La présentation de la soutenance de thèse

Architecture cognitive constructiviste:

Un modèle pour concevoir un agent automotivé capable de faire du sens et de construire des connaissances de l'environnement

Jianyong XUE

Encadrant: Salima Hassas

Co-encadrant: Olivier Georgeon

LIRIS, UMR 5205 CNRS

Université Claude Bernard Lyon 1

The presentation of the PhD thesis defense

Constructivist Cognitive Architecture:

A model for designing self-motivated agent capable of sense-making and knowledge construction of the environment

Jianyong XUE
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Co-supervisor: Olivier Georgeon

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Outline

- Introduction
- Related work
- Contributions
  - The Constructivist Cognitive Architecture (CCA)
  - Causality reconstruction with the CCA
  - Bottom-up hierarchical sequential learning in CCA
  - Methodology and experimental scenario with GAIT
- State-of-the-art comparison
- Discussion
- Conclusion and perspectives

Introduction: "Scientists in the crib"

Time lapse of a 9 month old baby playing with his toys. (*Francis Vachon, http://www.francisvachon.com*)

Infants are "scientists in the crib", who create, intentionally, events that are new, informative, and exciting to them.

Gopnik, Meltzoff, and Kuhl 2009

Introduction: Situations of artificial agents

Agent's performance in rich environment.

(Source: *DeepMind, https://youtu.be/hx_bgoTF7bs*)

Introduction

- Traditional learning approaches heavily rely on the availability of prior knowledge proposed by the system designer.

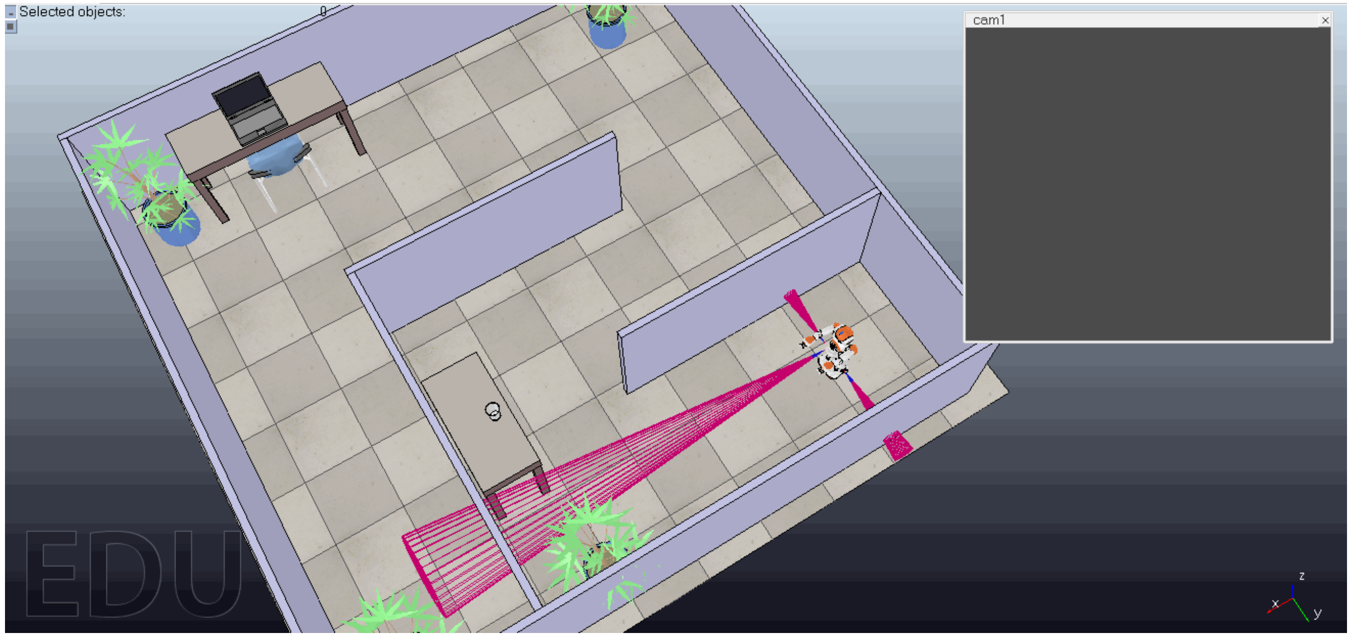
- The agent is usually designed for specific goals with a well-defined reward function, which incentivize it to maximize the accumulated reward from the achievement of these goals.

Introduction: A question

How can we use observations on infant play to design a self-motivated agent capable of sense-making and constructing its own knowledge of the environment, without predefined ontological knowledge and specific final goal states ?

Introduction: Problem statement

Let's see the following scenario:



A NAO robot is placed in an unfamiliar environment.

- The agent has no predefined knowledge of the ontology of the world (environment + itself).
- A set of innate actions enable it to perform elementary functions like: moving forward, turning direction and sensing the environment, etc.
- Specifically, the agent receives feedback from action but ignores its meaning.

Introduction: Challenges

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- Environment-agnosticism.
- Autonomous and active learning.
- Progressive and incremental learning.
- Learning of regularities of interaction.
- Acquirement of adaptation and flexibility.

Introduction: Motivation

- **Knowledge construction through interaction with the environment.** The agent has capabilities to discover, learn and exploit regularities of interactions to master the sensorimotor contingencies.
- **Higher-level sequential learning with constructivist paradigm.** Based on the theory of constructivism, the agent learns structured behaviors and reorganizes them into a higher-level hierarchy.
- **Context adaptation and generating proper behaviors.** The agent recognizes the context and activates hierarchical sequential system for proposing appropriate behaviors to interact with the environment.

Related work

- Discoveries on infant's cognitive development

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  - Infant's cognitive development as a progressive reorganization of mental processes which occurs due to biological maturation and interaction experience with the environment (*The constructivism, Piaget 1957*).

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Discoveries on infant's cognitive development

- Infant's cognitive development as a progressive reorganization of mental processes which occurs due to biological maturation and interaction experience with the environment (*The constructivism, Piaget 1957*).
- Primitives of infant's world model are acquired rather than innate, and the development follows a constructivist paradigm in the hierarchical progression (Cohen, Chaput, and Cashon 2002).

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- Discoveries on infant’s cognitive development
  - Infant’s cognitive development as a progressive reorganization of mental processes which occurs due to biological maturation and interaction experience with the environment (*The constructivism, Piaget 1957*).
  - Primitives of infant’s world model are acquired rather than innate, and the development follows a constructivist paradigm in the hierarchical progression (Cohen, Chaput, and Cashon 2002).
  - Infants learn more effectively about objects that violate expectations and engaged in hypothesis-testing behaviors that reflected the particular kind of unexpected seen (*Stahl and Feigenson, Science 2015*).

Related work

- Learning structured behaviors with observations on infant play

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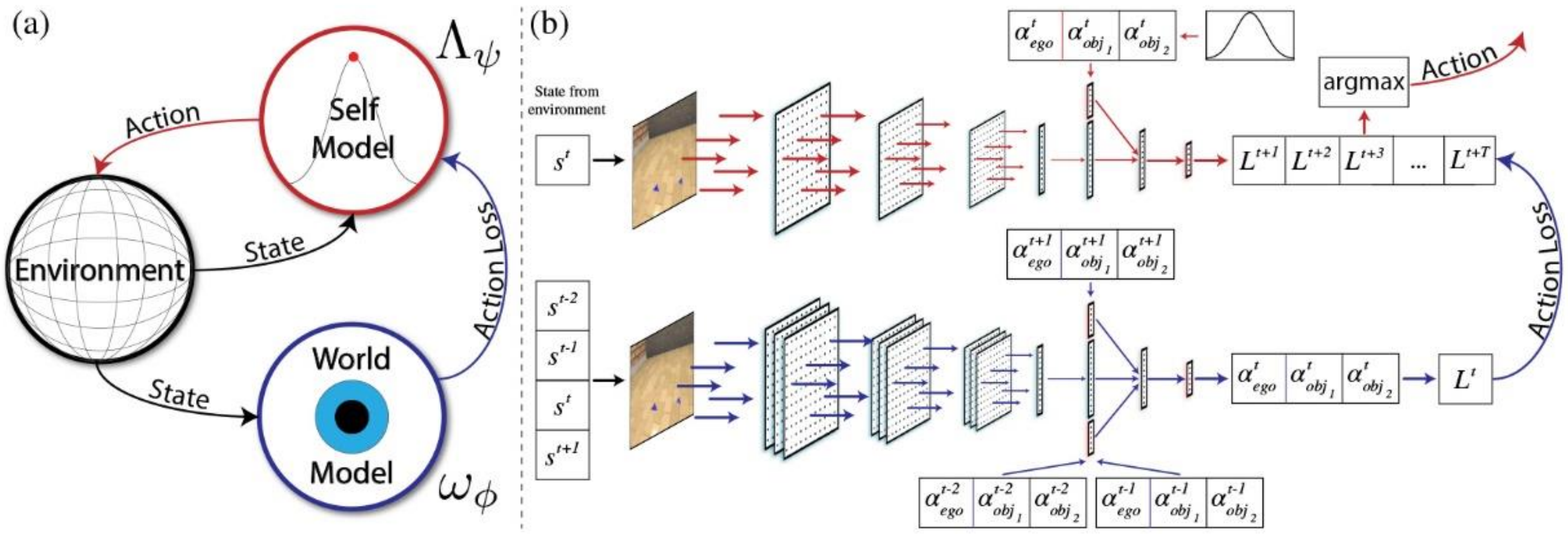

Intrinsically-motivated self-aware agent architecture.

Learning to play with intrinsically-motivated, self-aware agents
(*Haber, Mrowca, Fei-Fei, et al. NeurIPS 2018*)

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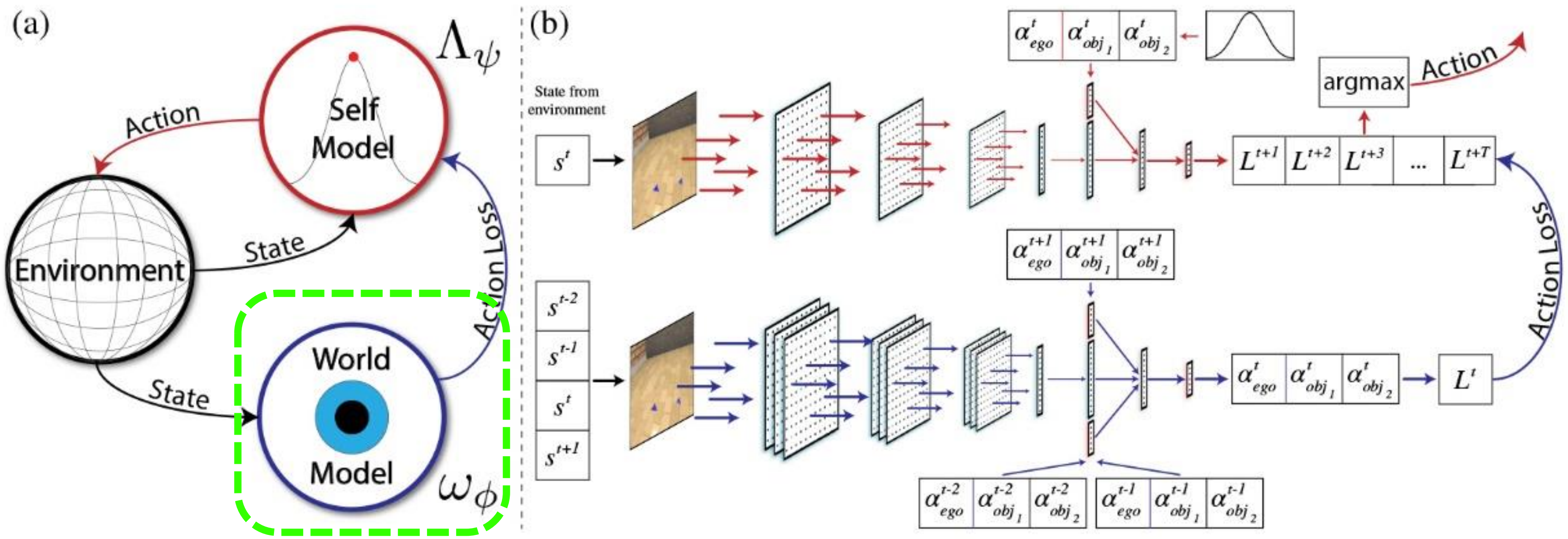

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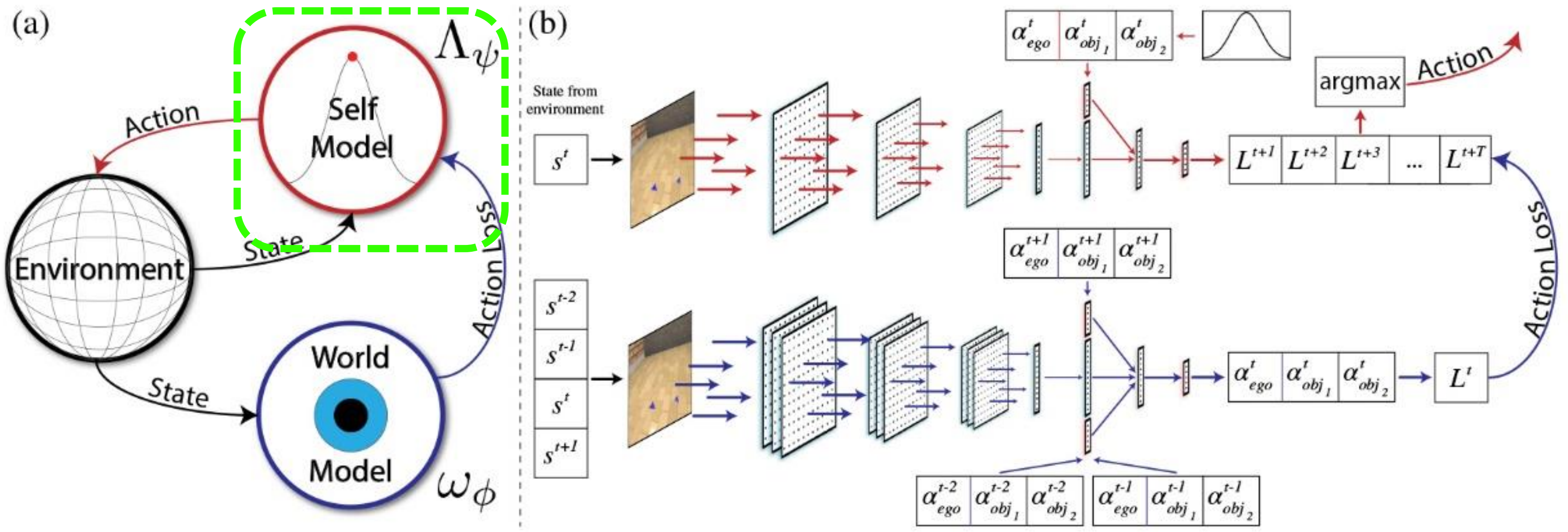

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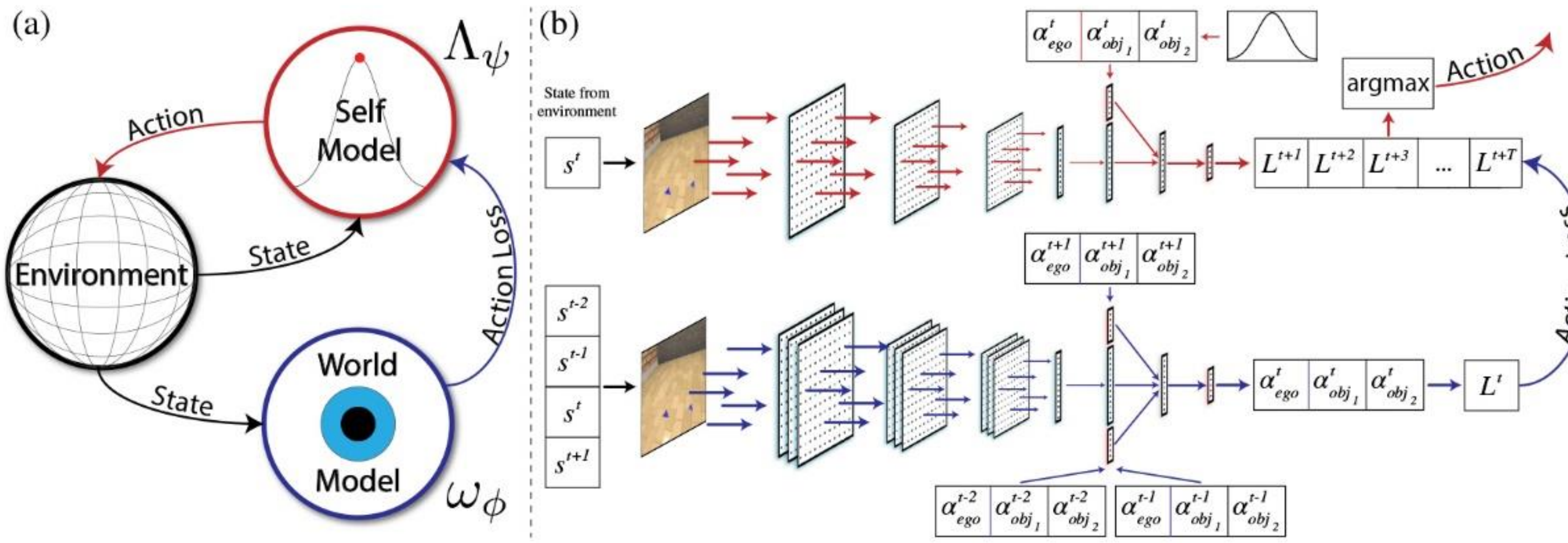

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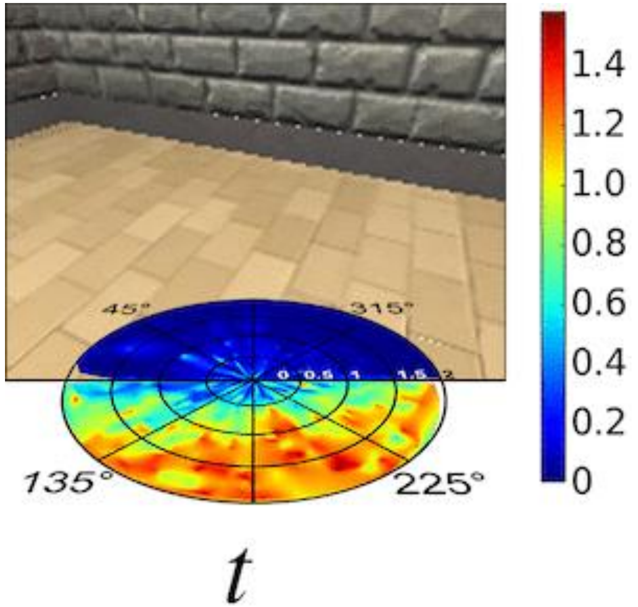

Self-aware agent navigates to objects and plans behavior for interaction.

Learning to play with intrinsically-motivated, self-aware agents
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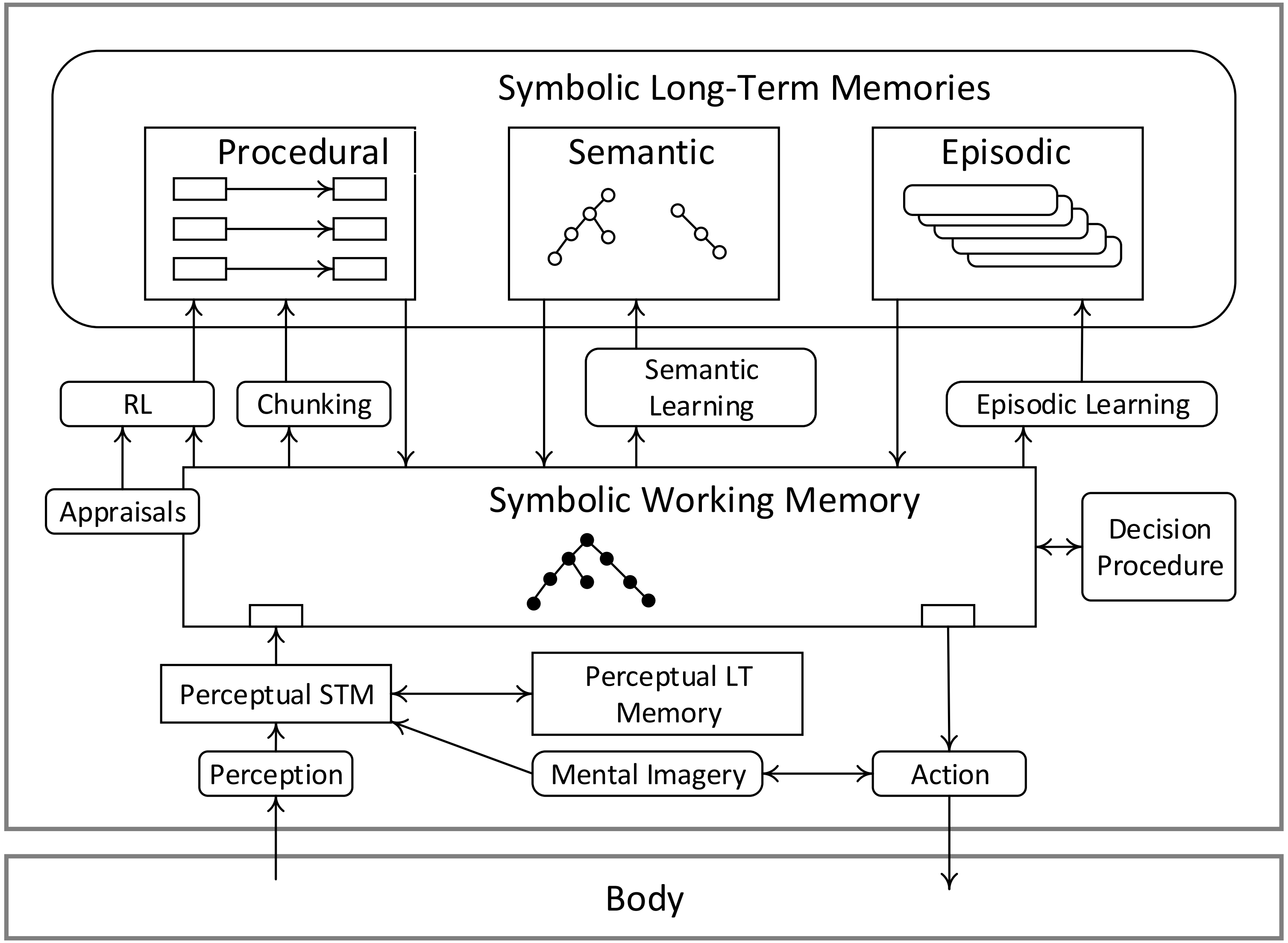
Related work

- The Soar Cognitive Architecture



The structure of Soar 9 (*Laird and Congdon 2015*)

Related work

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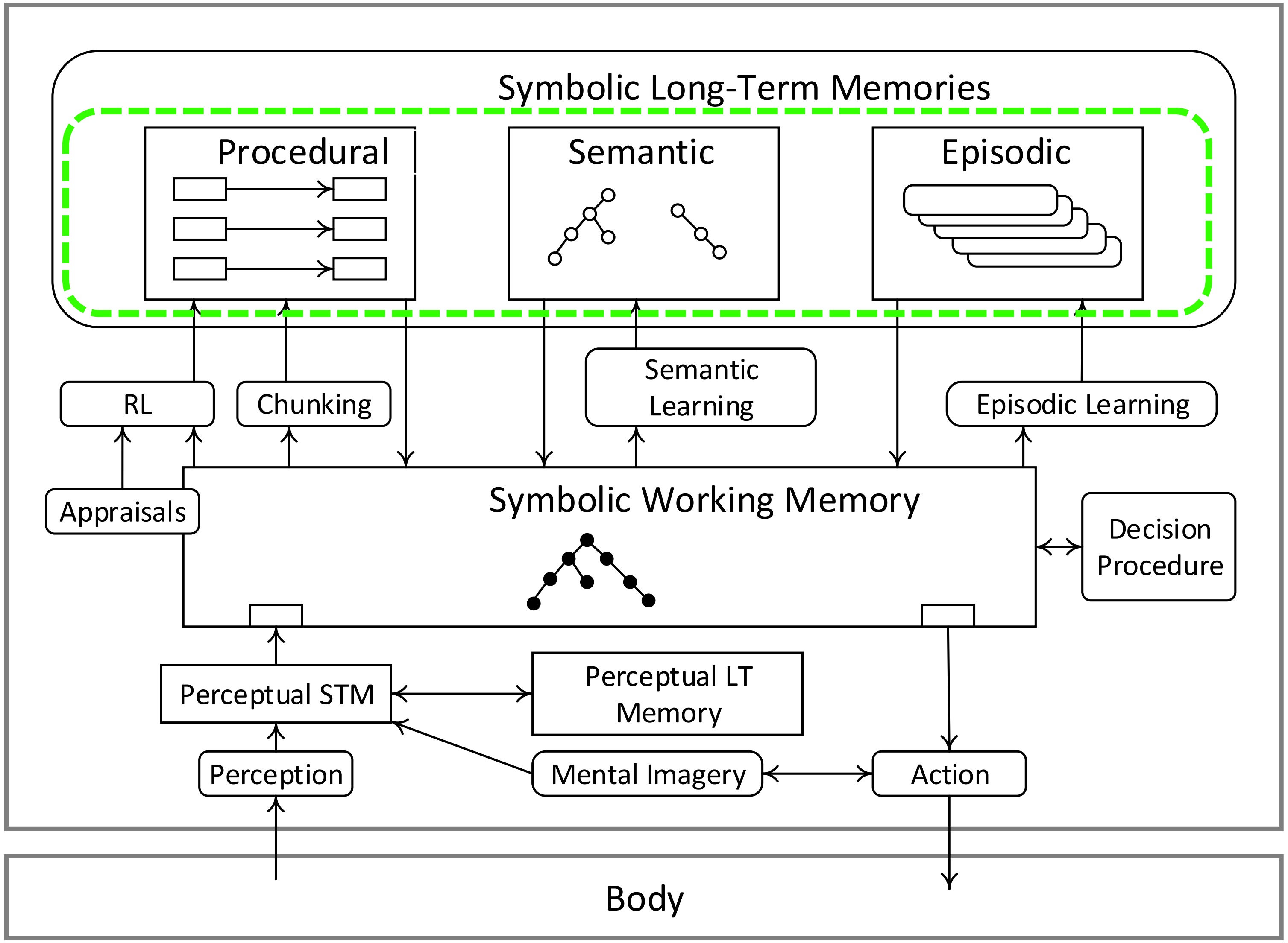

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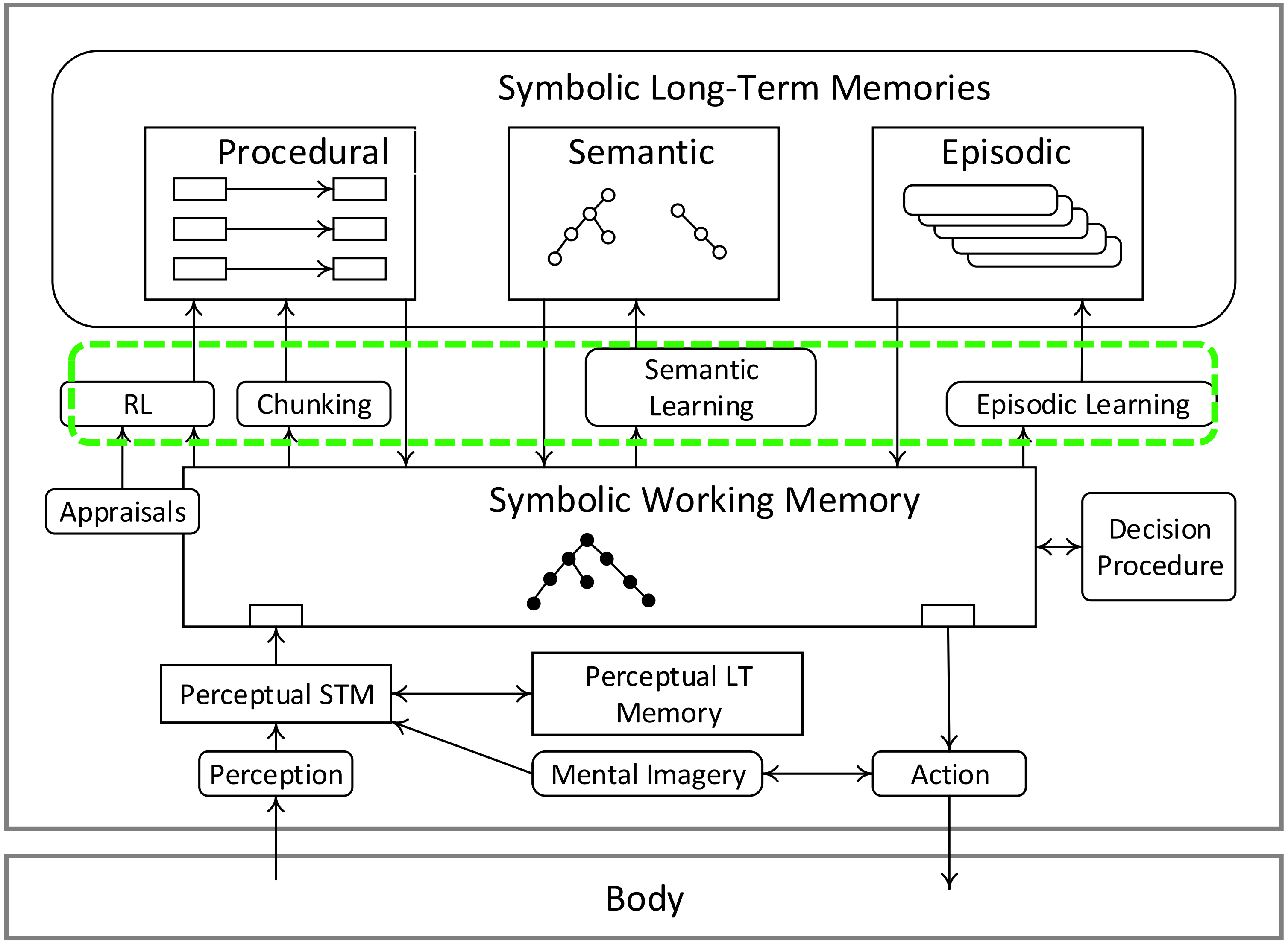

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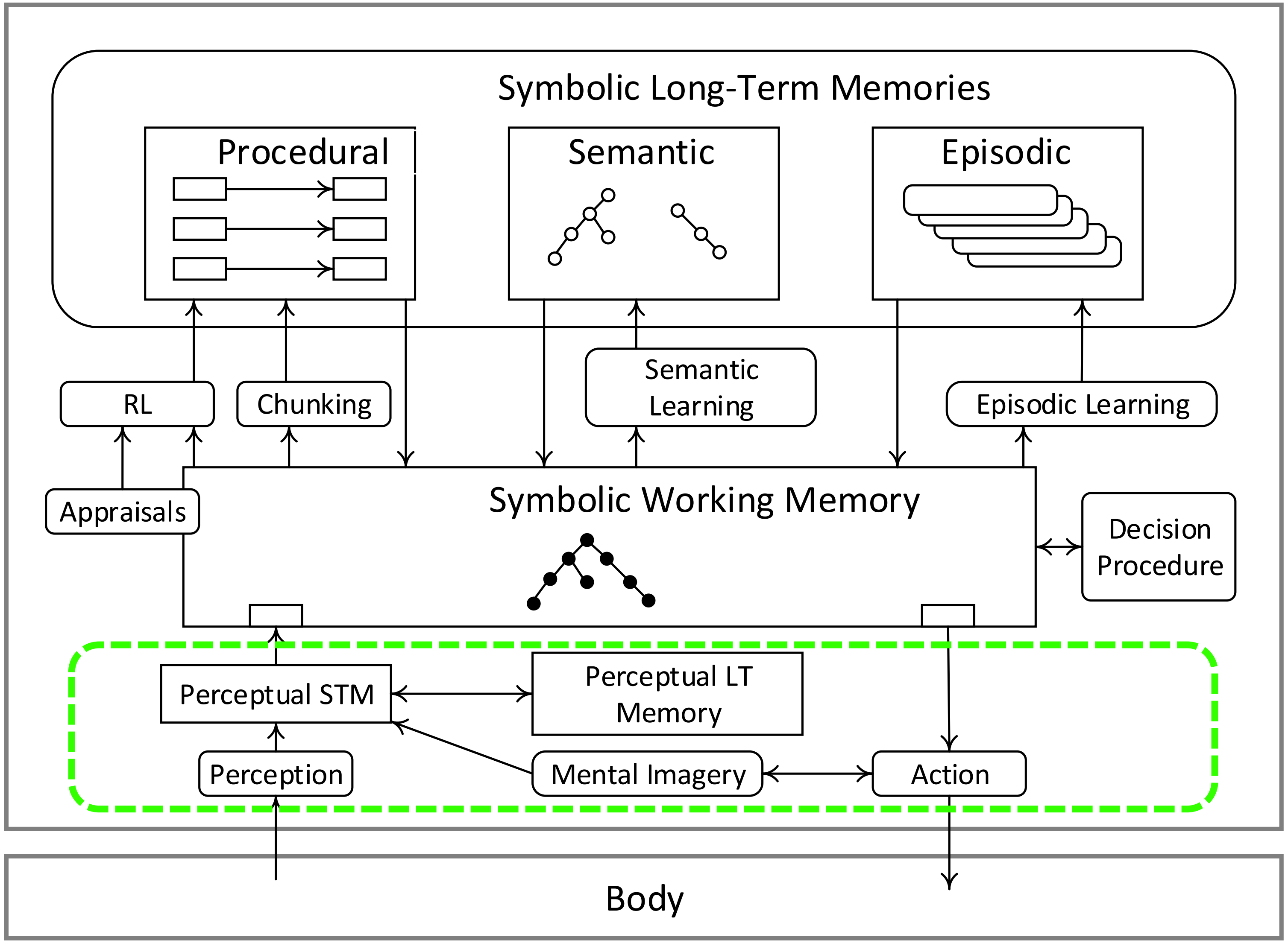

