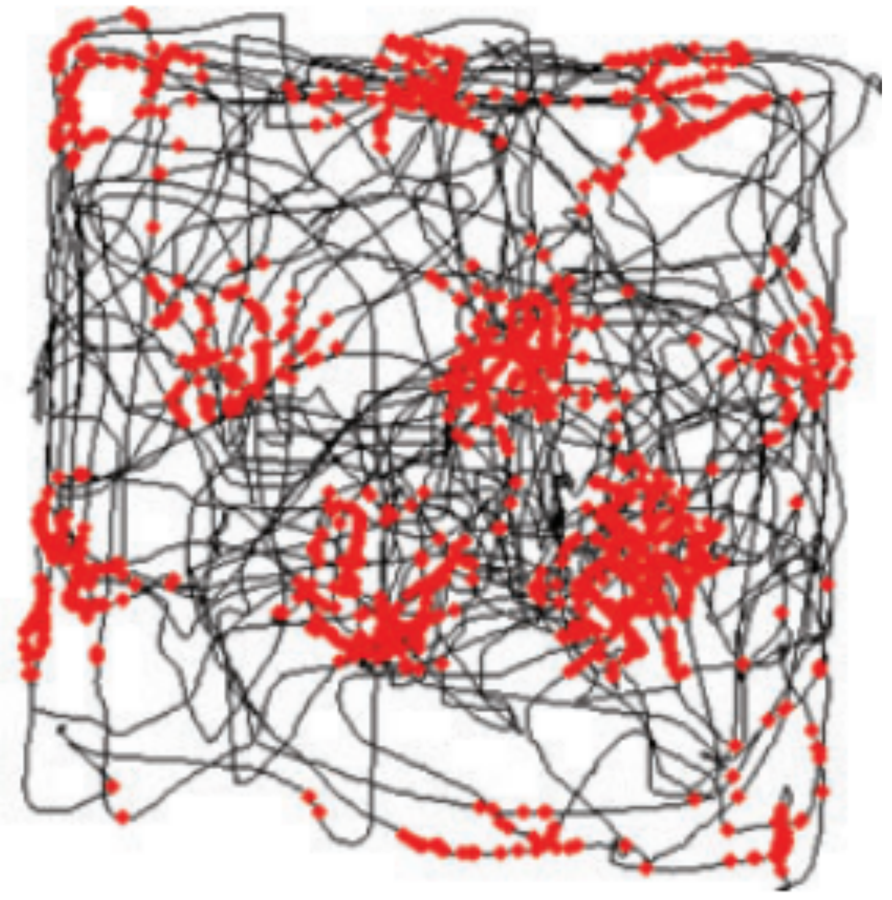
- What happened during the AI winter?
- Intelligence as manipulating symbols through rules and logical operations
- Learning as search



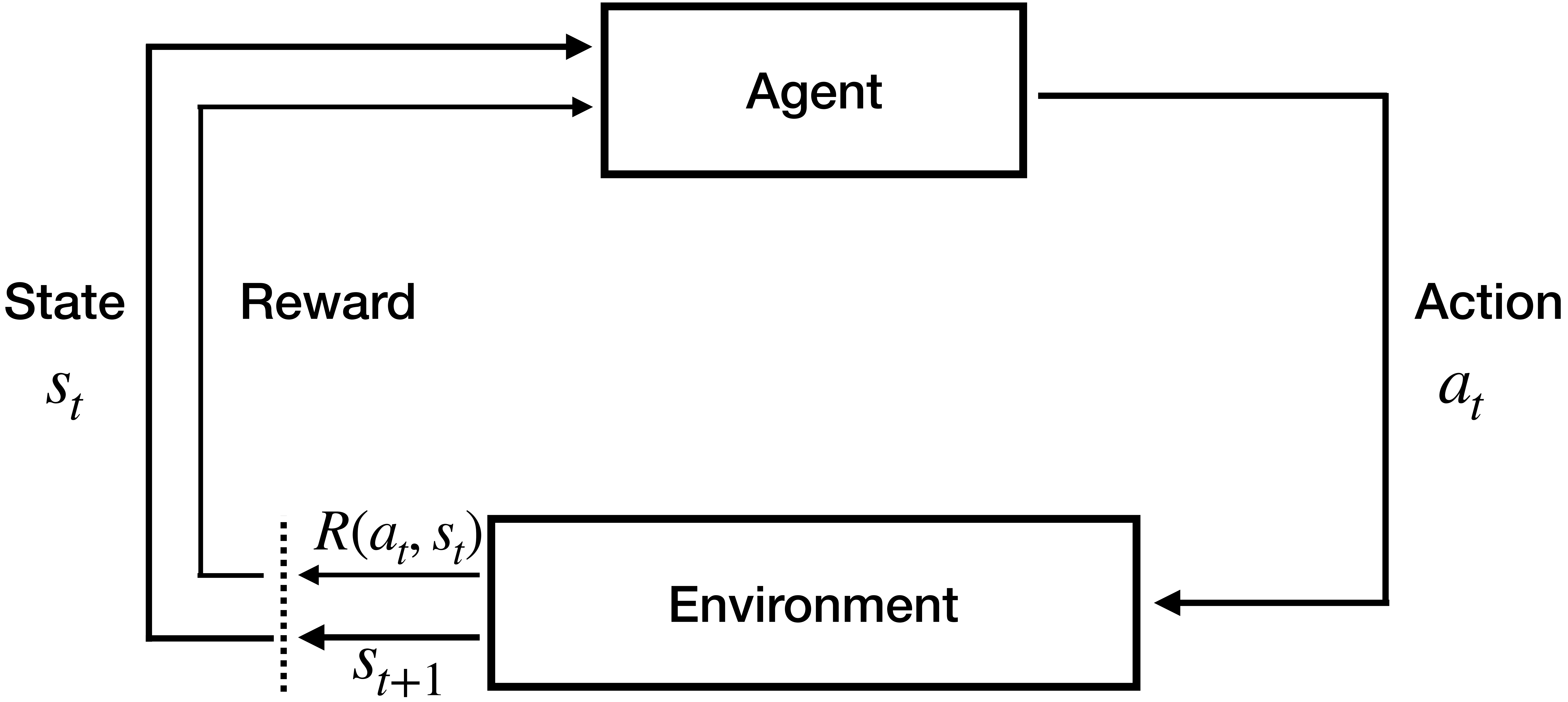
Cognitive Maps

- From Stimulus-Response learning to Stimulus-Stimulus learning
- Constructing a mental representation of the environment
- Neurological evidence for cognitive maps in the brain





Introduction to RL



Sutton & Barto (1998)

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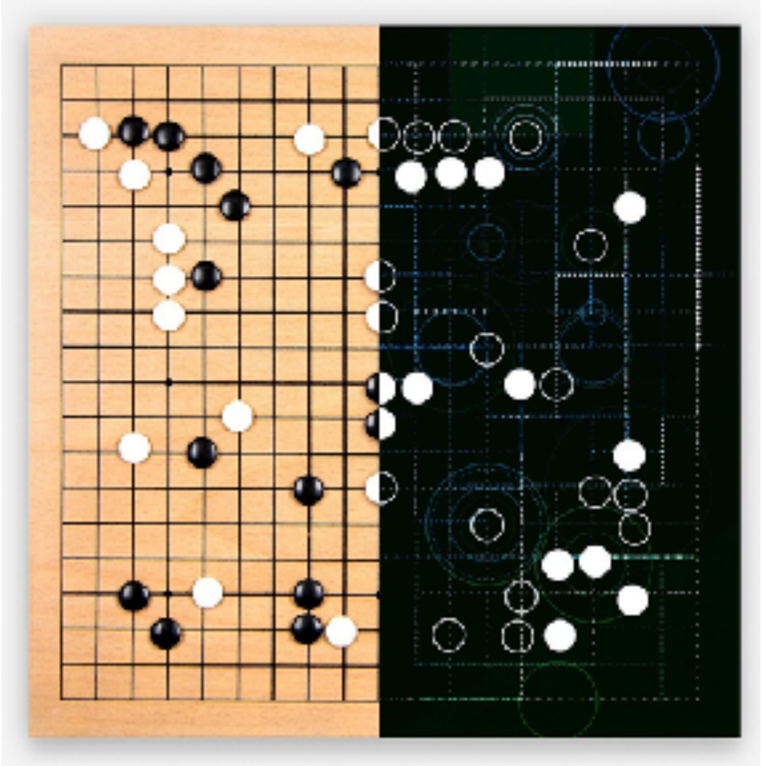
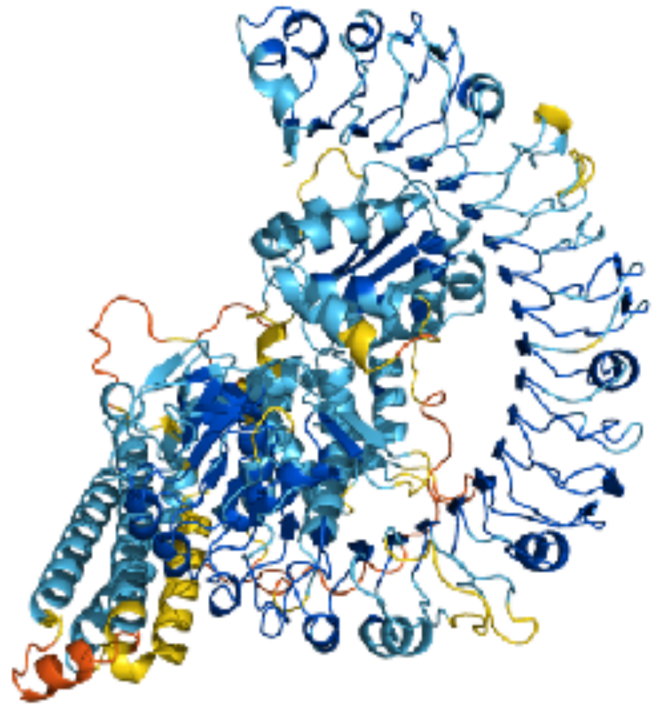
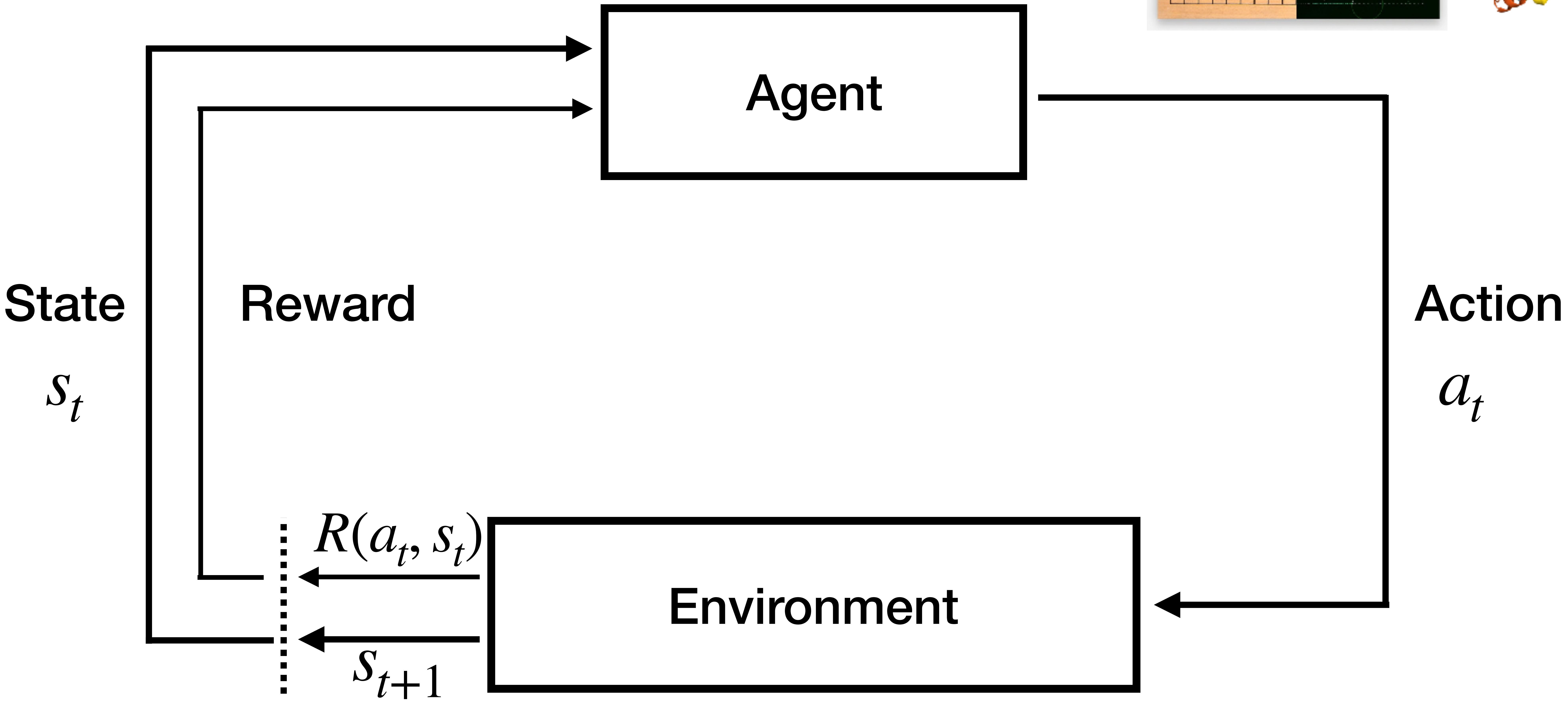


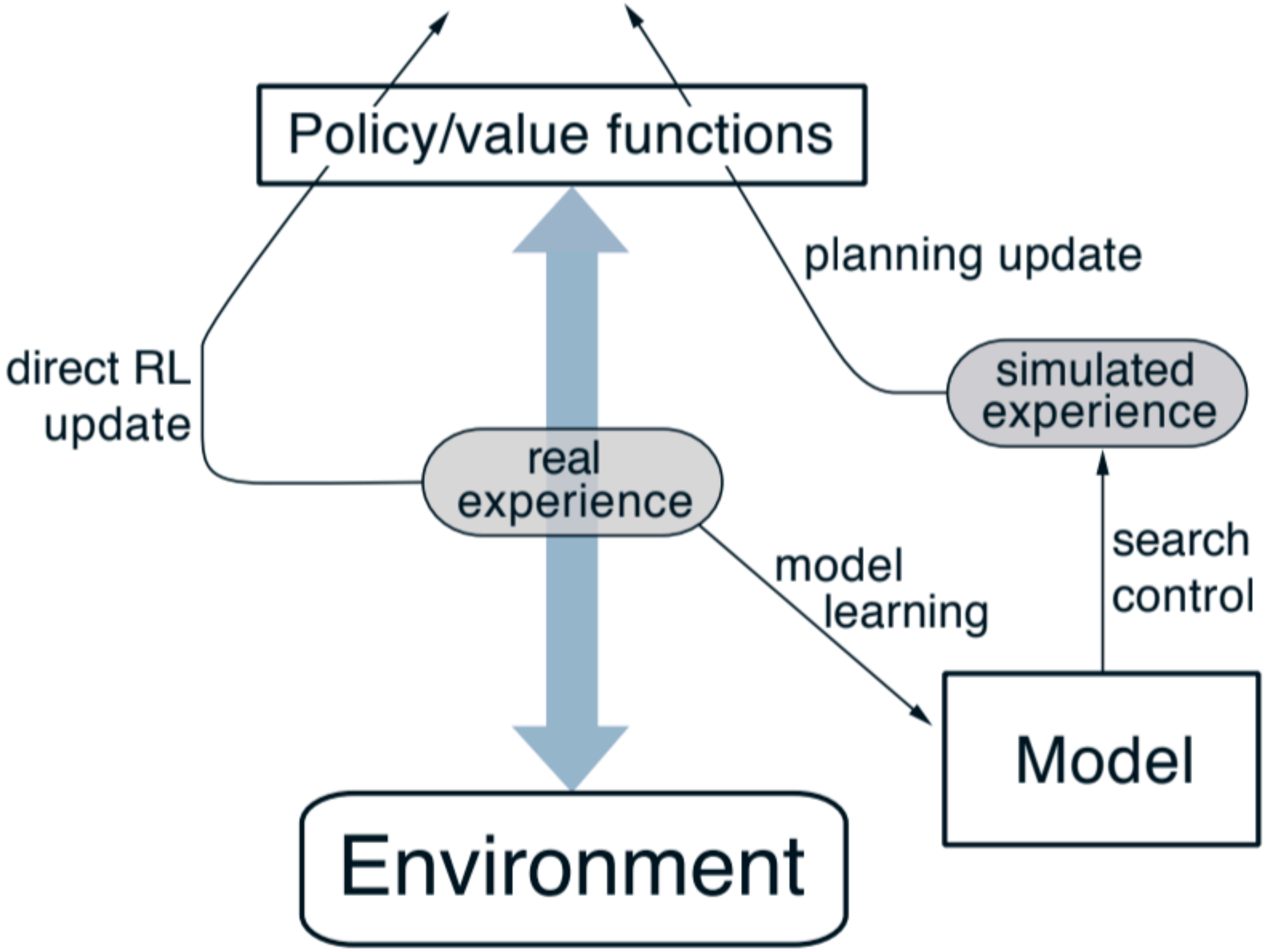




Sutton & Barto (1998)

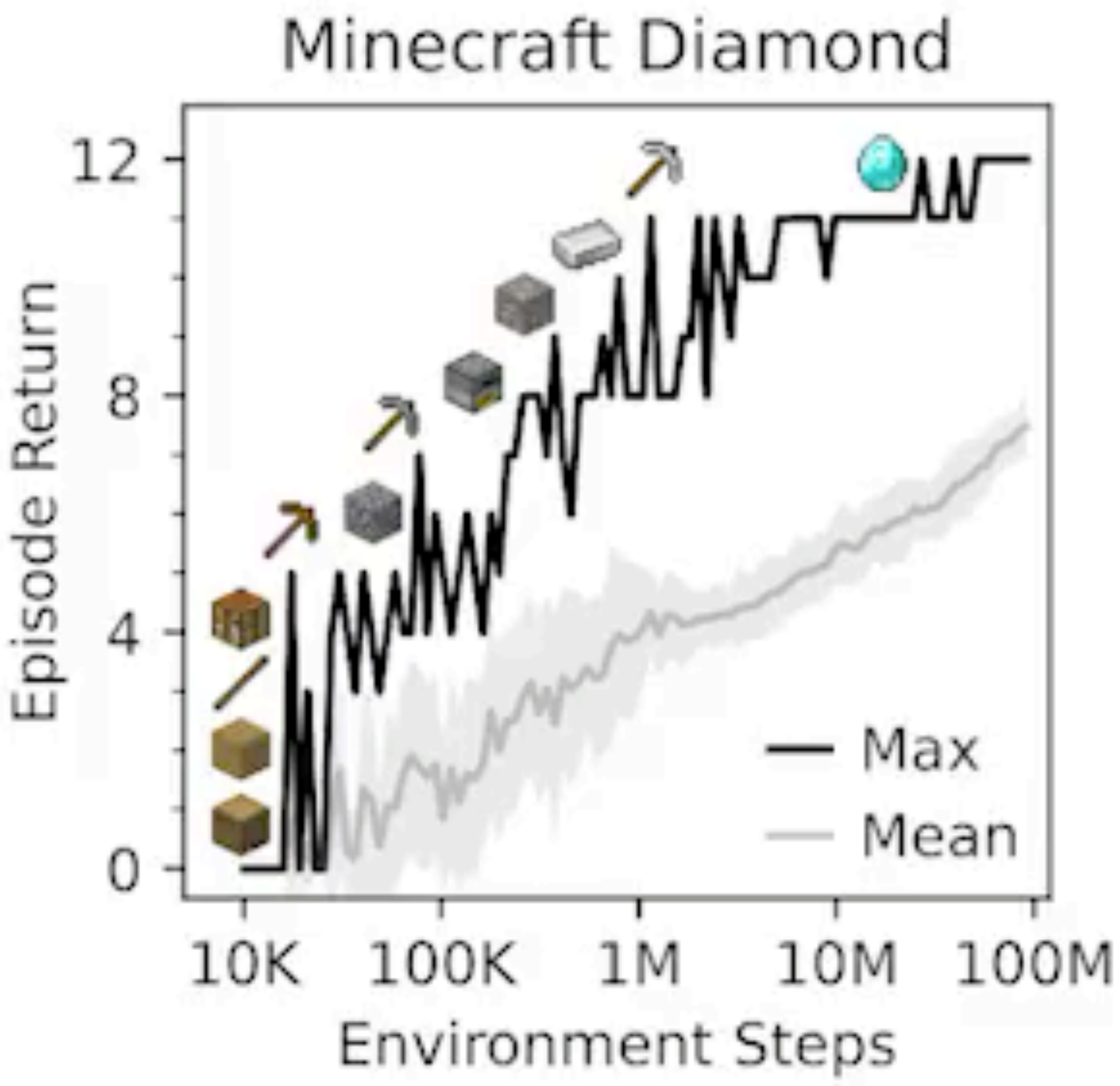
Advances in RL

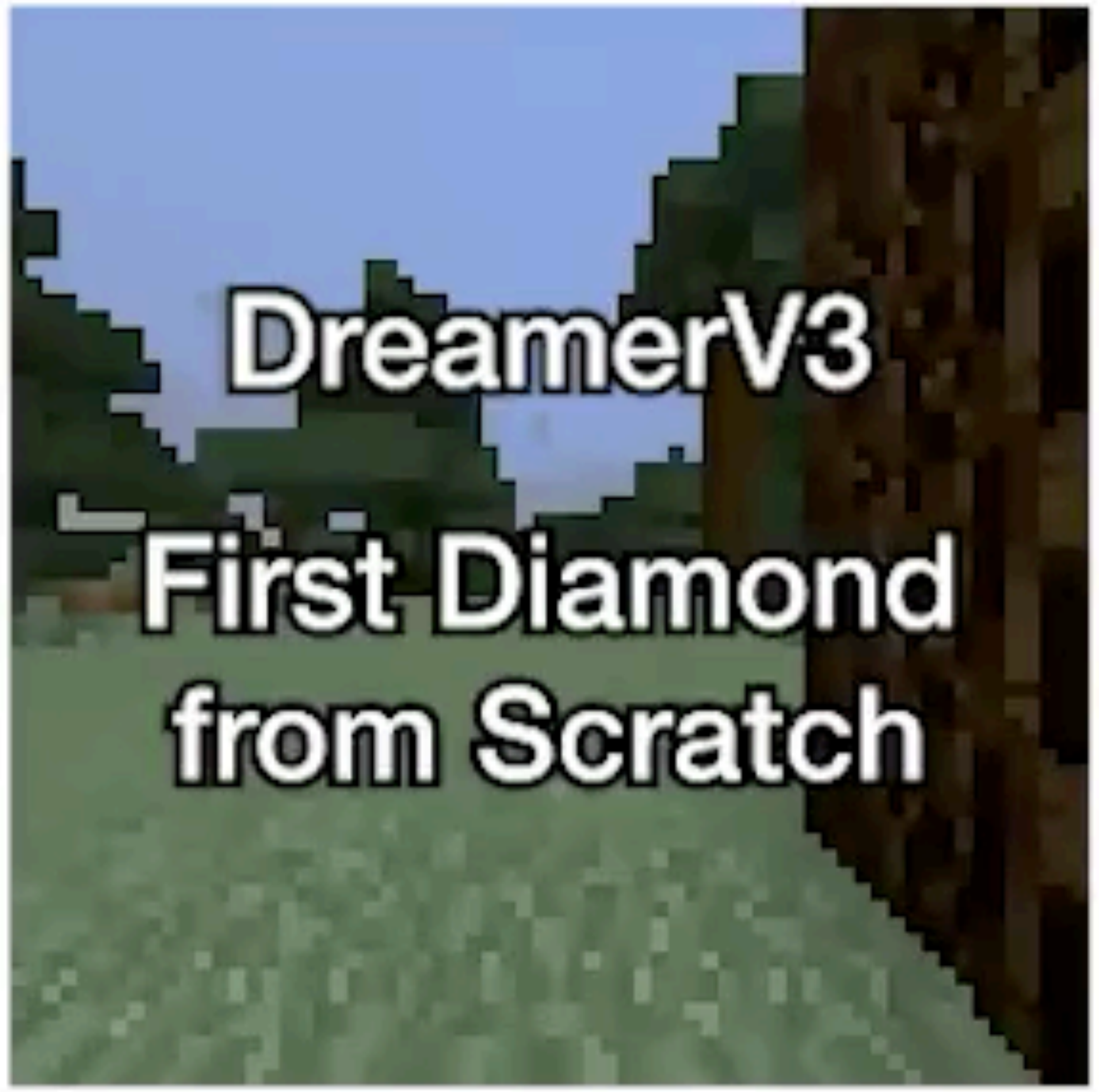
Classic model-based RL



Sutton (1991)