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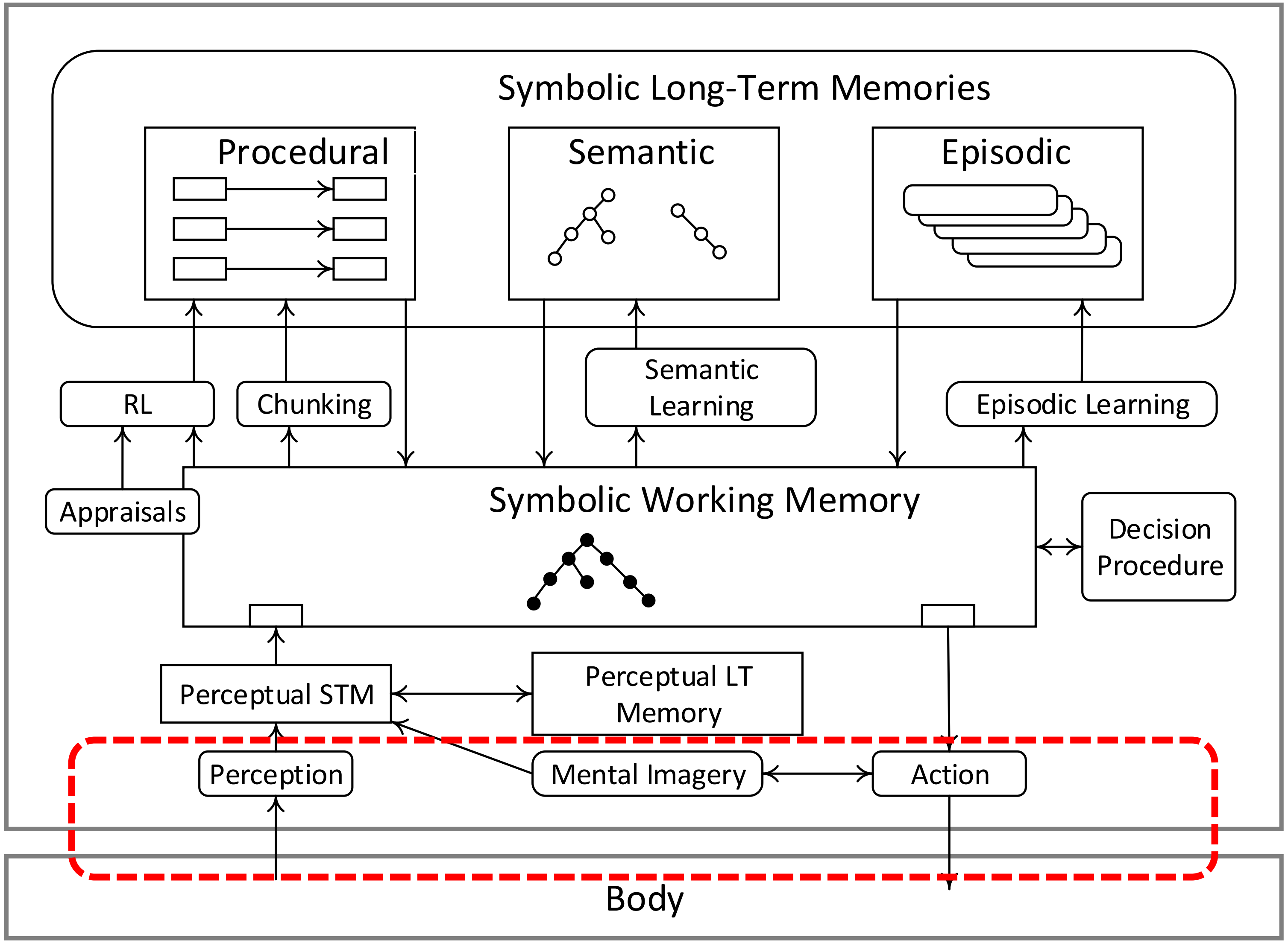

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Contributions

- The Constructivist Cognitive Architecture (CCA)
- Causality reconstruction with the CCA
- Bottom-up hierarchical sequential learning in CCA
- Methodology and experimental scenario with GAIT

Contribution 1: The Constructivist Cognitive Architecture (CCA)

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- The CCA design:
  - The primitive interaction

$$\underbrace{i_t}_{\text{primitive interaction}} = < \underbrace{e_t}_{\text{experiment}} , \underbrace{f_t}_{\text{feedback}} >, \underbrace{valence}_{\text{natural preference}}$$

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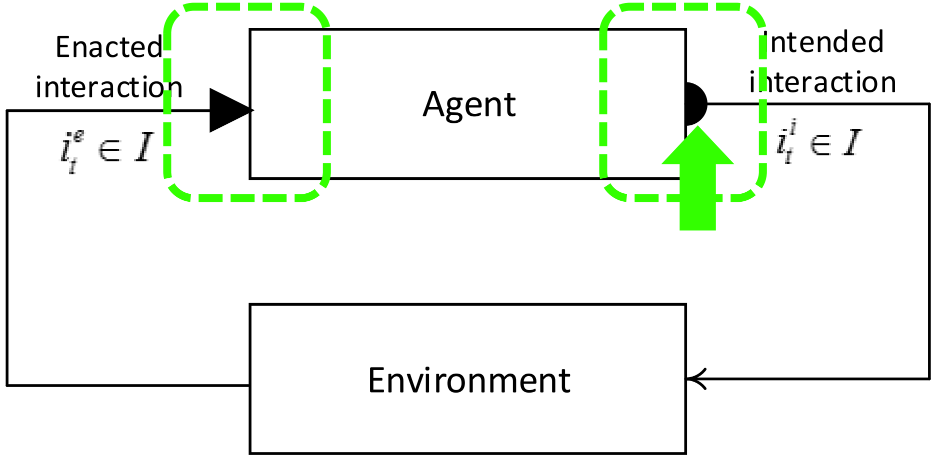

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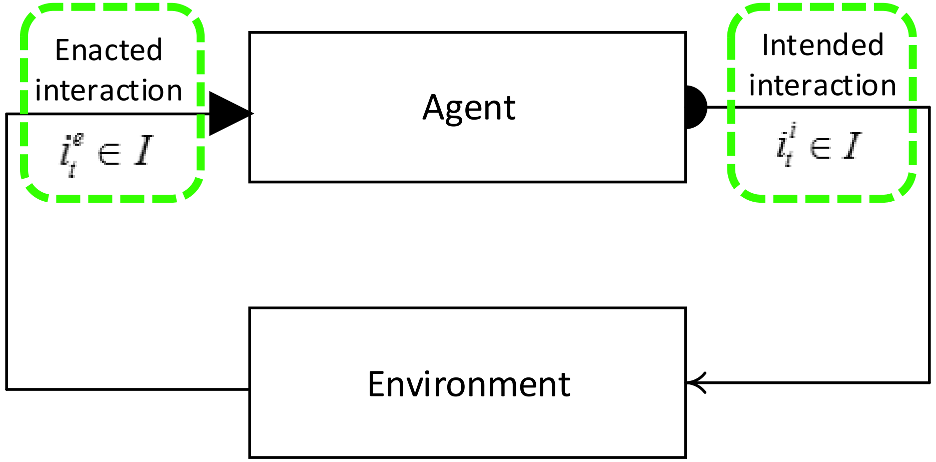

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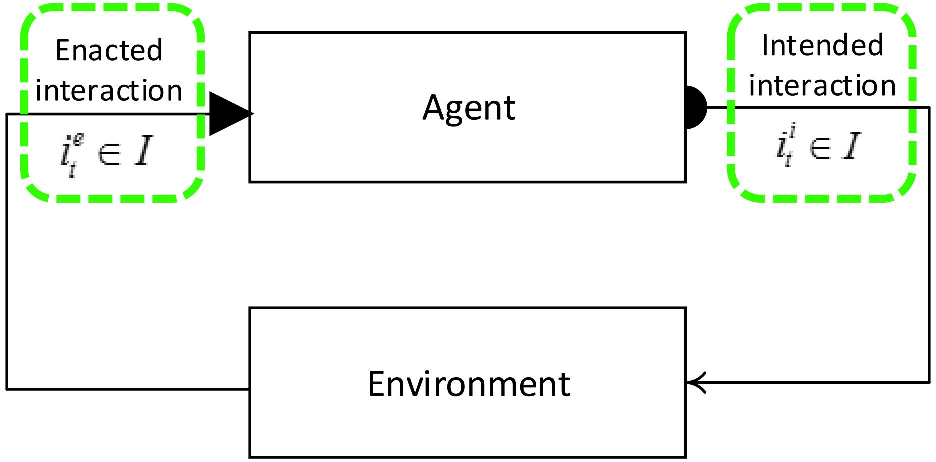

if $i_t^i = i_t^e$, the enaction of i_t^i is considered a *success*, otherwise a *failure*.

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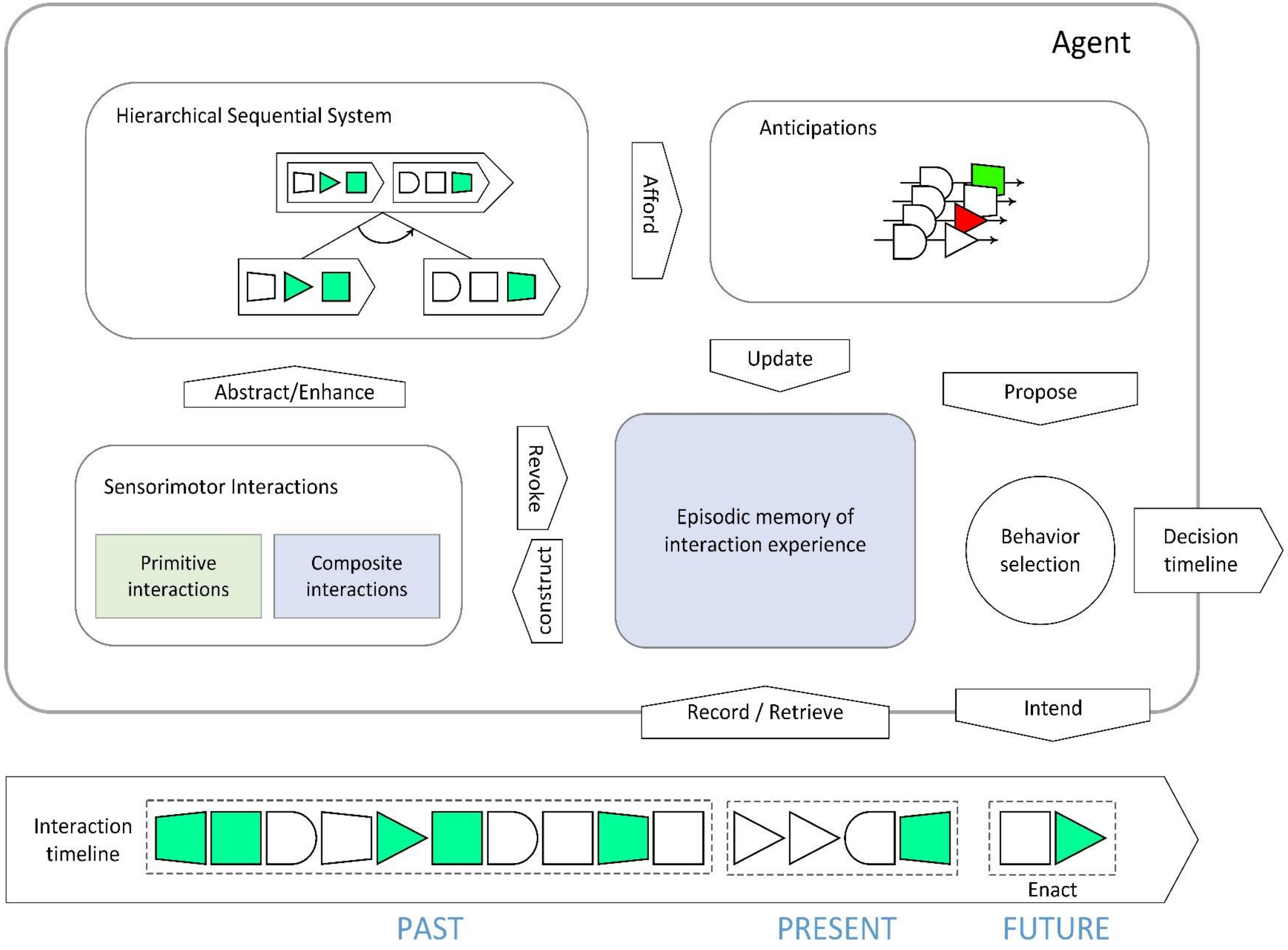
- The CCA structure



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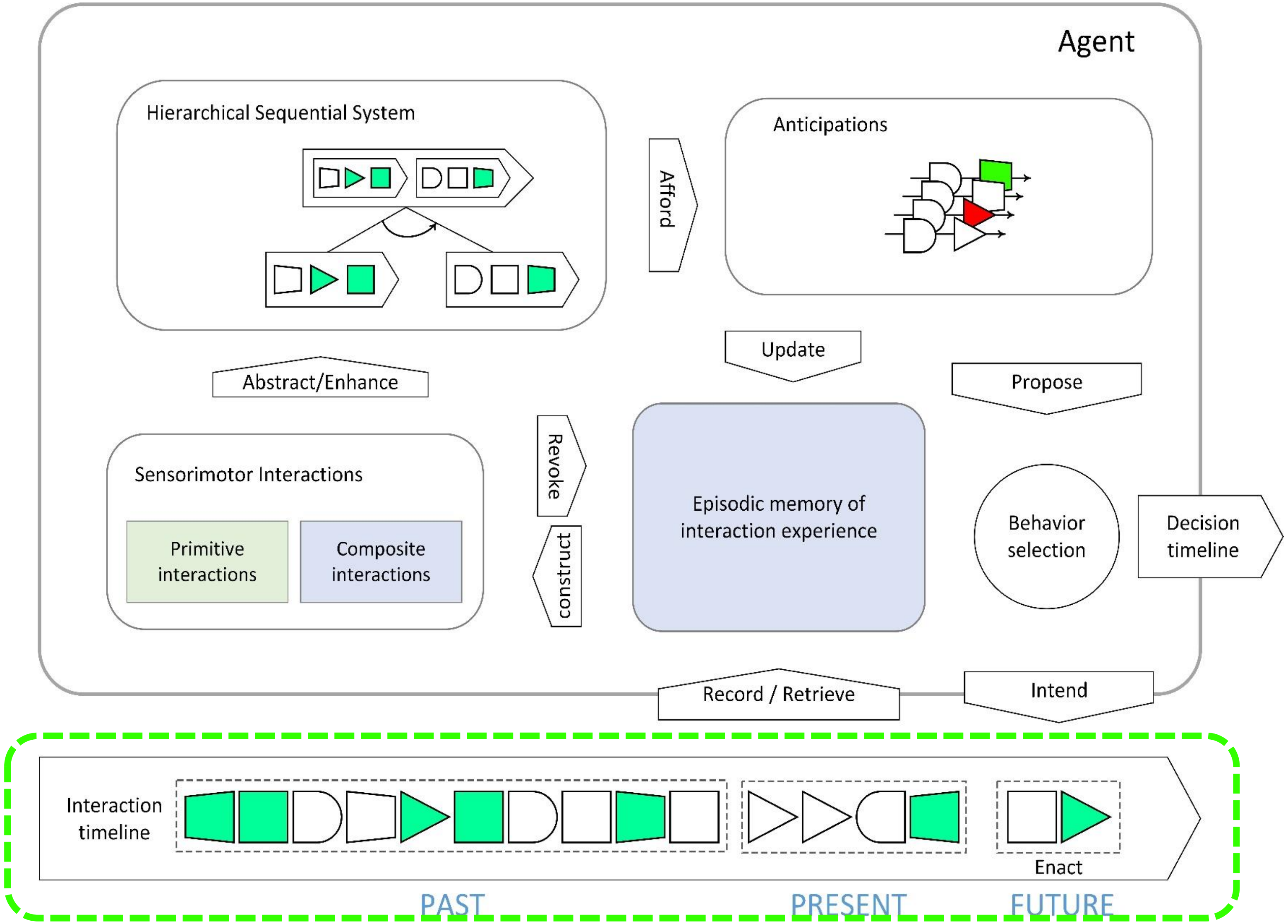
The CCA structure

- The timeline of enacted interactions.



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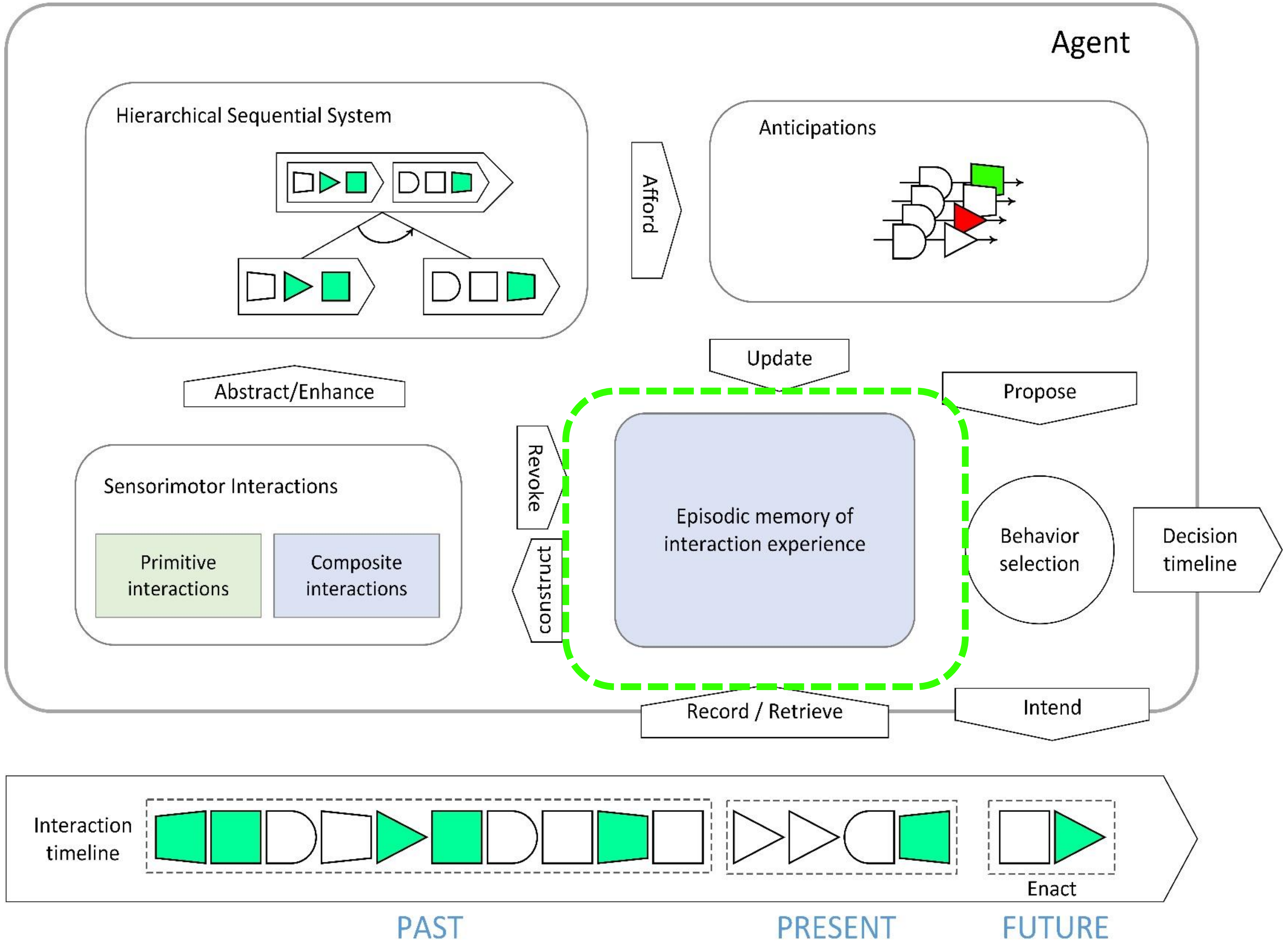
- The timeline of enacted interactions.
- The episodic memory of interaction experiences.



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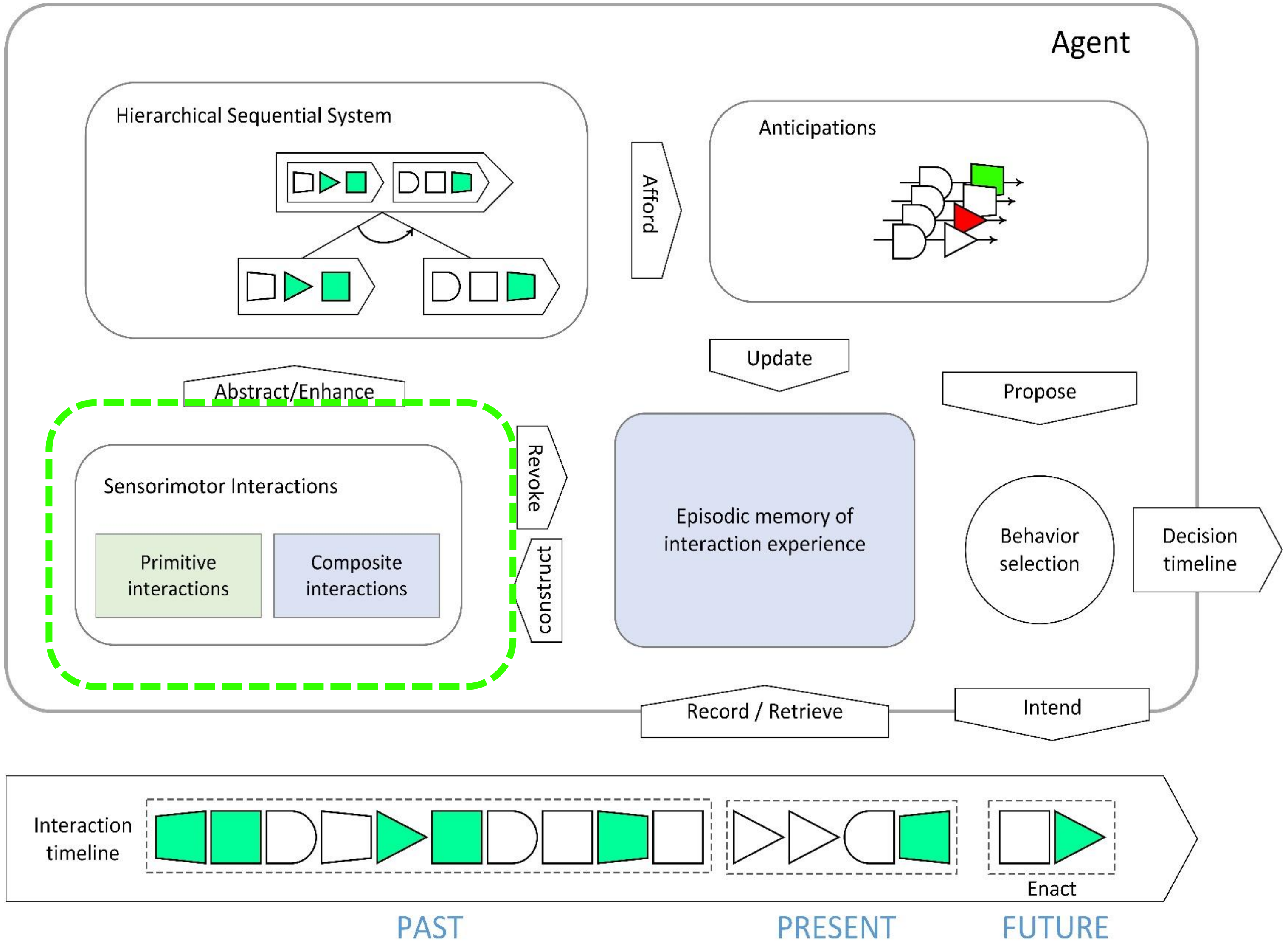
- The implementation of episodic memory with interactions.



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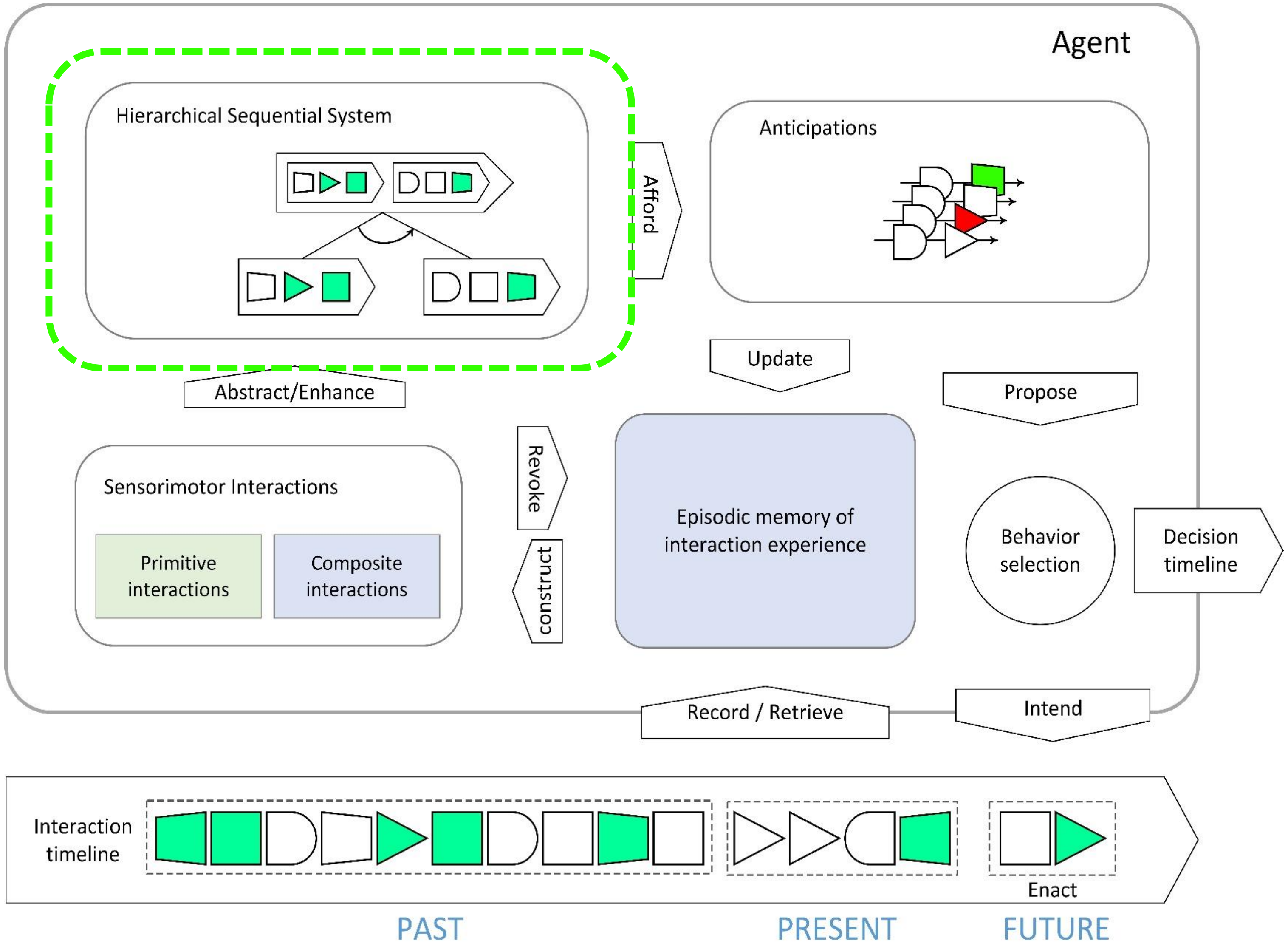

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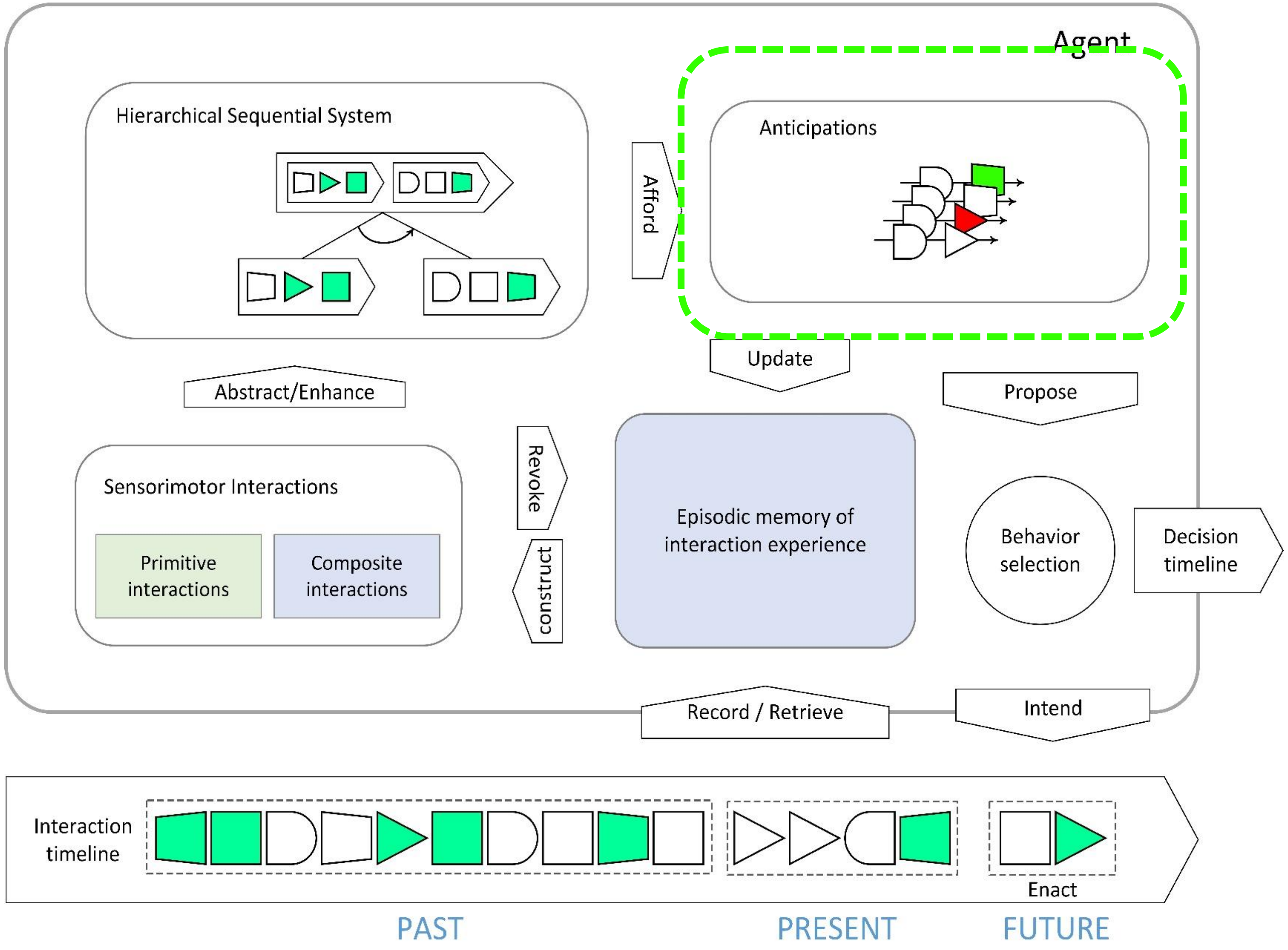
- The proposition mechanism of anticipations



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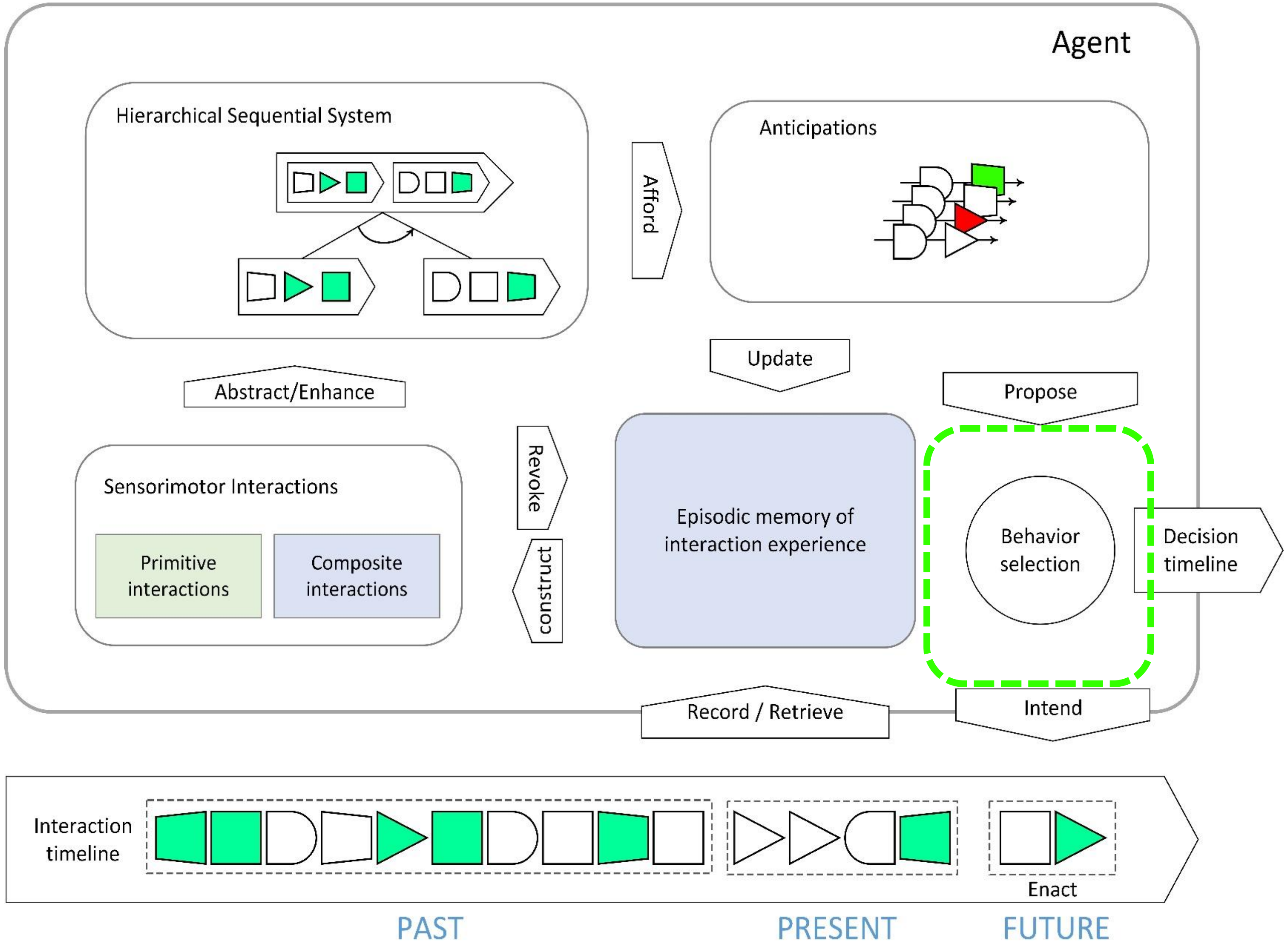