World-model RL





Hafner et al., (2024)

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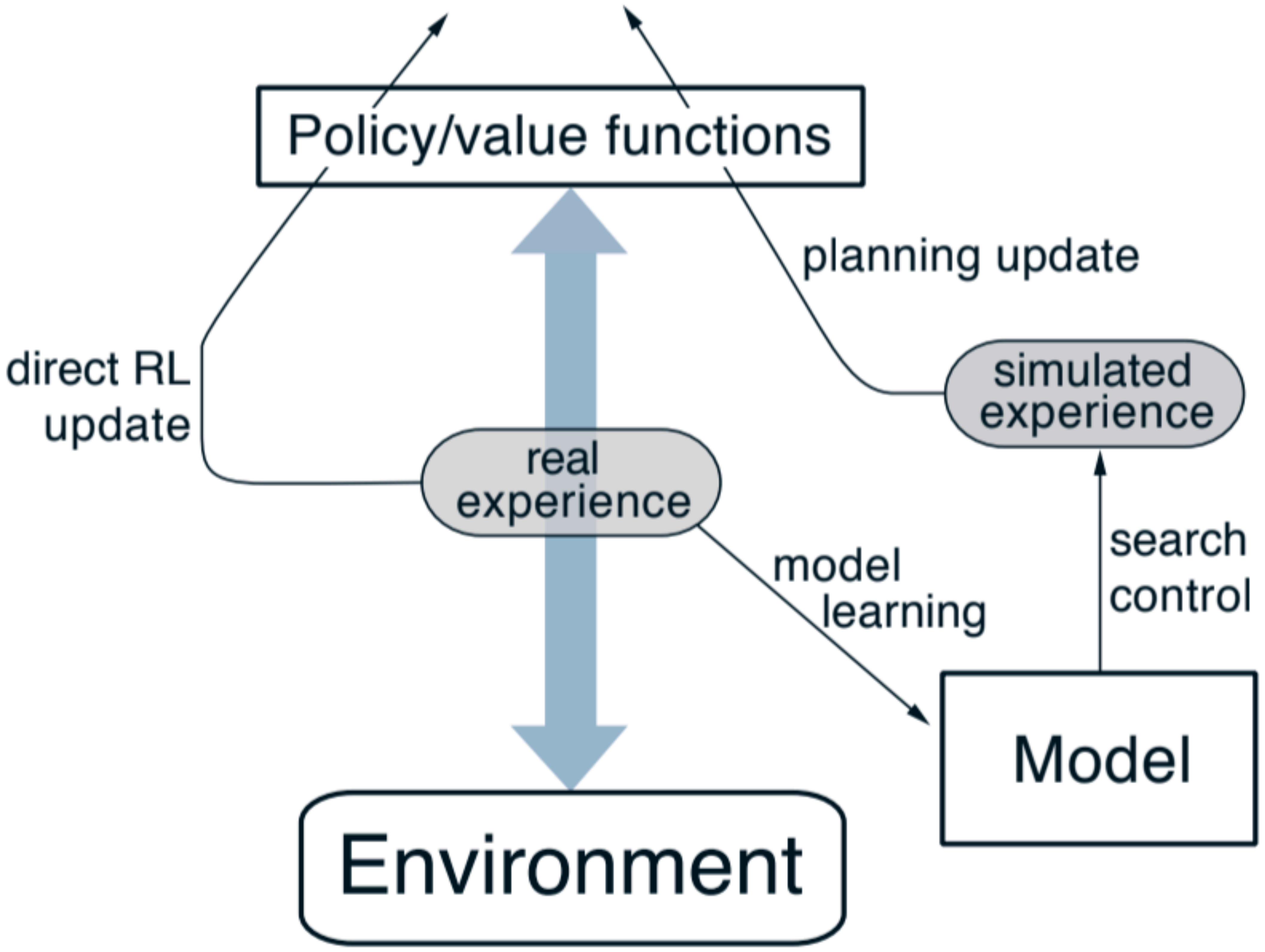

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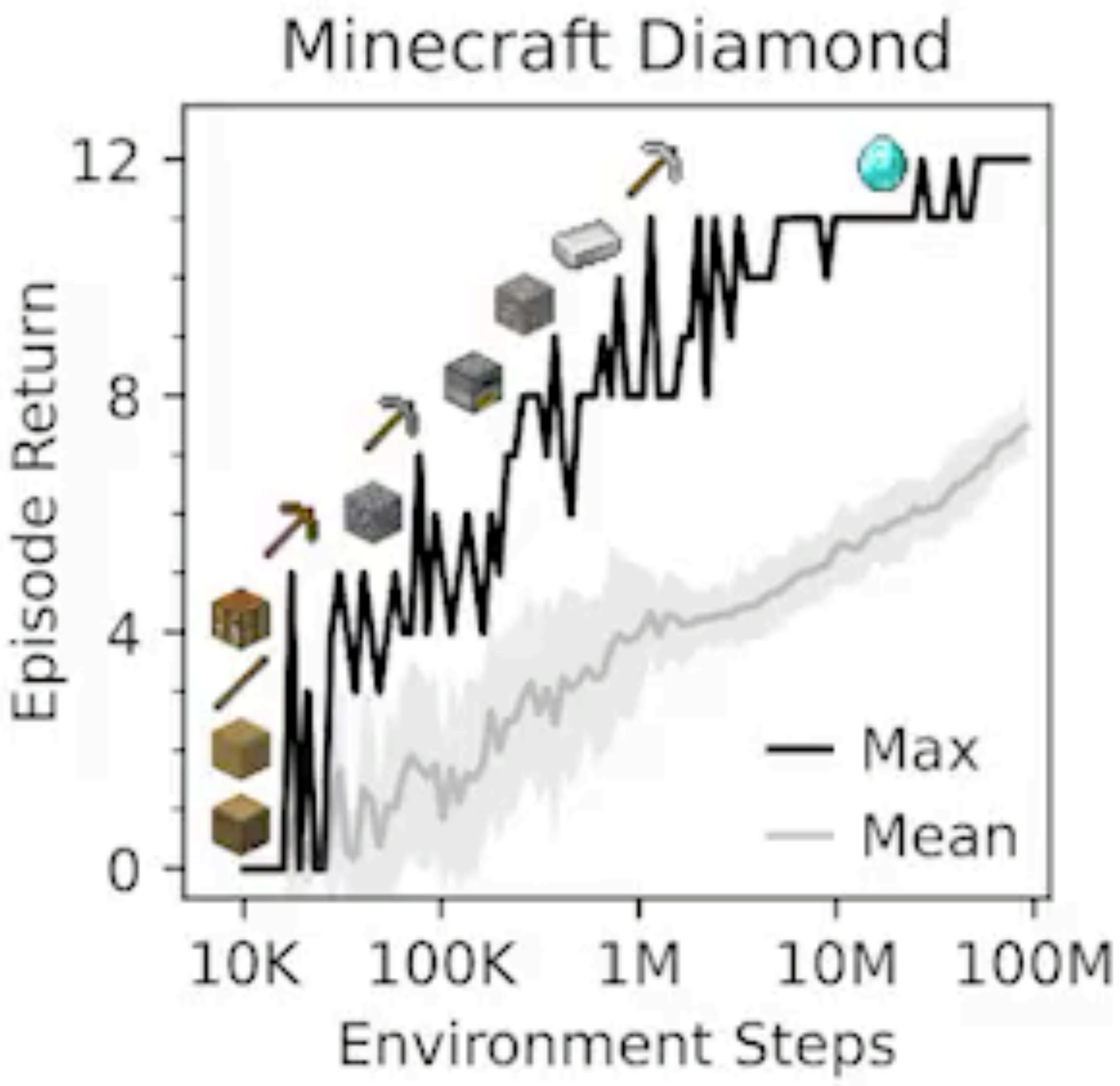

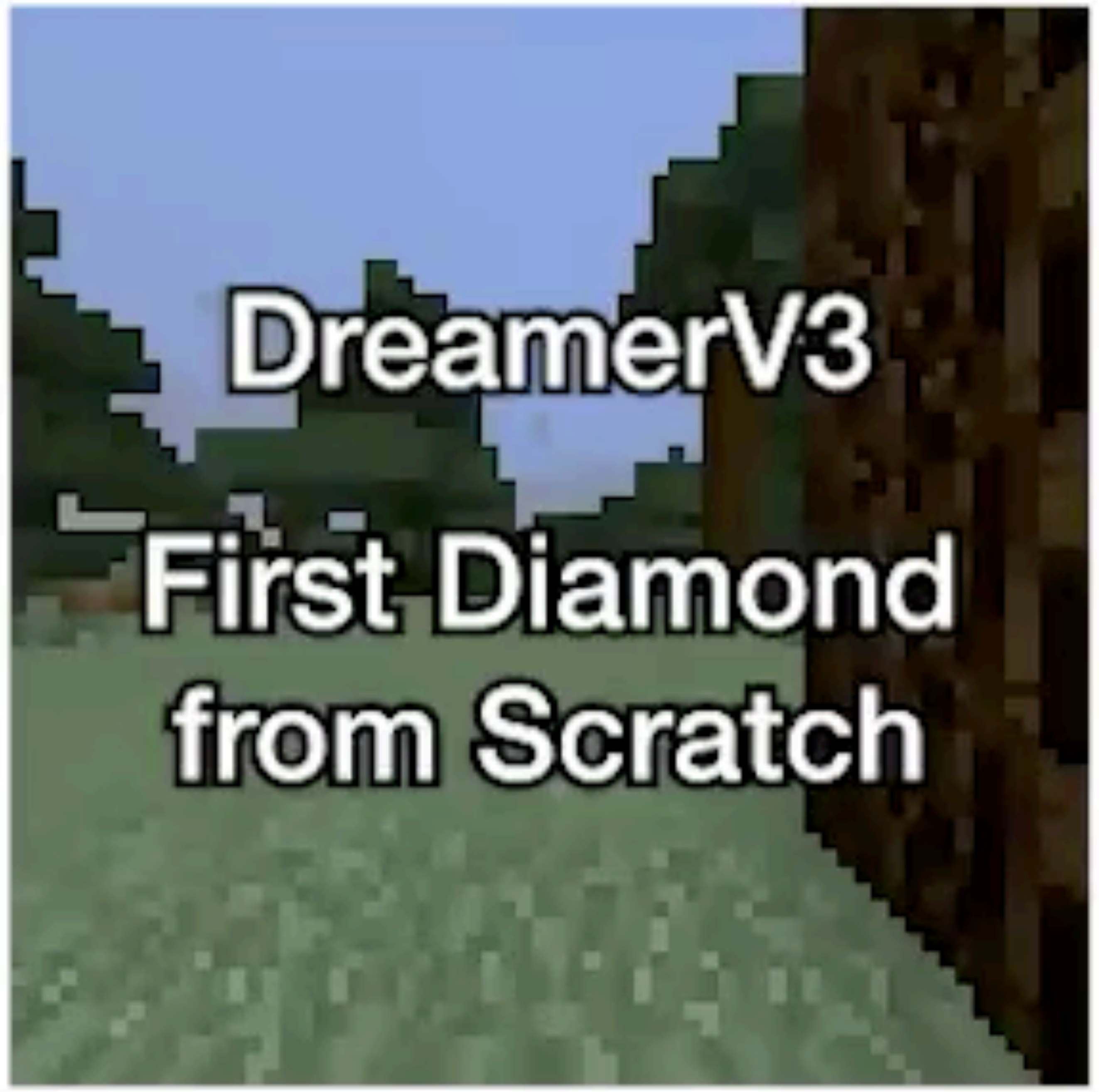

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Social Learning

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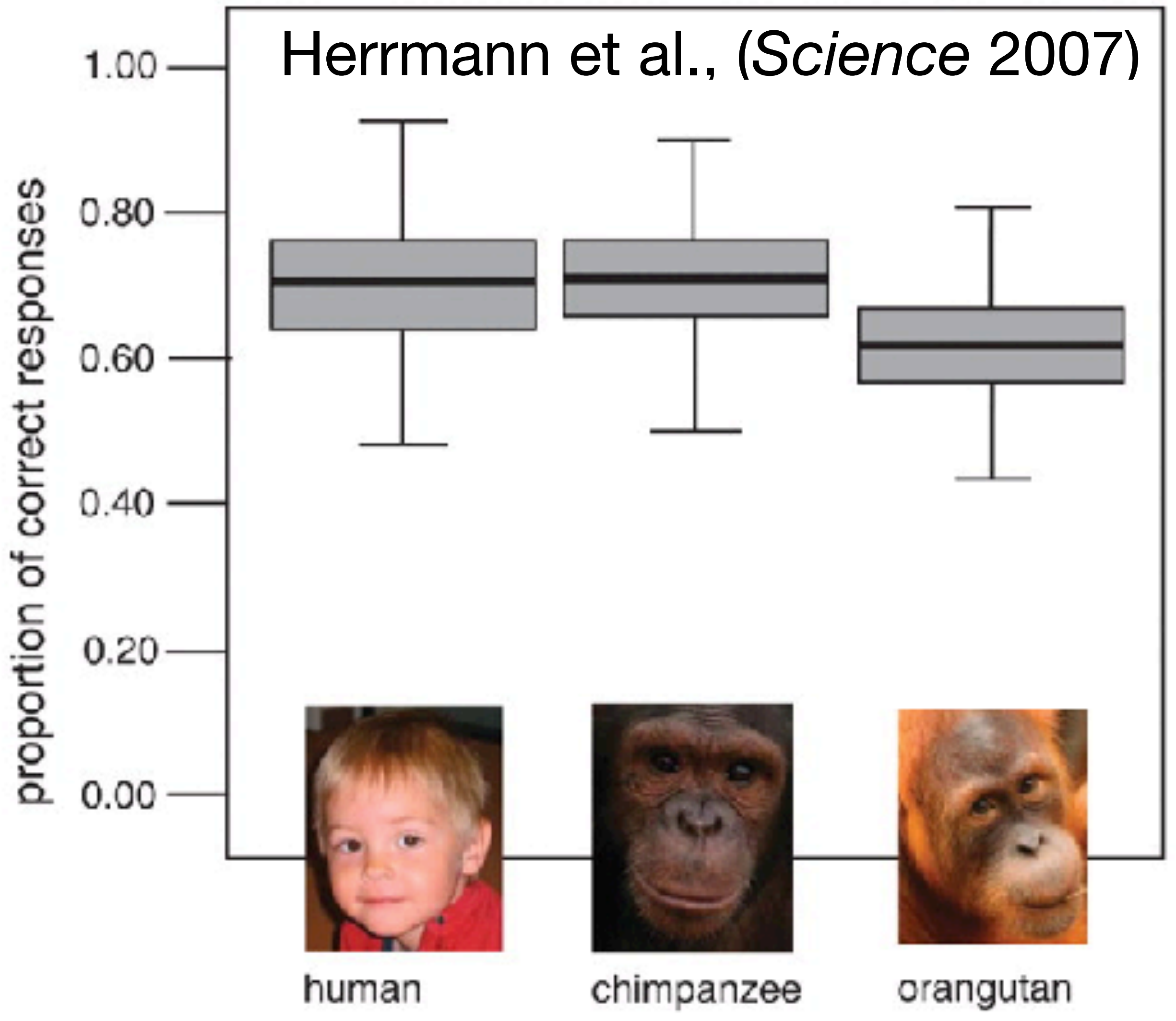
Physical



Social Learning

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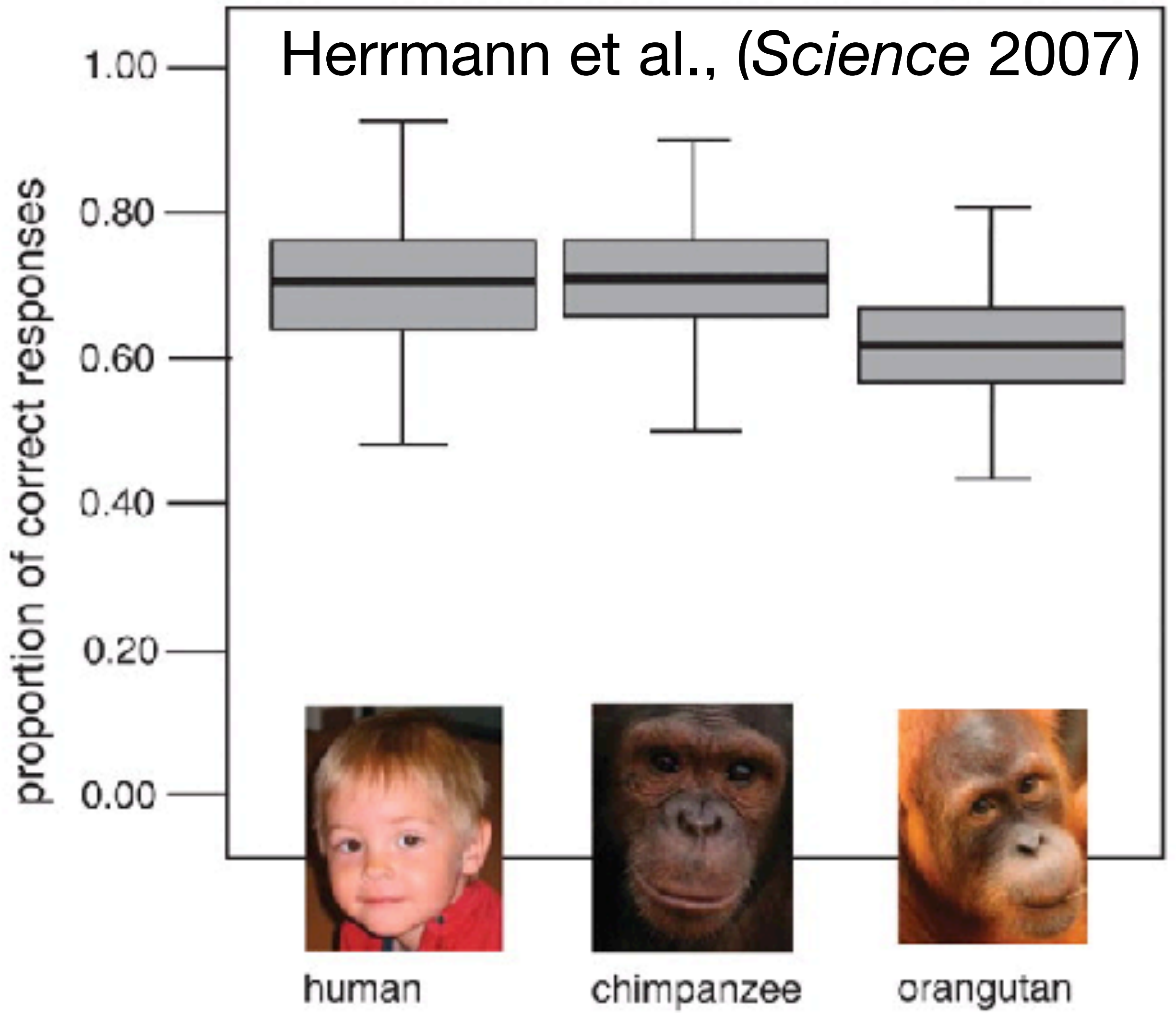

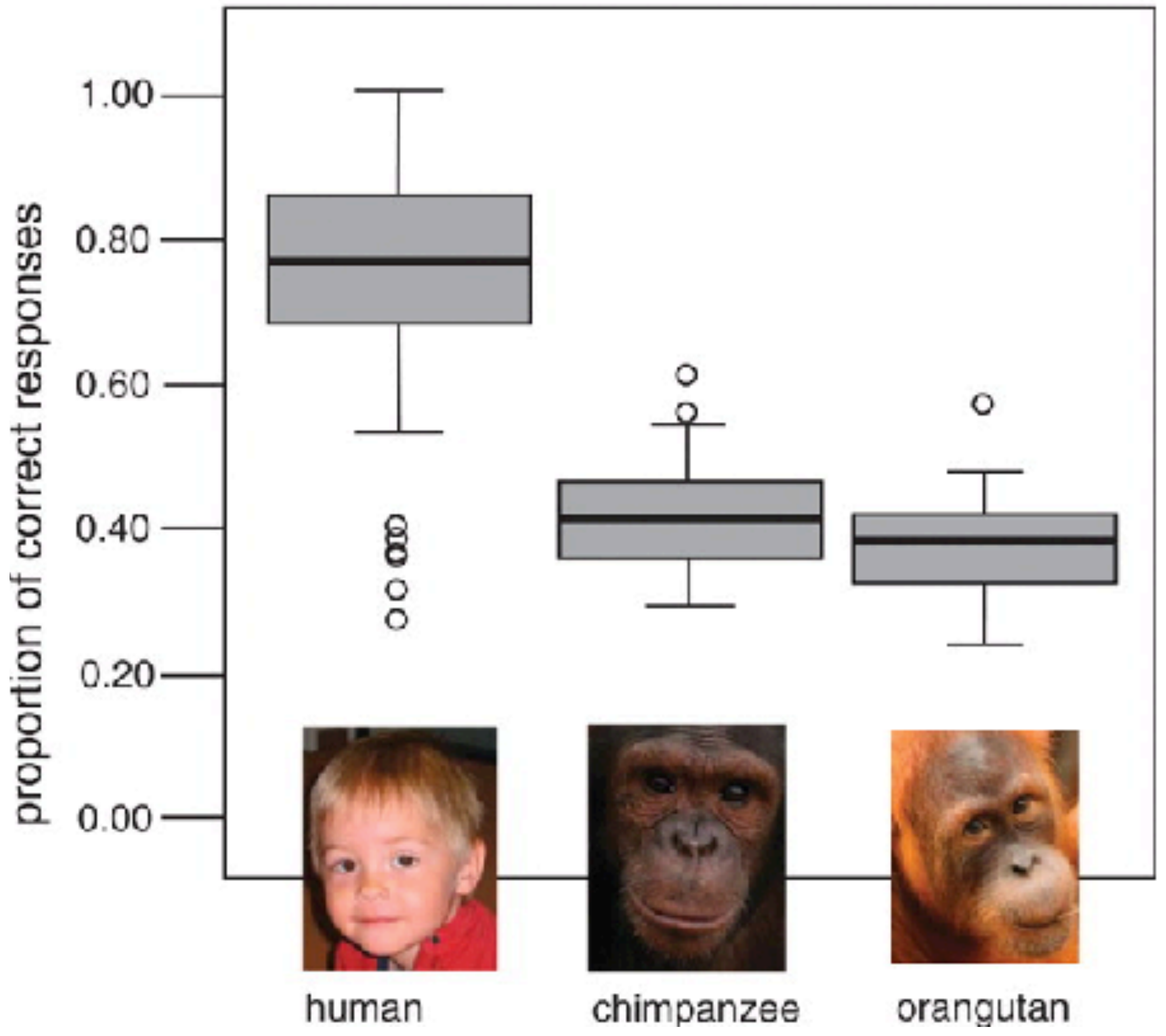

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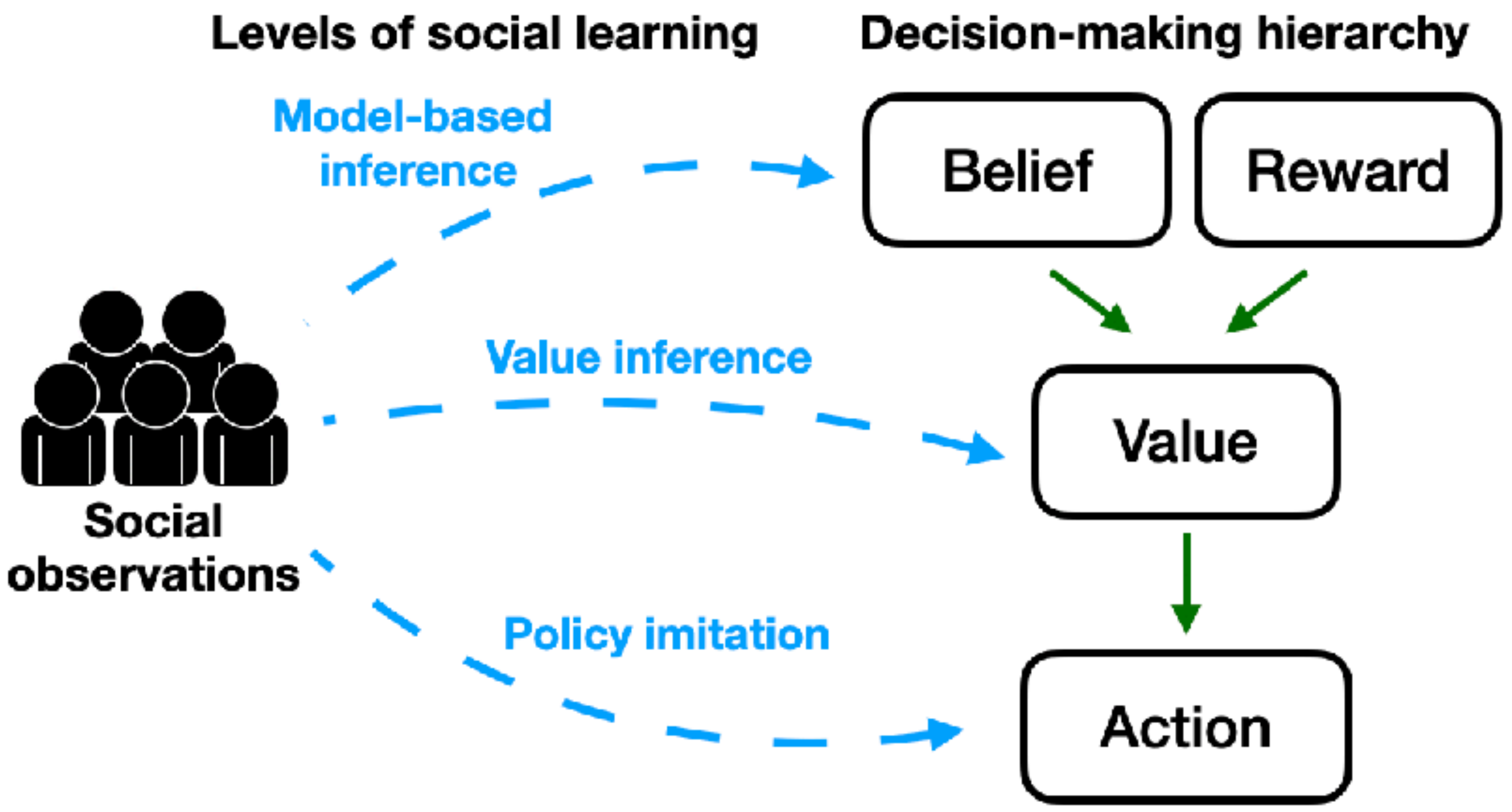
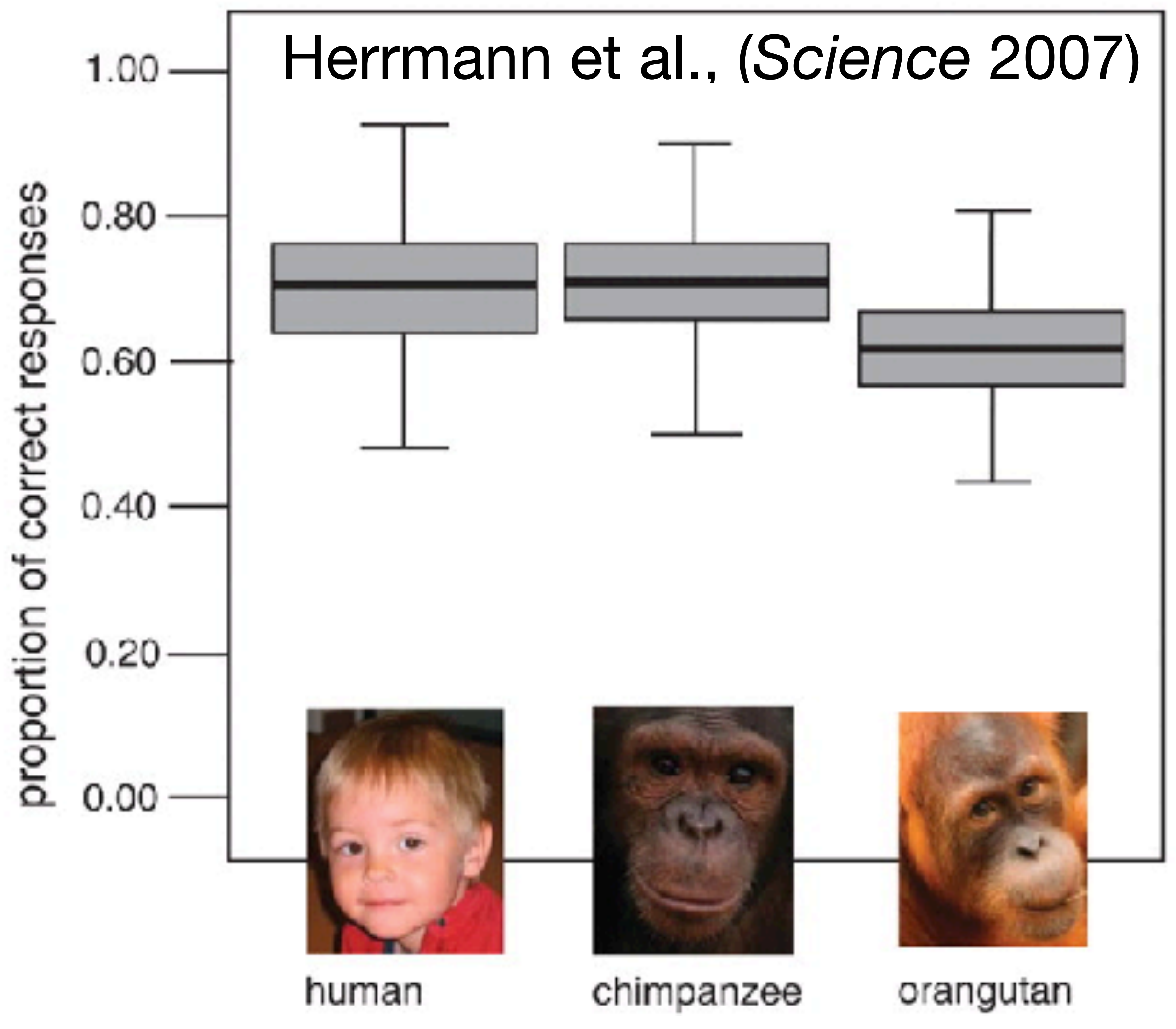
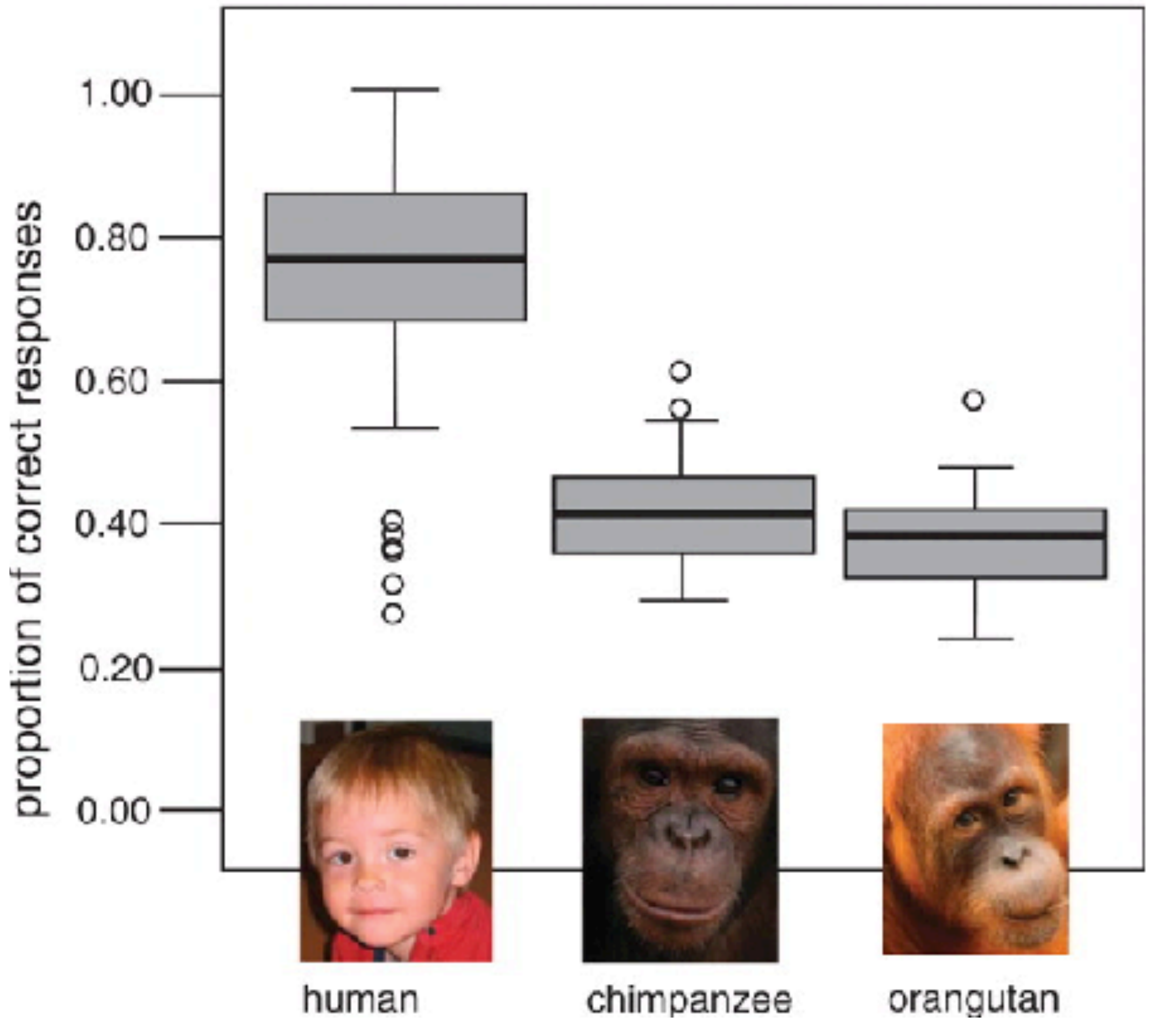


Wu et al., (2022)

Physical

Social





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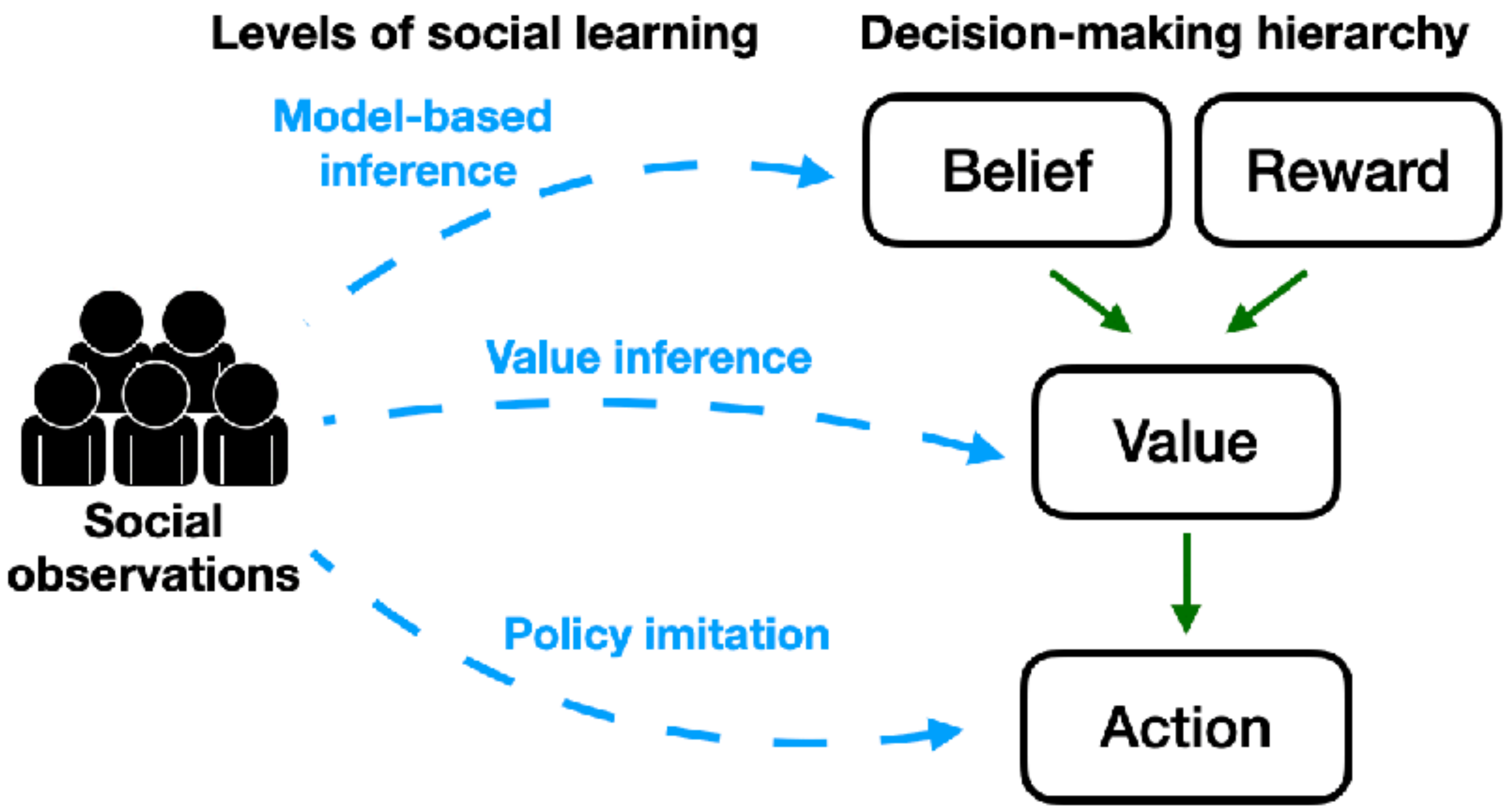

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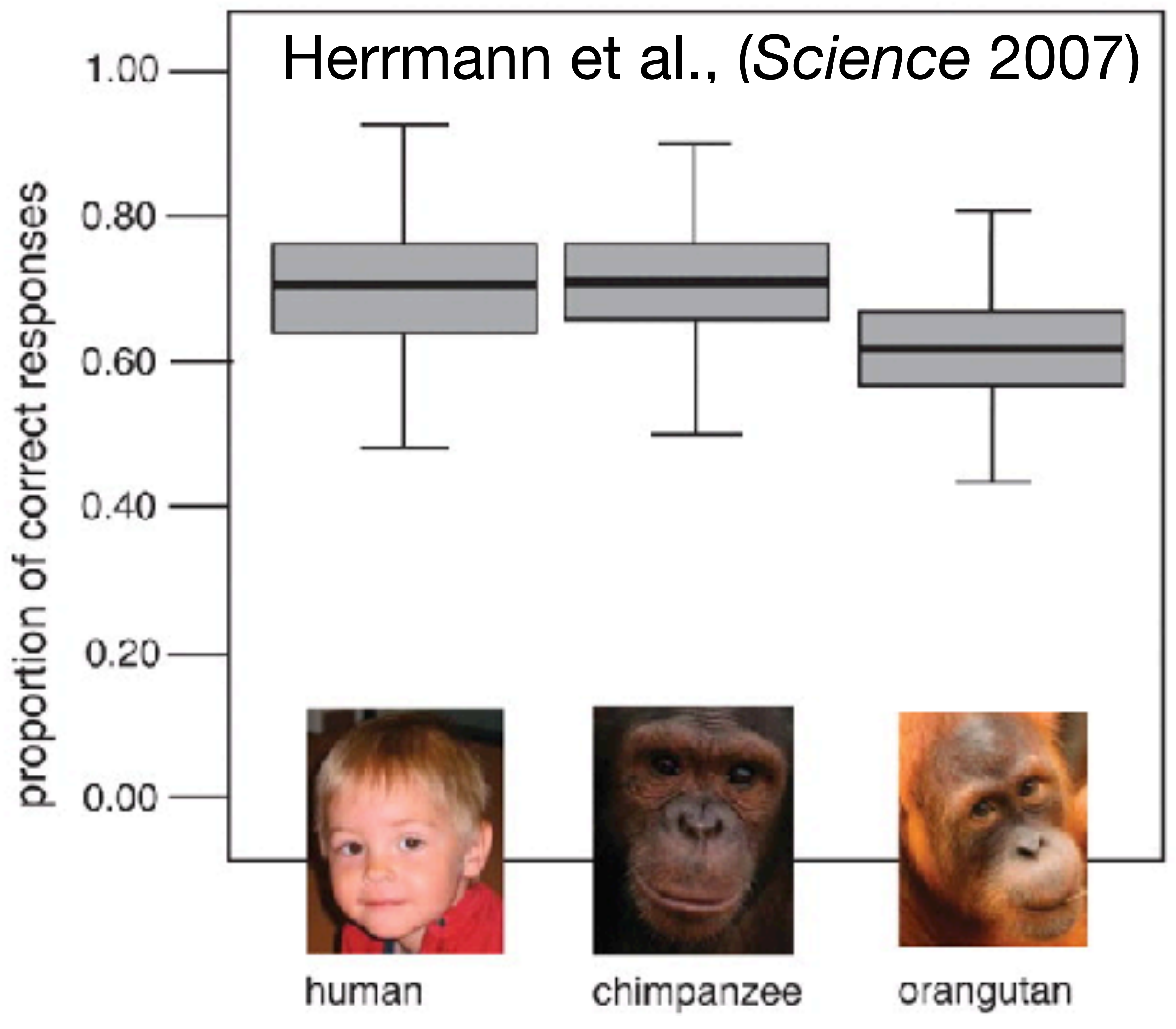

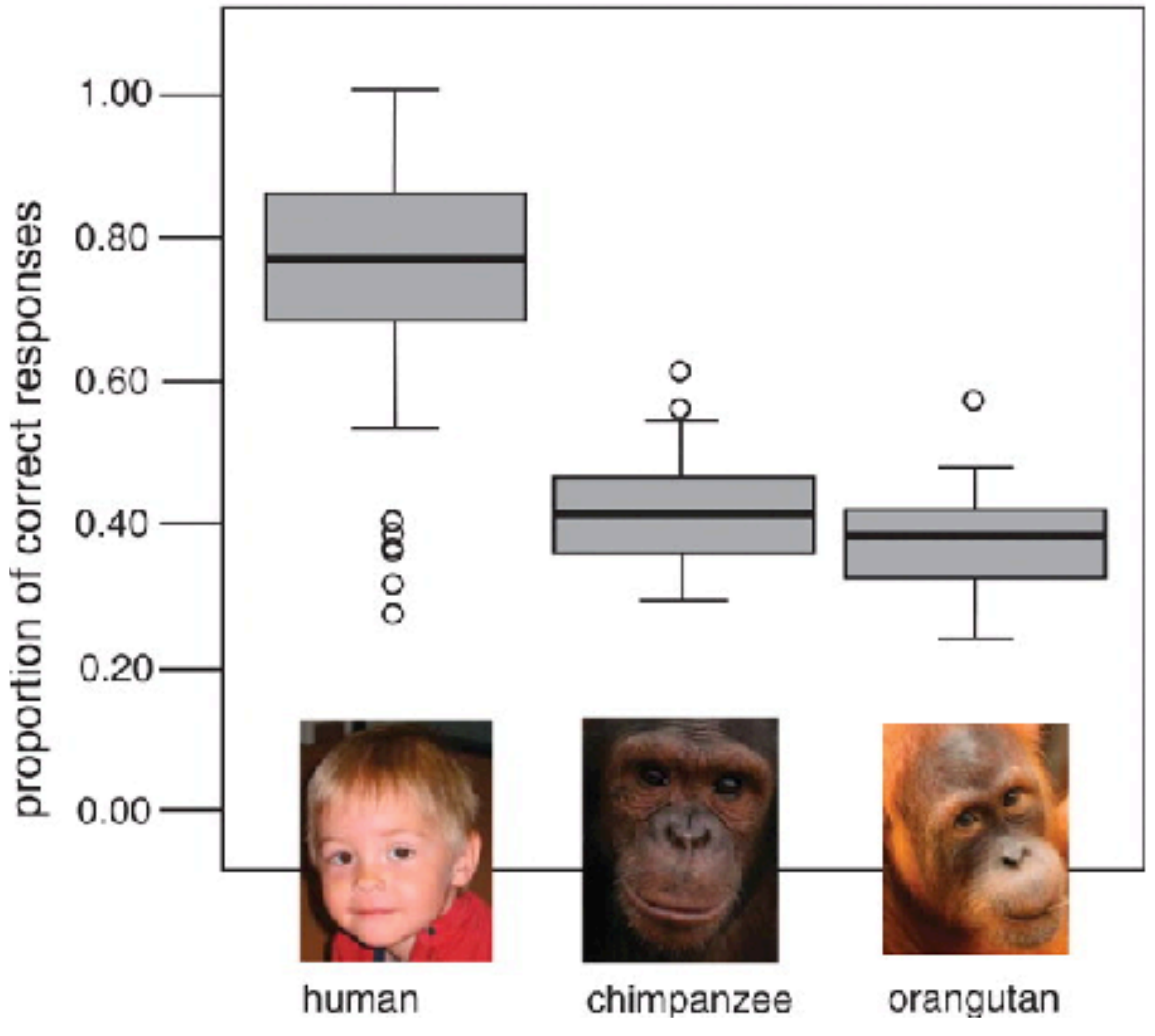

Witt et al., (*PNAS* 2024)

Compression

Which is the Monopoly Man?