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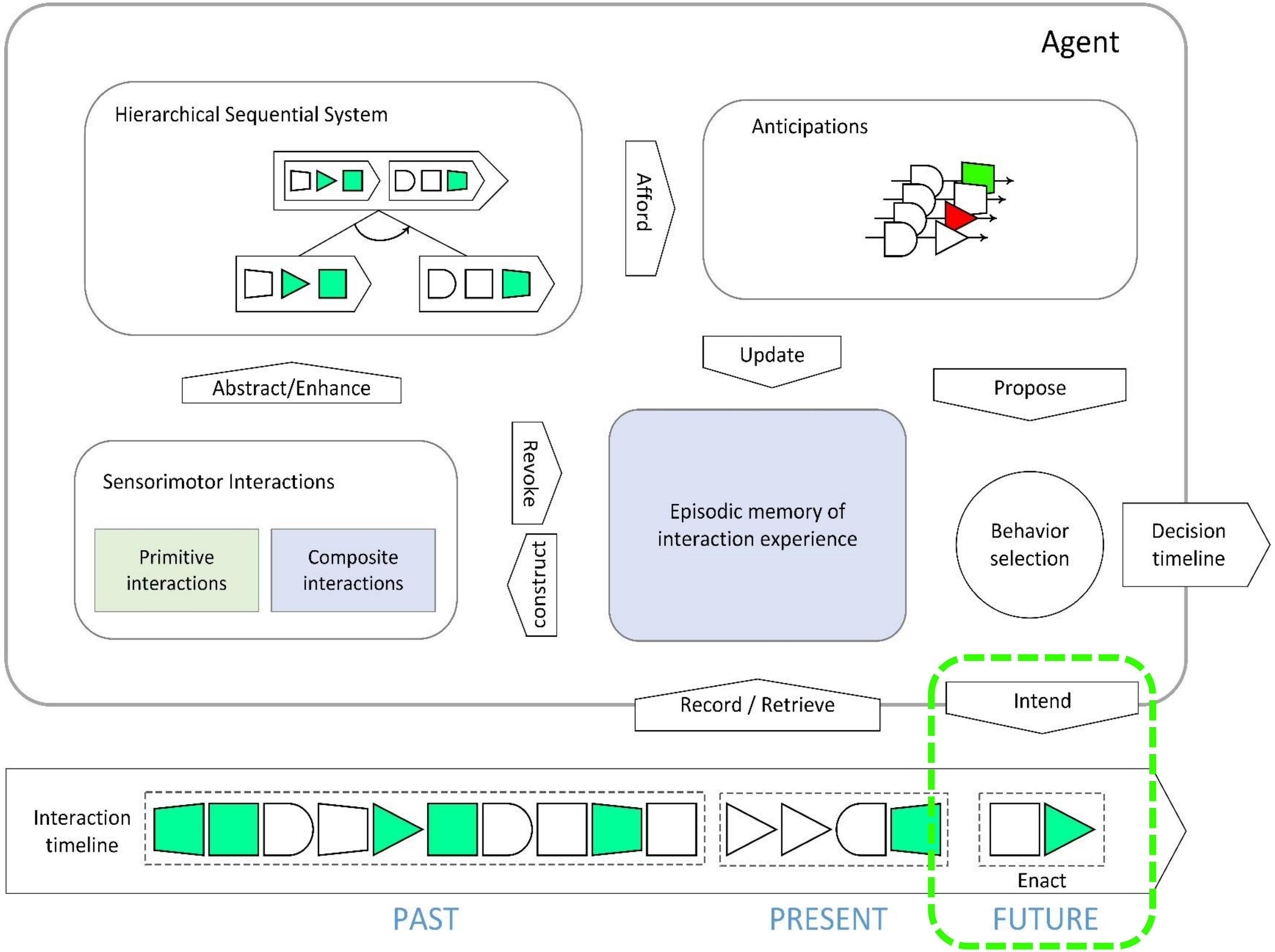
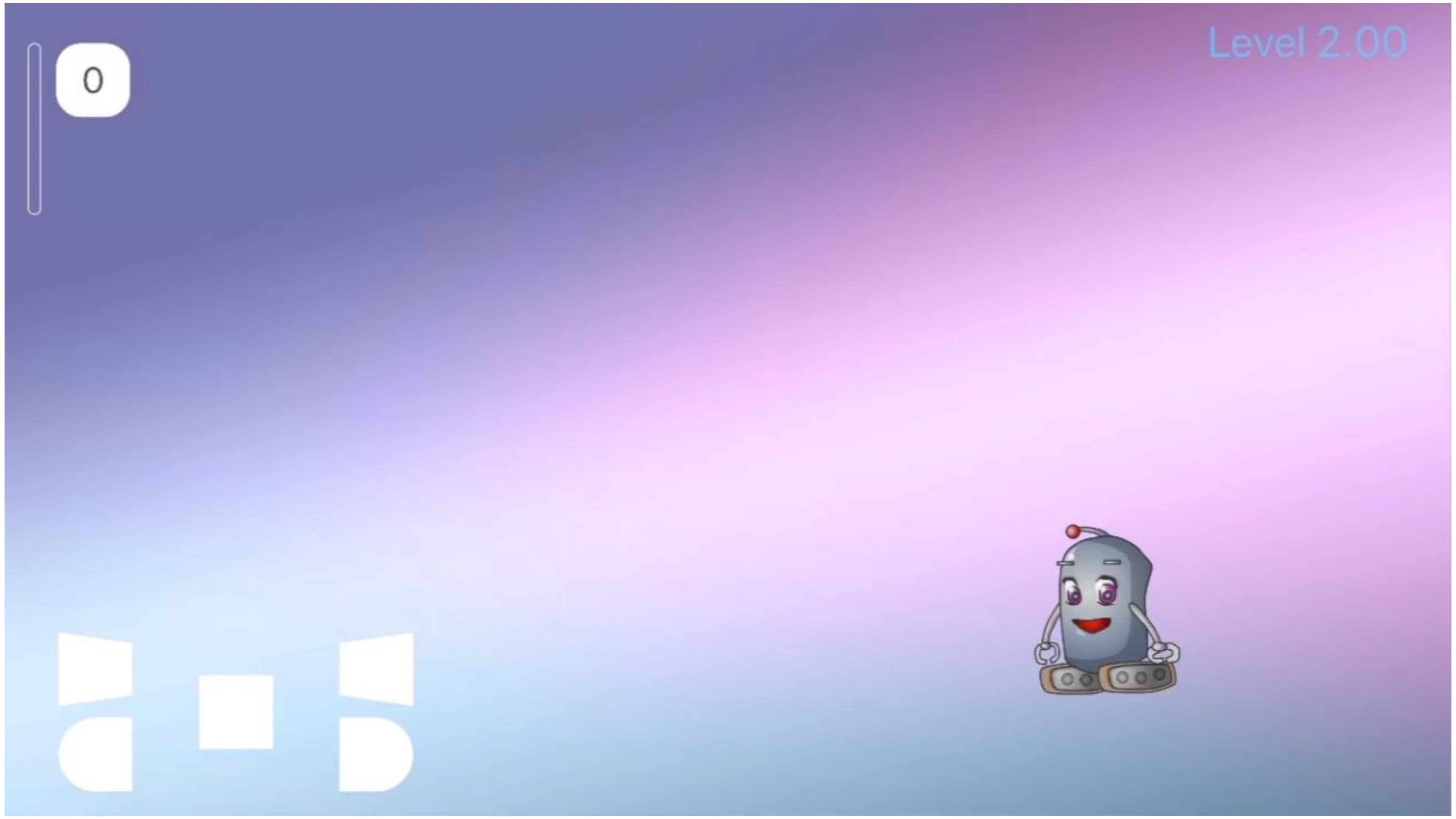


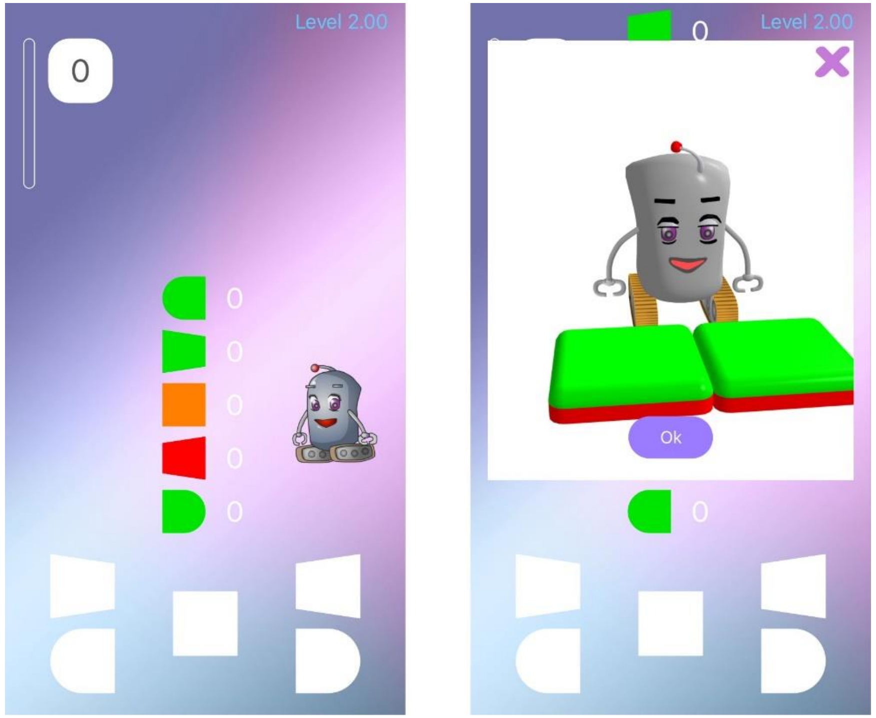
Contribution 2: Causality reconstruction with the CCA

- The Little AI (*Georgeon 2017*) *the Level 2.00*



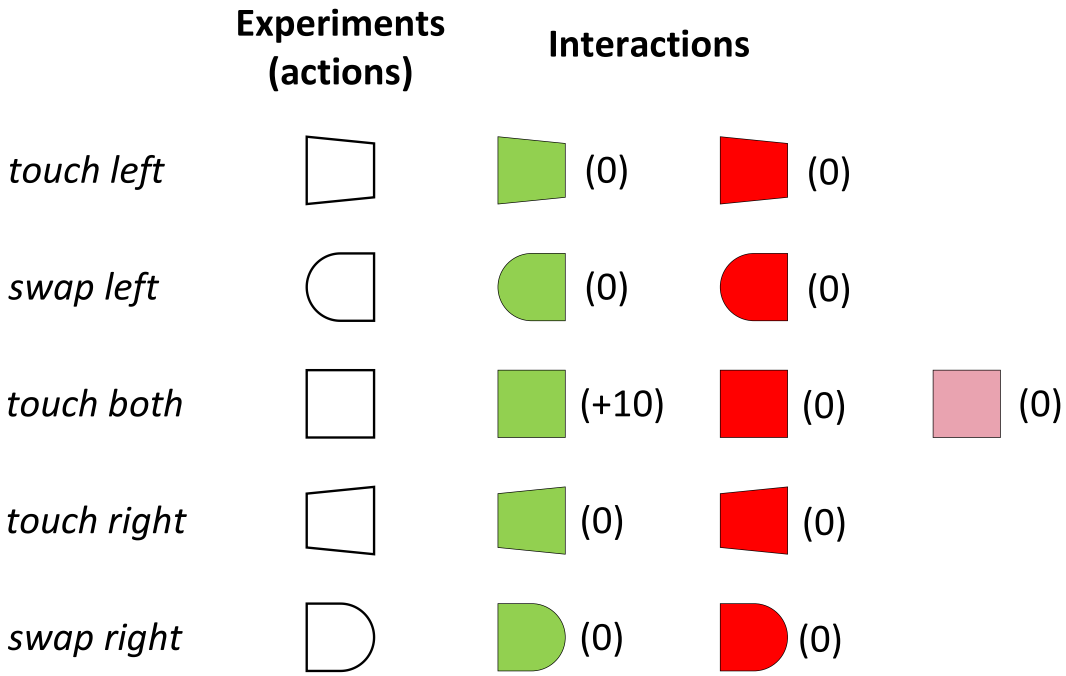
Contribution 2: Causality reconstruction with the CCA

Interaction scenario



a) The initial interaface b) The 3D interaface

Little AI interface.



Five experiments with eleven interactions.

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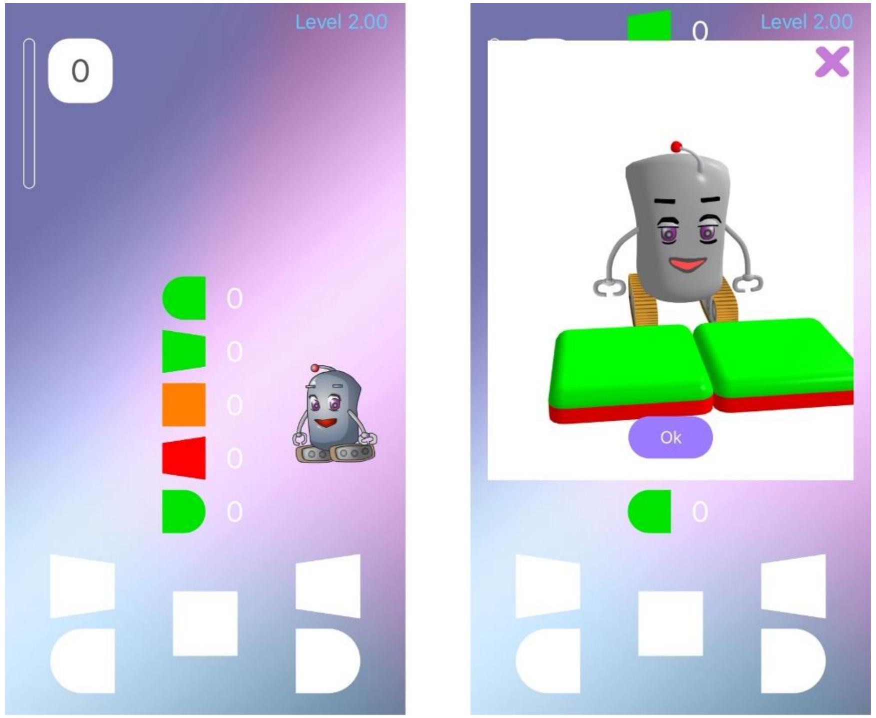

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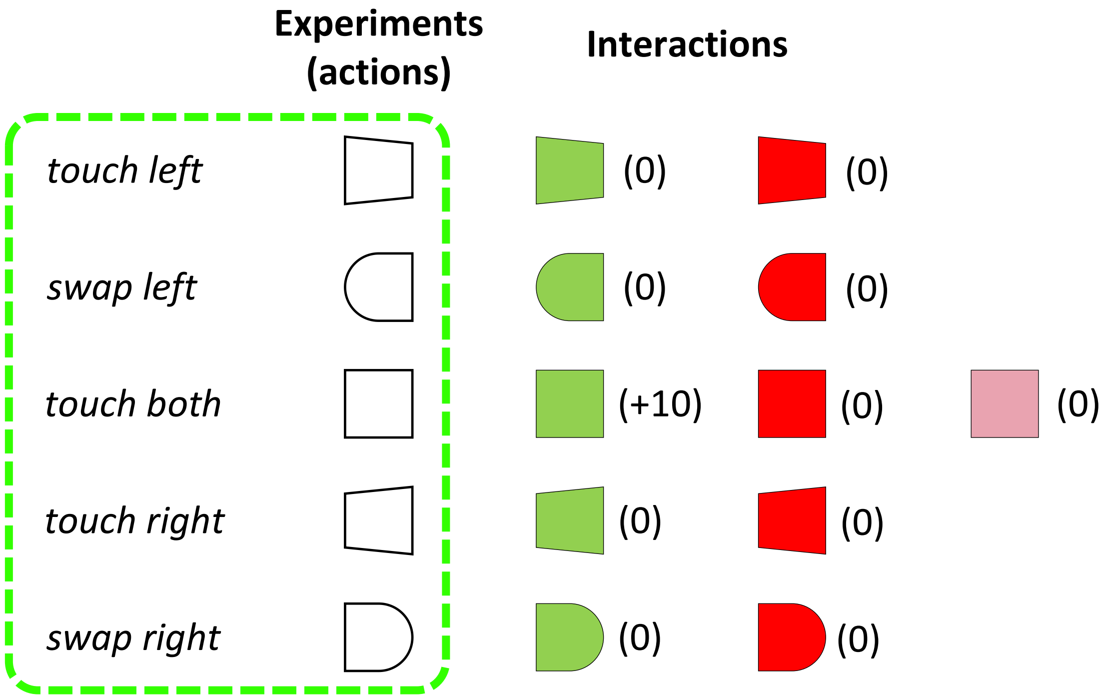

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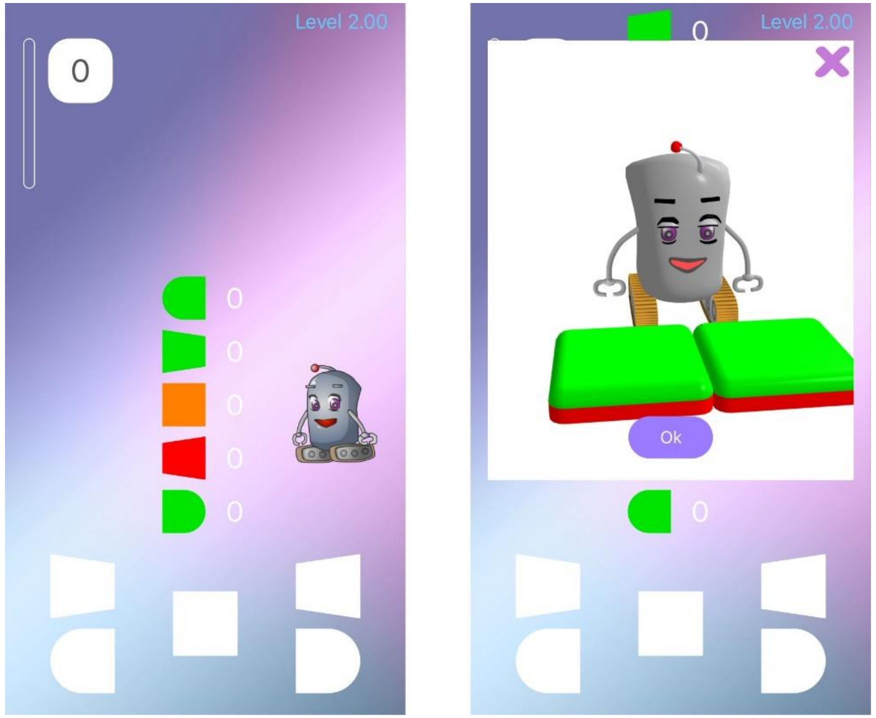

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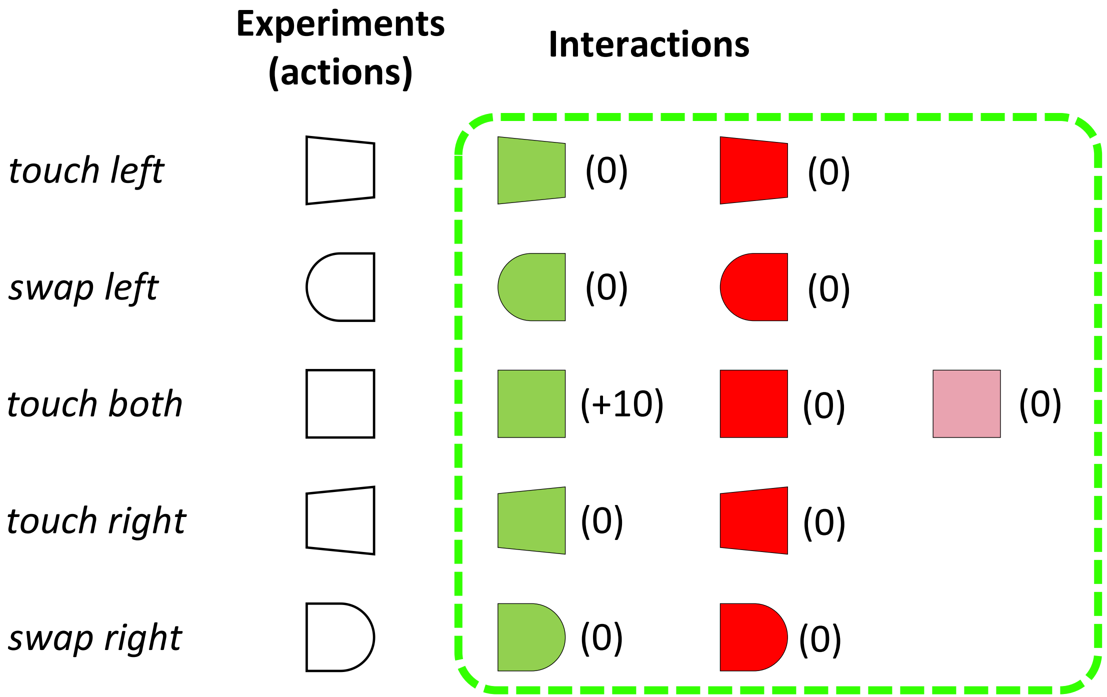

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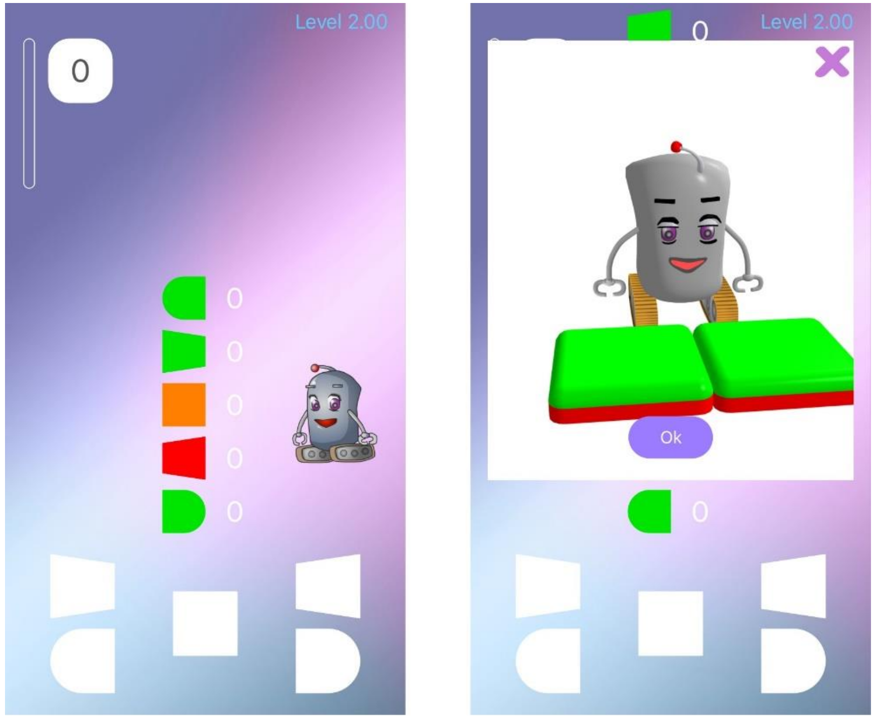

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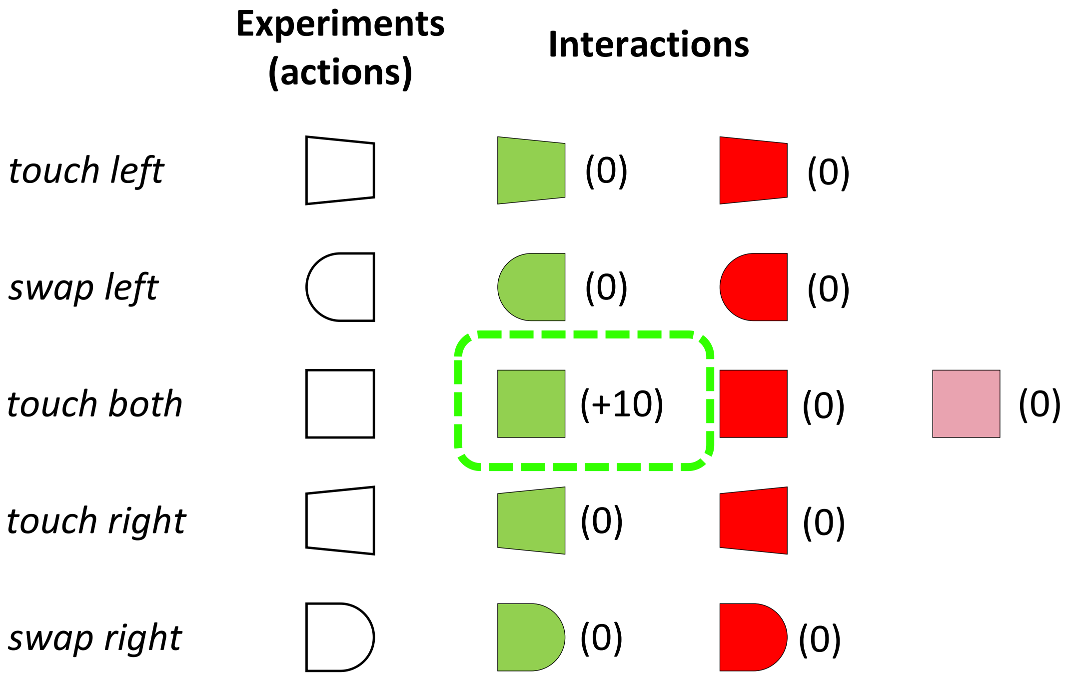

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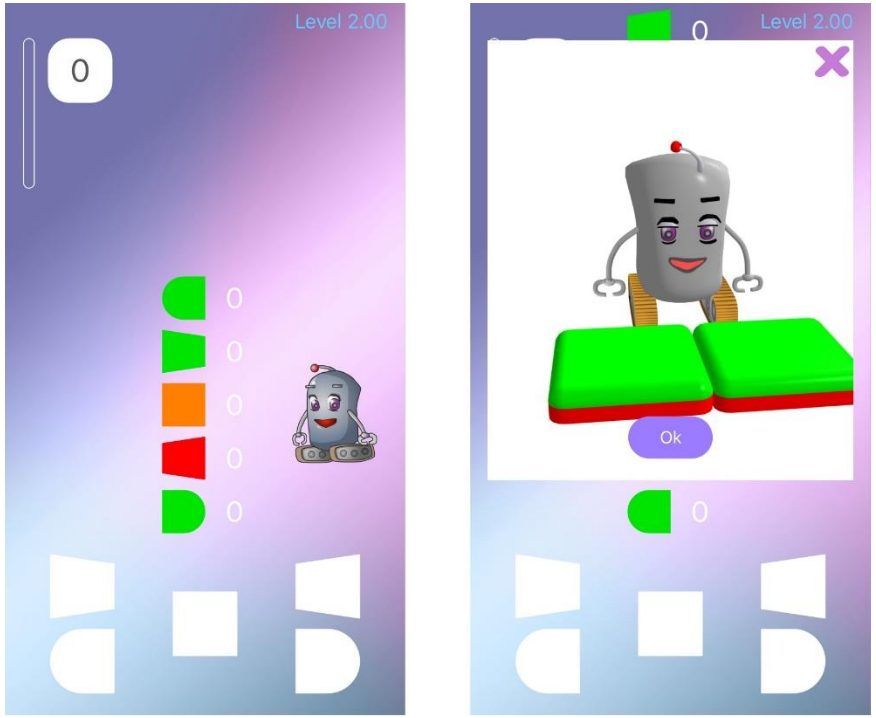

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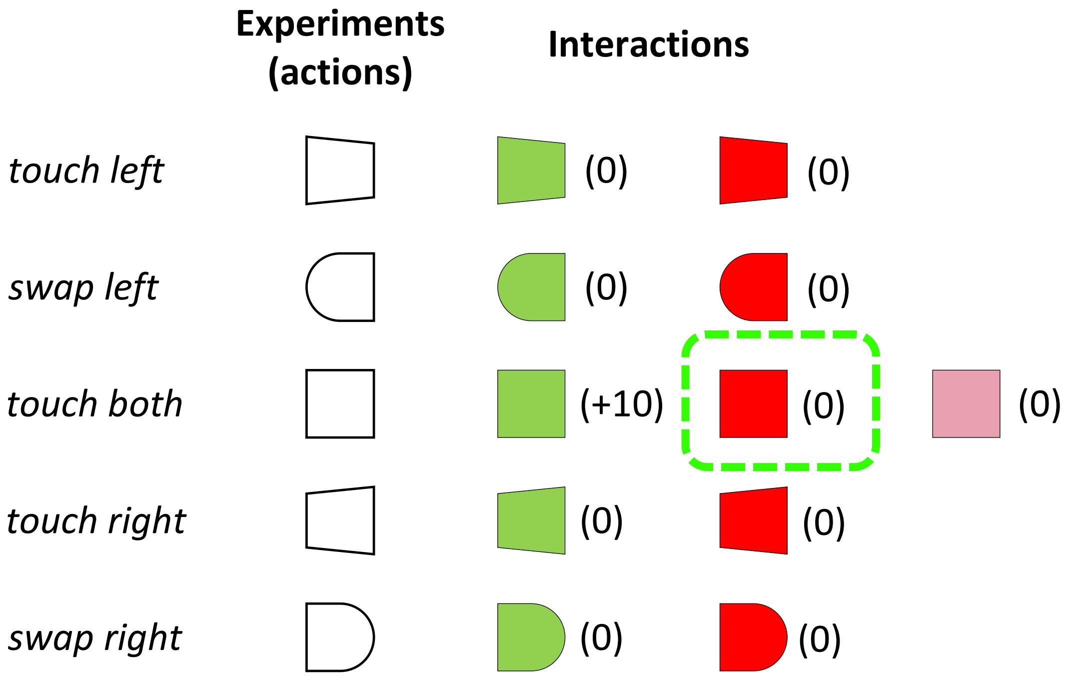

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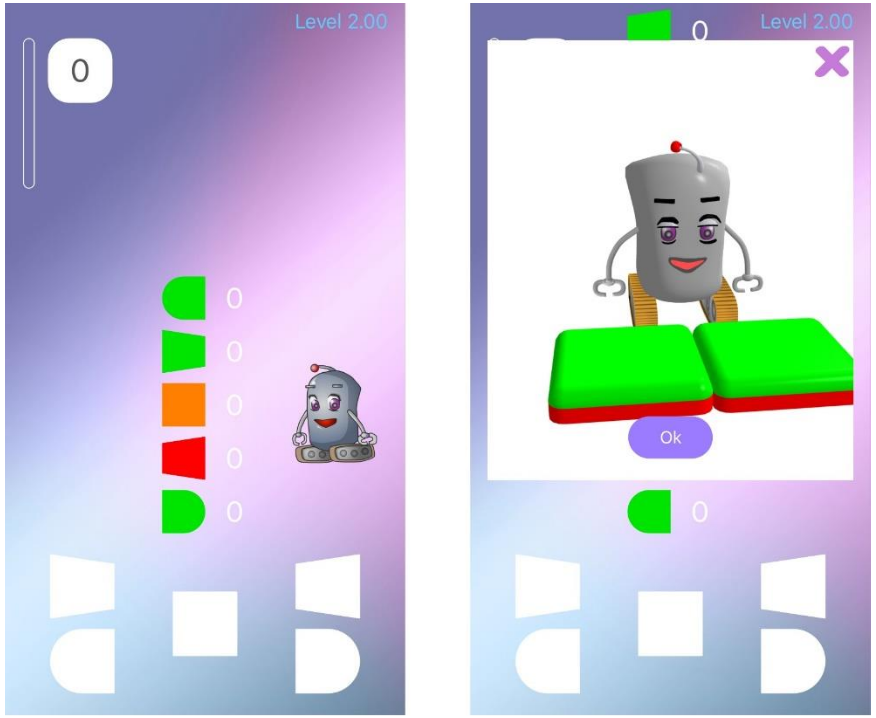

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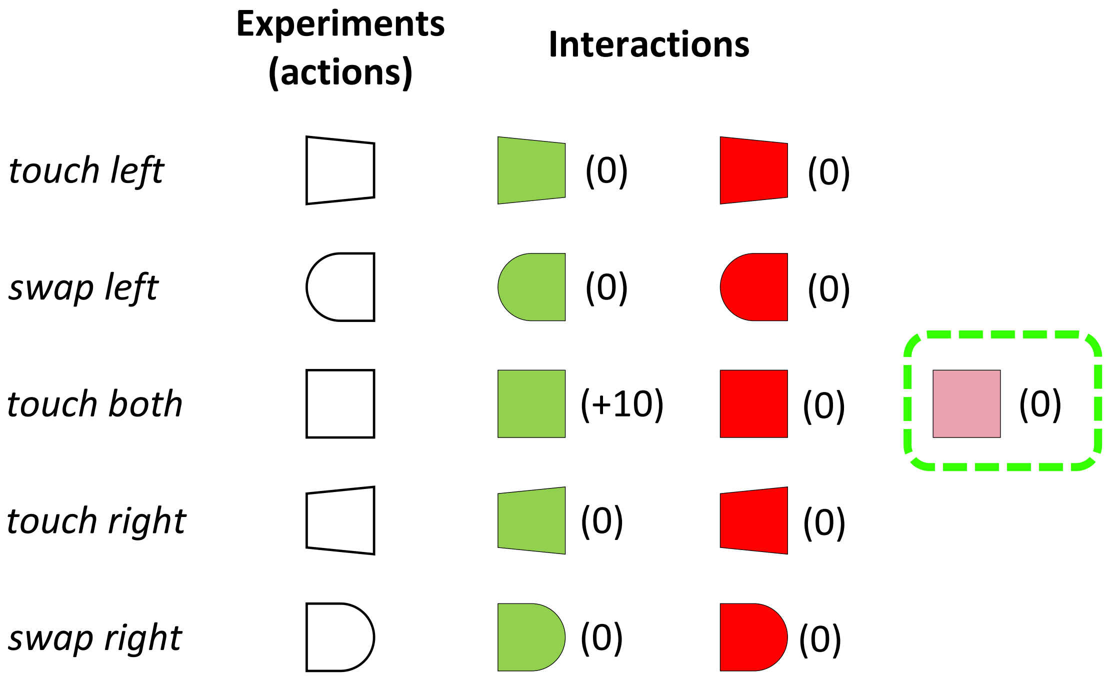

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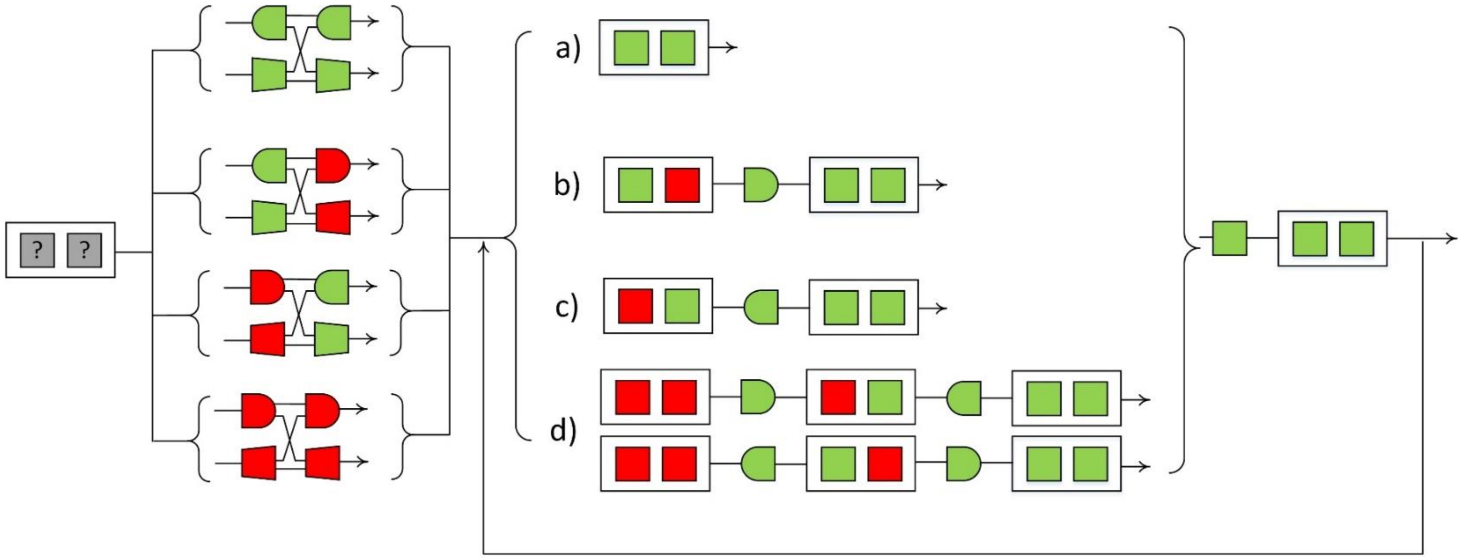
Contribution 2: Causality reconstruction with the CCA

The regularities of interaction



The regularities of interactions that we expect the causal acquisition model to develop.