- Biological intelligence has limited resources
  - Memory, energy, time horizon, motivation, etc…
- Artificial agents have very different limitations
- However, compression offers a common framework for how to both try to minimize distortion given maximum rate of information
- However, we see different patterns of distortions and downstream effects on learning

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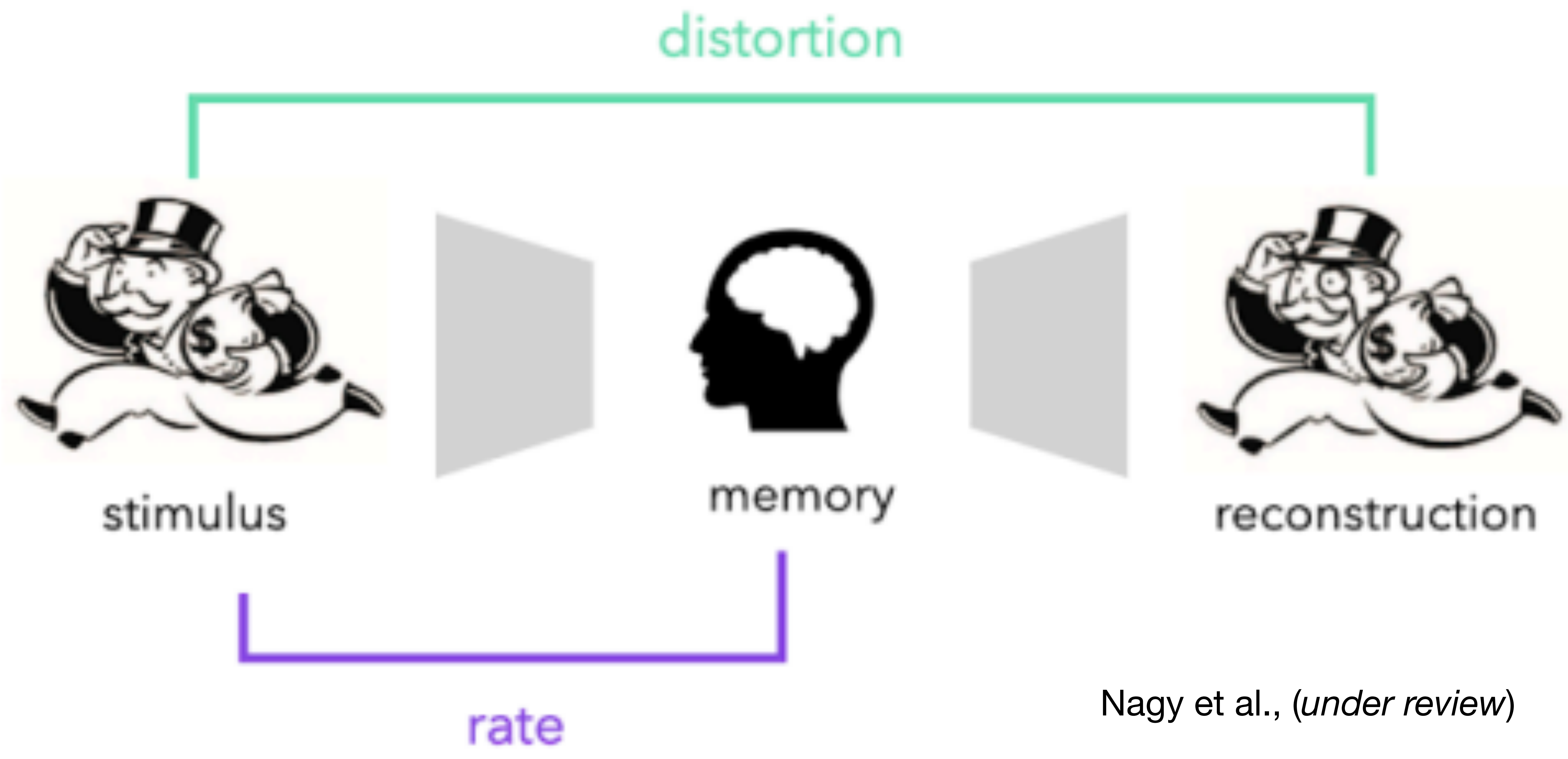

Nagy et al., (*under review*)

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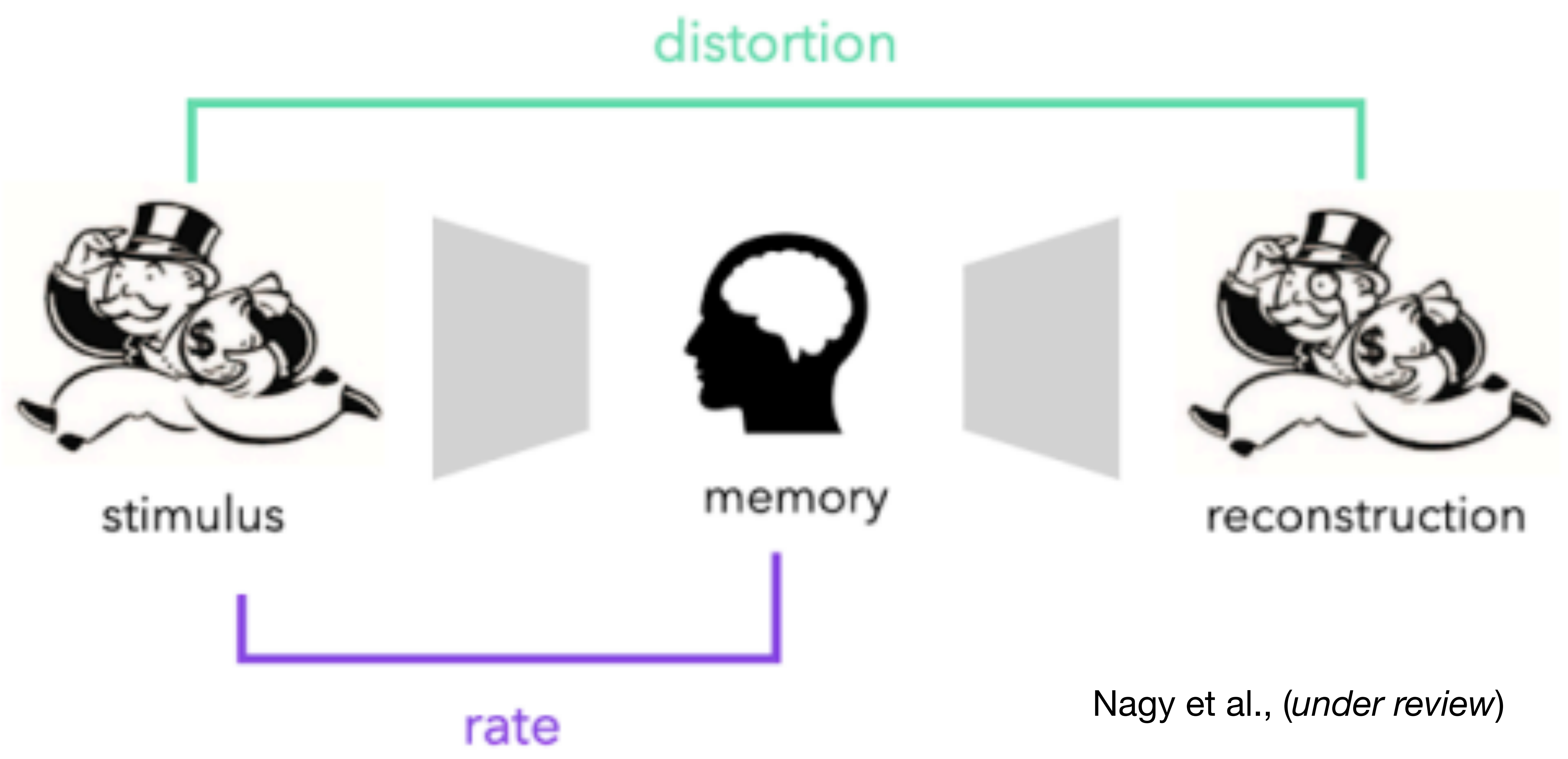

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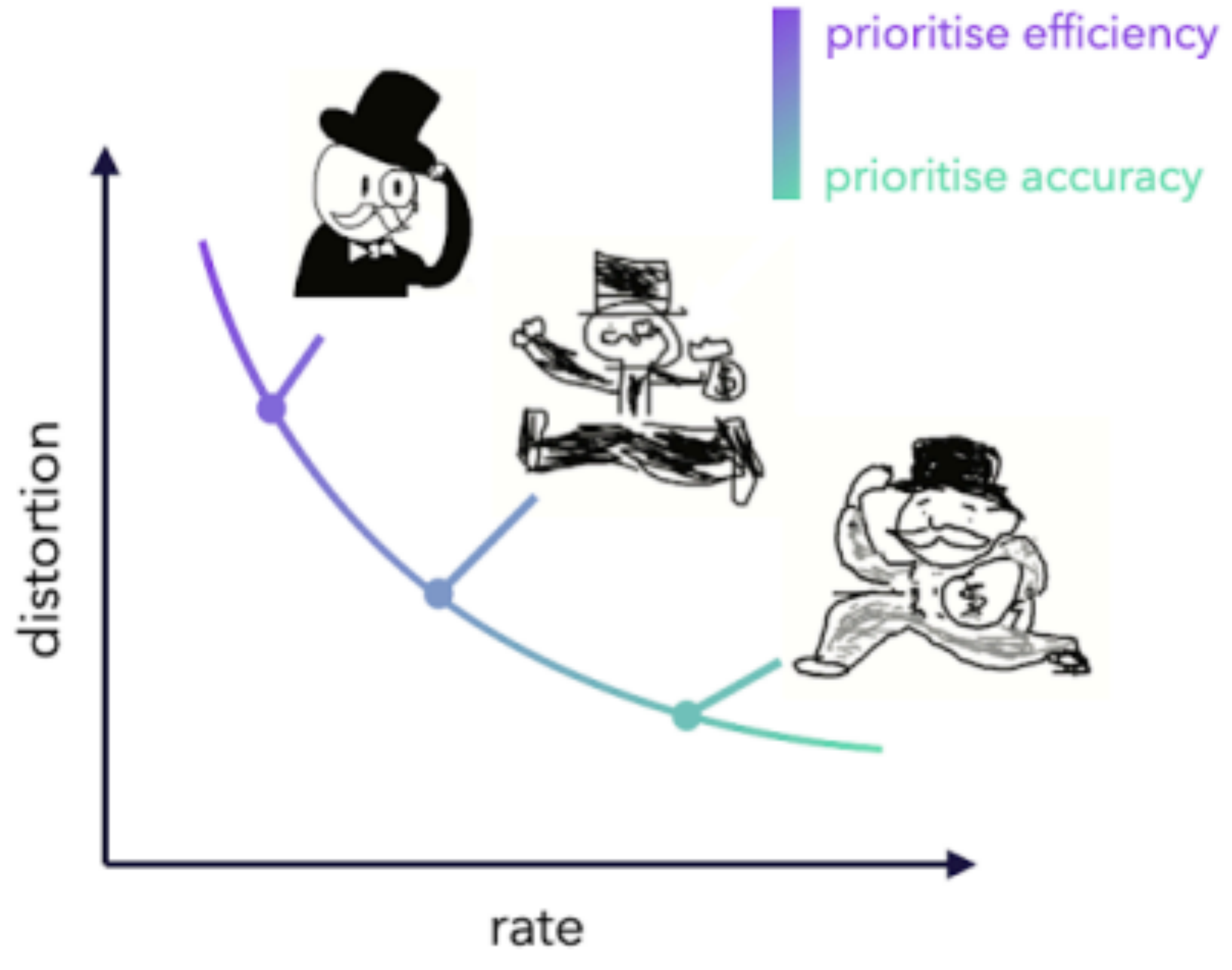

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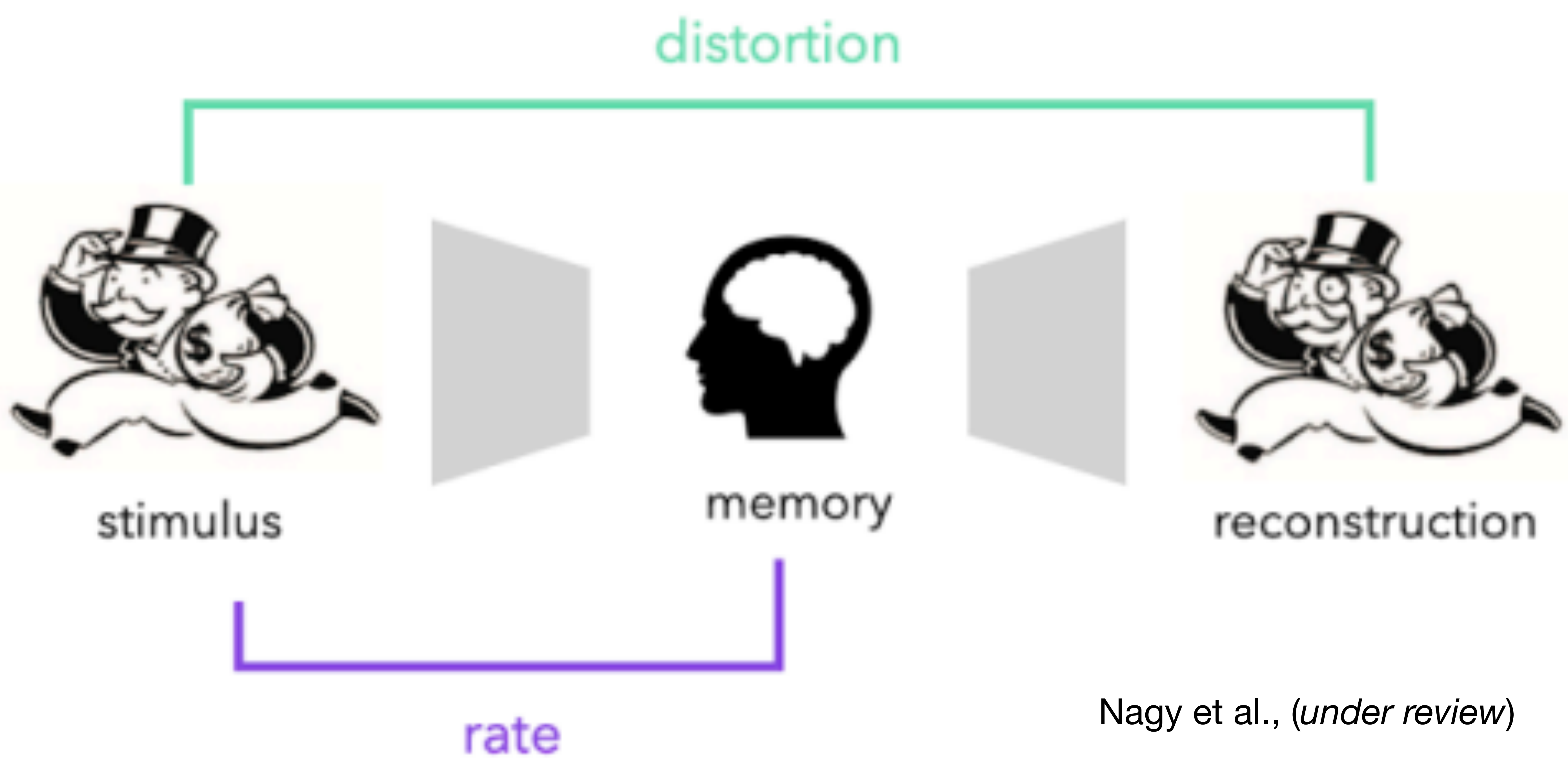

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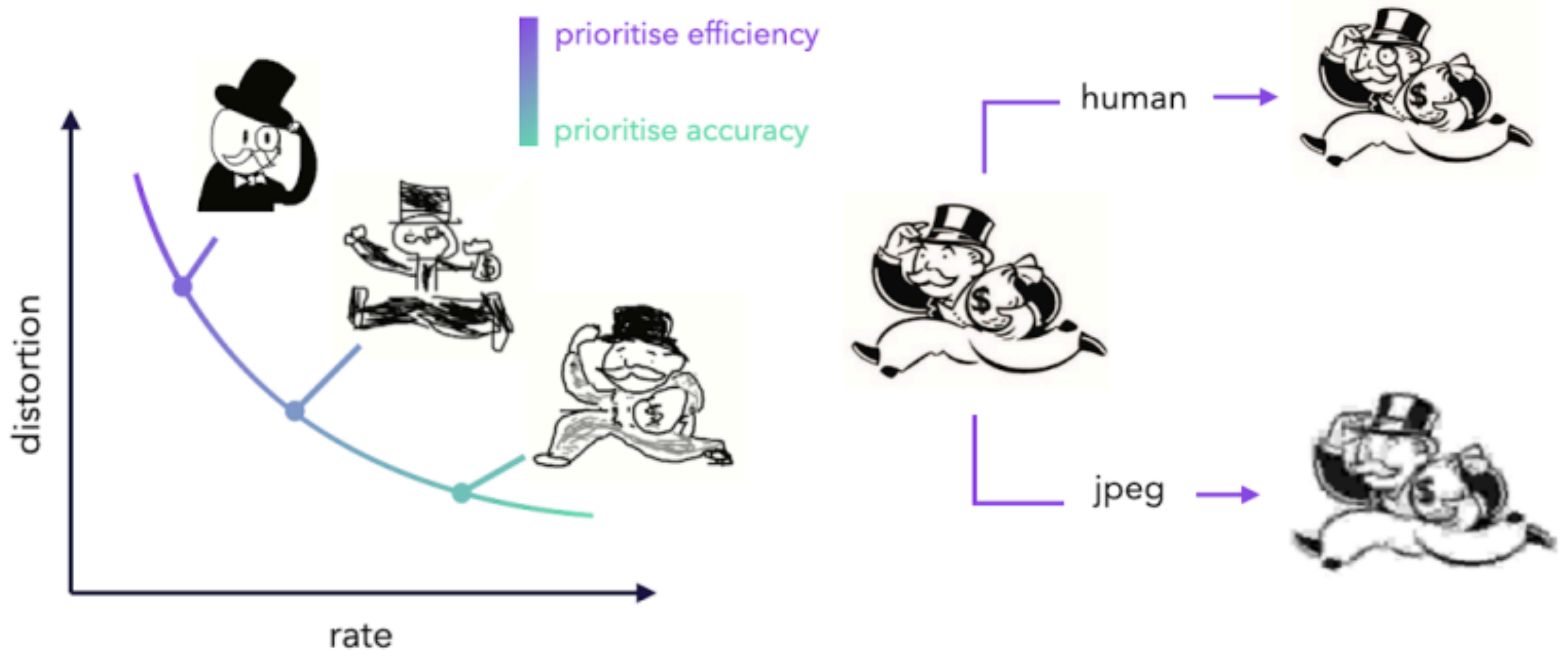
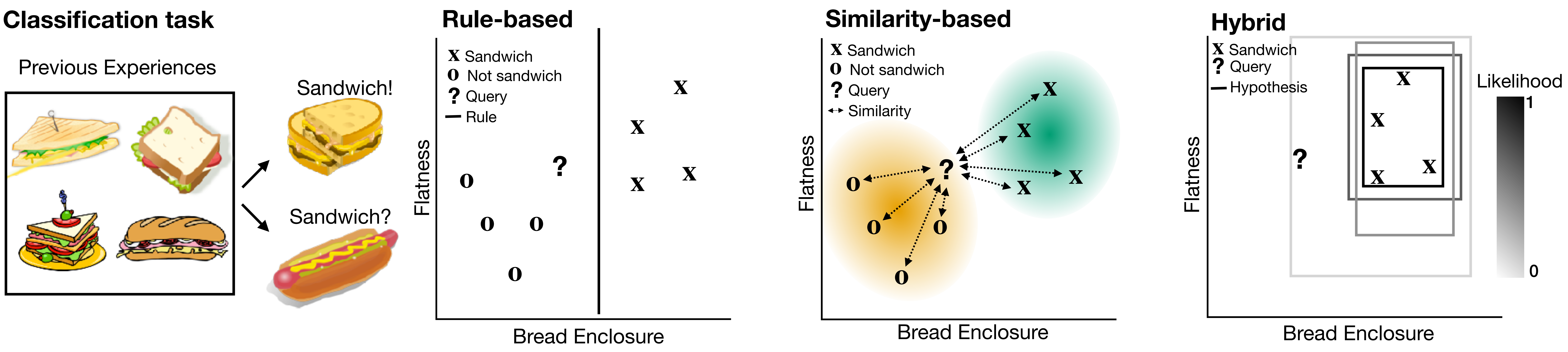


Concepts and Categories (Generalization 1)

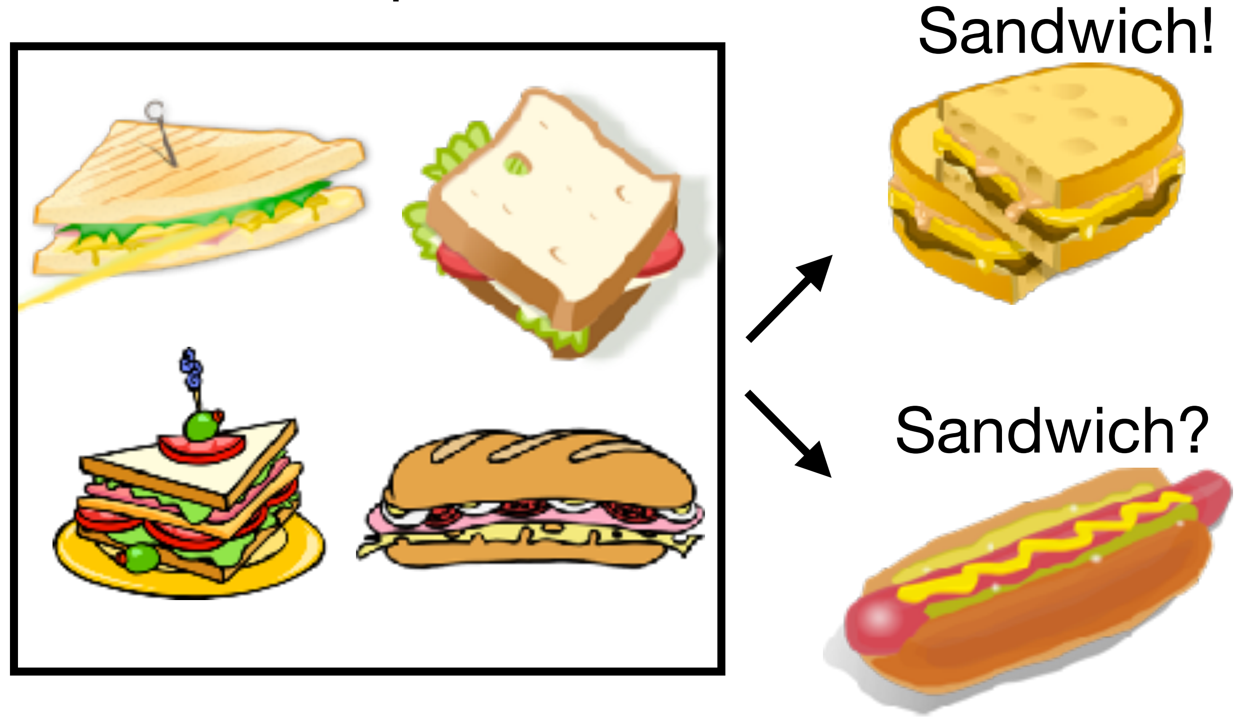


Wu et al., (AnnRevPsych *in press*)