Contribution 2: Causality reconstruction with the CCA

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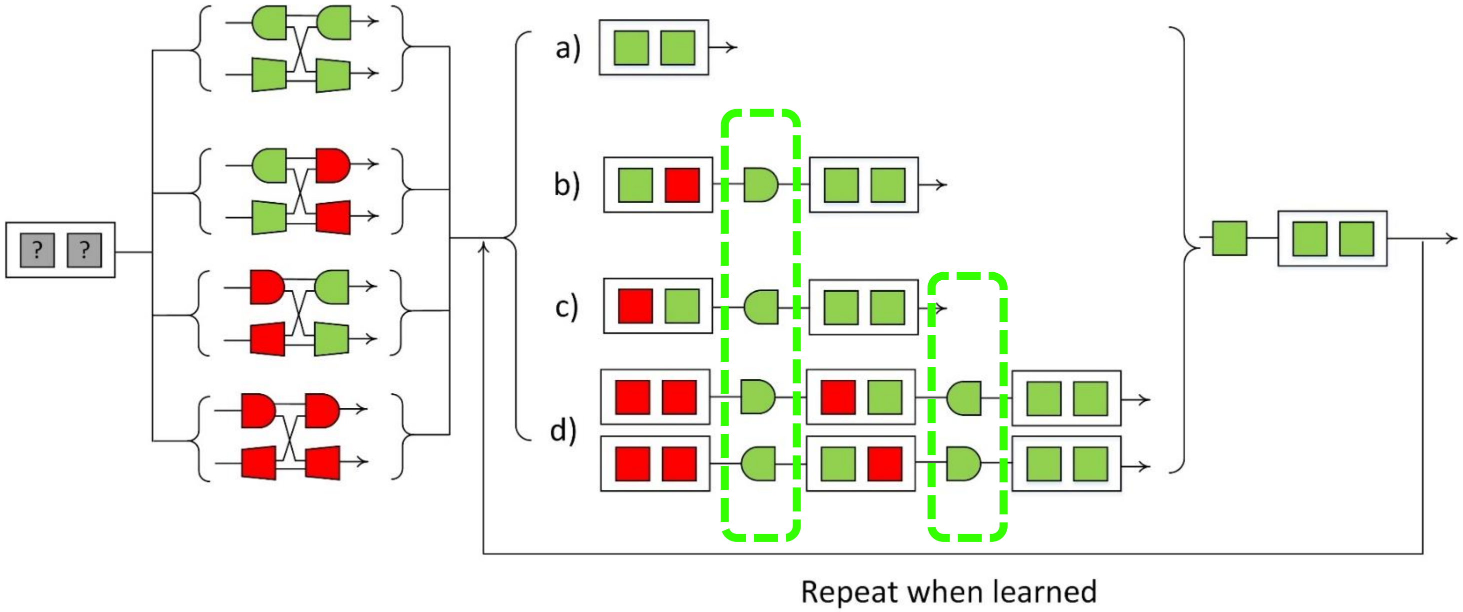

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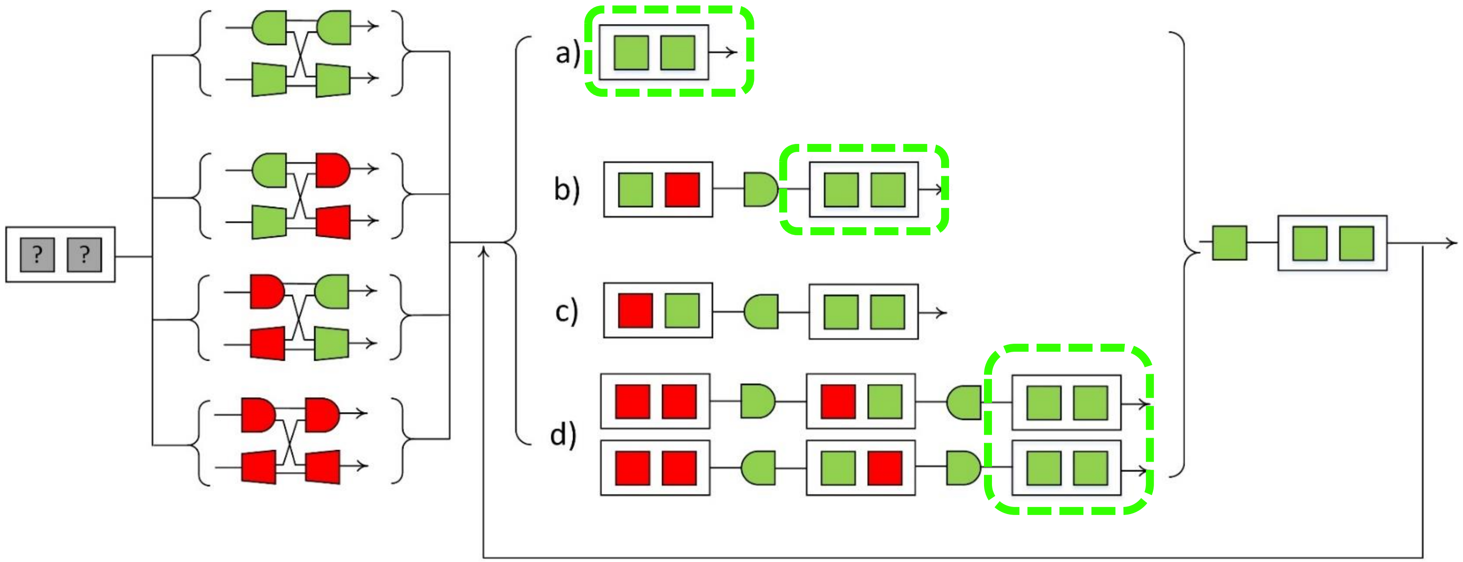

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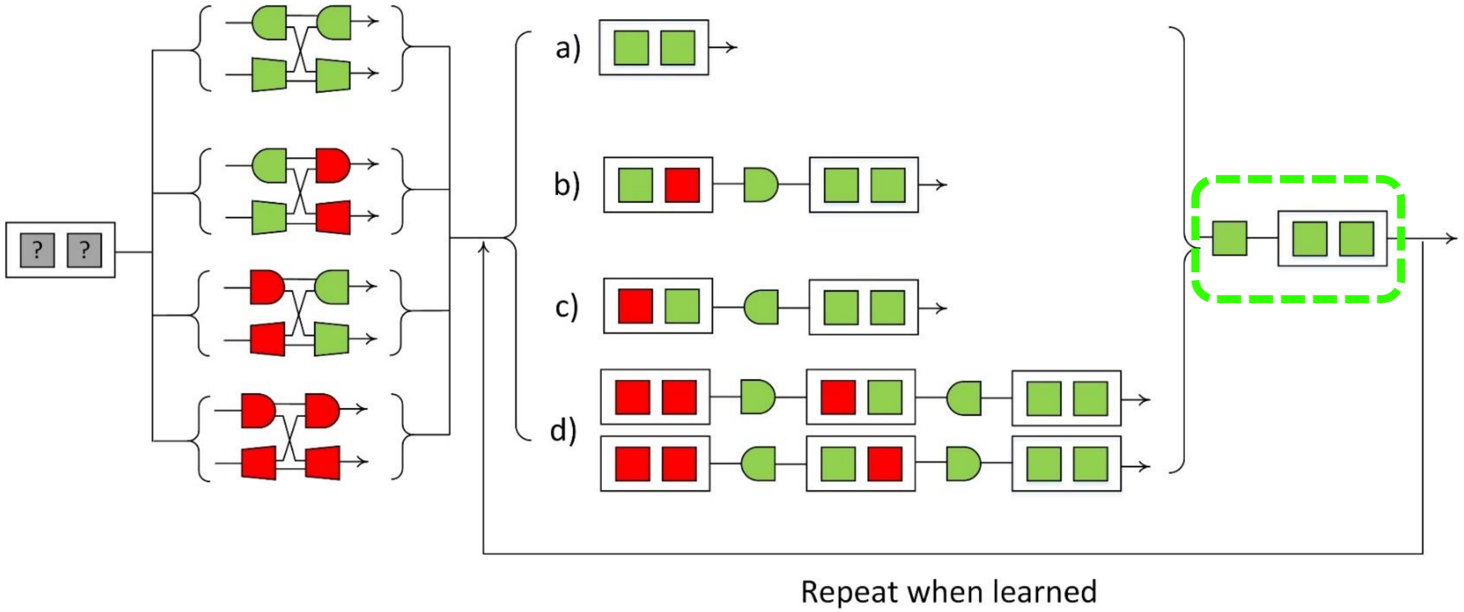


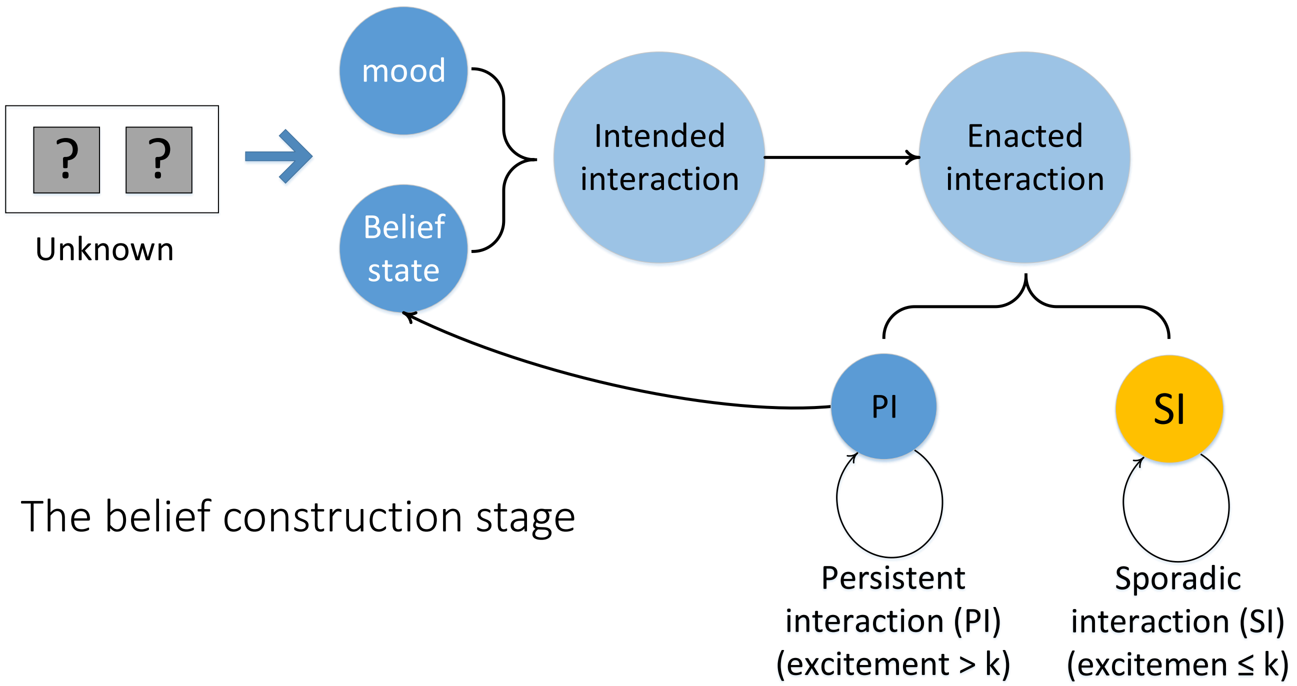
The regularities of interactions that we expect the causal acquisition model to develop.

Contribution 2: Causality reconstruction with the CCA

- Modeling Causal Acquisition with CCA

Contribution 2: Causality reconstruction with the CCA

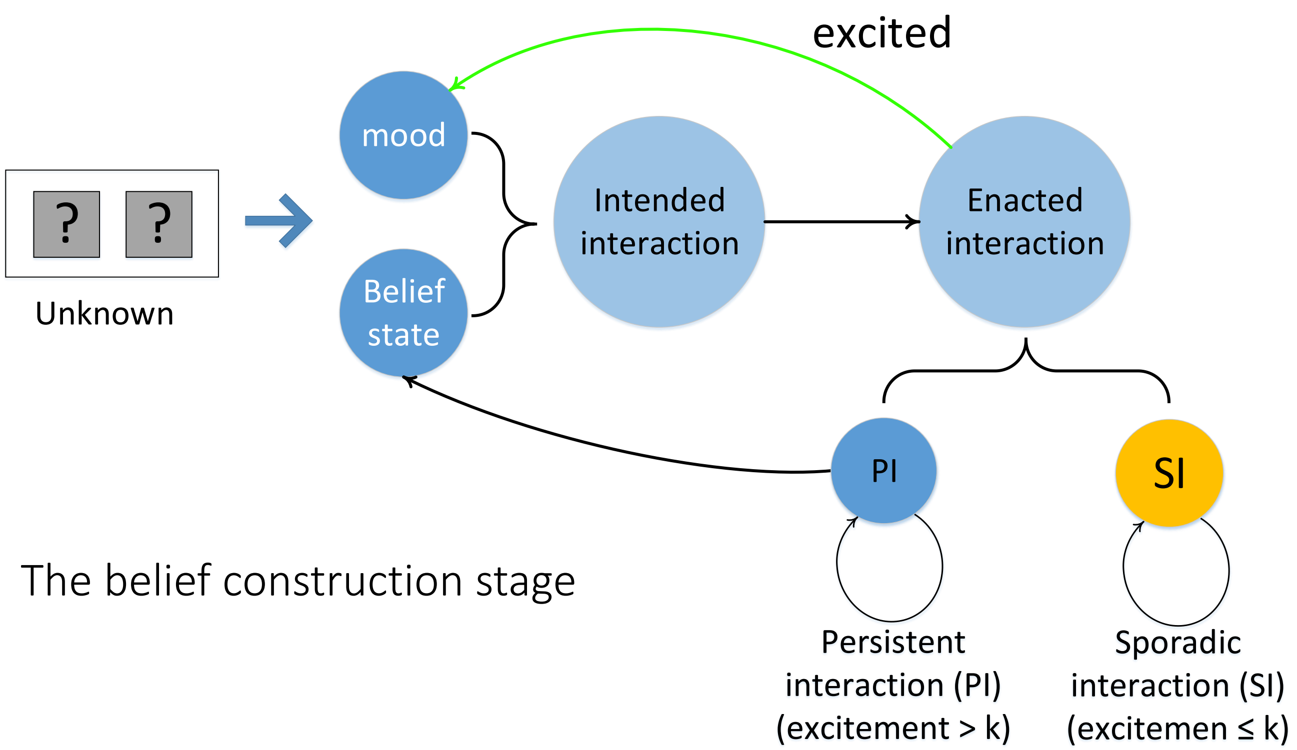
Modeling Causal Acquisition with CCA



The belief construction stage

Contribution 2: Causality reconstruction with the CCA

Modeling Causal Acquisition with CCA



The belief construction stage

Contribution 2: Causality reconstruction with the CCA

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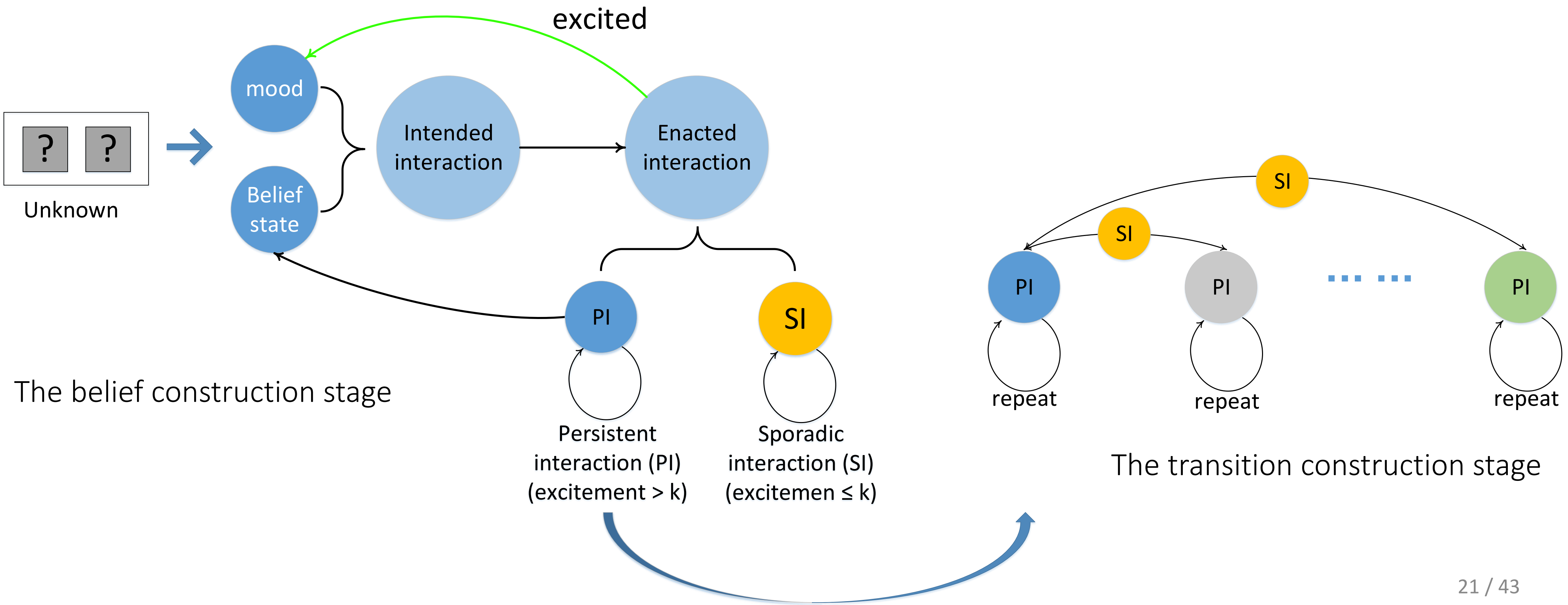
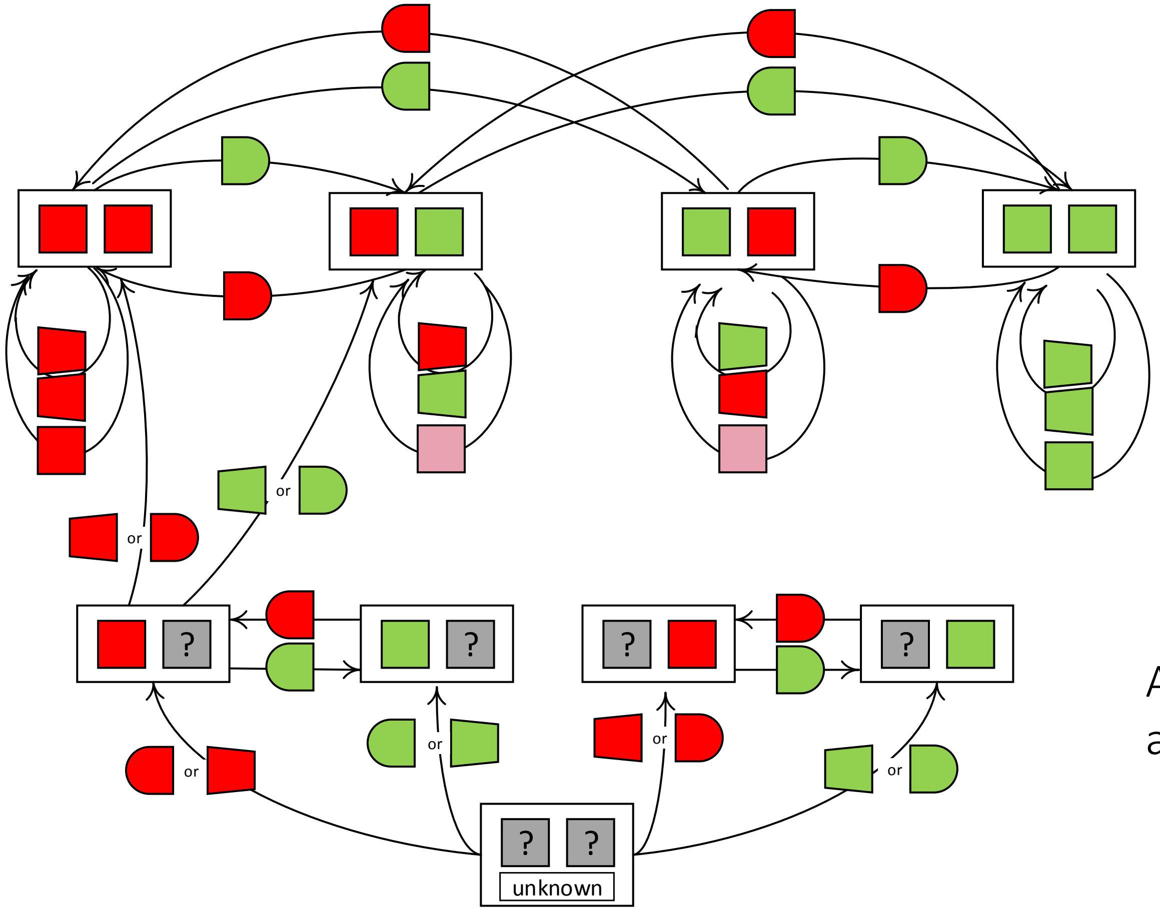


Contribution 2: Causality reconstruction with the CCA

The result of the casual model



A causal model (Petri Net) learned by the agent from regularities of interactions.

Contribution 2: Causality reconstruction with the CCA

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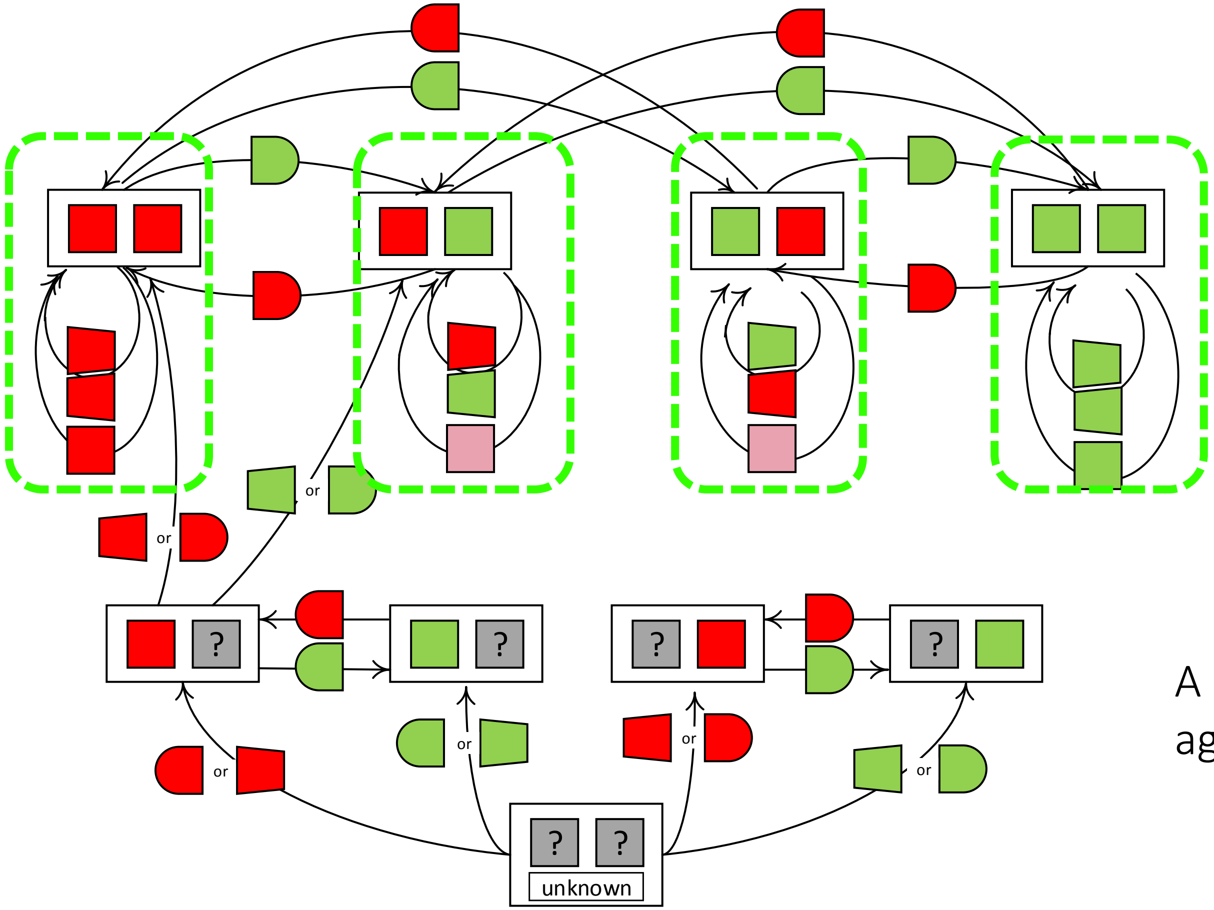

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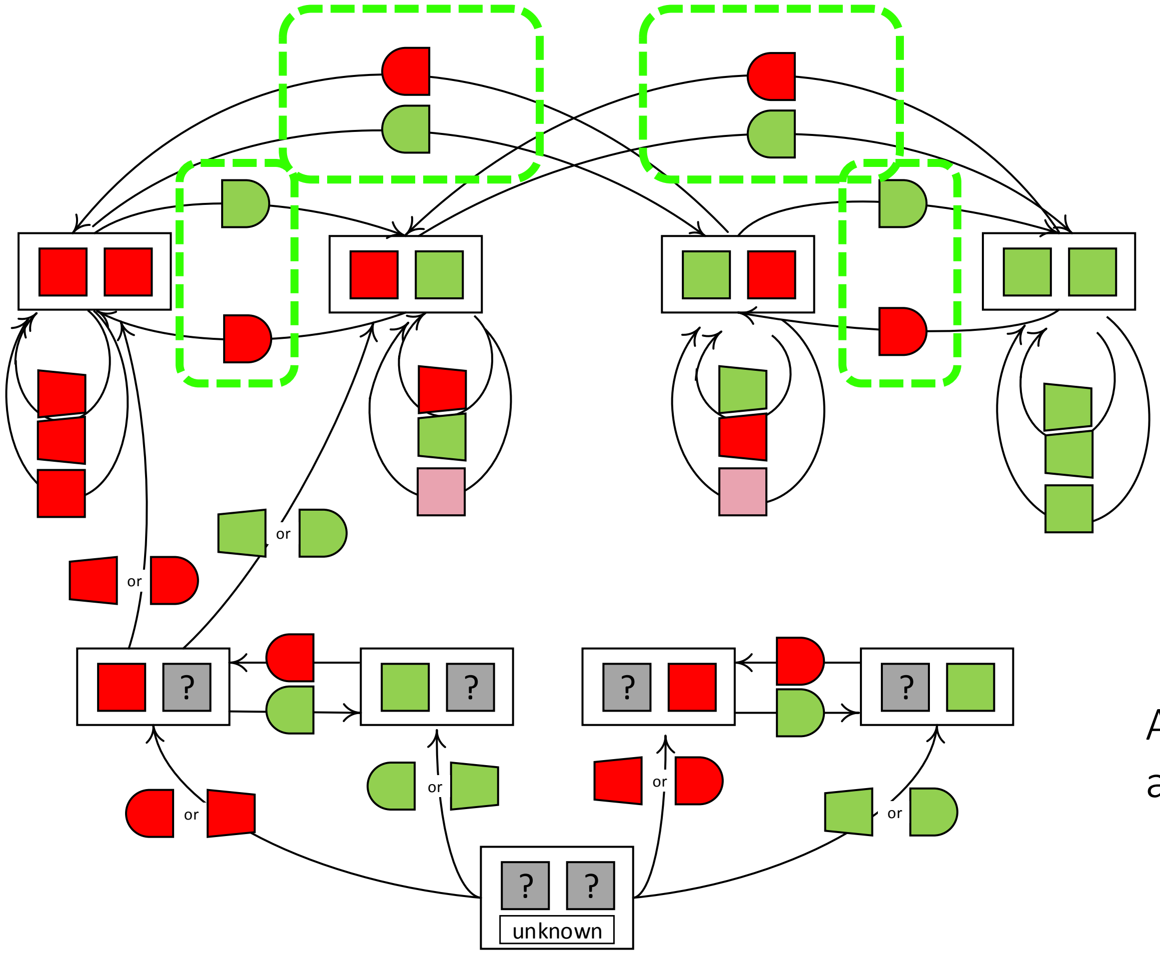

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Contribution 2: Causality reconstruction with the CCA

Behavioral traces analysis

Trace of the first 350 interaction cycles in our experiment.

- Line 1: intended experiences.
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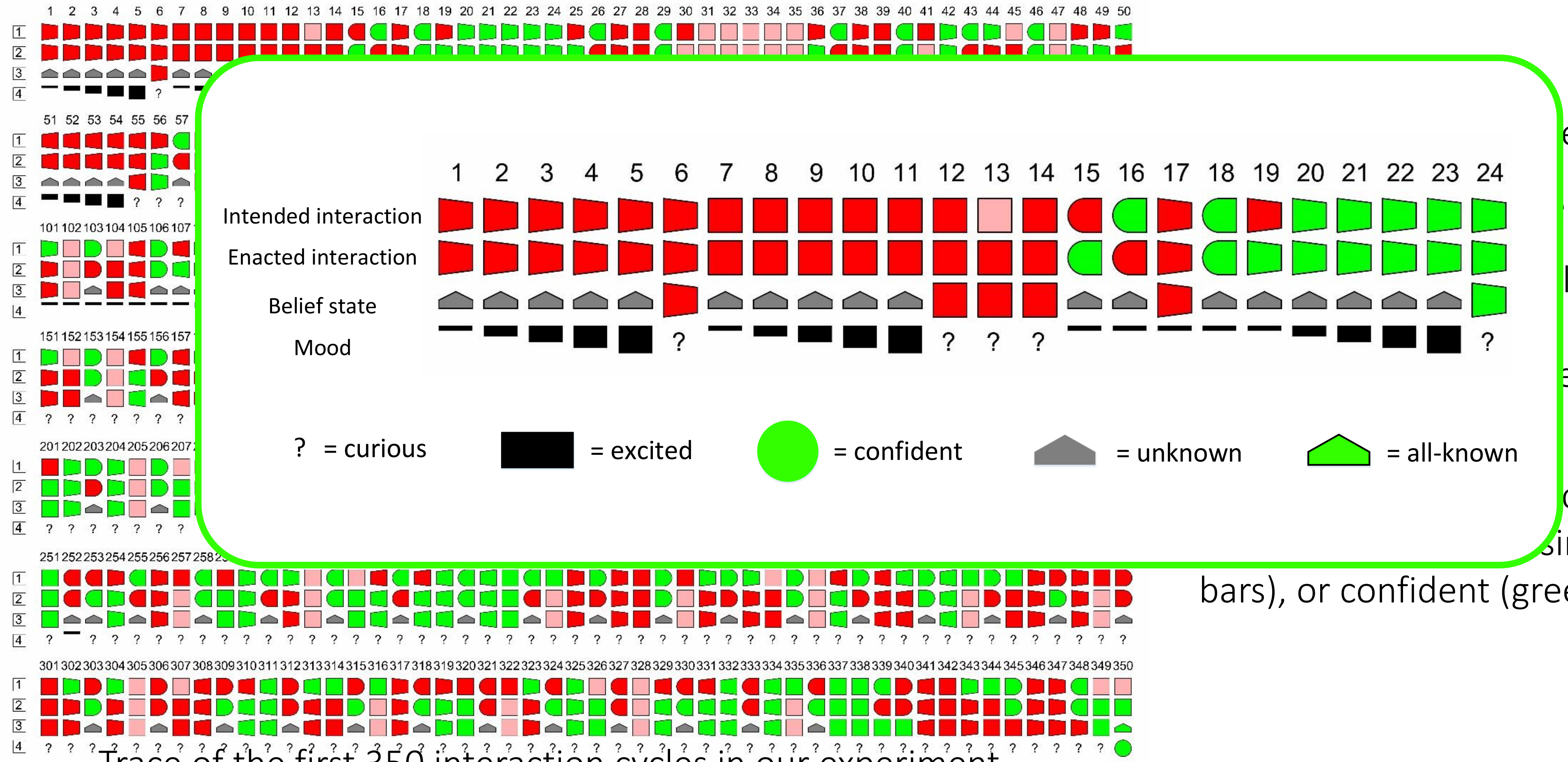

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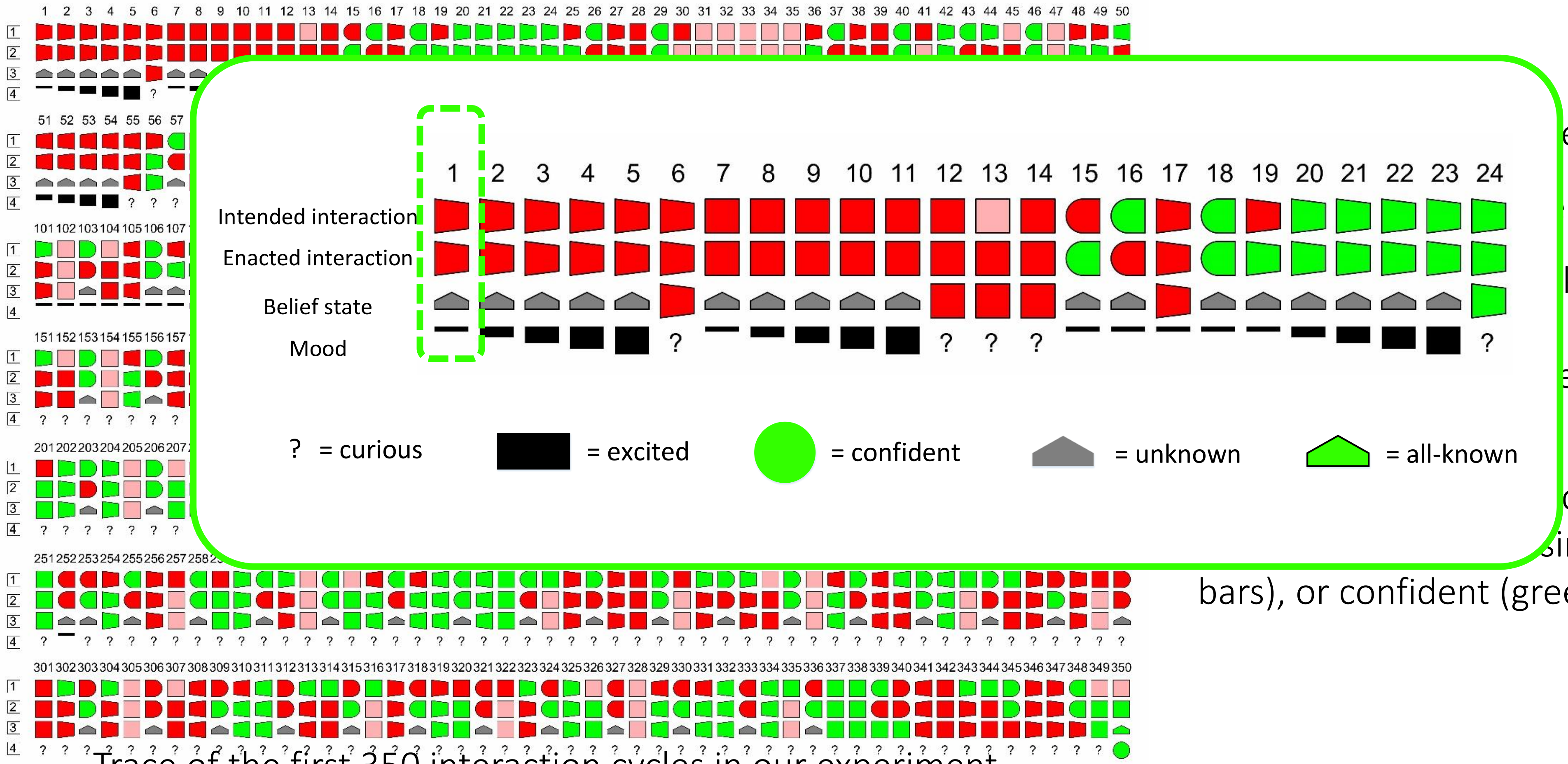