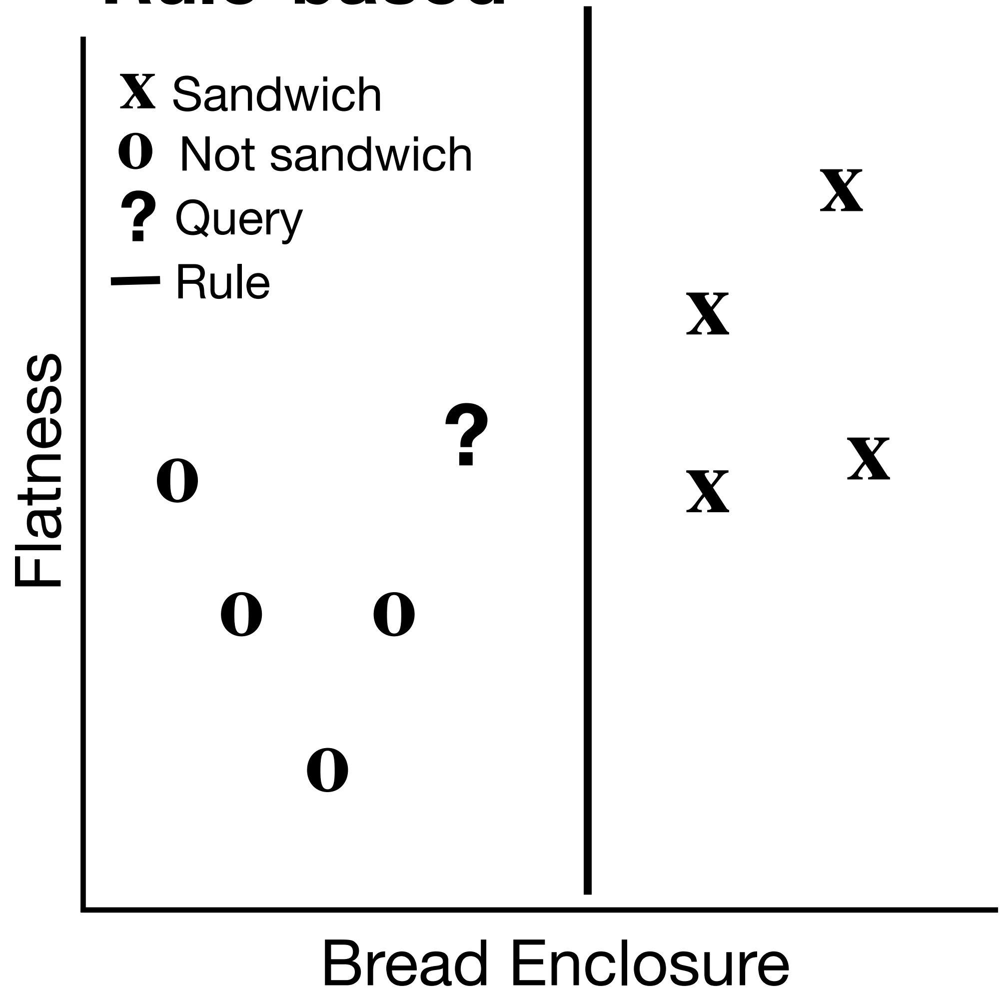
Concepts and Categories (Generalization 1)

Classification task

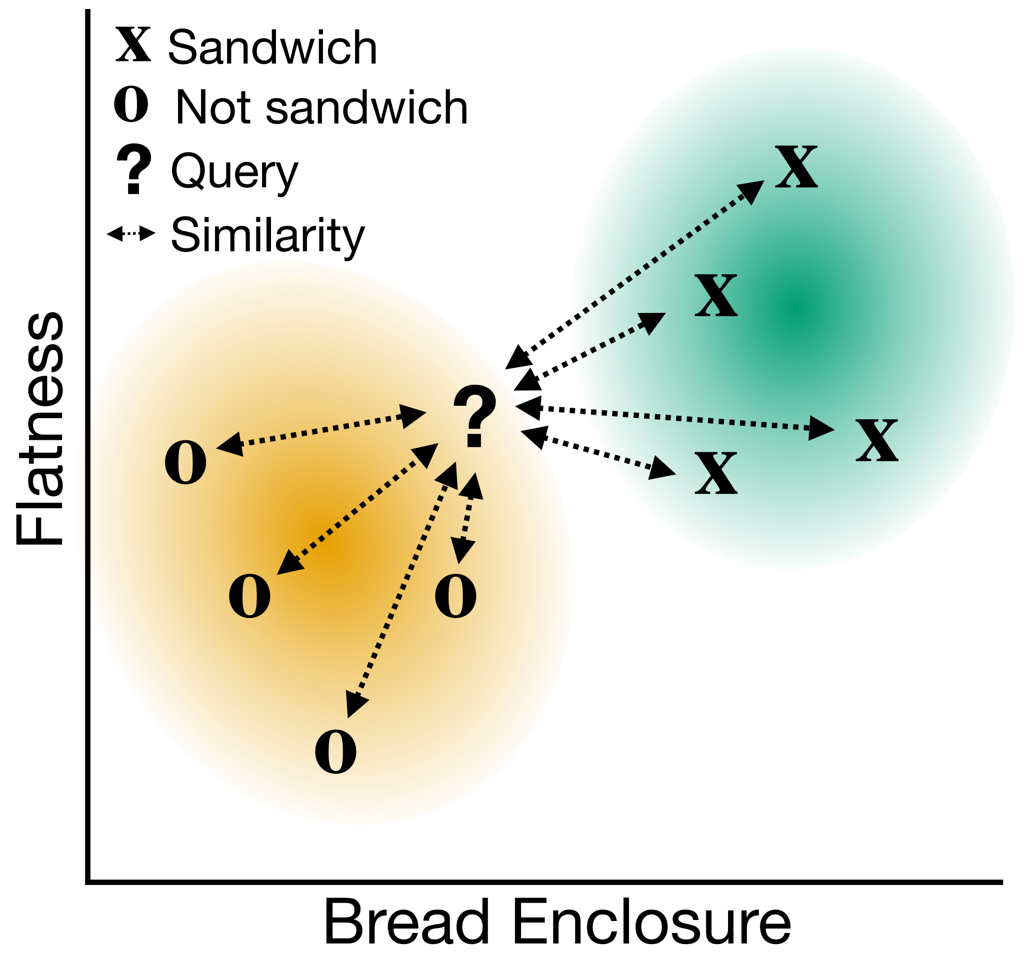
Previous Experiences



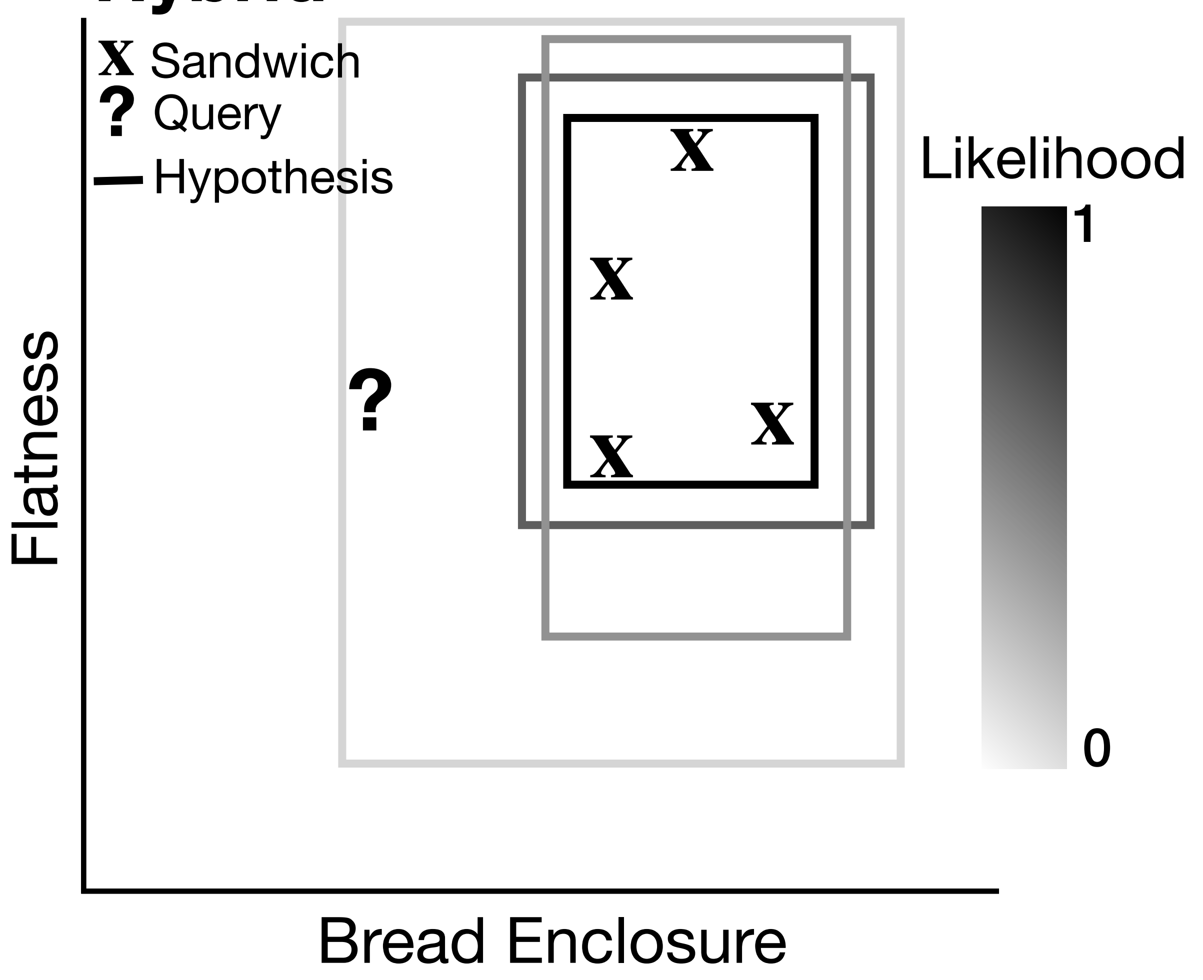
Rule-based

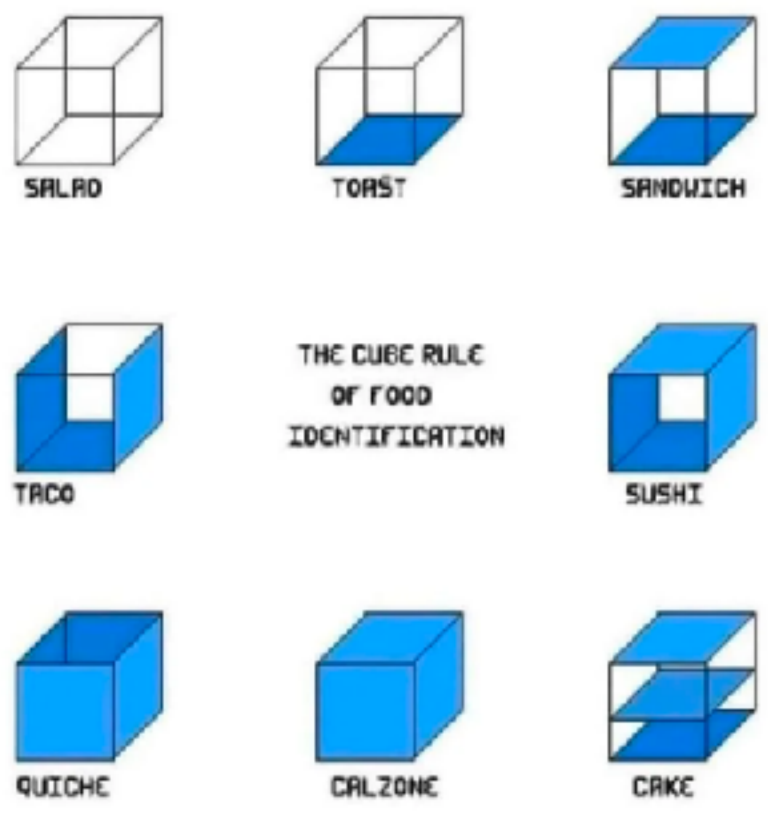


Similarity-based



Hybrid

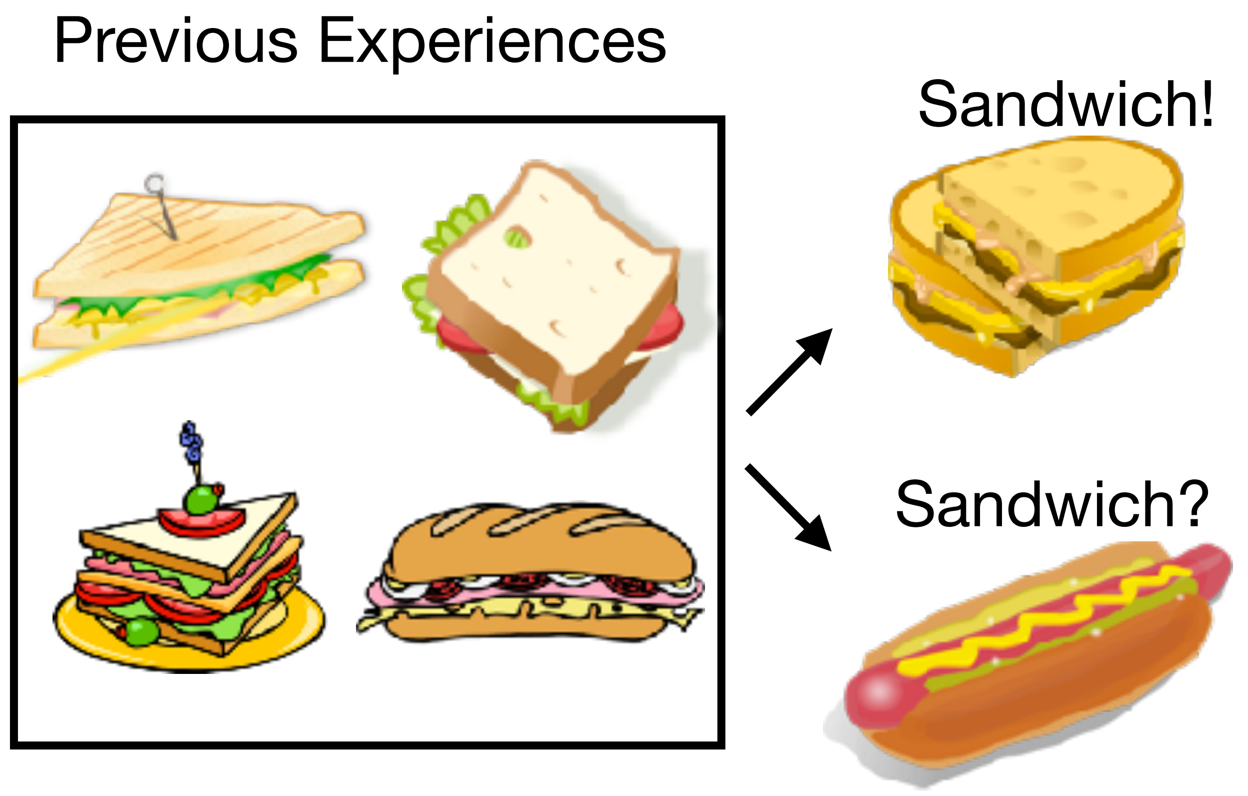




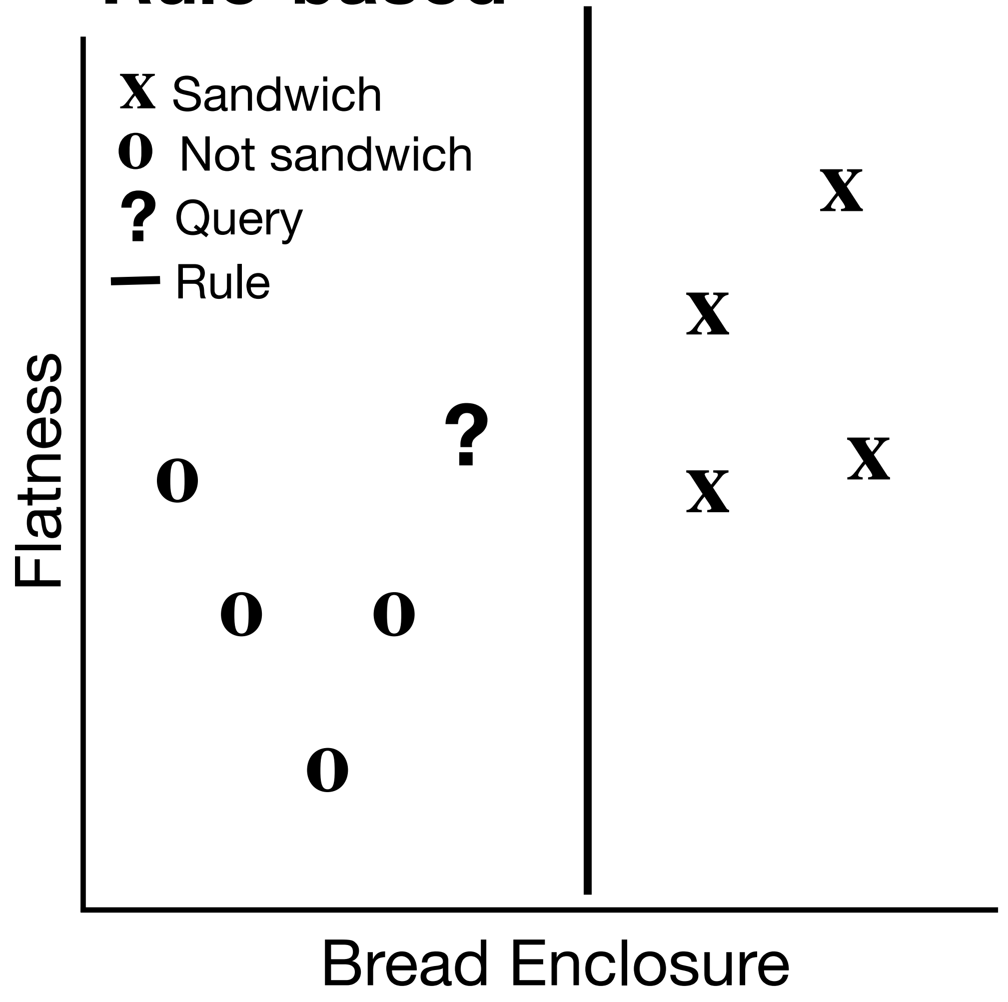
Wu et al., (AnnRevPsych *in press*)

Concepts and Categories (Generalization 1)