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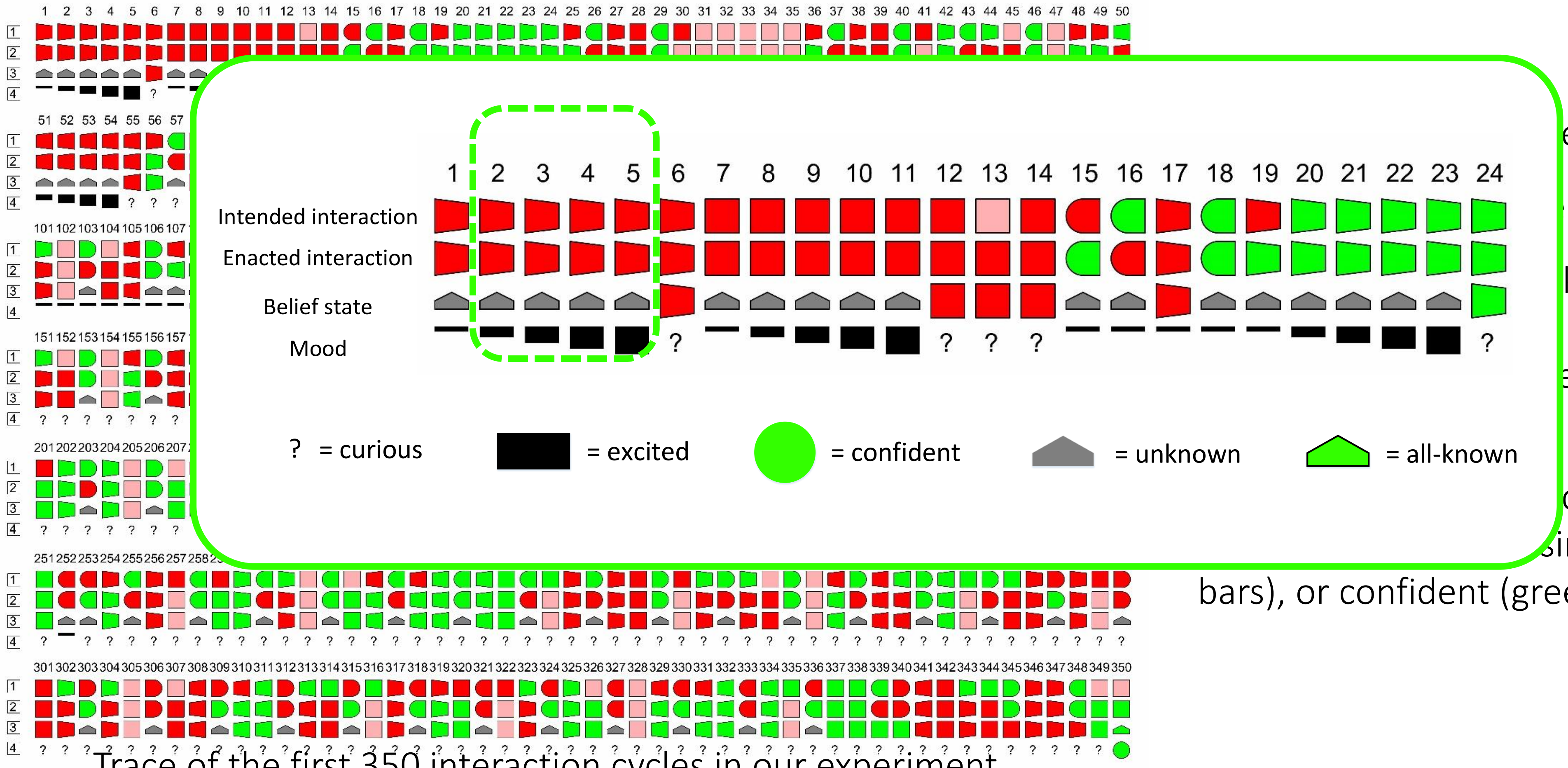

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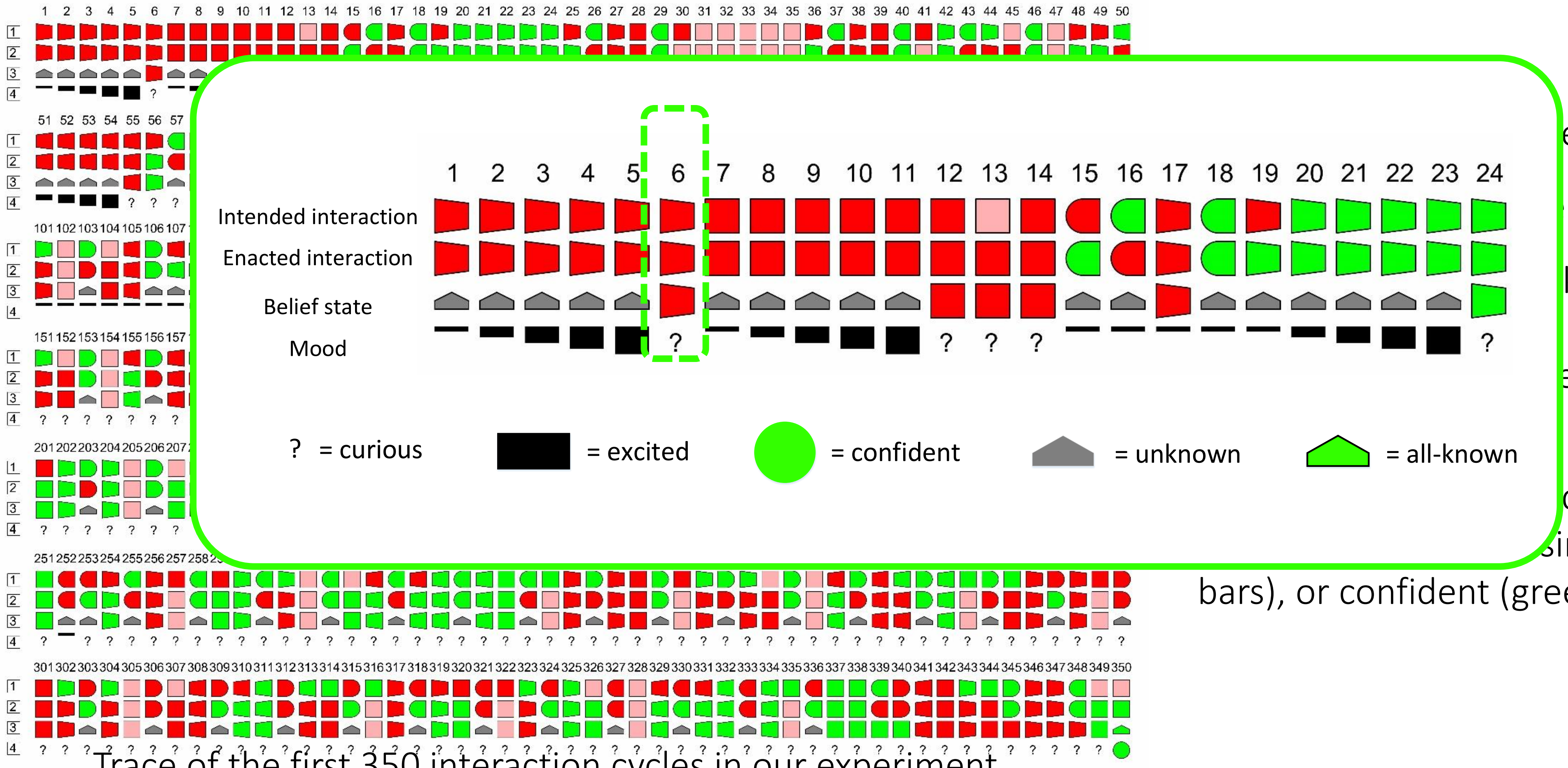

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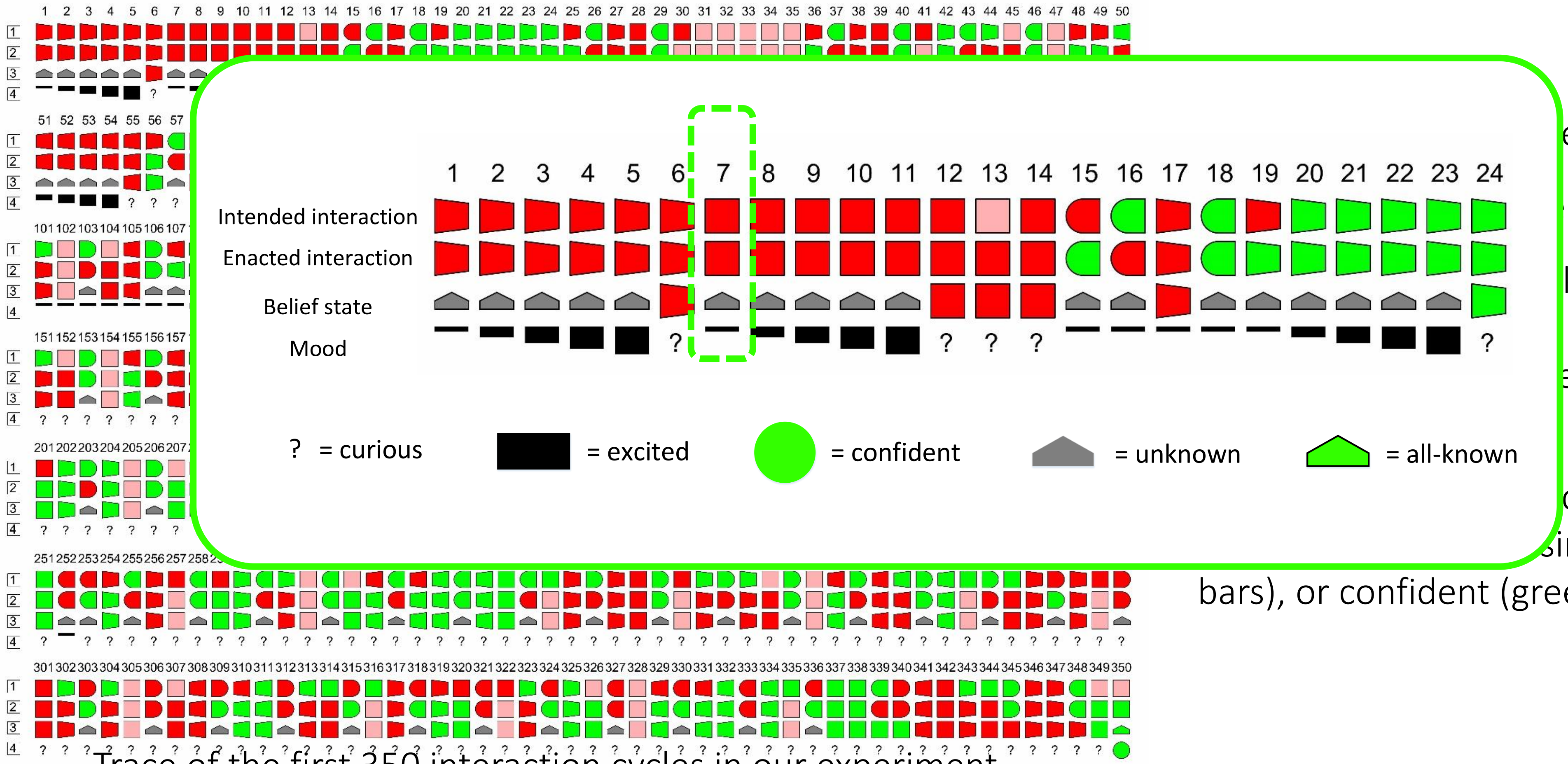

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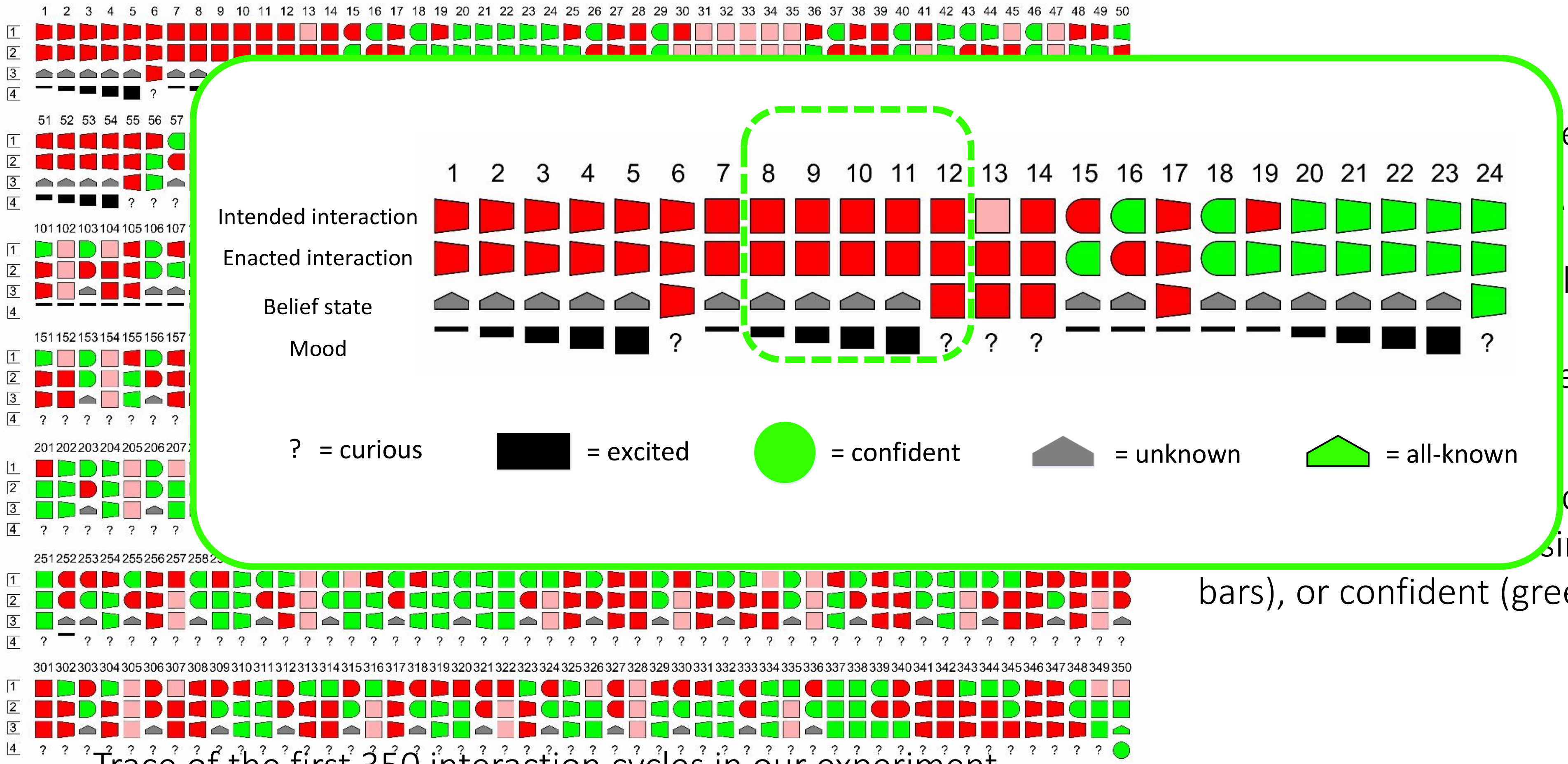

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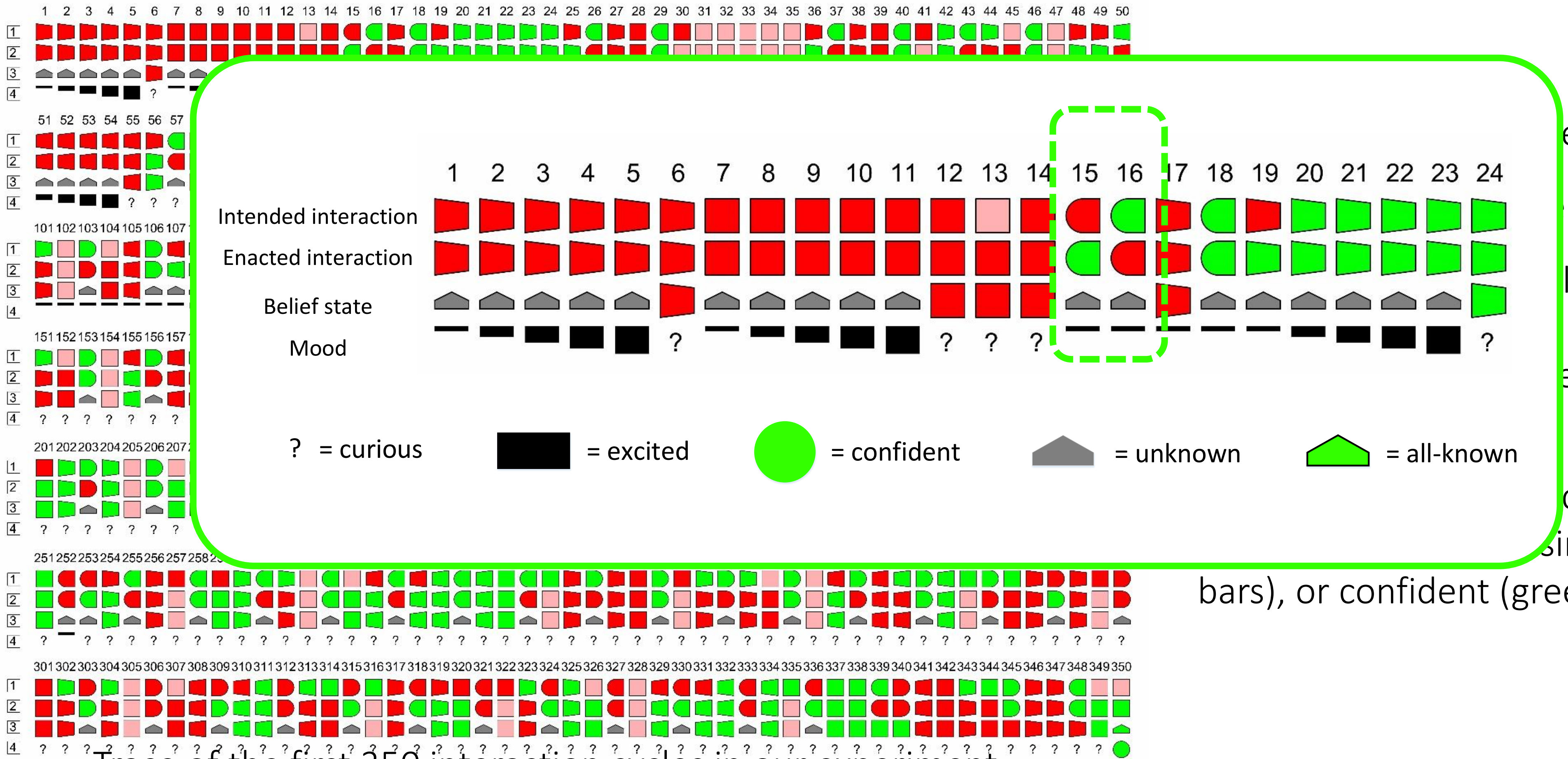

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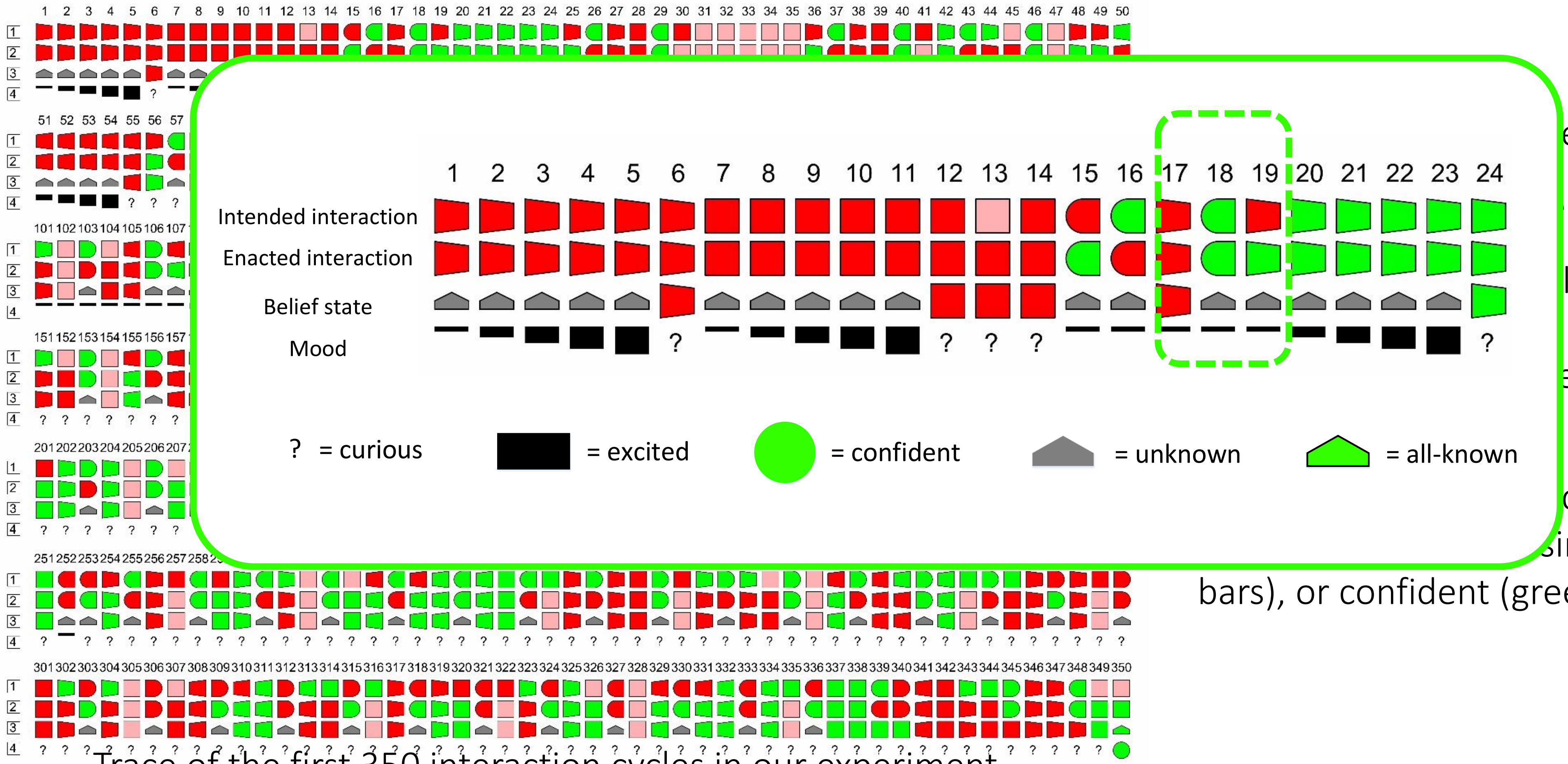

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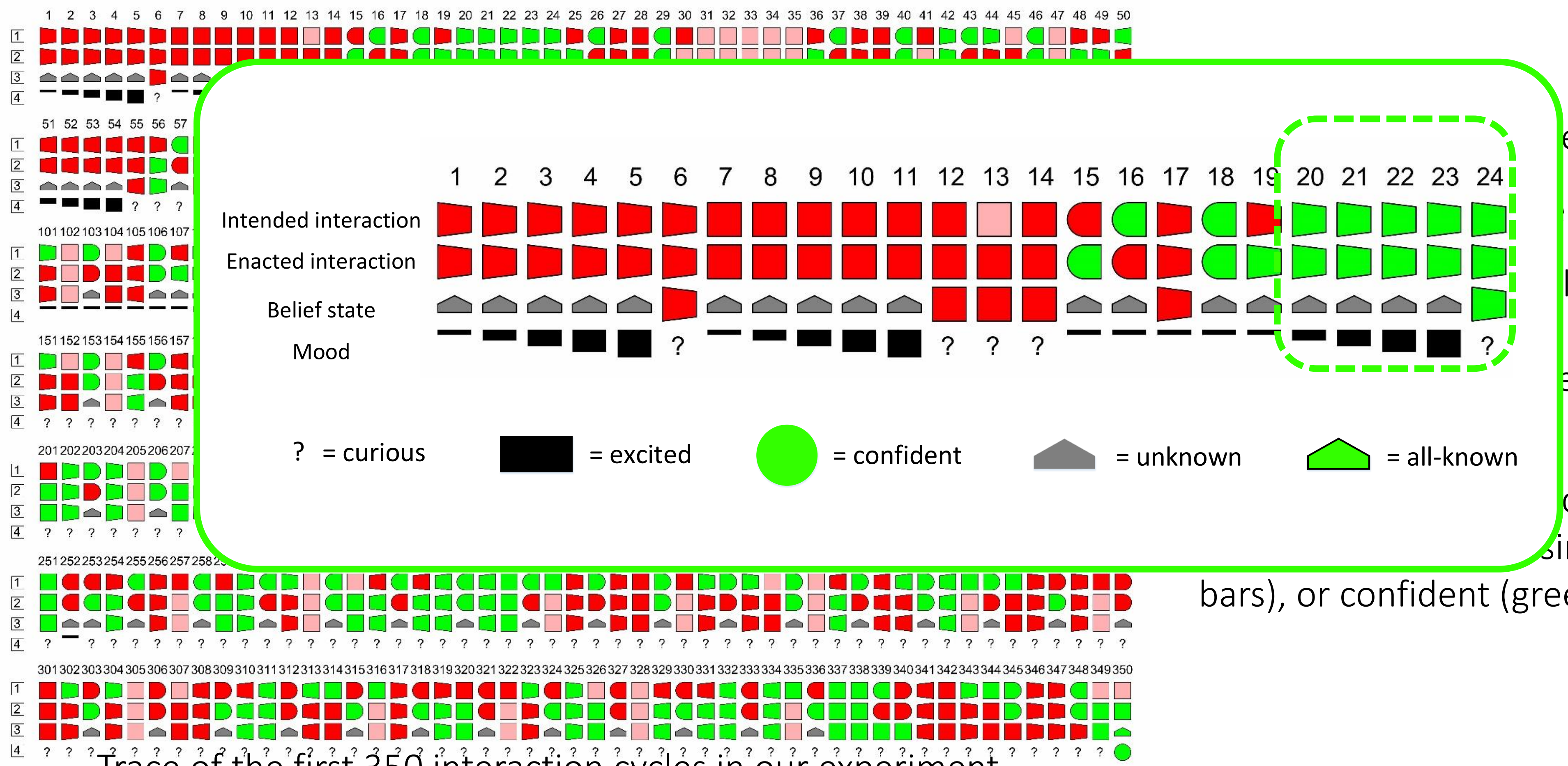

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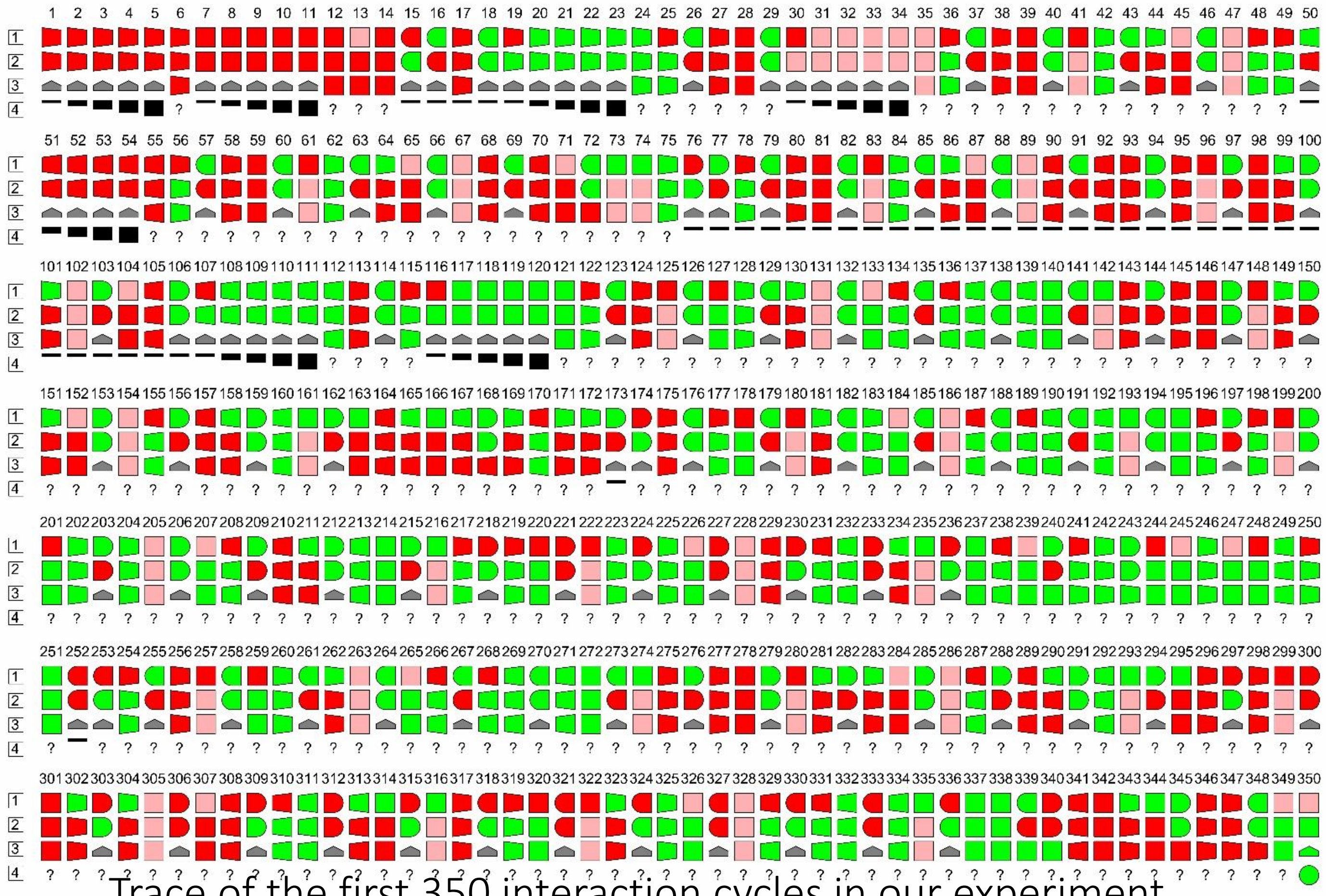

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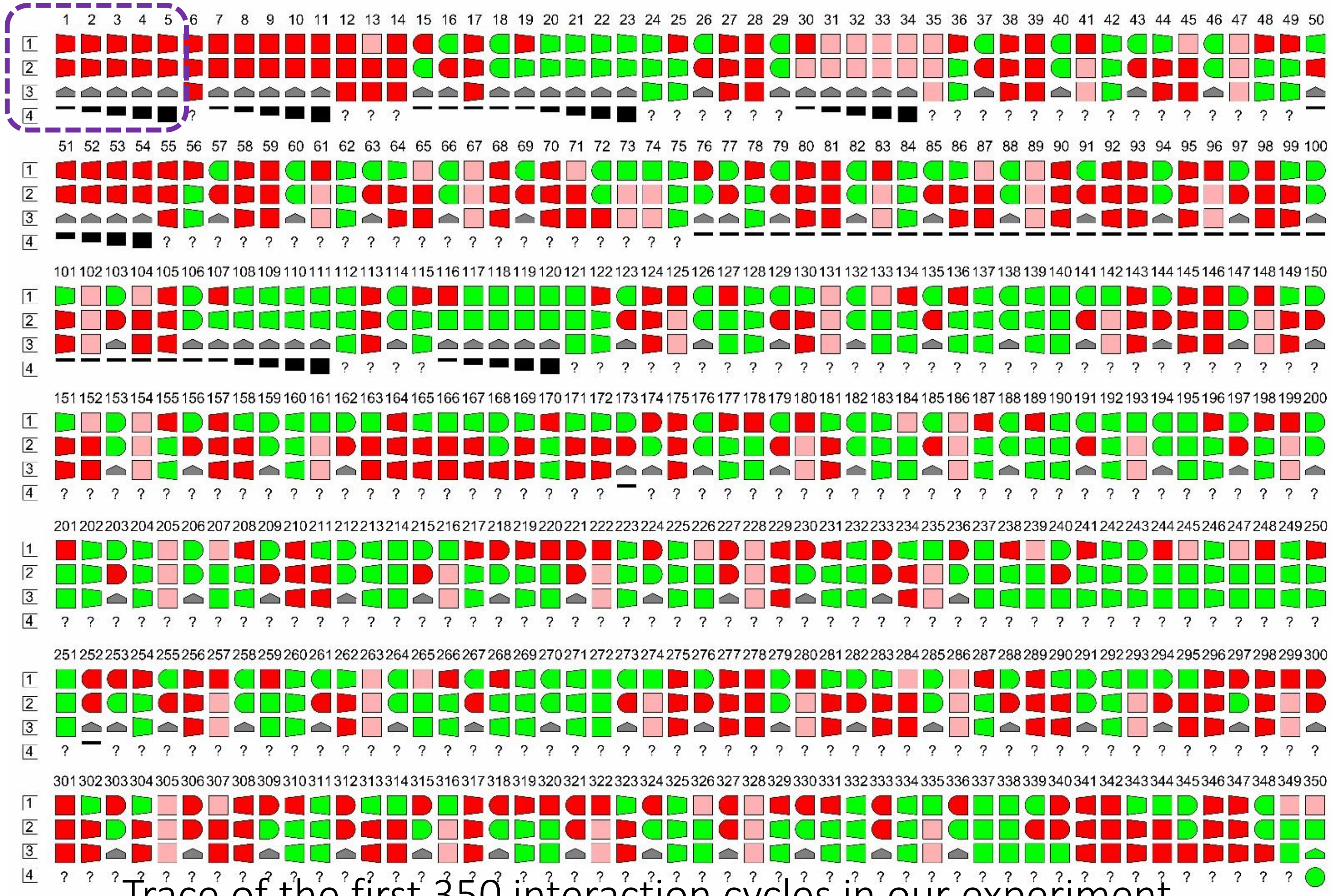