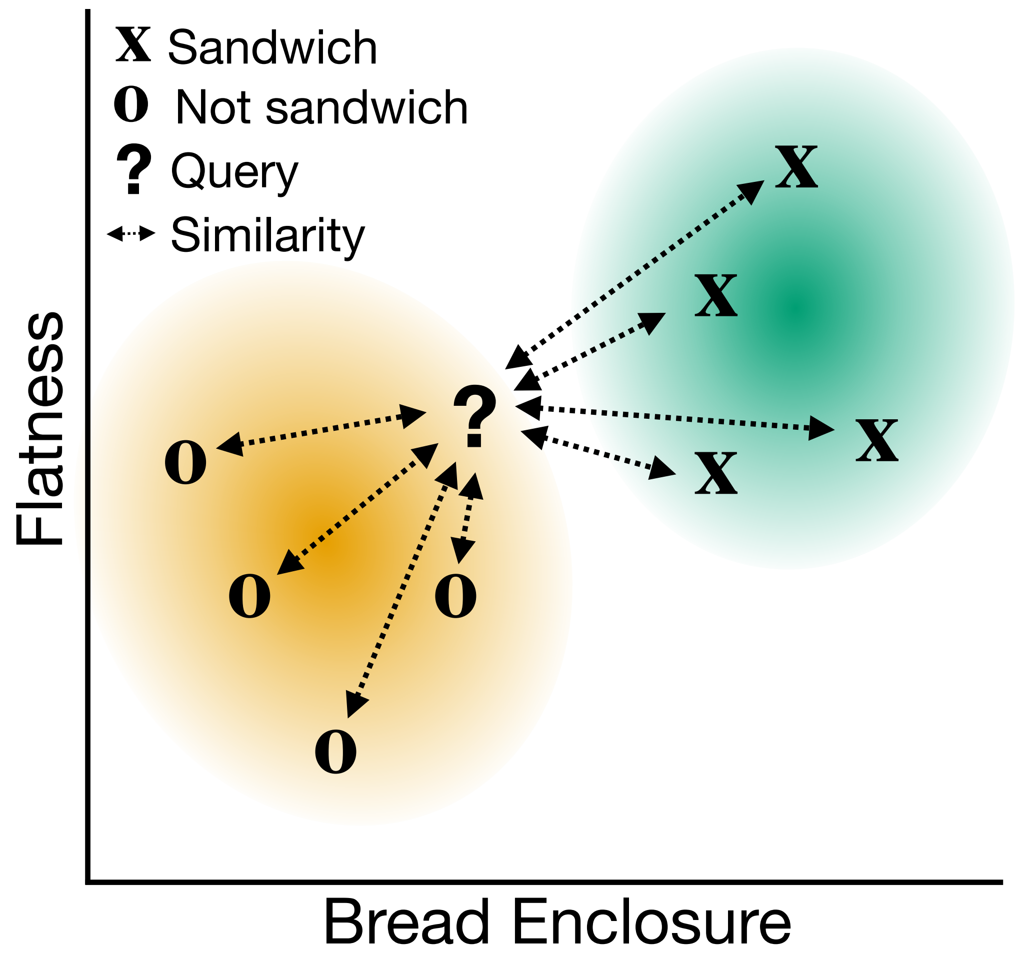
Classification task



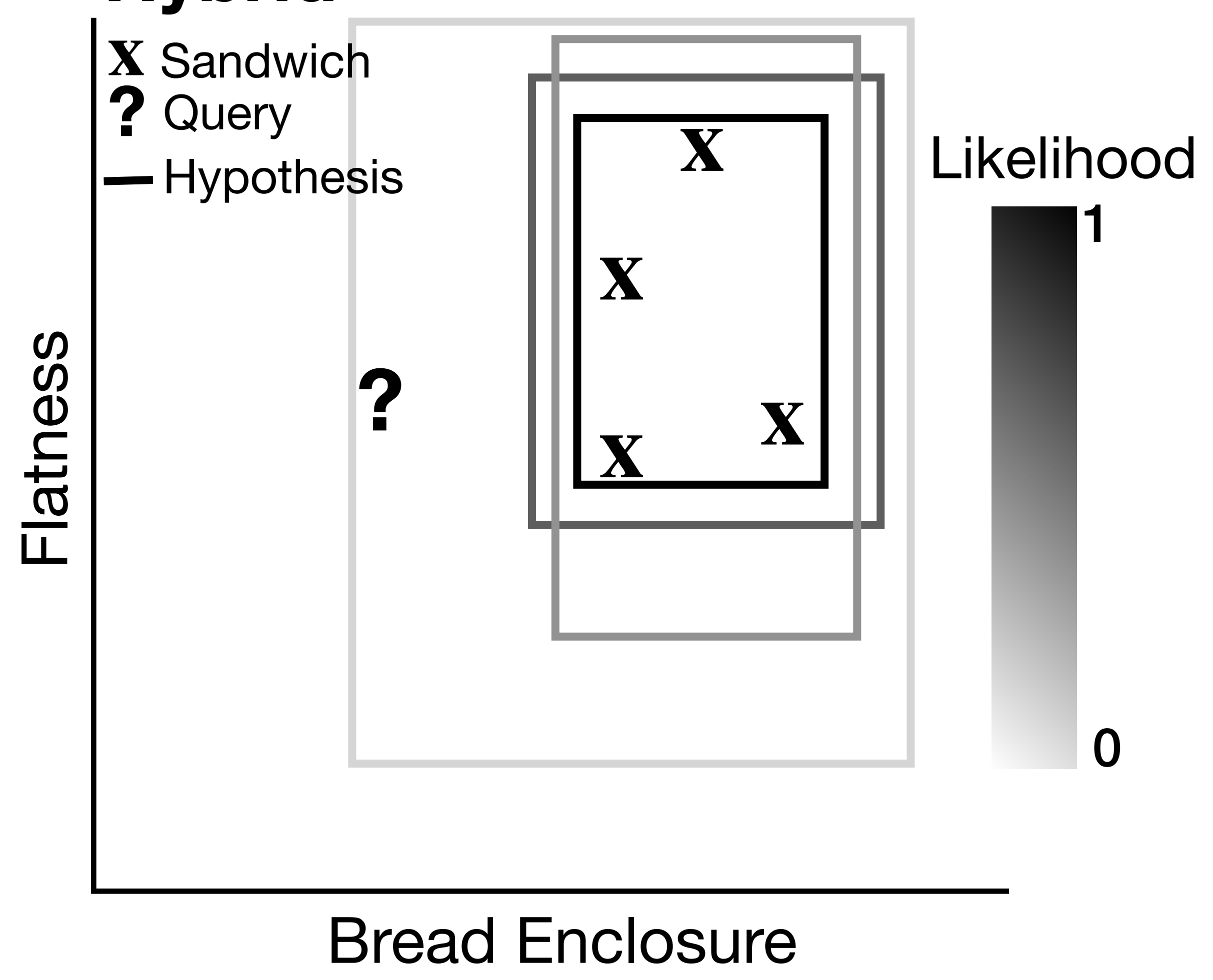
Rule-based

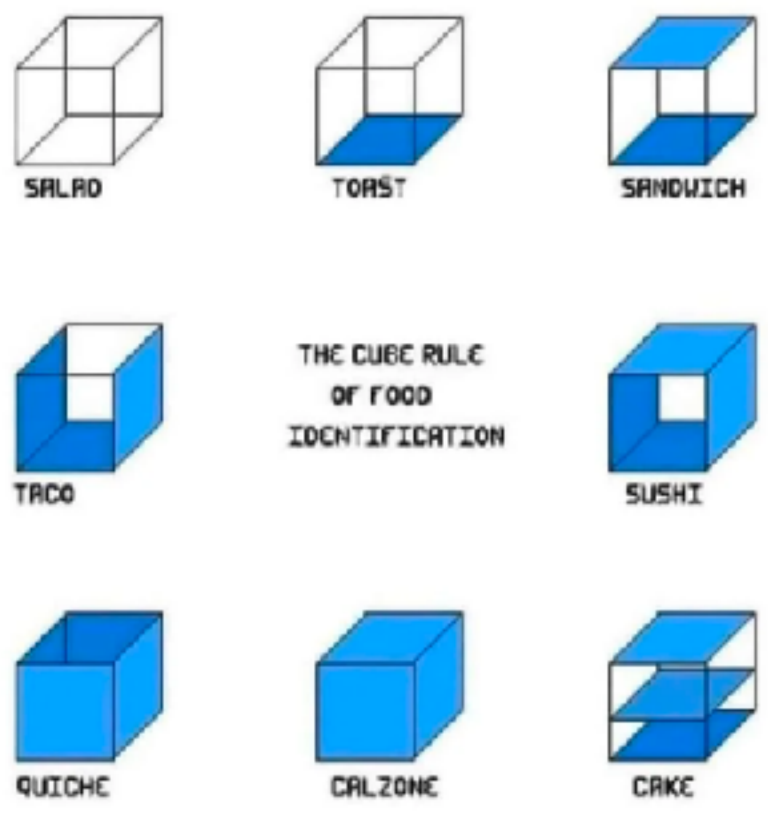


Similarity-based

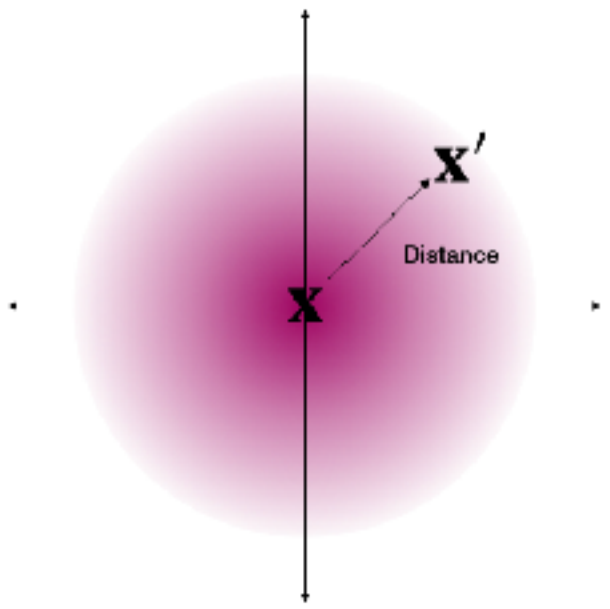


Hybrid

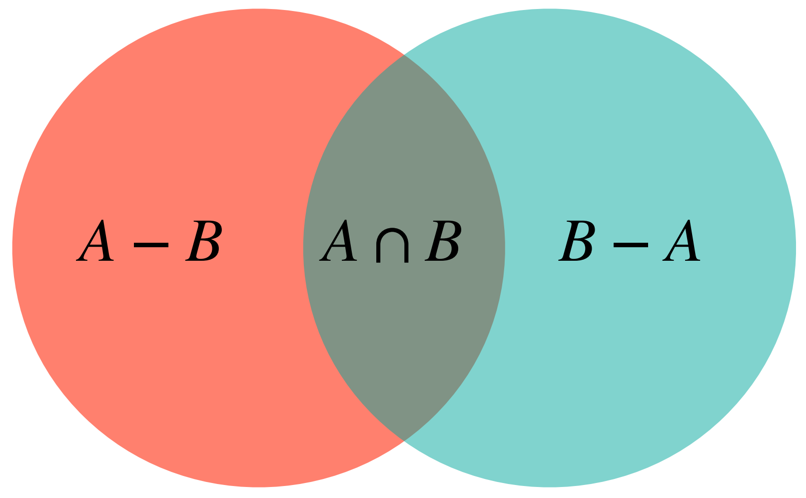




Metric

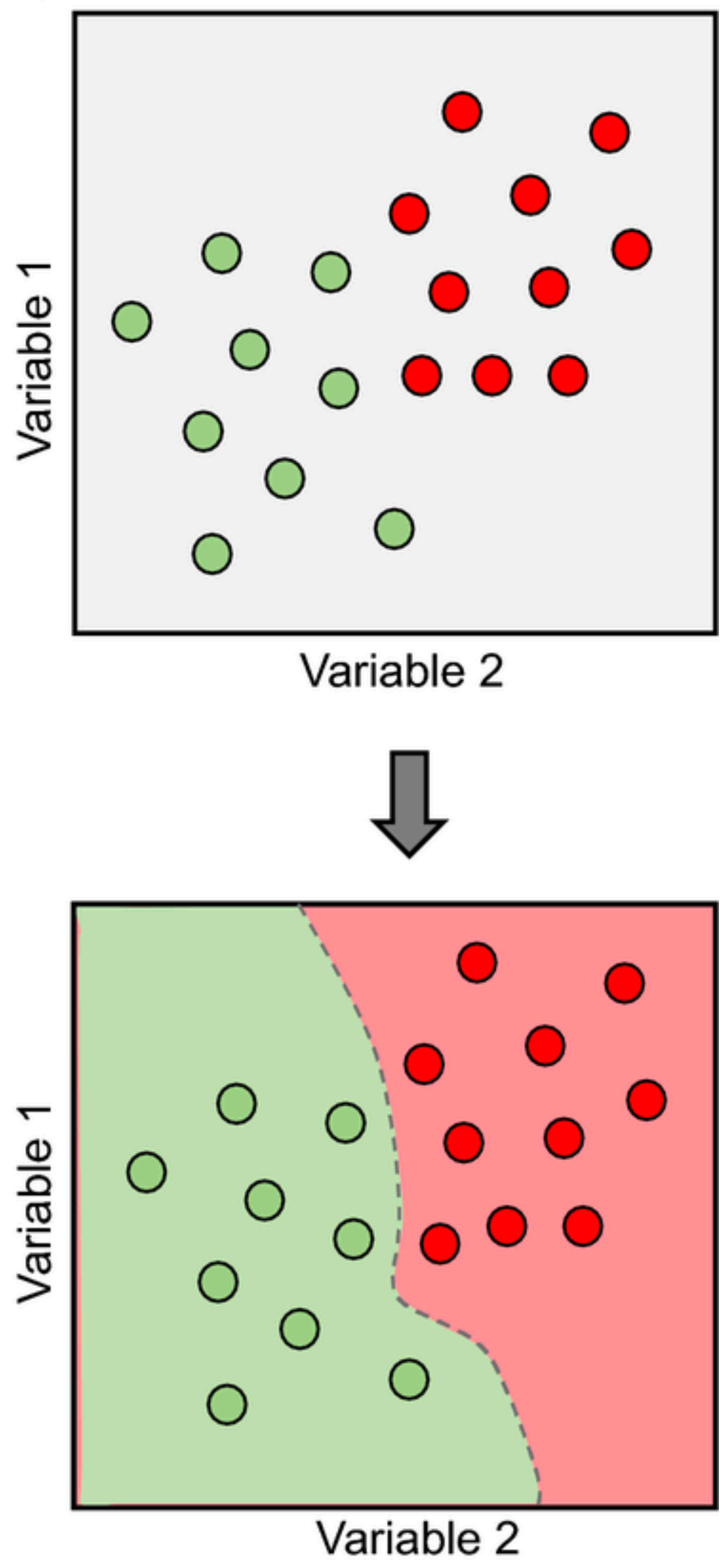


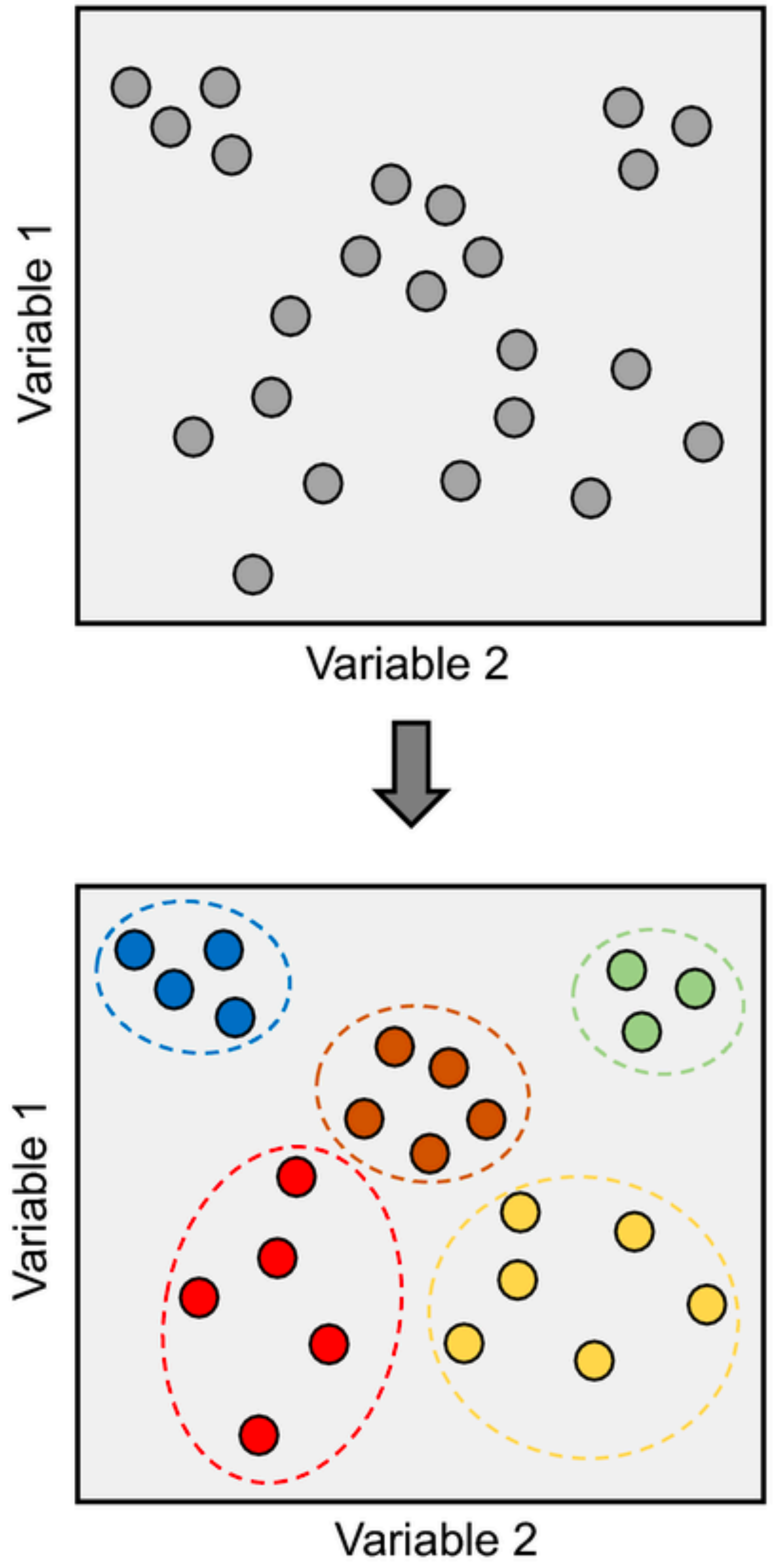
Set



Wu et al., (AnnRevPsych *in press*)

Supervised and Unsupervised Learning

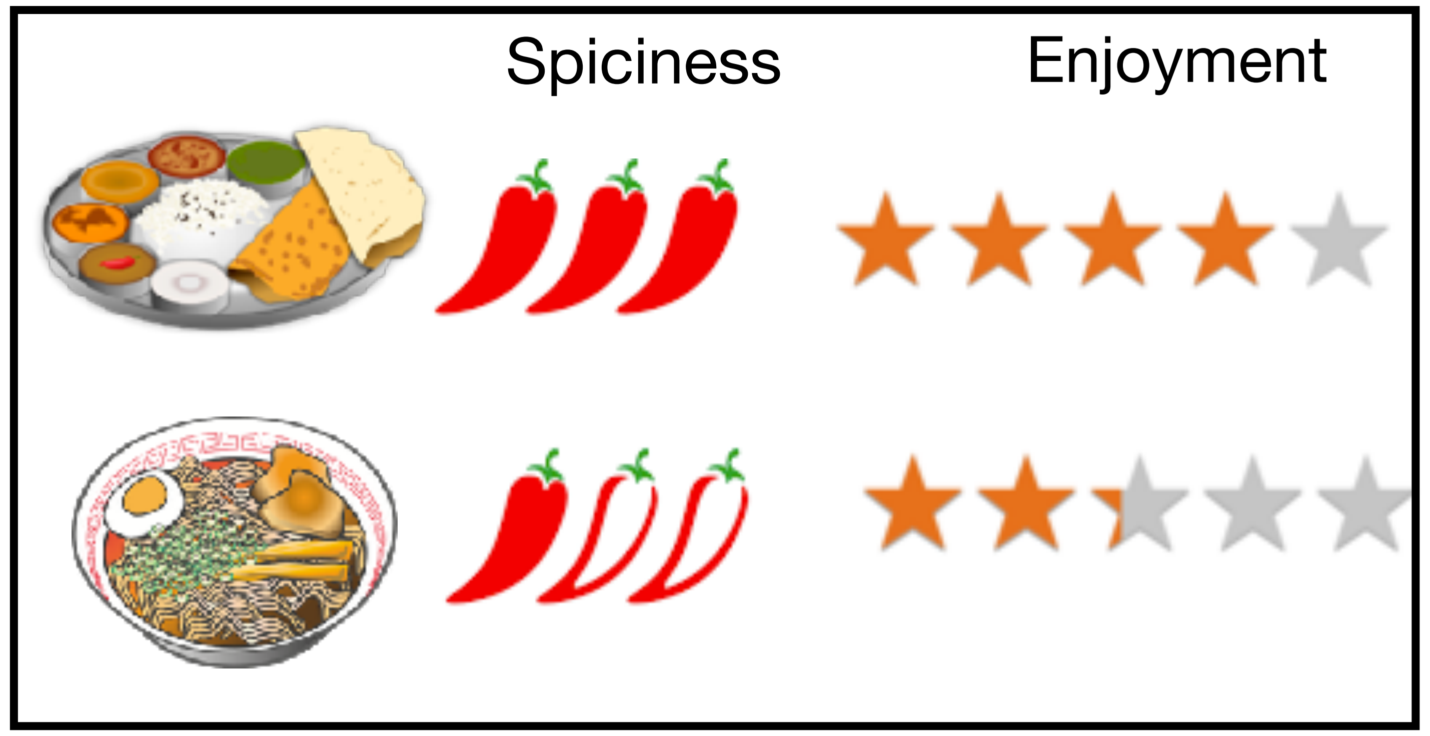


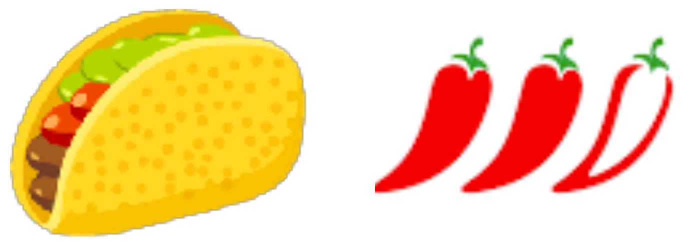


Function Learning (Generalization 2)

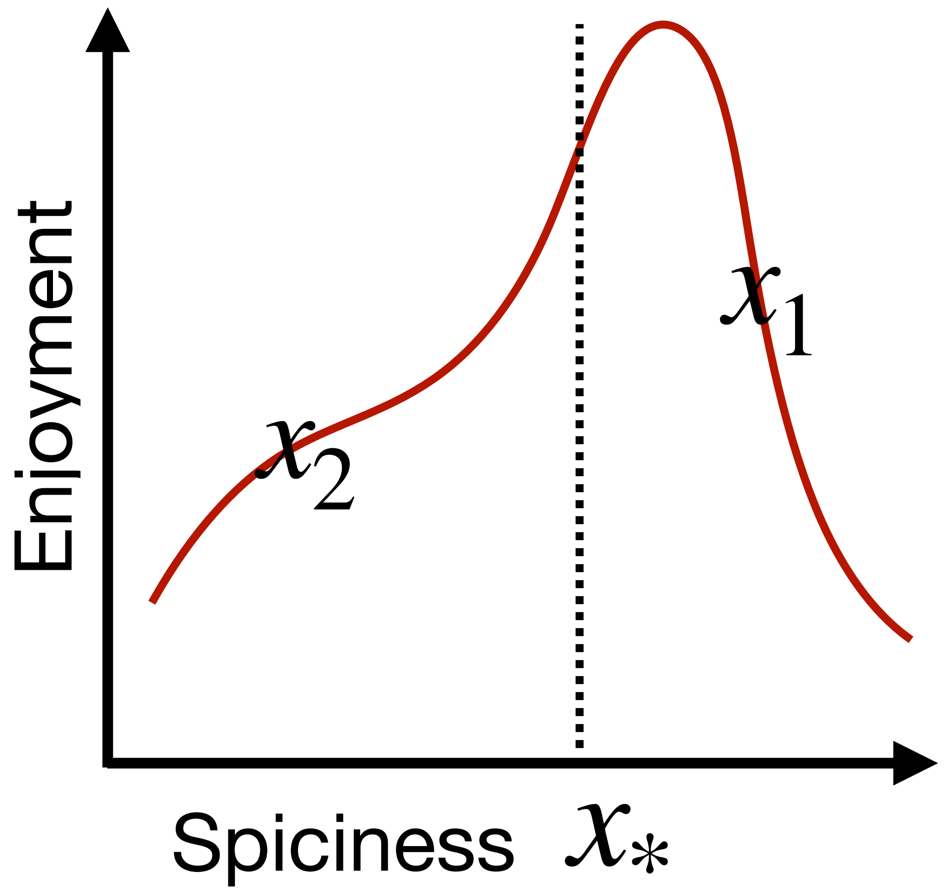
Regression task

Previous Experiences





?