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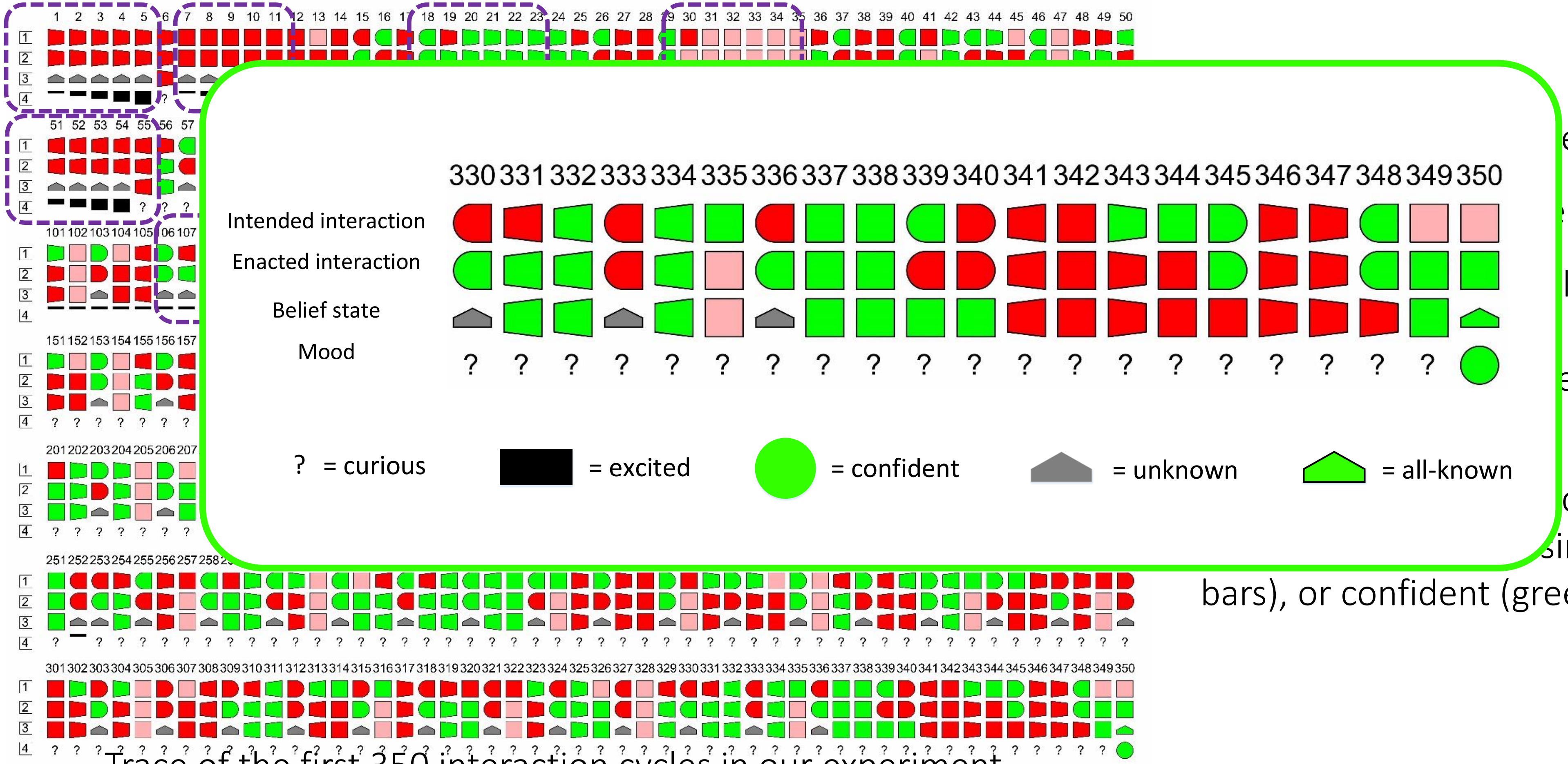

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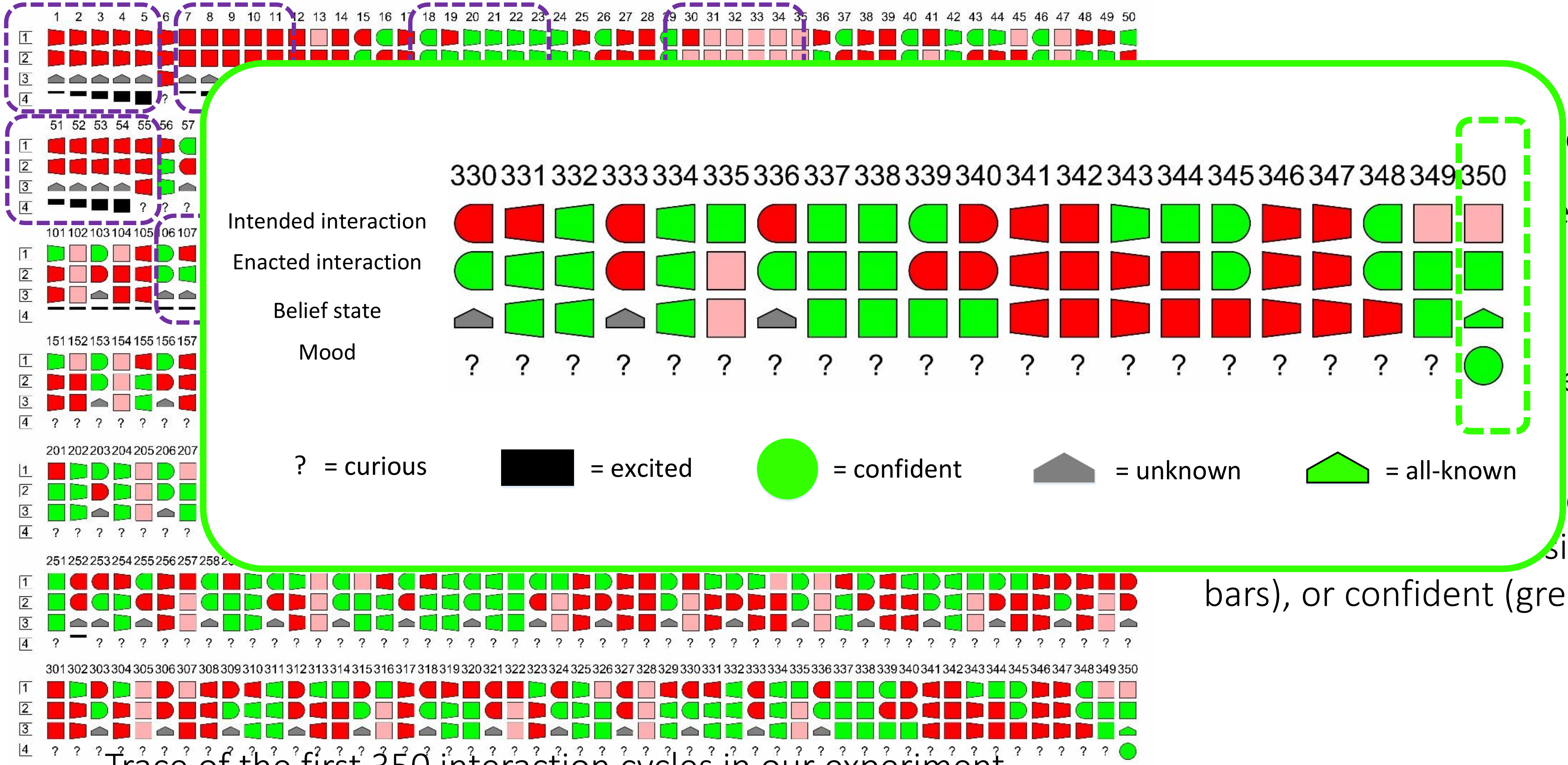

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Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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- Interaction scenario

The Small-Loop-Problem environment.

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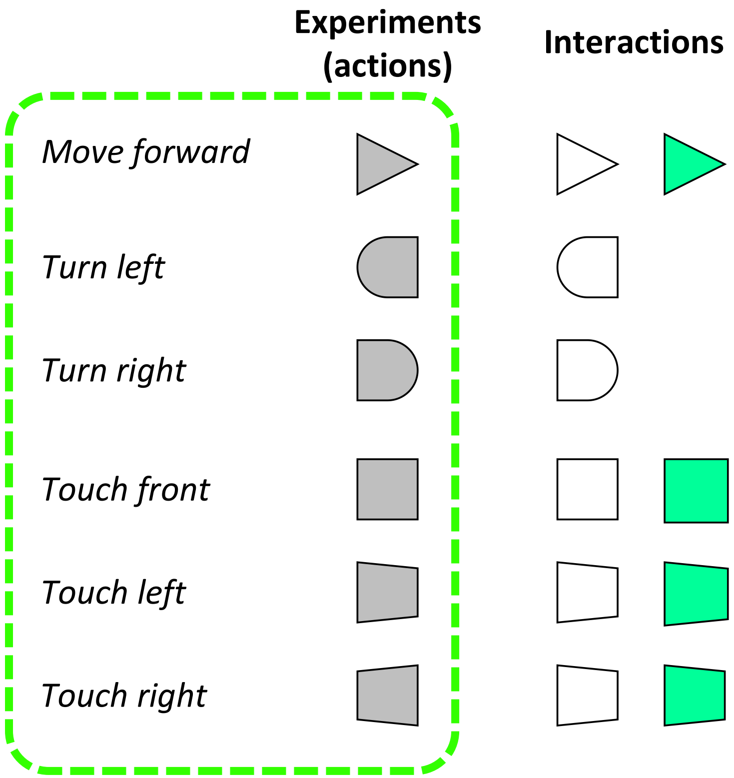

Six experiments with ten interactions.

Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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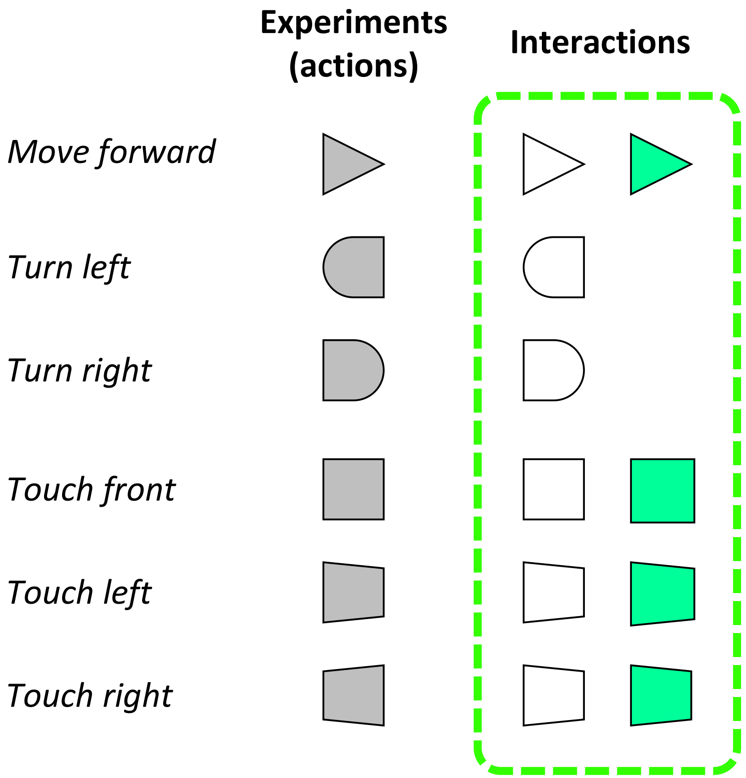

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- The learning process of BEL-CA

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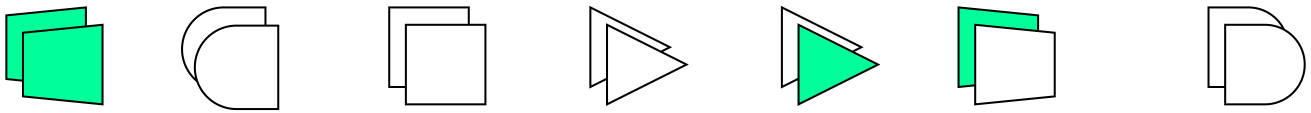

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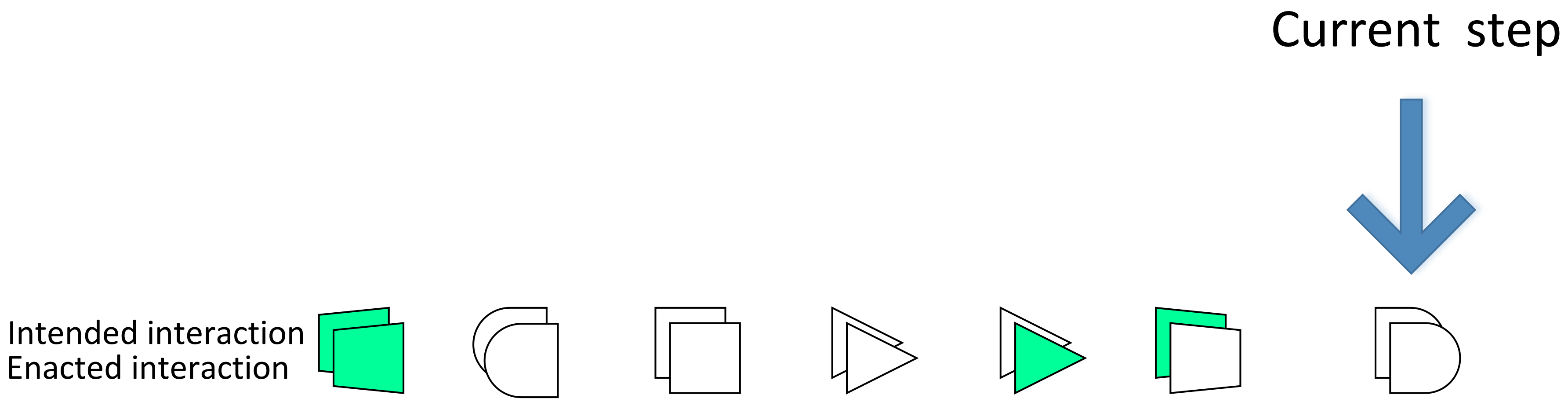

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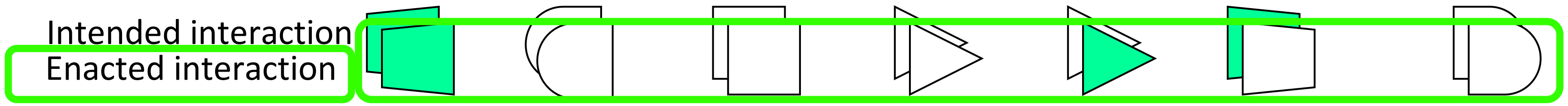
Current step



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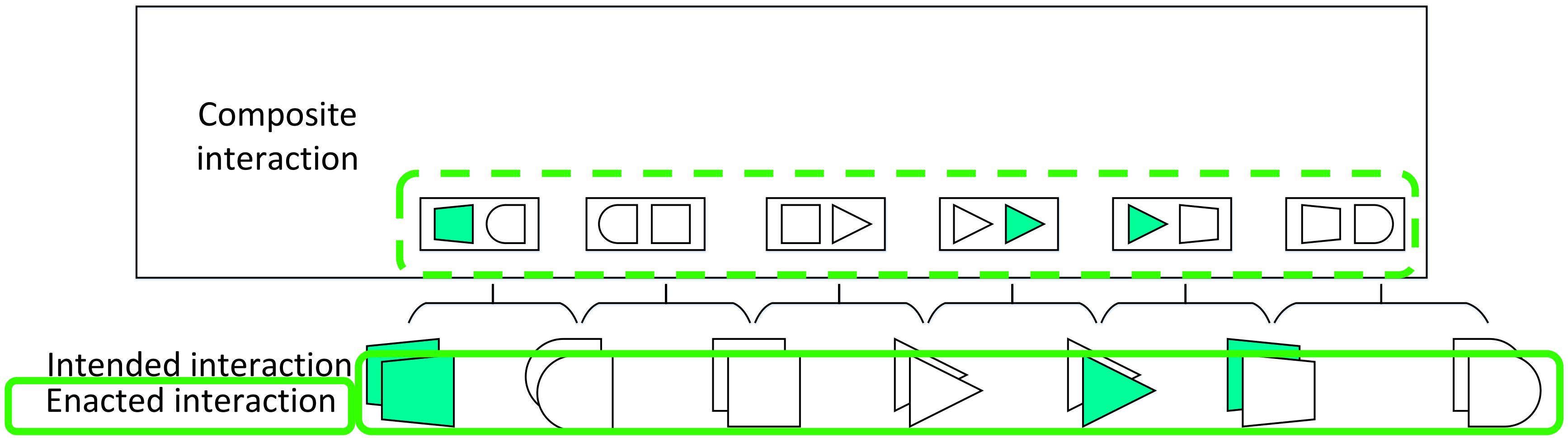

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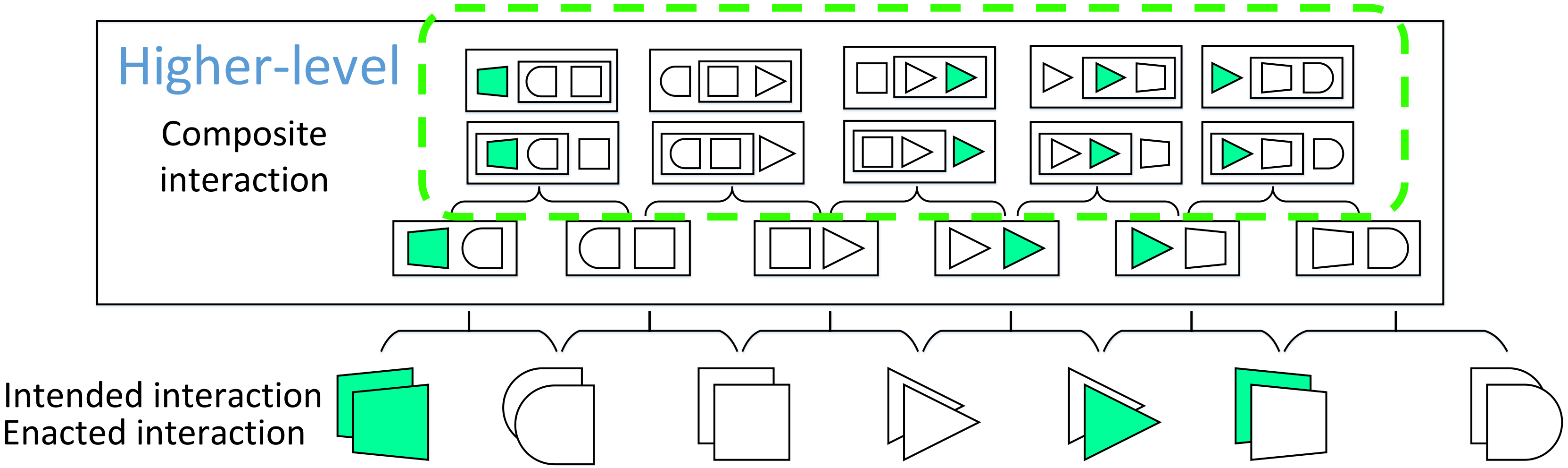

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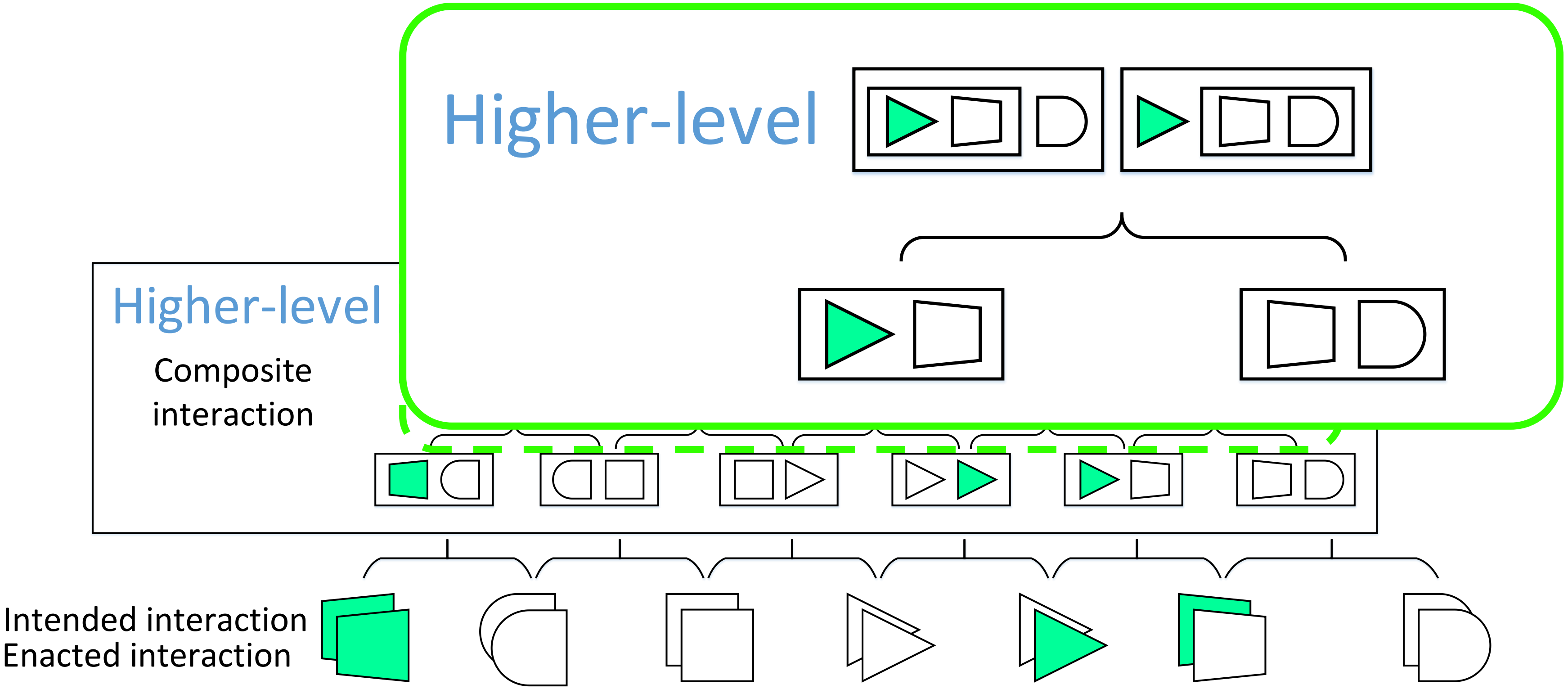

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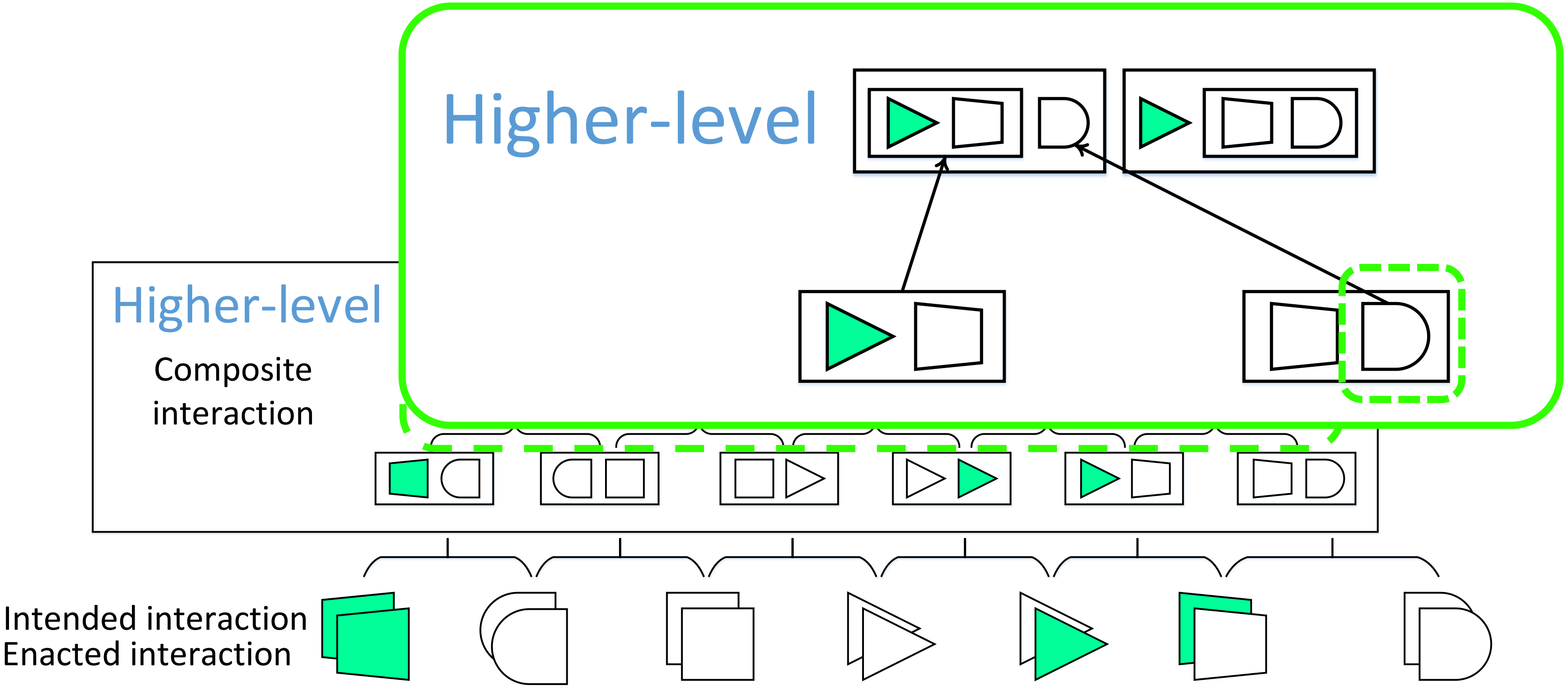

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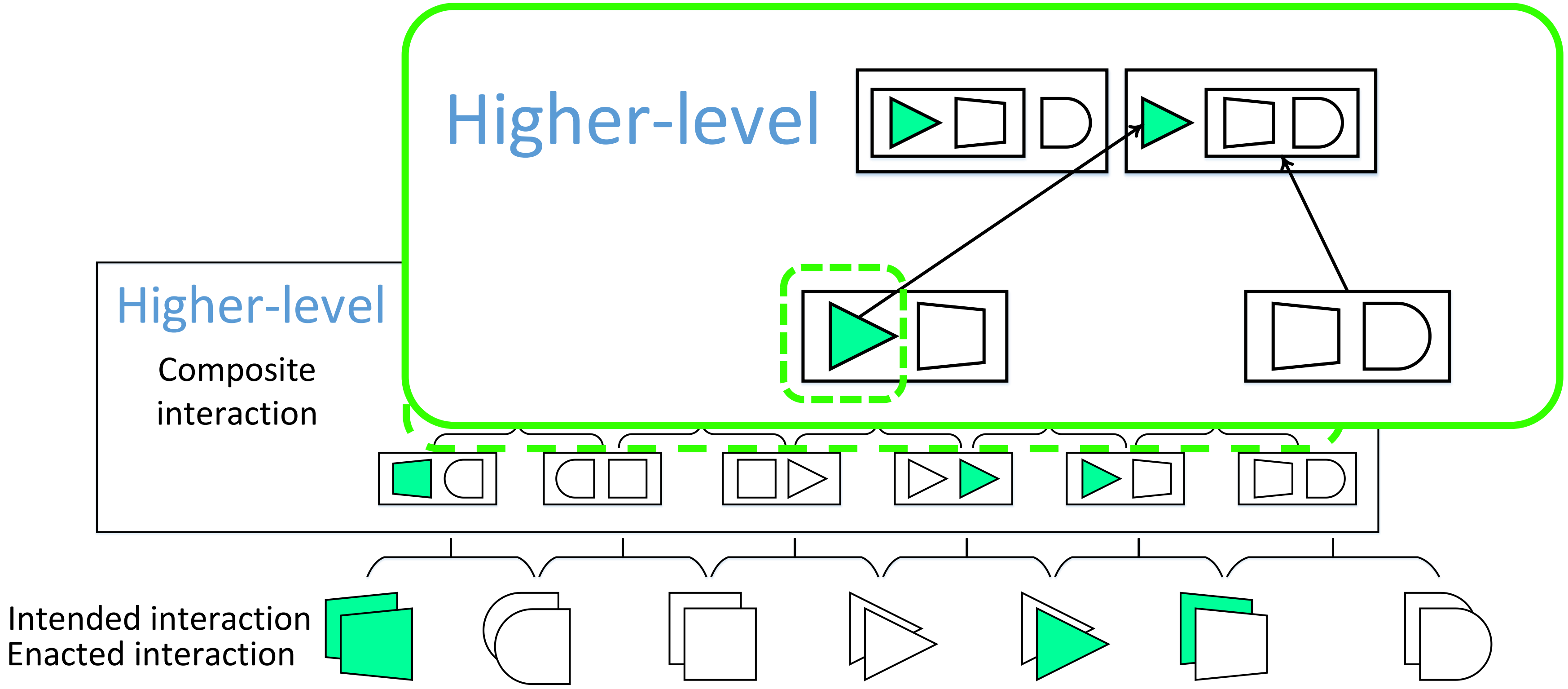

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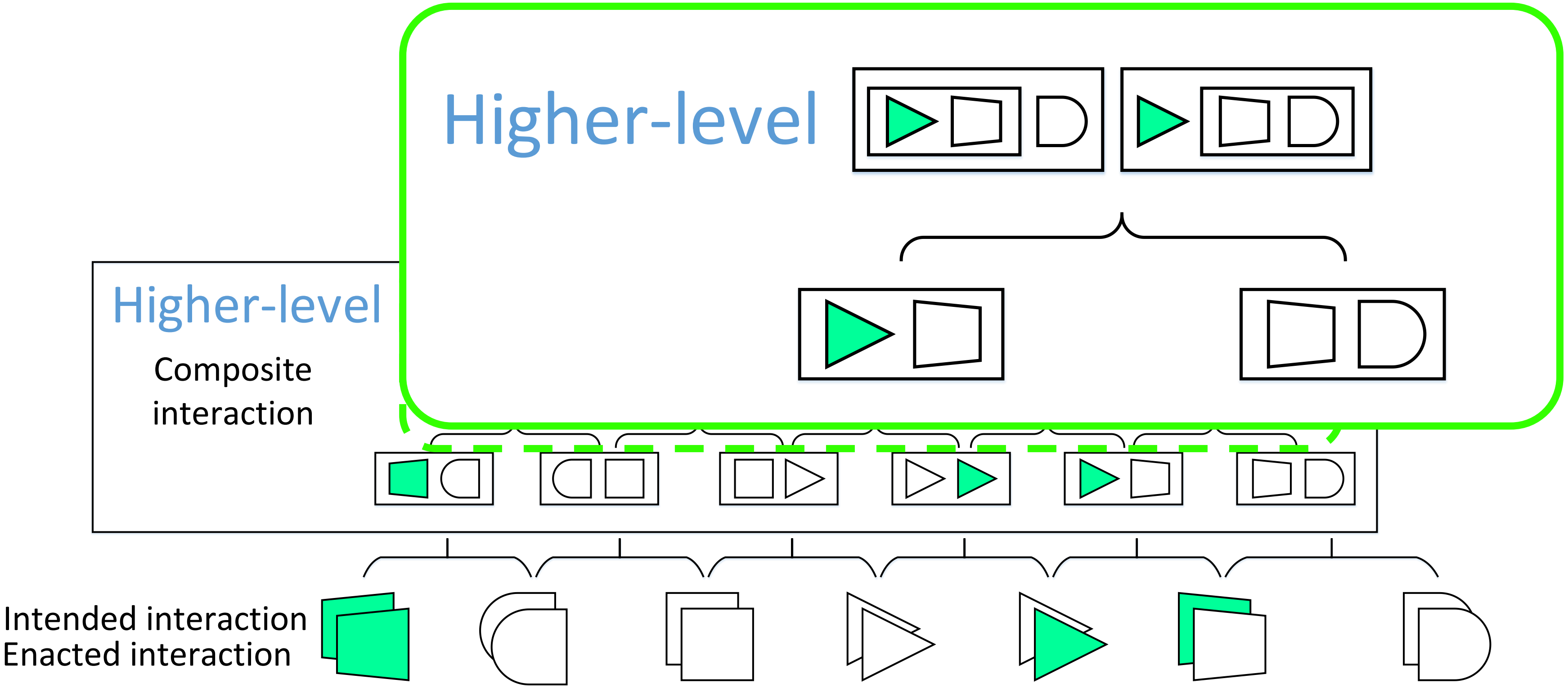

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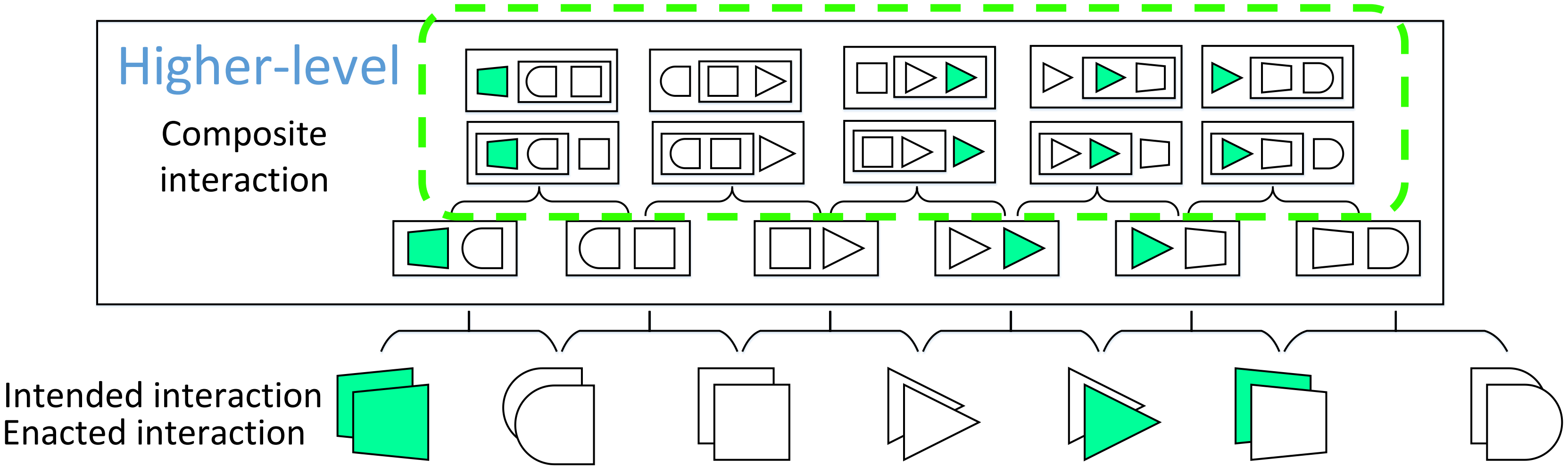

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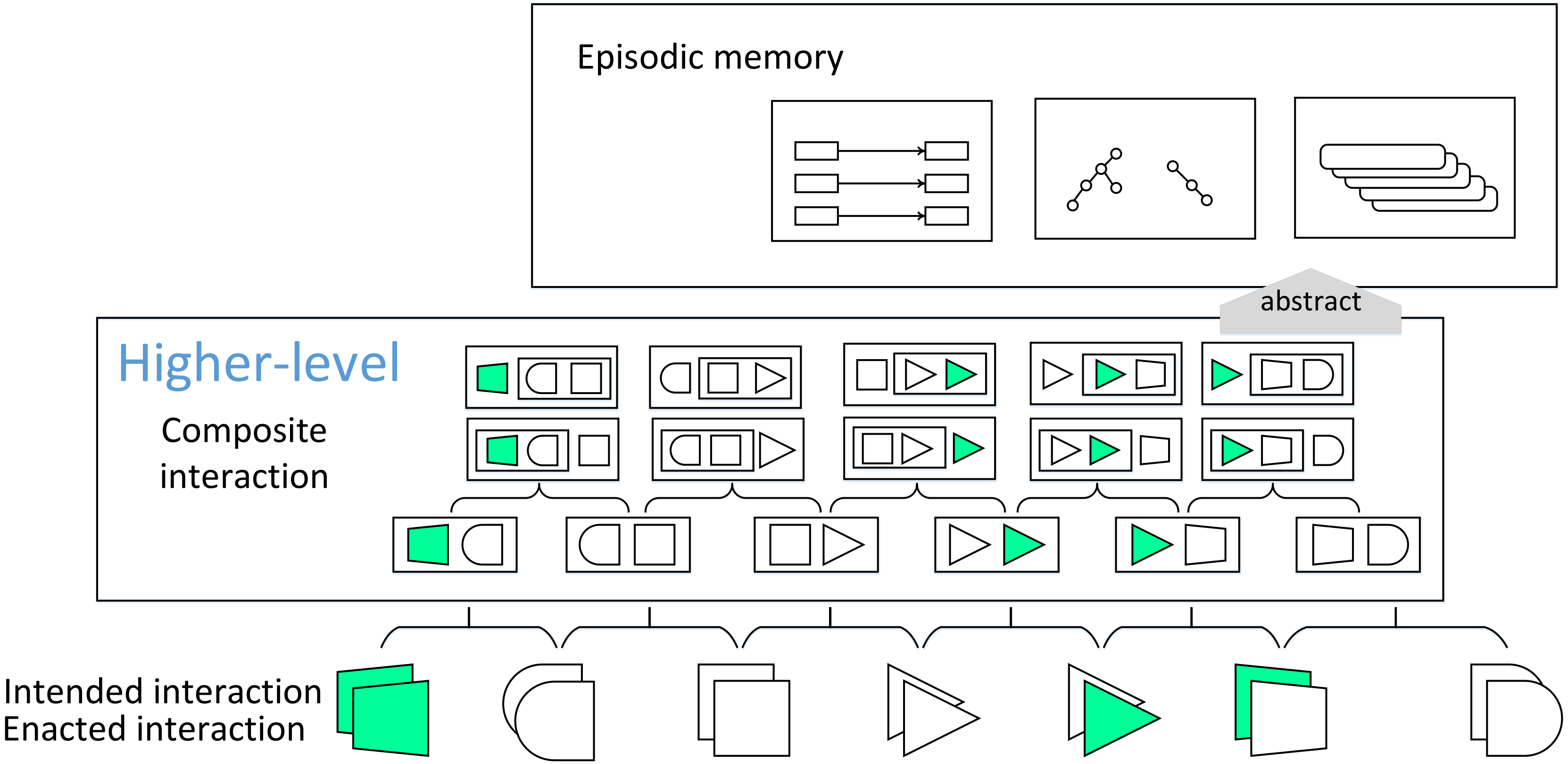

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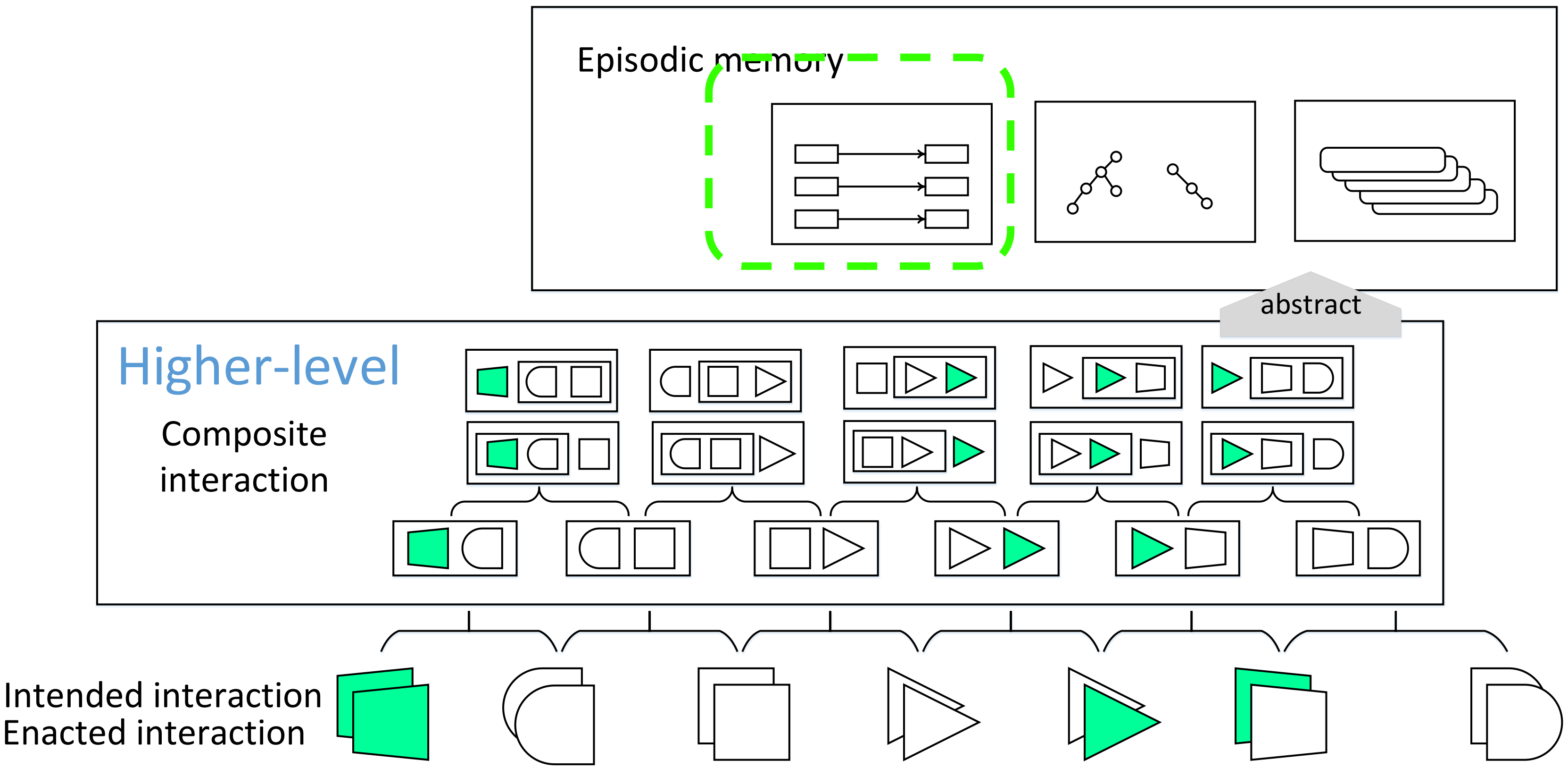

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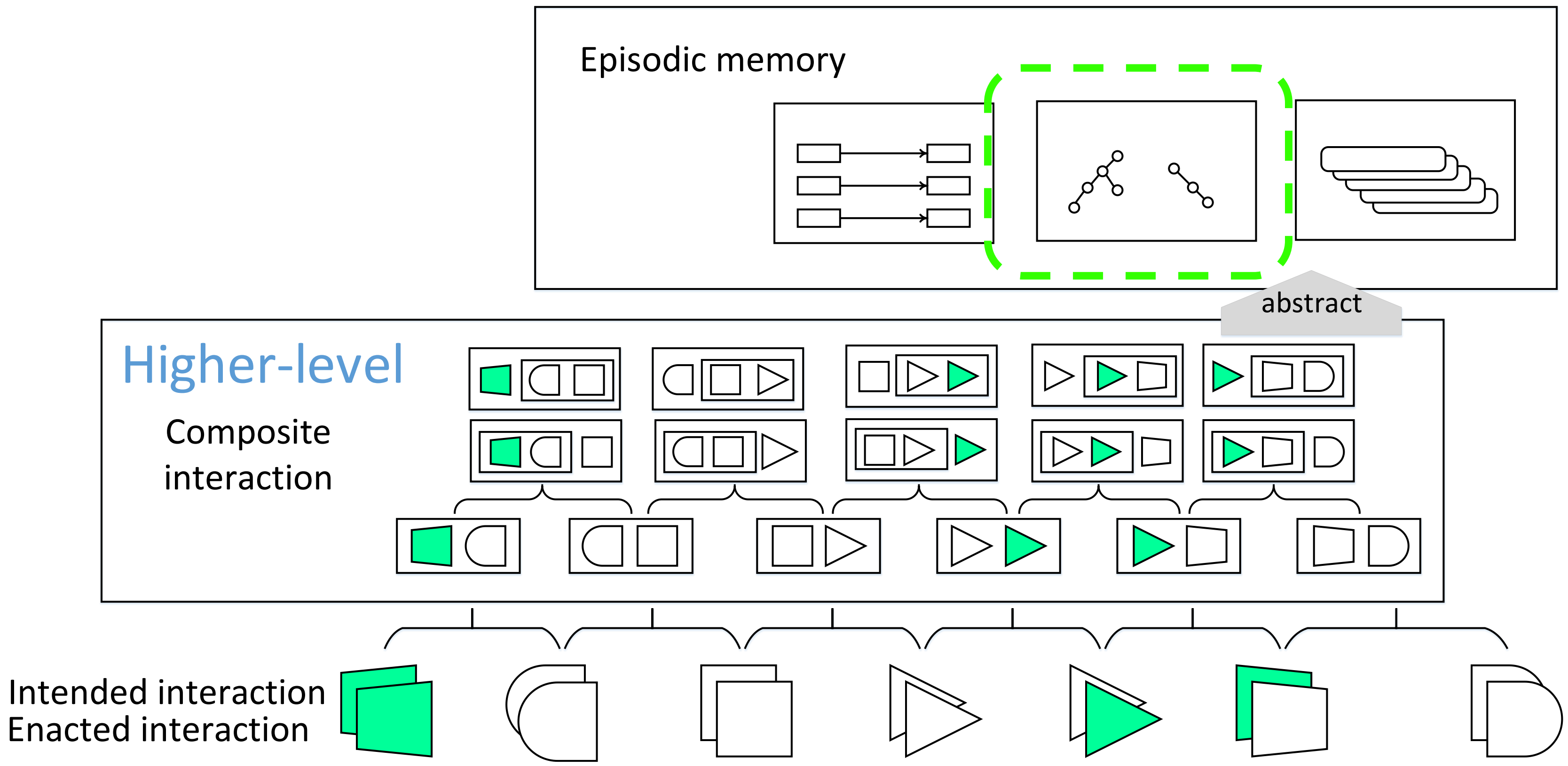

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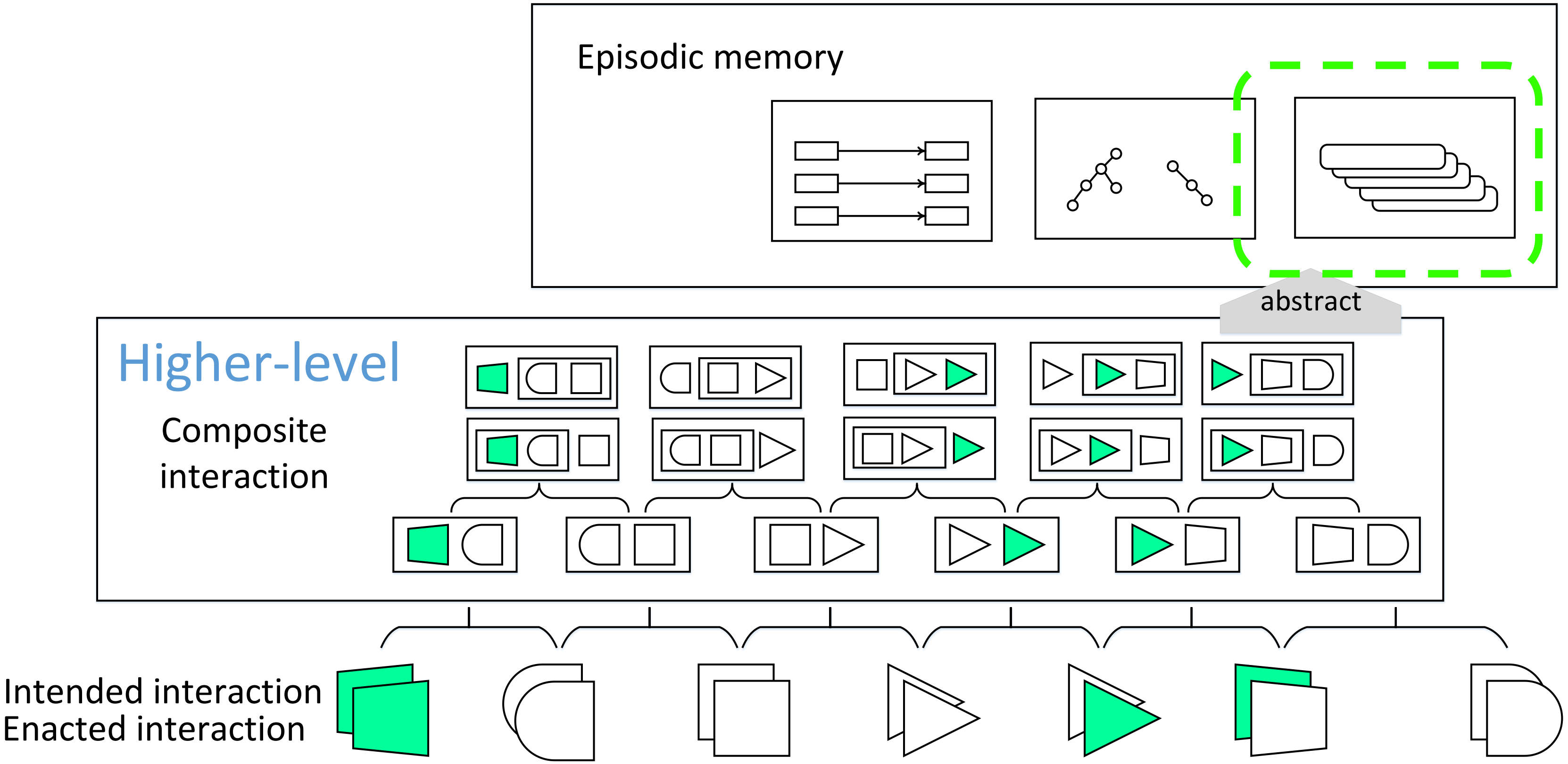

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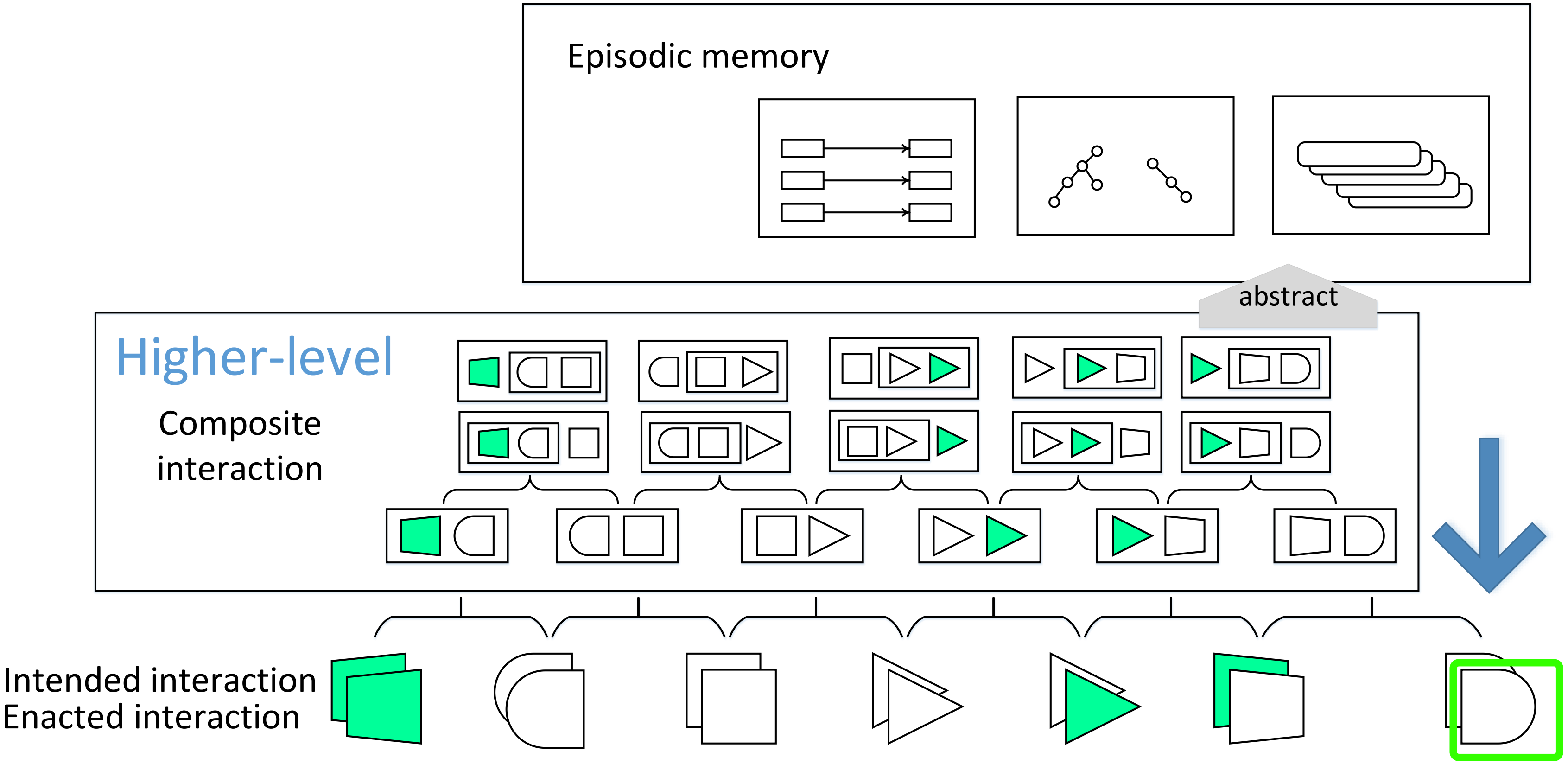

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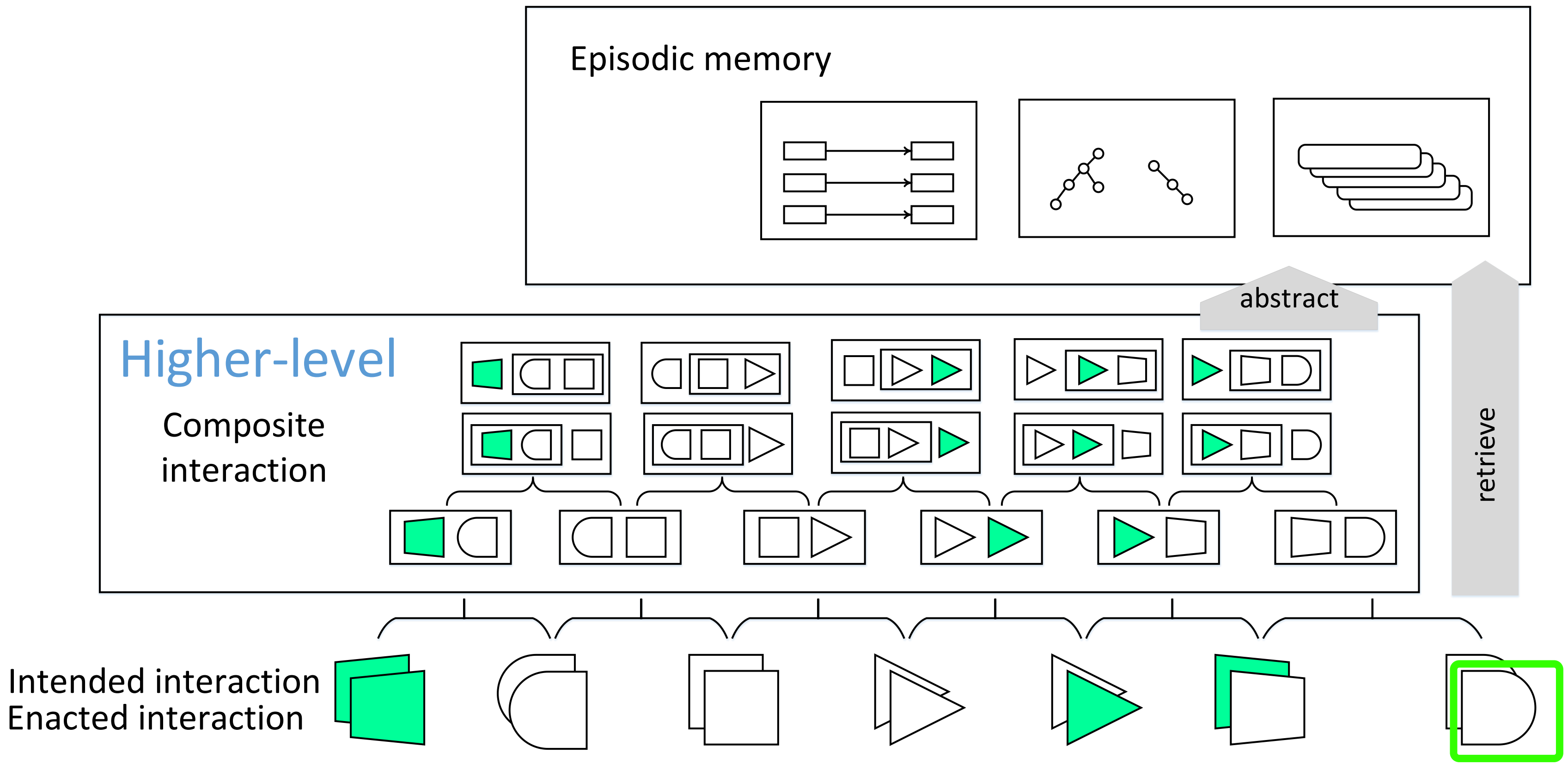

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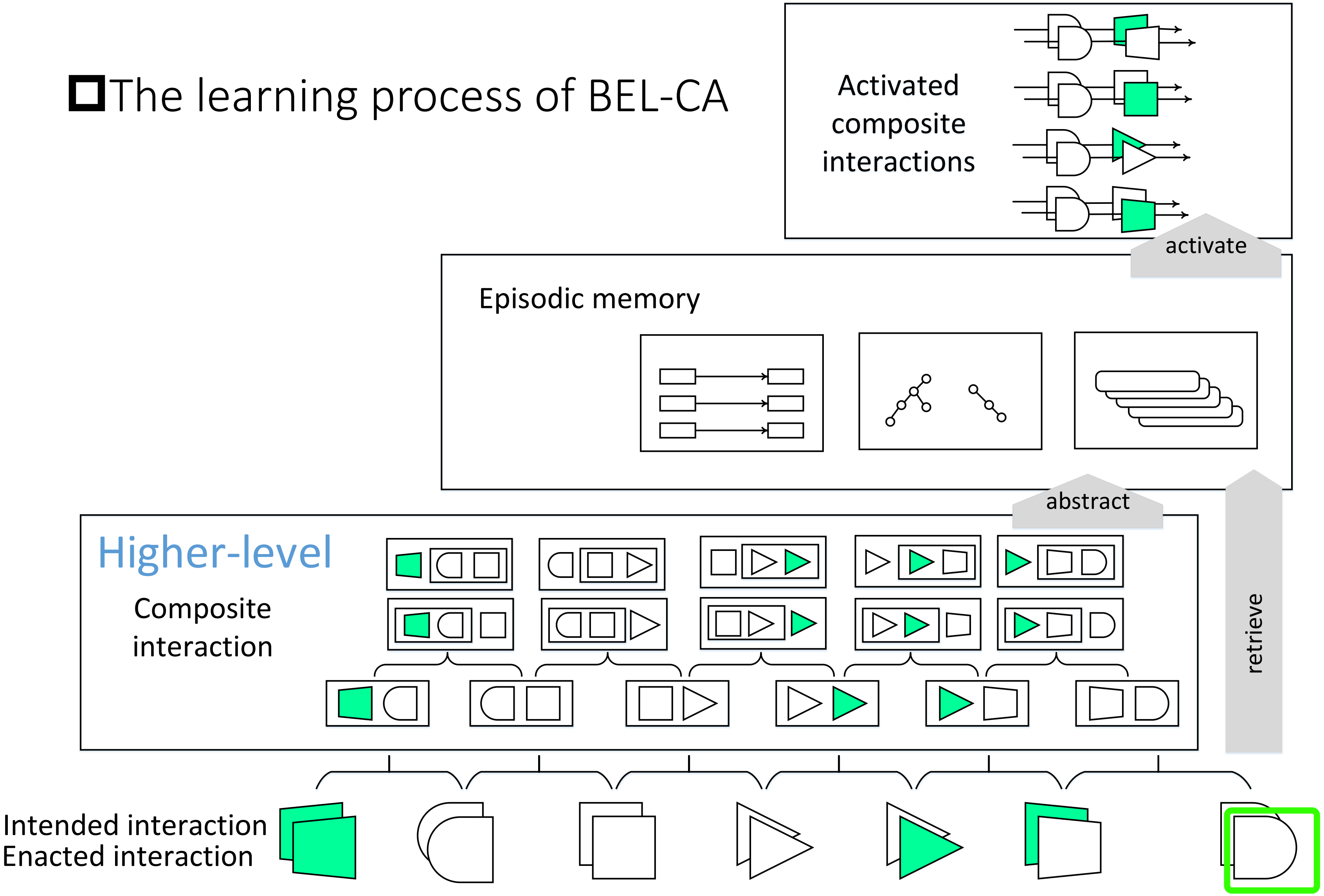

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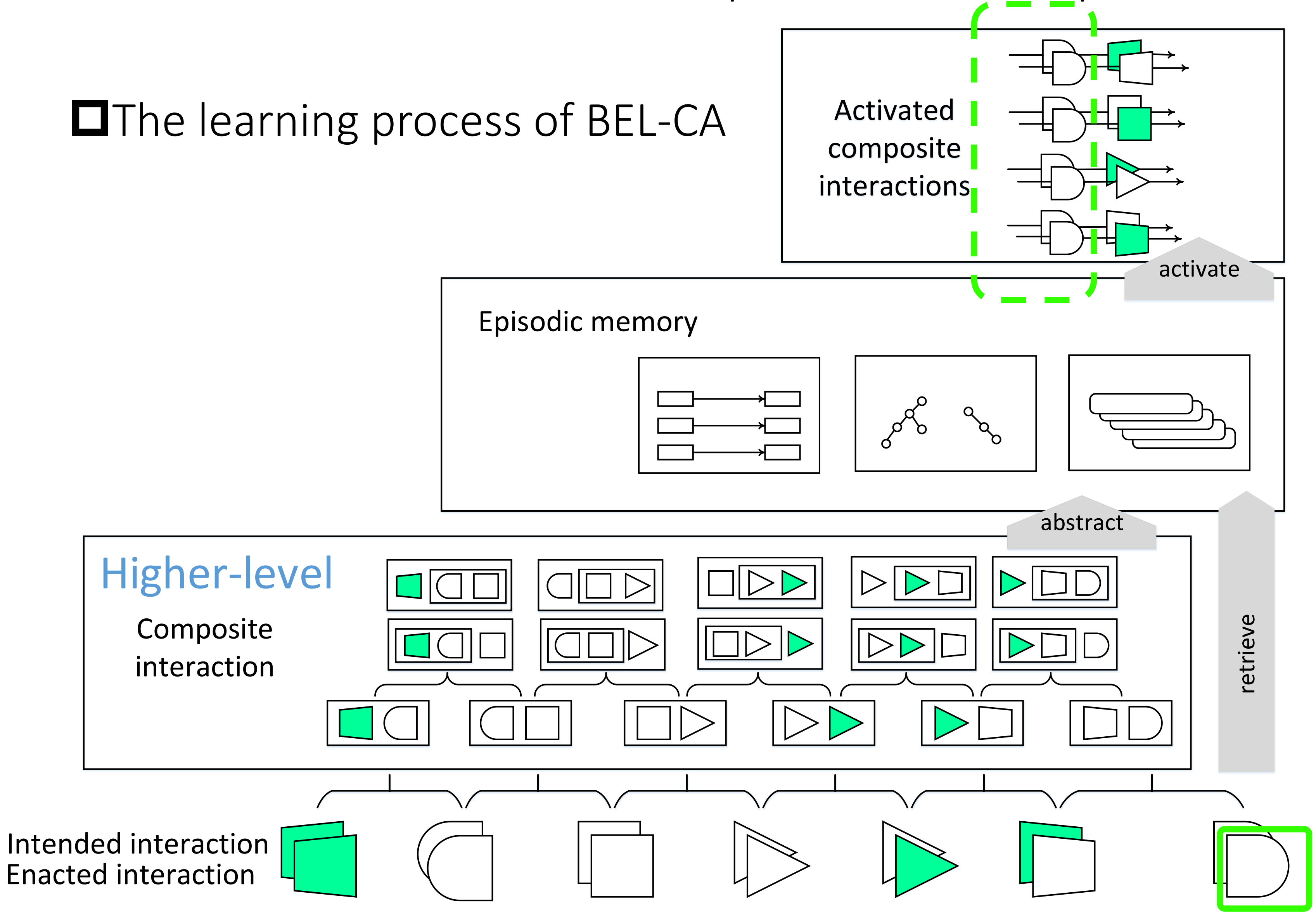

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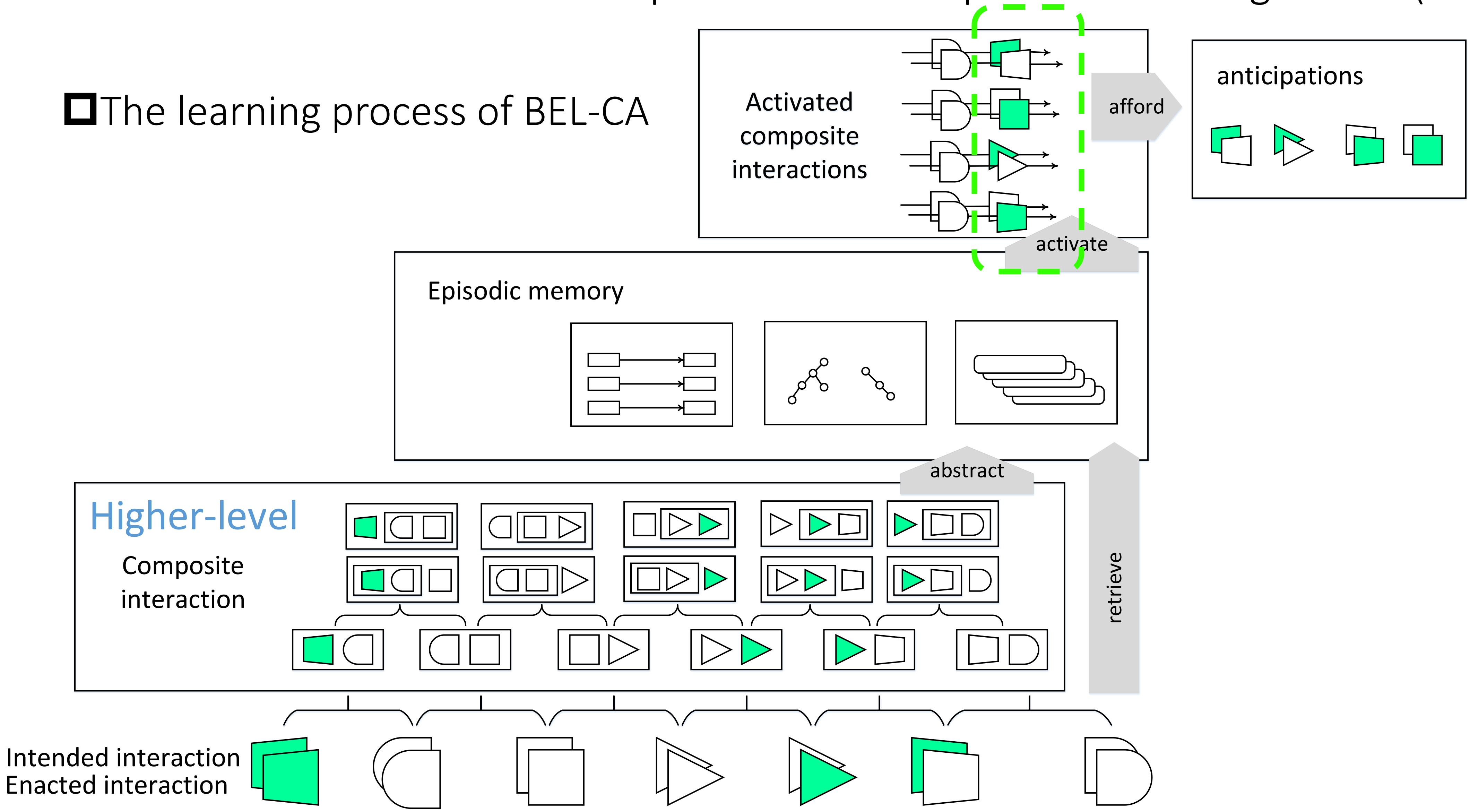