Function Learning (Generalization 2)

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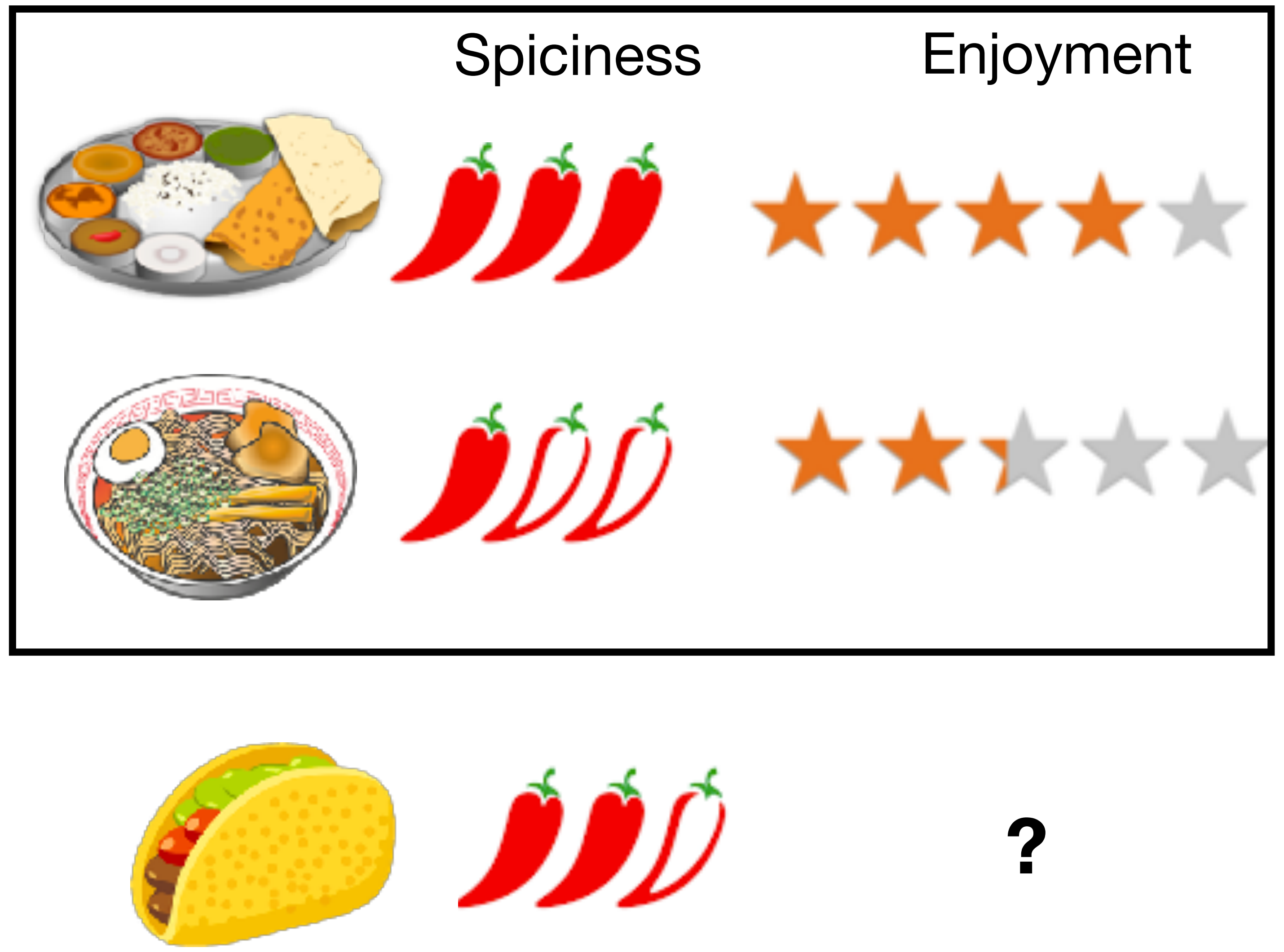
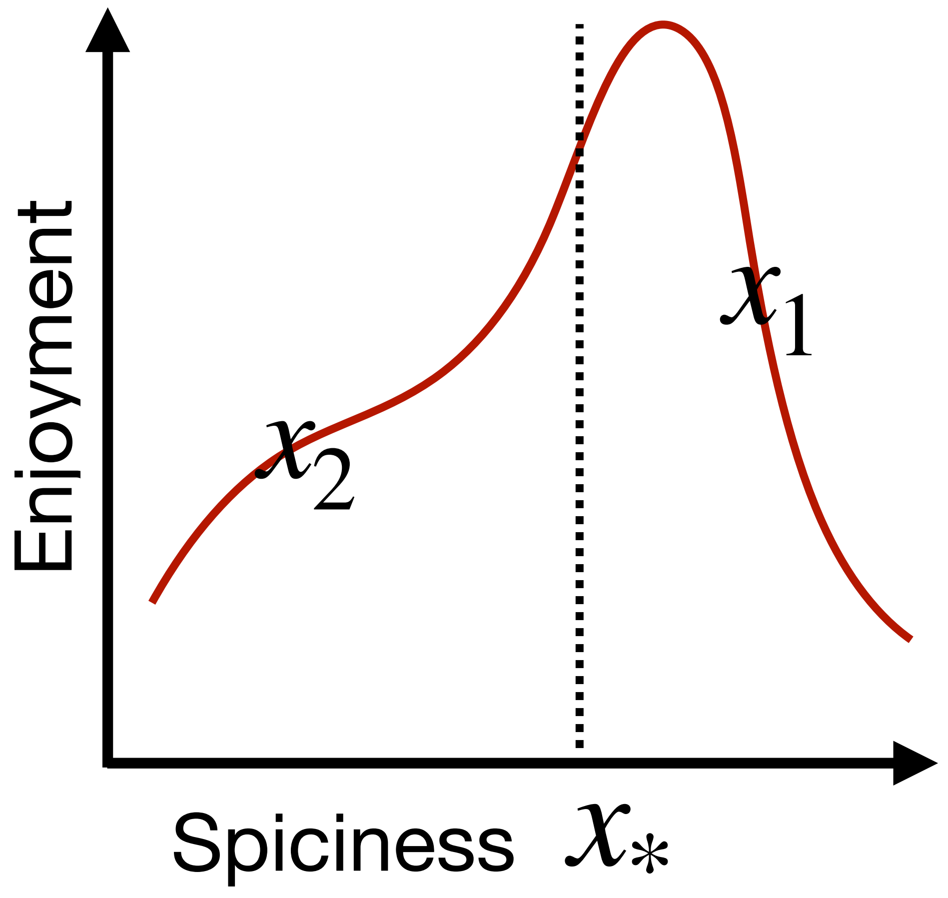
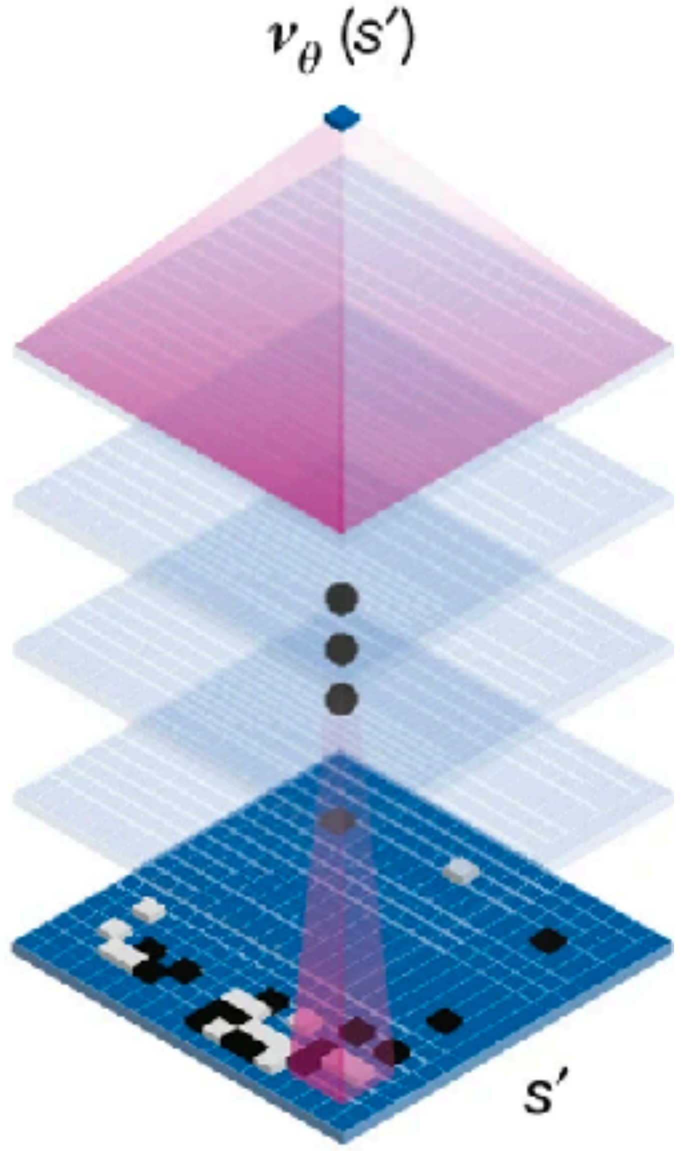




Value approximation in RL

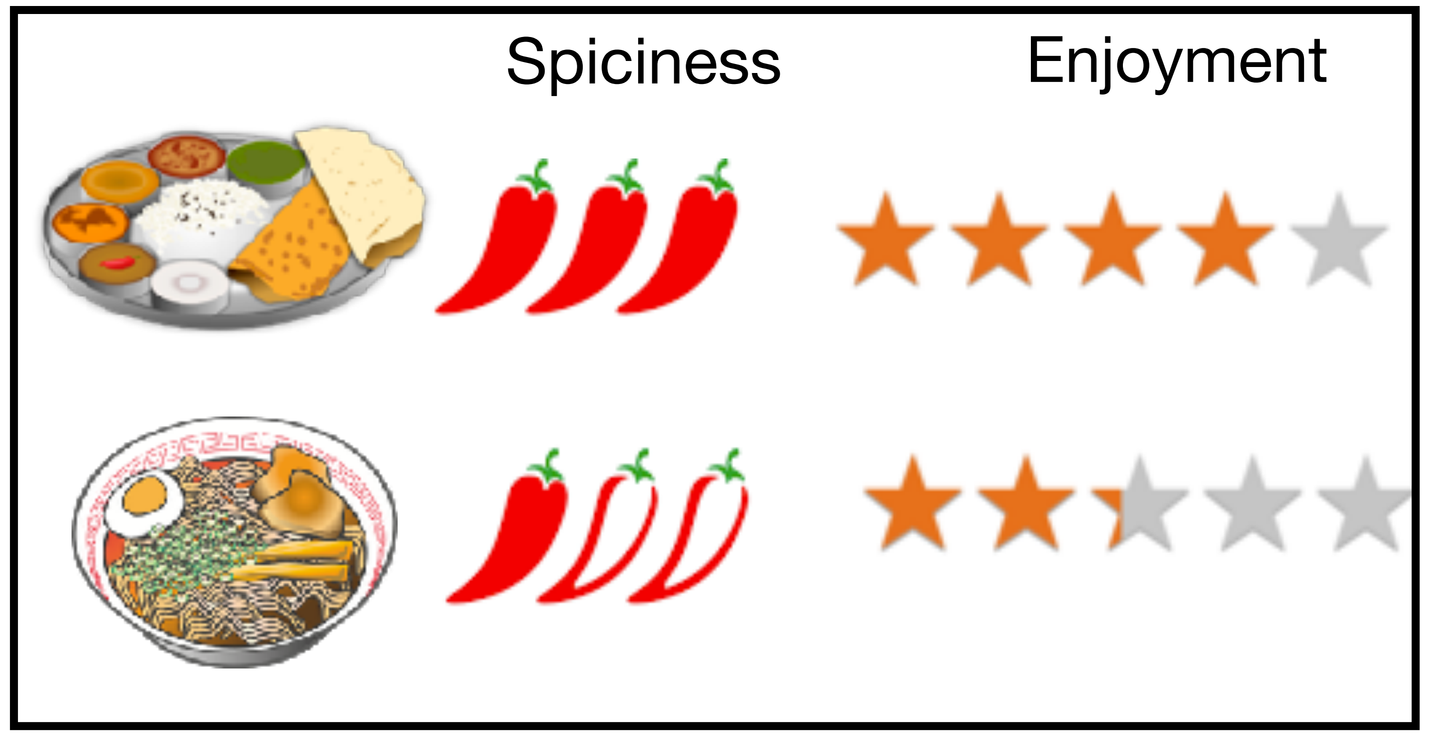


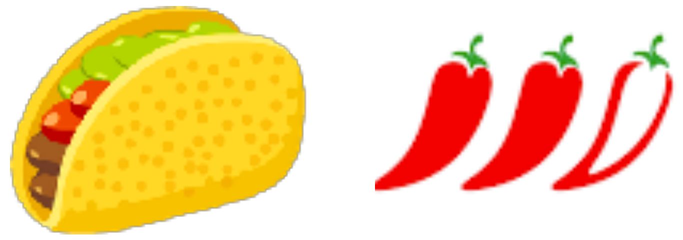
Silver et al., (2016)

Function Learning (Generalization 2)

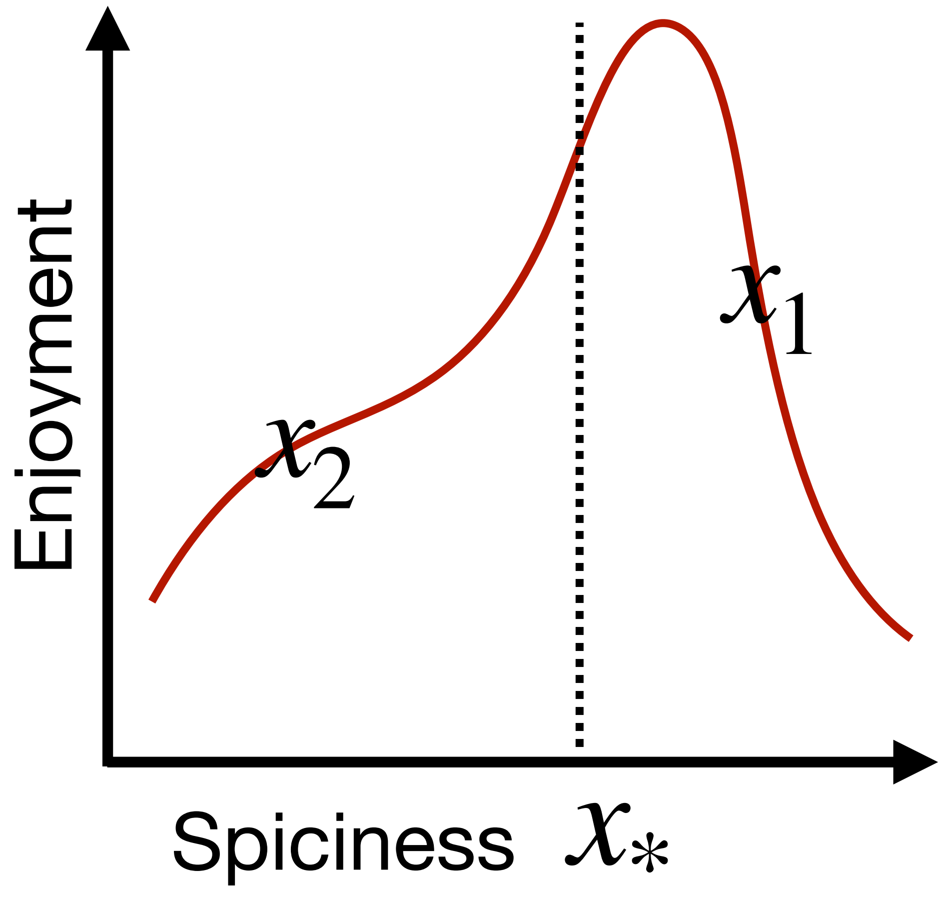
Regression task

Previous Experiences

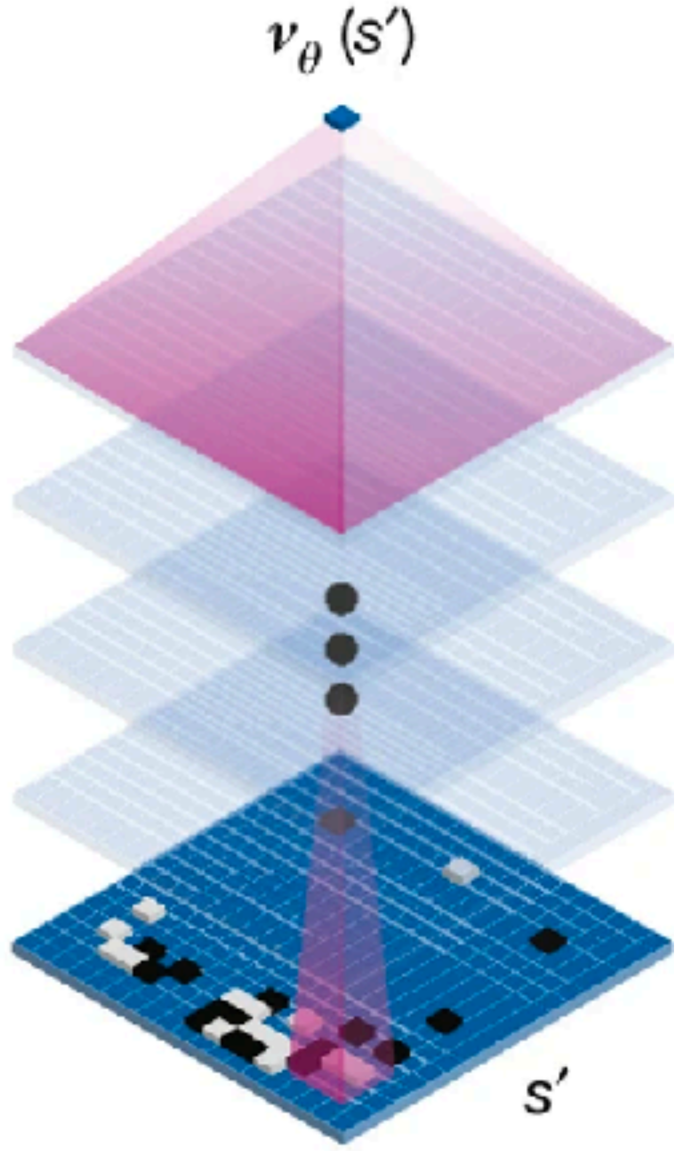




?

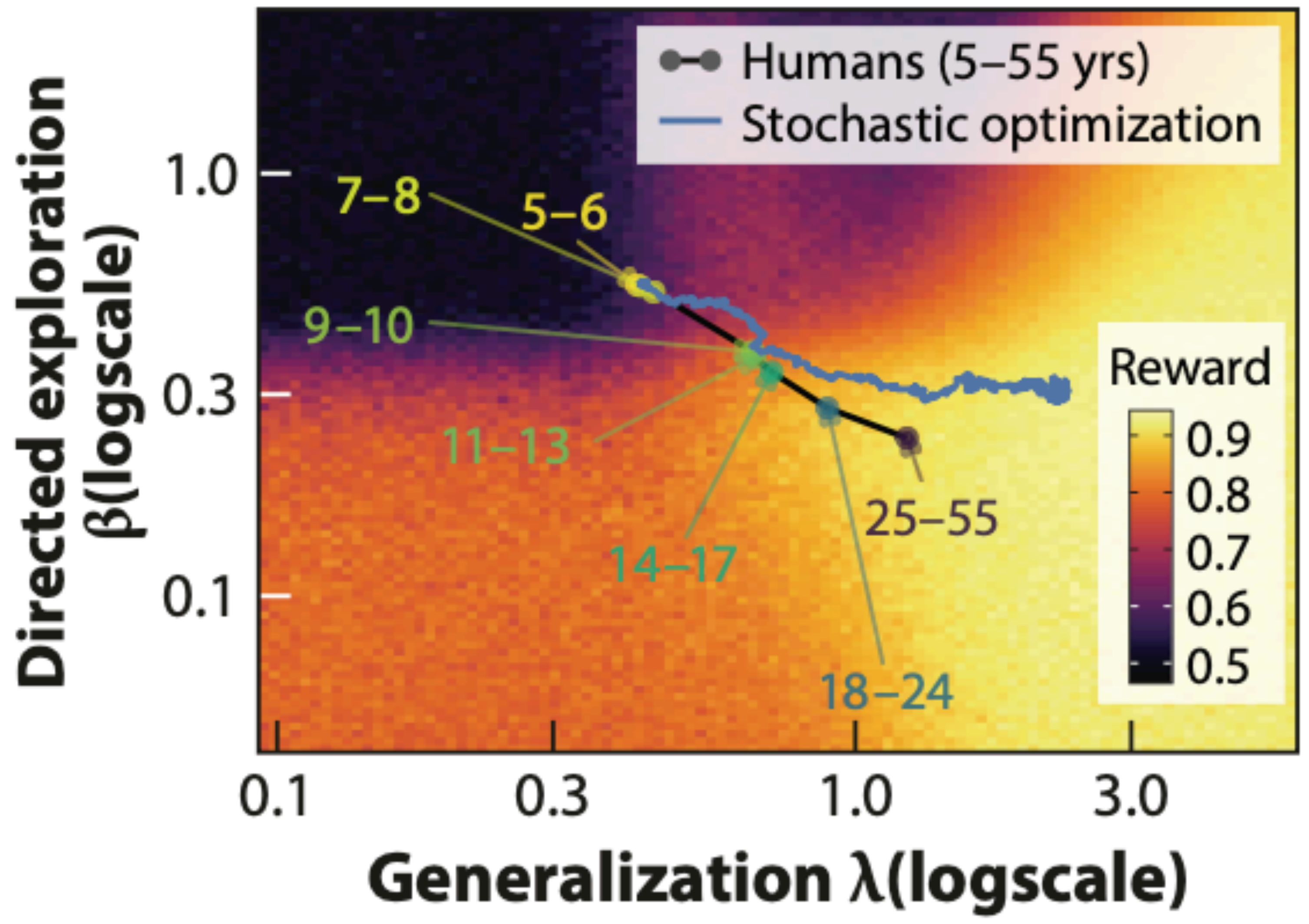


Value approximation in RL



Silver et al., (2016)

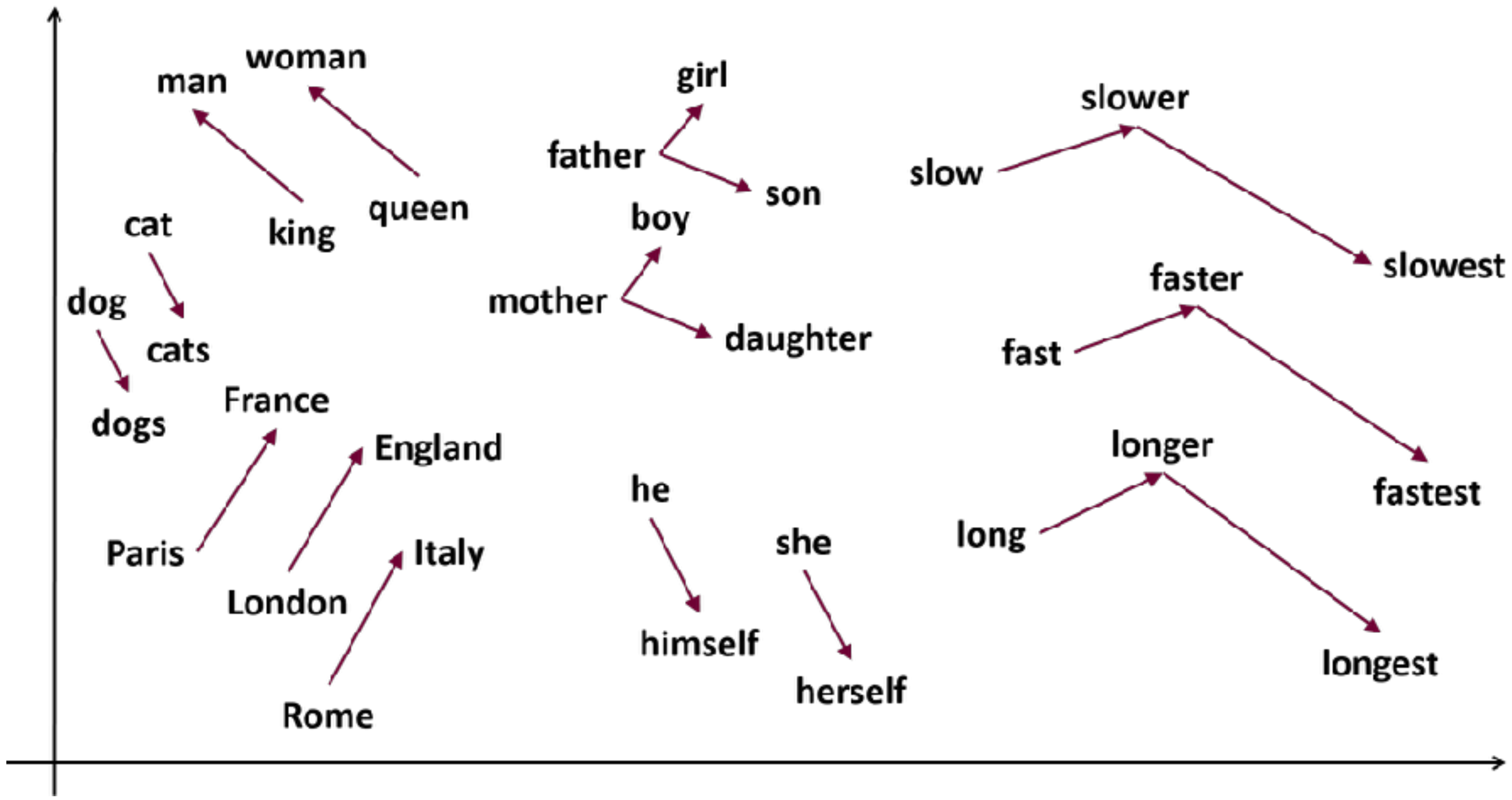
Plays an important role in human RL



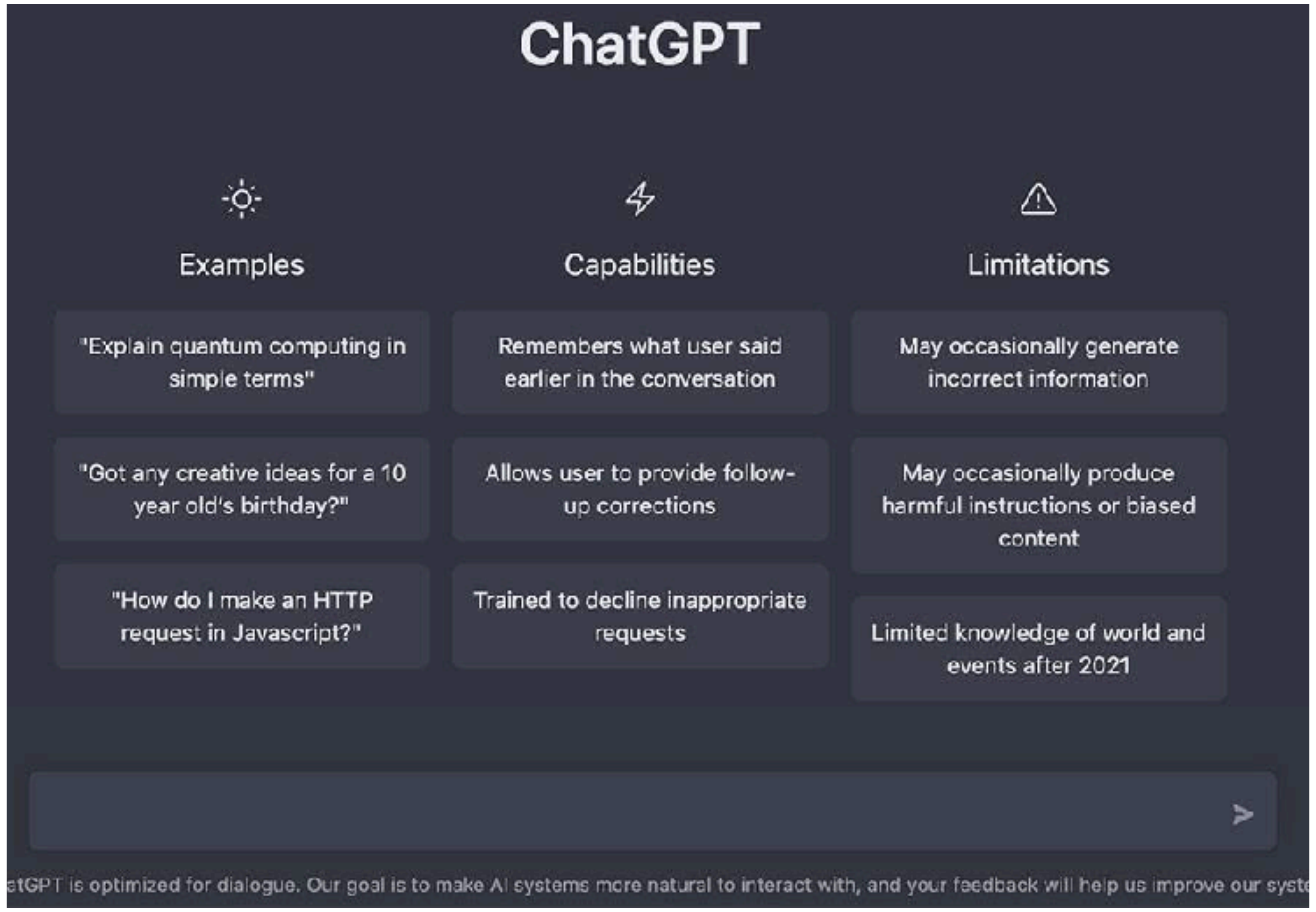
Giron et al., (NHB 2023)

Language and Semantics

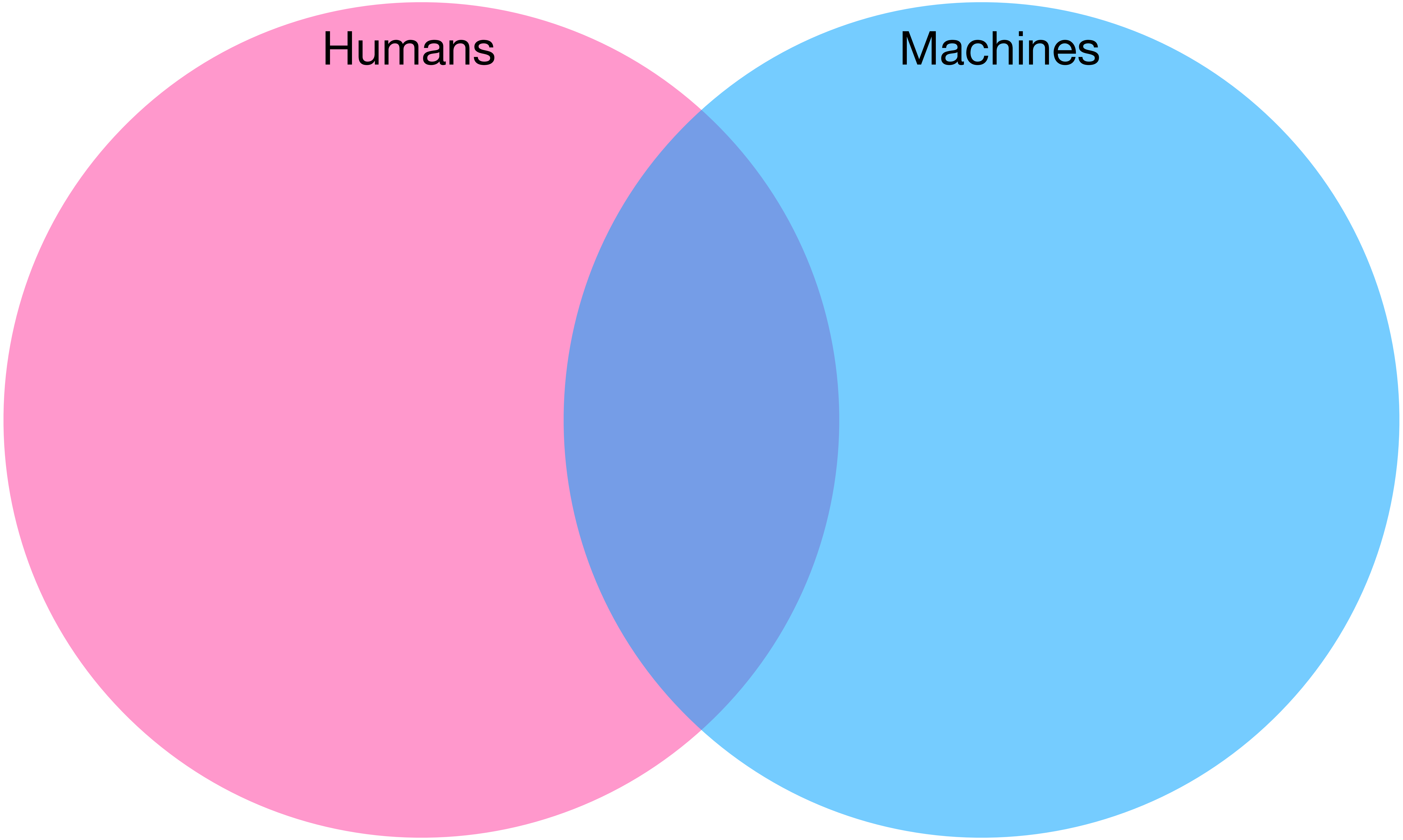
Vector Space Semantics



Large Language Models



General Principles



What is learning?

Split into groups of 2-4 and
come up with some definitions

Marr’s Levels of Analysis (1982)

Computational

Algorithmic

Implementation

Marr's Levels of Analysis (1982)

Computational

What is the goal of the system?
How does it behave?

Algorithmic

Implementation

Marr's Levels of Analysis (1982)

Computational

What is the goal of the system?
How does it behave?

Algorithmic

Which representations
and computations?

Implementation

Marr's Levels of Analysis (1982)

Computational

What is the goal of the system?
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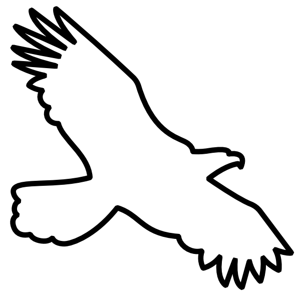
How is the system realized?

Marr's Levels of Analysis (1982)



Flight

Computational

What is the goal of the system?
How does it behave?

Flapping

Algorithmic

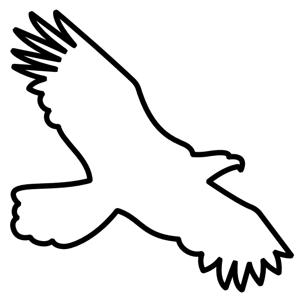
Which representations
and computations?

Feathers

Implementation

How is the system realized?

Marr's Levels of Analysis (1982)



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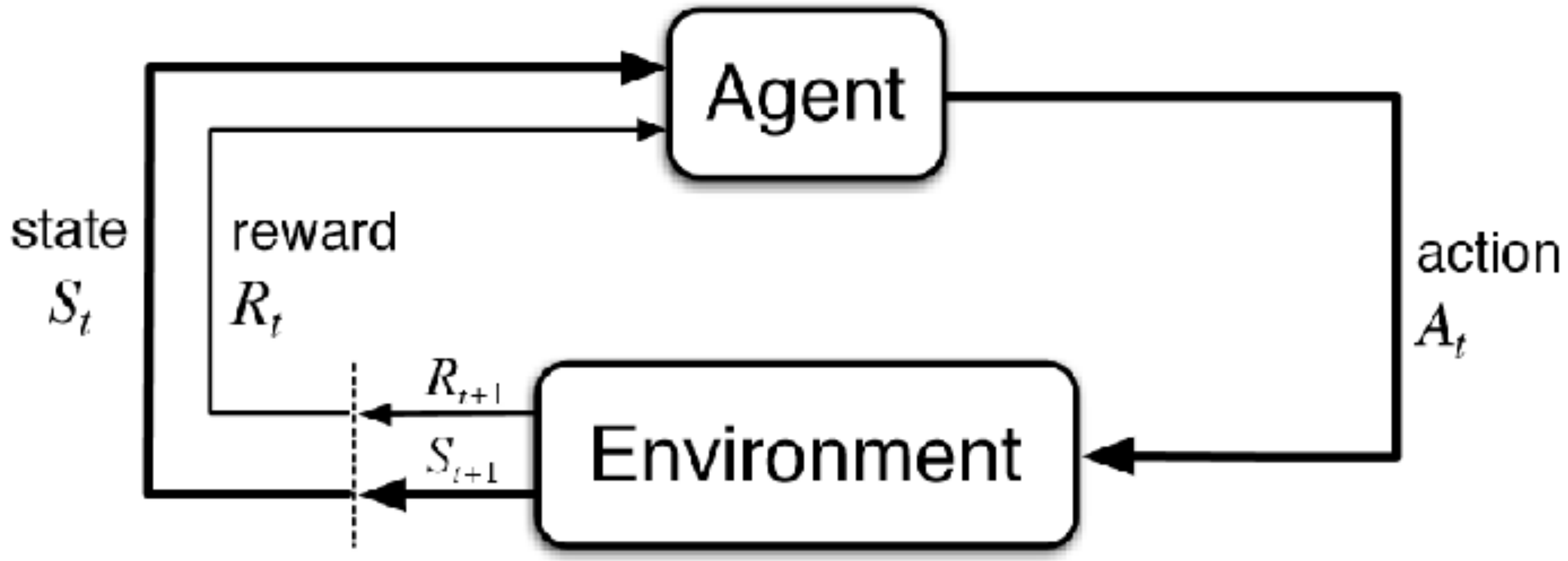

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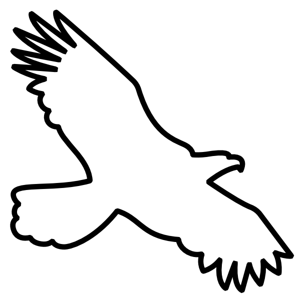

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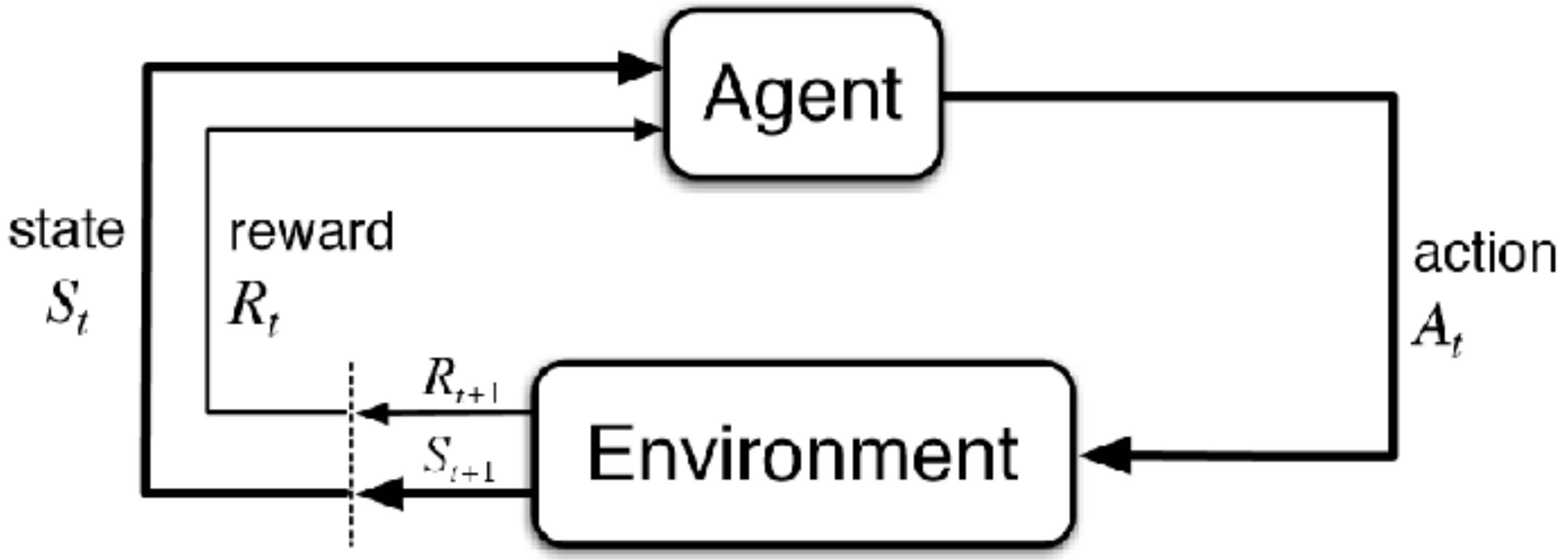
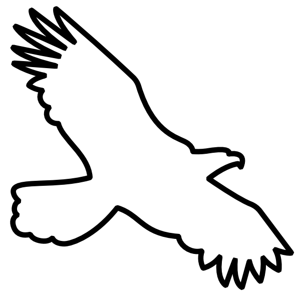


Initialize $Q(s, a)$ arbitrarily
Repeat (for each episode):
  Initialize s
  Repeat (for each step of episode):
    Choose a from s using policy derived from Q (e.g., ε-greedy)
    Take action a, observe r, s'
    $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$
    $s \leftarrow s'$;
  until s is terminal

Marr's Levels of Analysis (1982)



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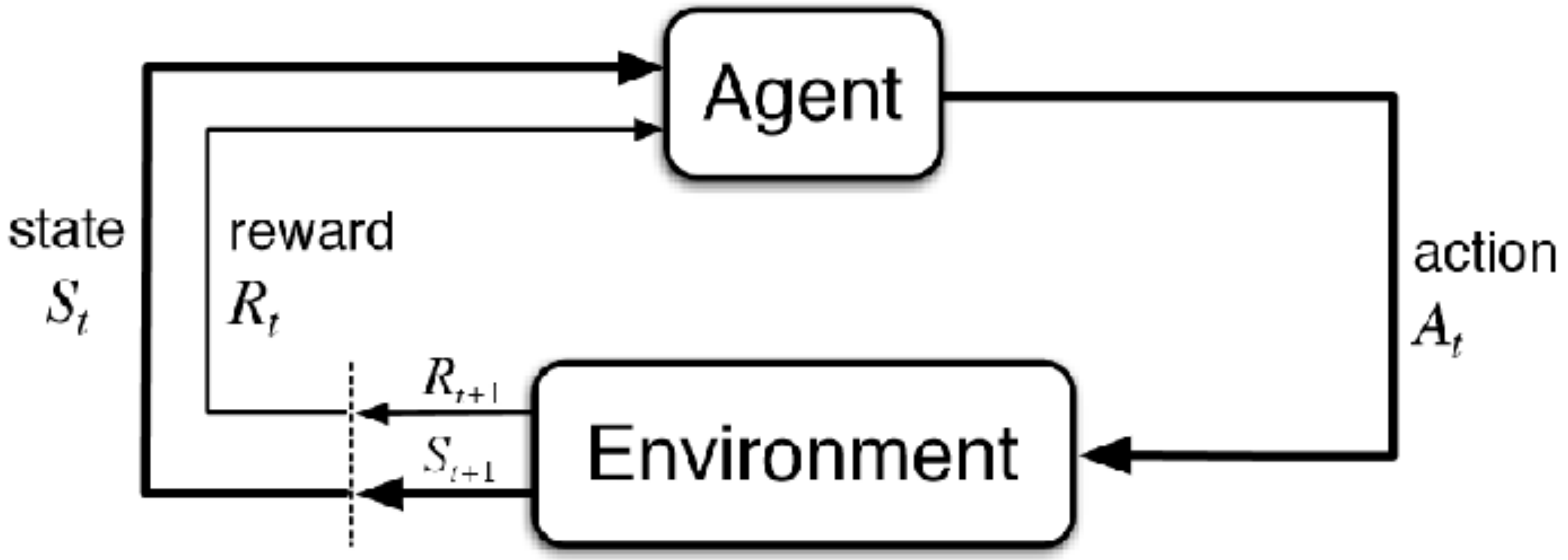

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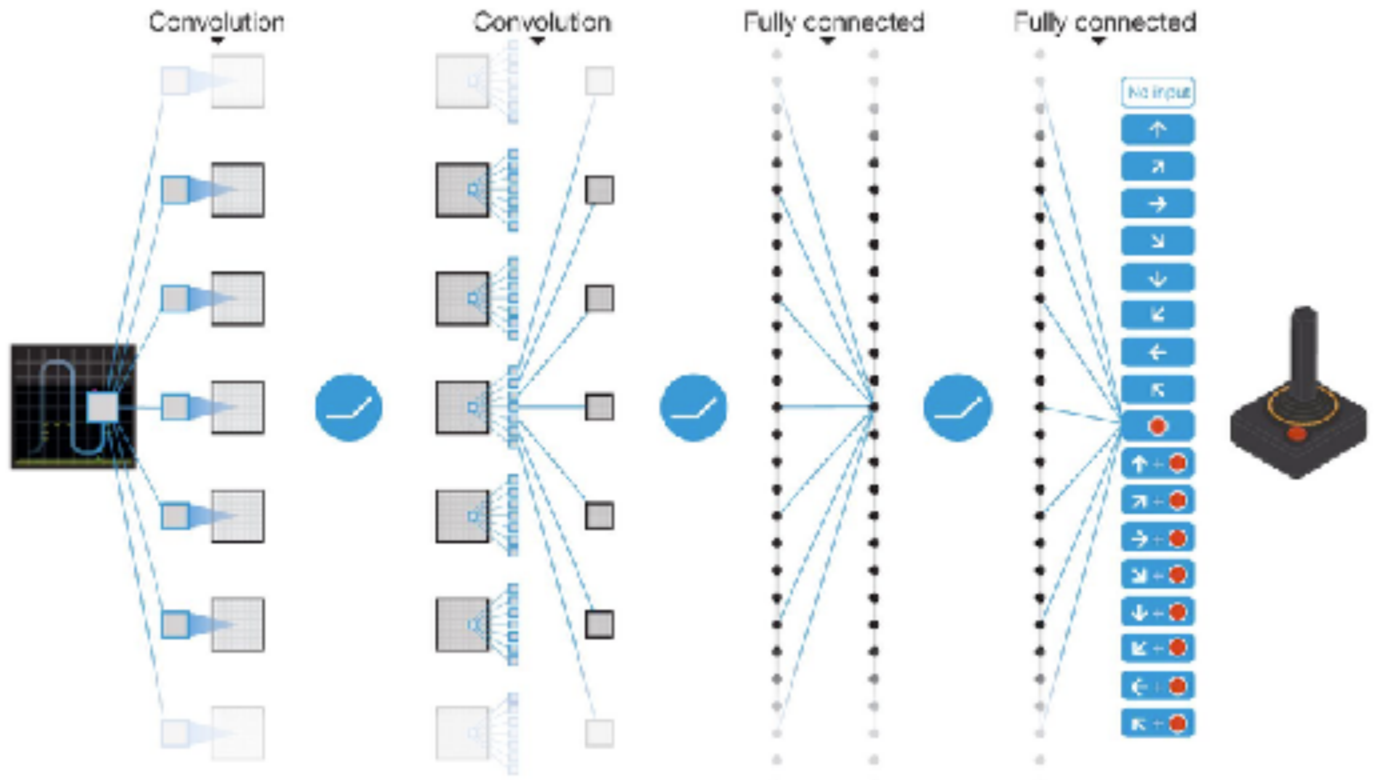

Categorize each definition of “learning” using Marr’s levels

In the same groups, come up with some answers for each arrow

How can machines inform our understanding of human learning?

How can human learning inform the development of machine learning?

See you next week

- Don’t forget to finish your assigned reading before the tutorial tomorrow
  - Spicer & Sanborn (2019)
  - The tutorial is in the AI Building (3rd floor seminar room)
- Next week, we look at the the origins of research on biological and artificial learning