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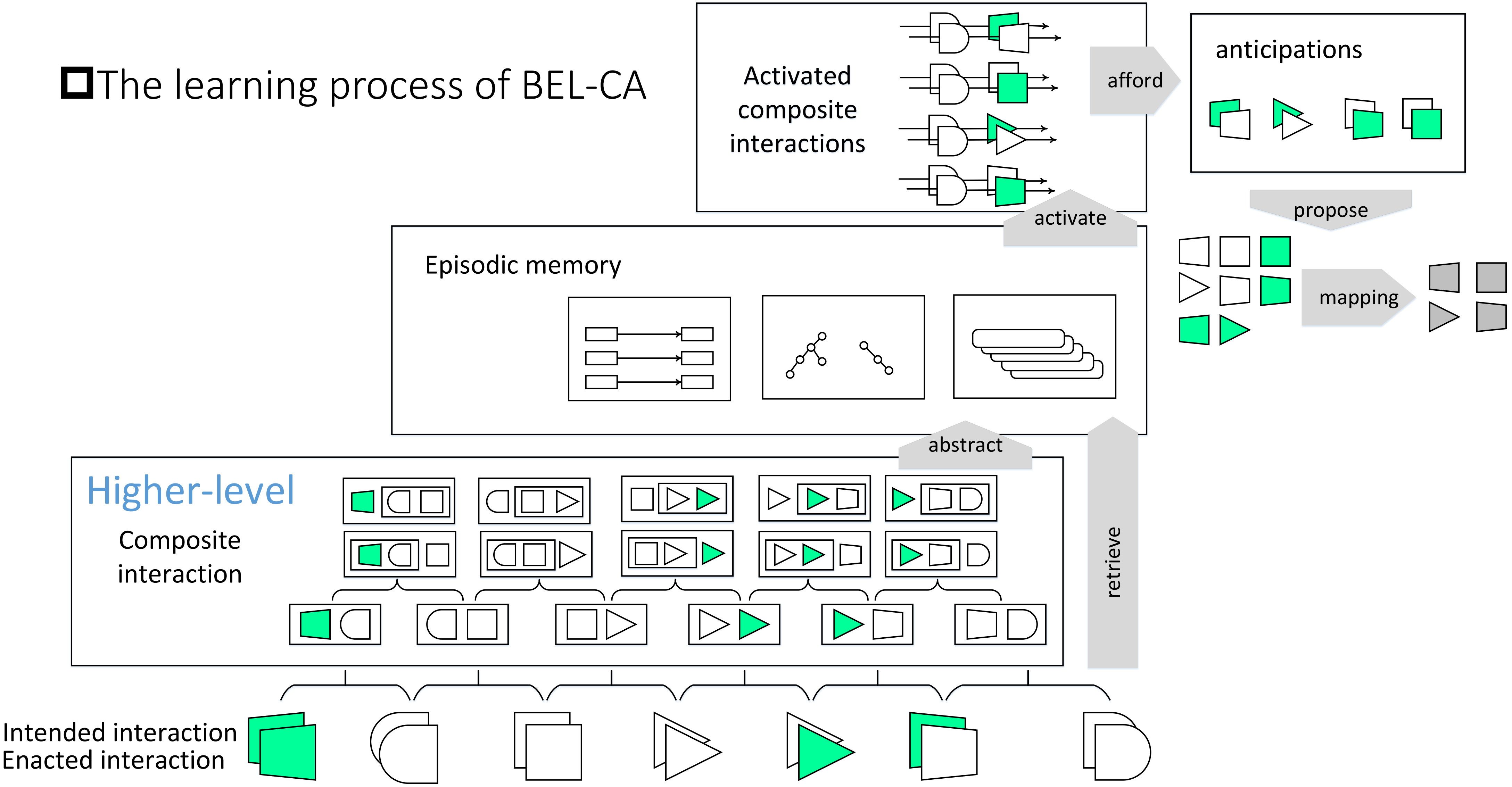

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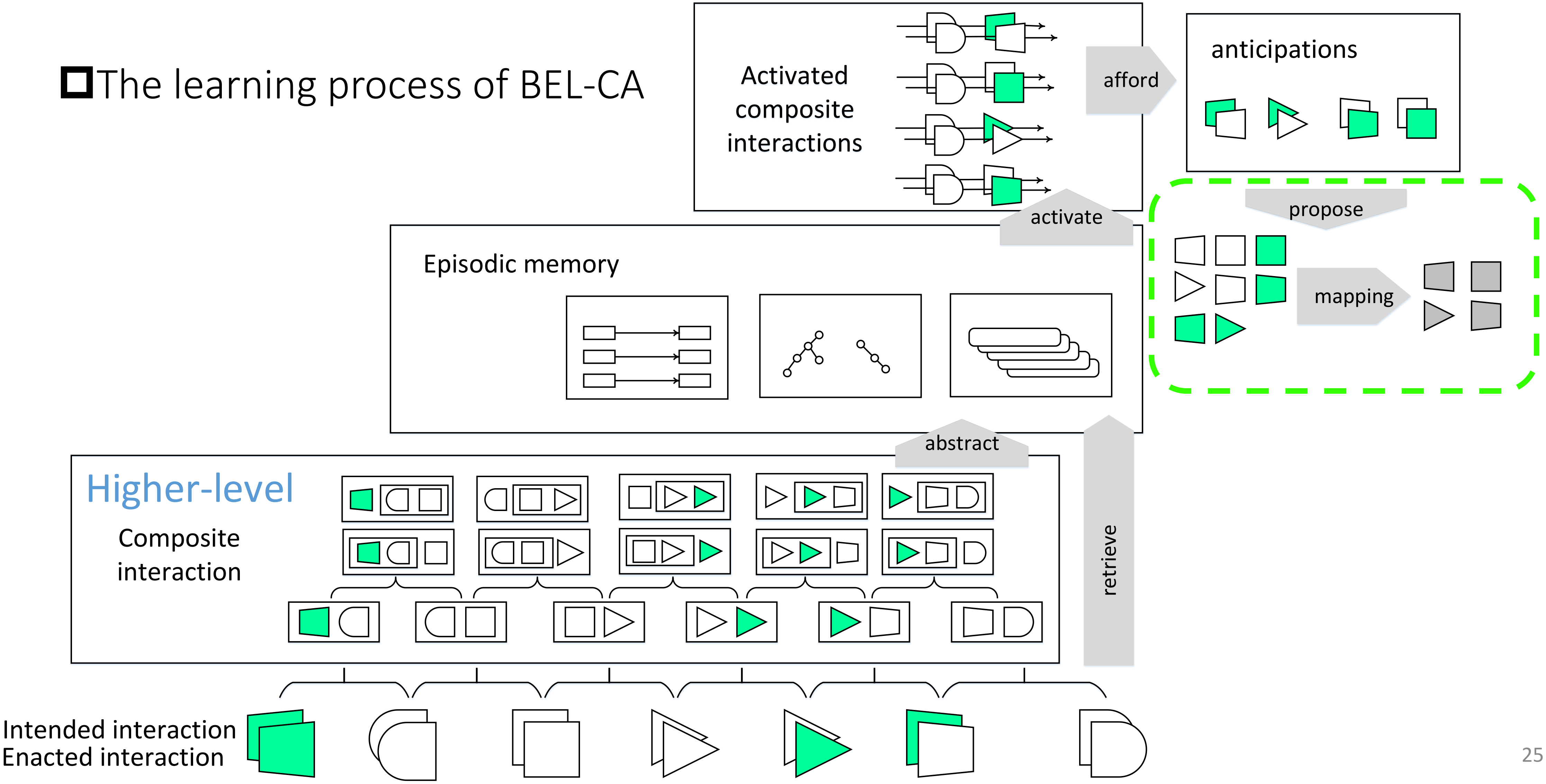

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The mapping from anticipations to innate experiments

Intended inte
Enacted interaction

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Current enacted interaction is:

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Enacted interaction

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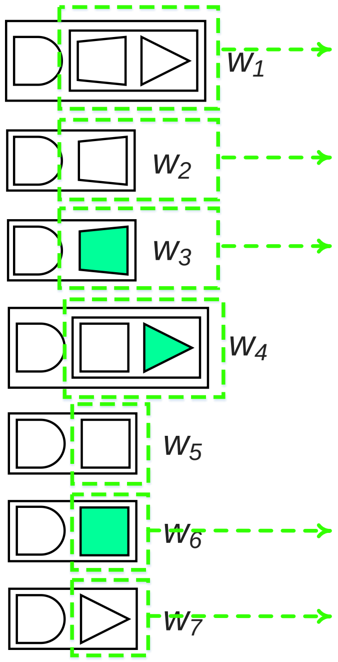

Activated interactions

Current enacted interaction is:

Intended inte...

Enacted interaction

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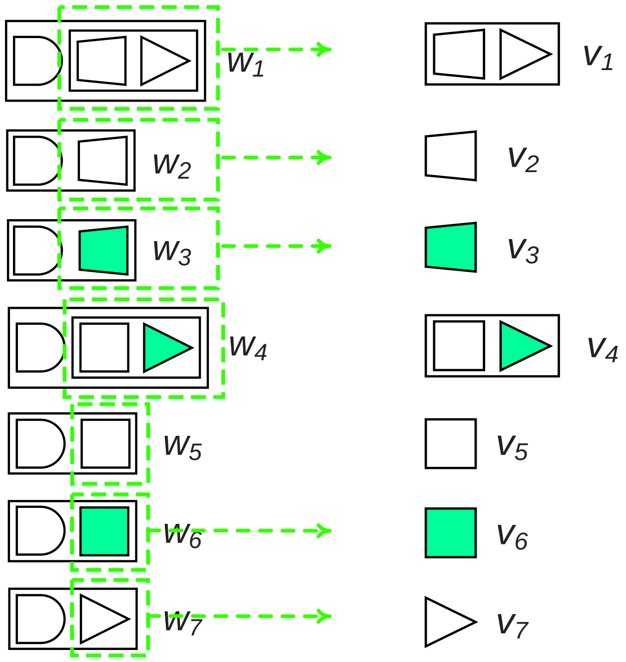
The mapping from anticipations to innate experiments



Activated interactions
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Anticipations from post-interactions

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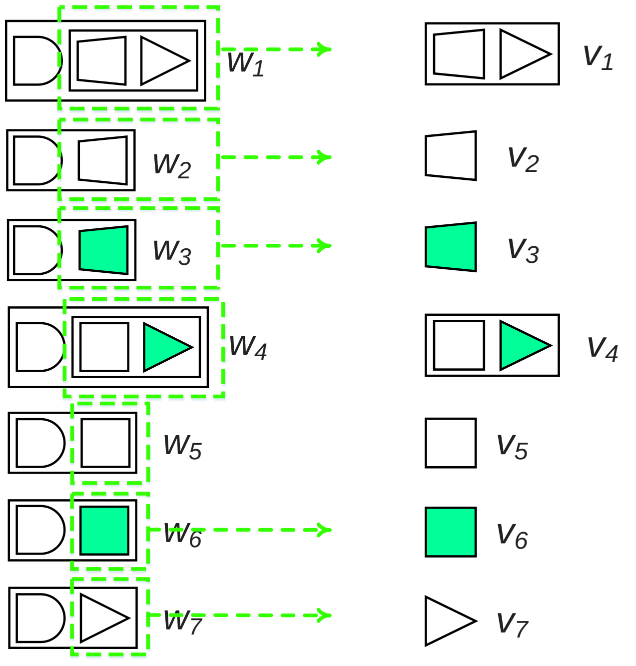

$p_1 = w_1 \times v_1$

$p_2 = w_2 \times v_2$

$p_3 = w_3 \times v_3$

$p_4 = w_4 \times v_4$

$p_5 = w_5 \times v_5$

$p_6 = w_6 \times v_6$

$p_7 = w_7 \times v_7$

Activated interactions
Current enacted interaction is:

Anticipations from post-interactions

Proclivities calculation

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Intended inte...
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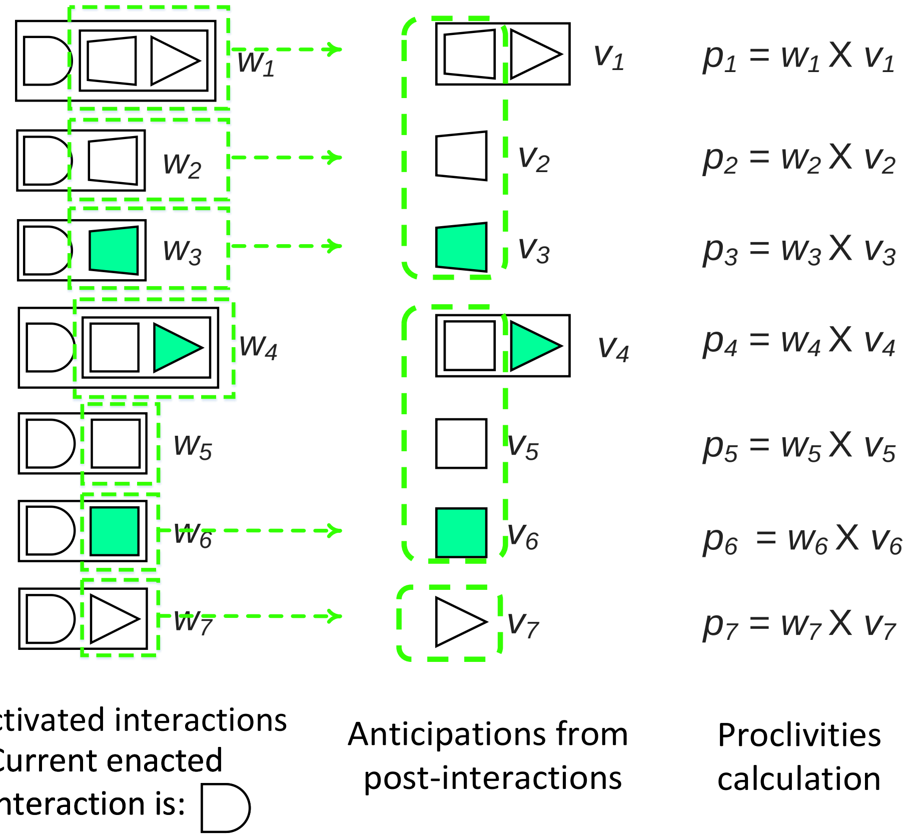

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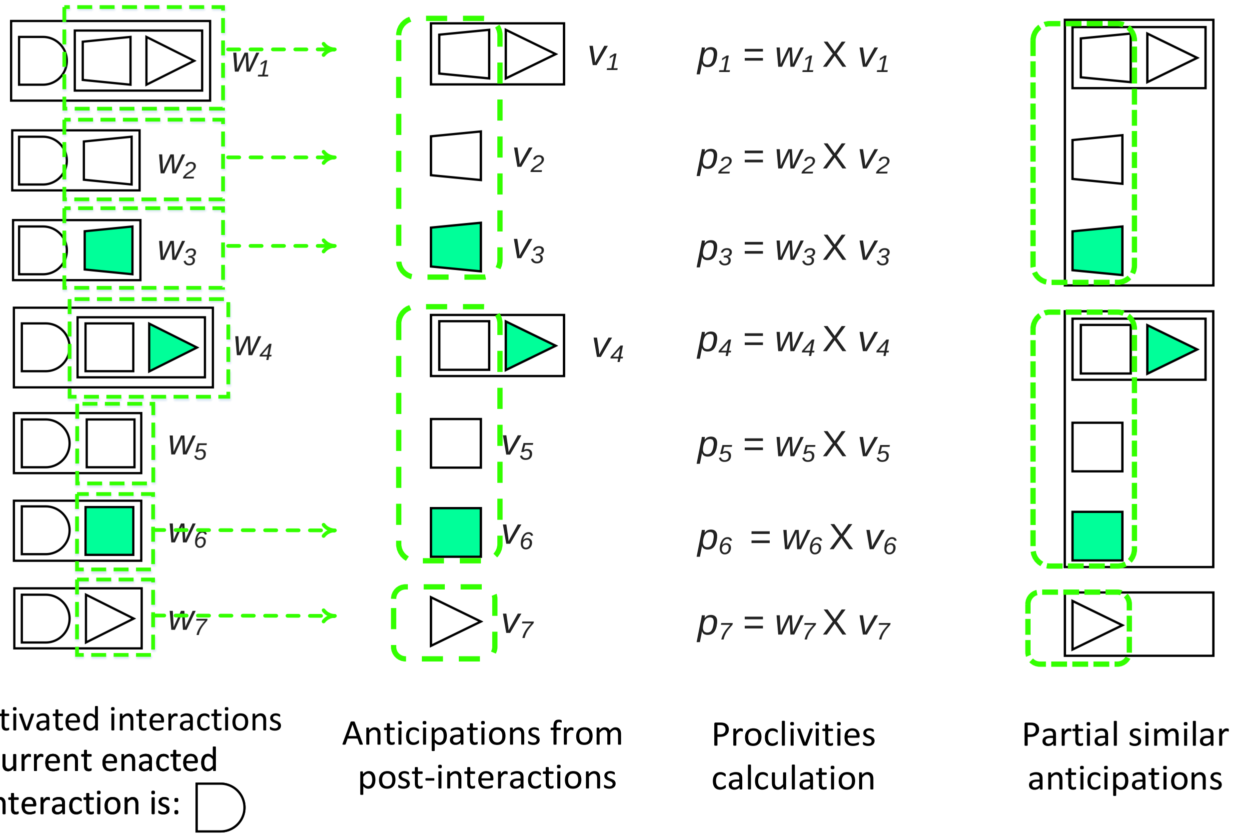

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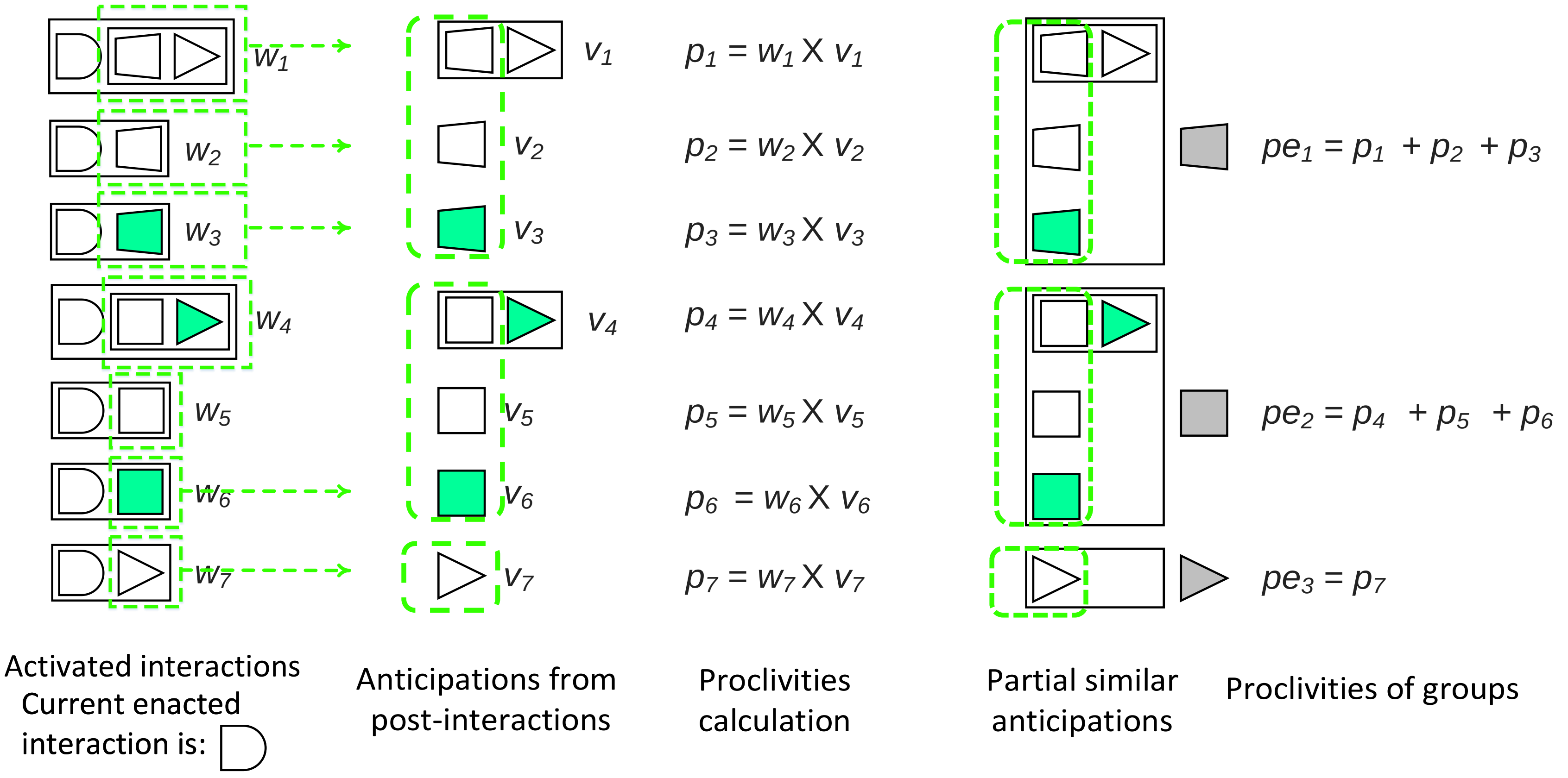

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Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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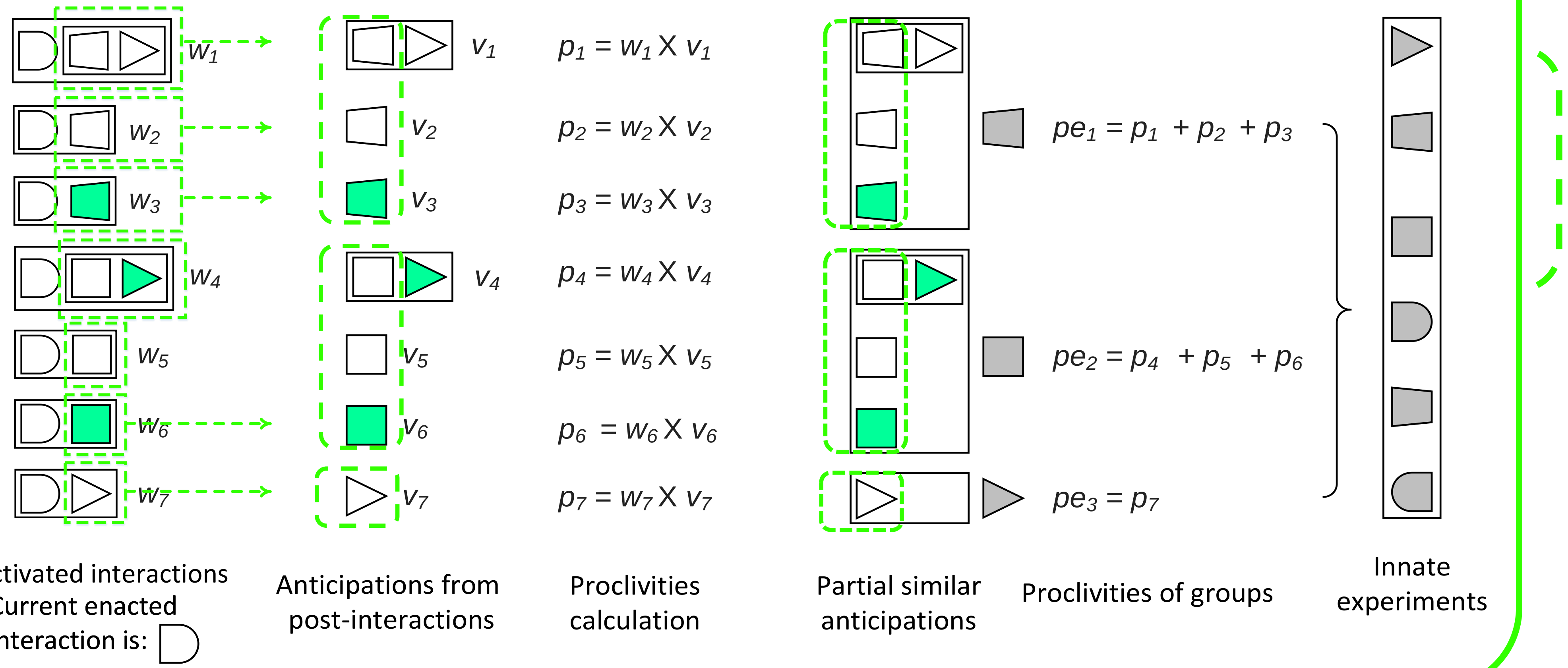
The mapping from anticipations to innate experiments

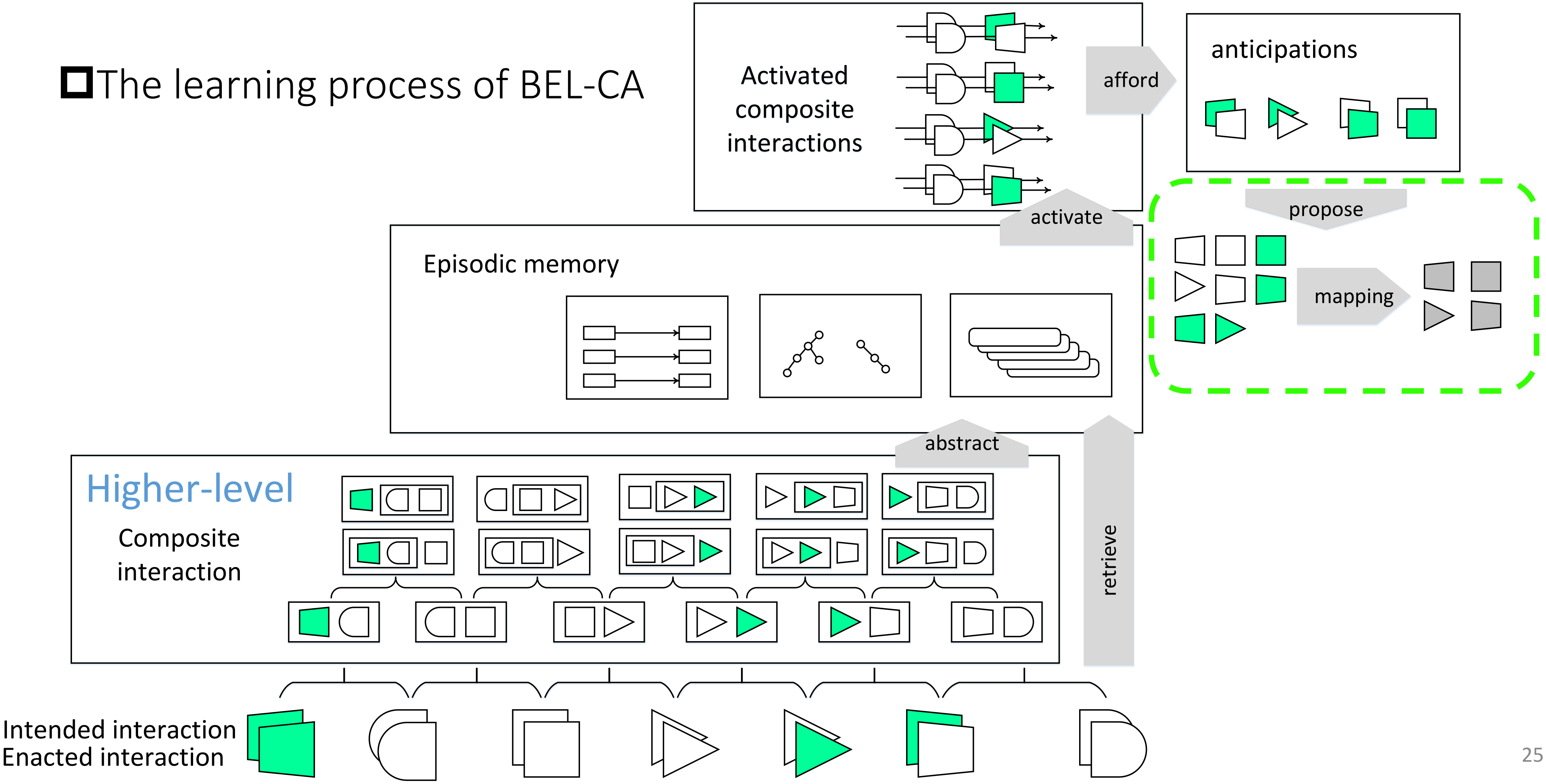


Intended inte

Enacted interaction

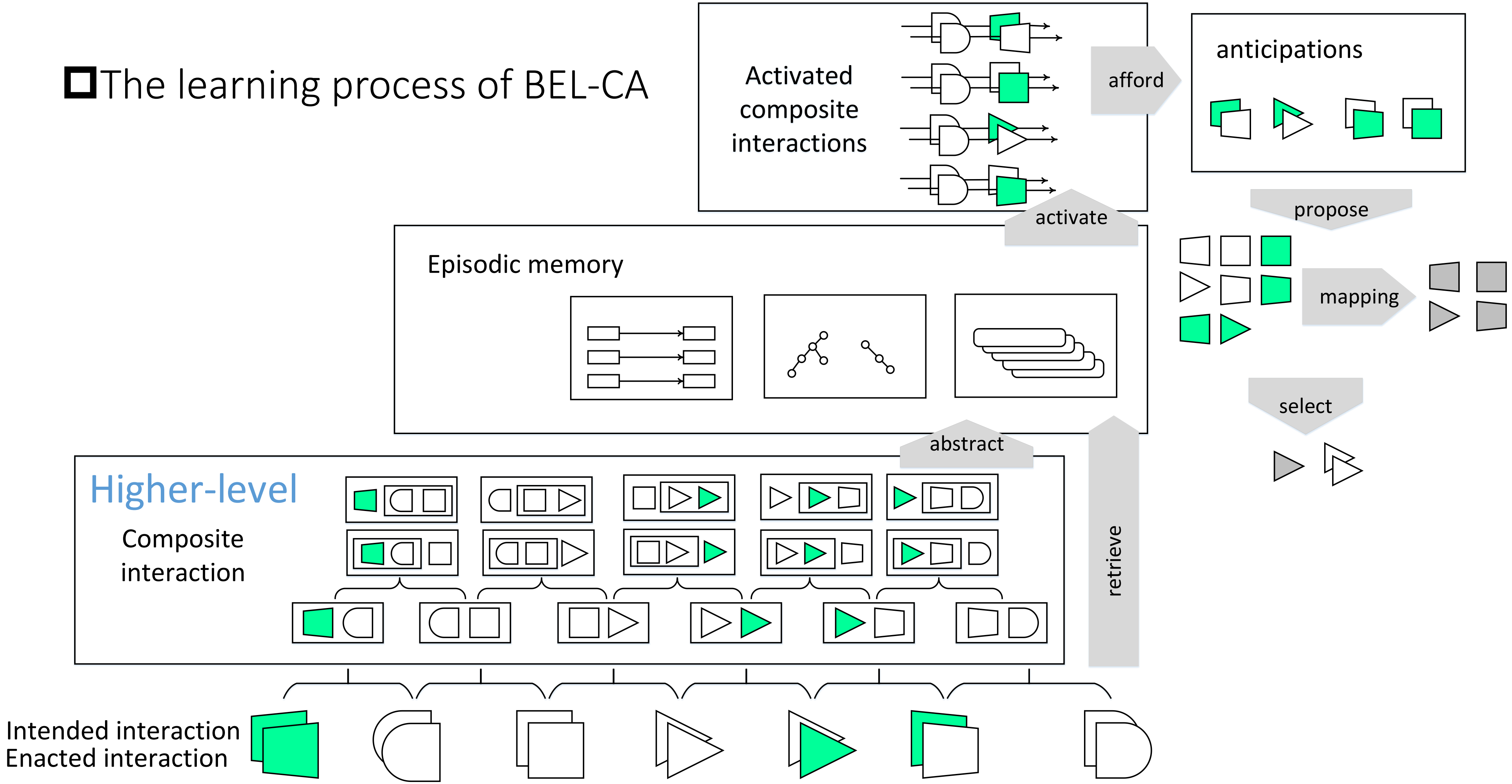
Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

- The learning process of BEL-CA



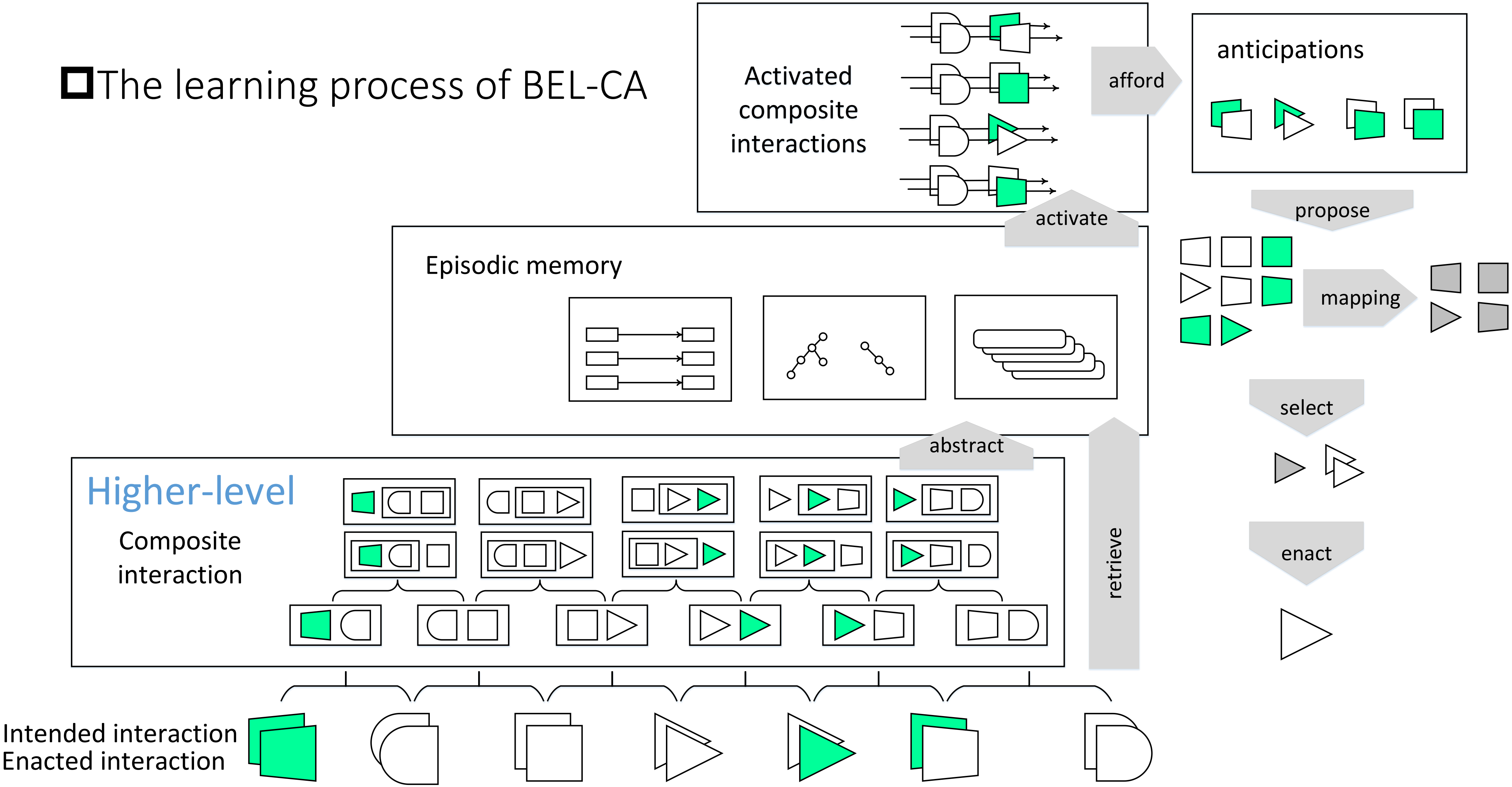
Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

- The learning process of BEL-CA



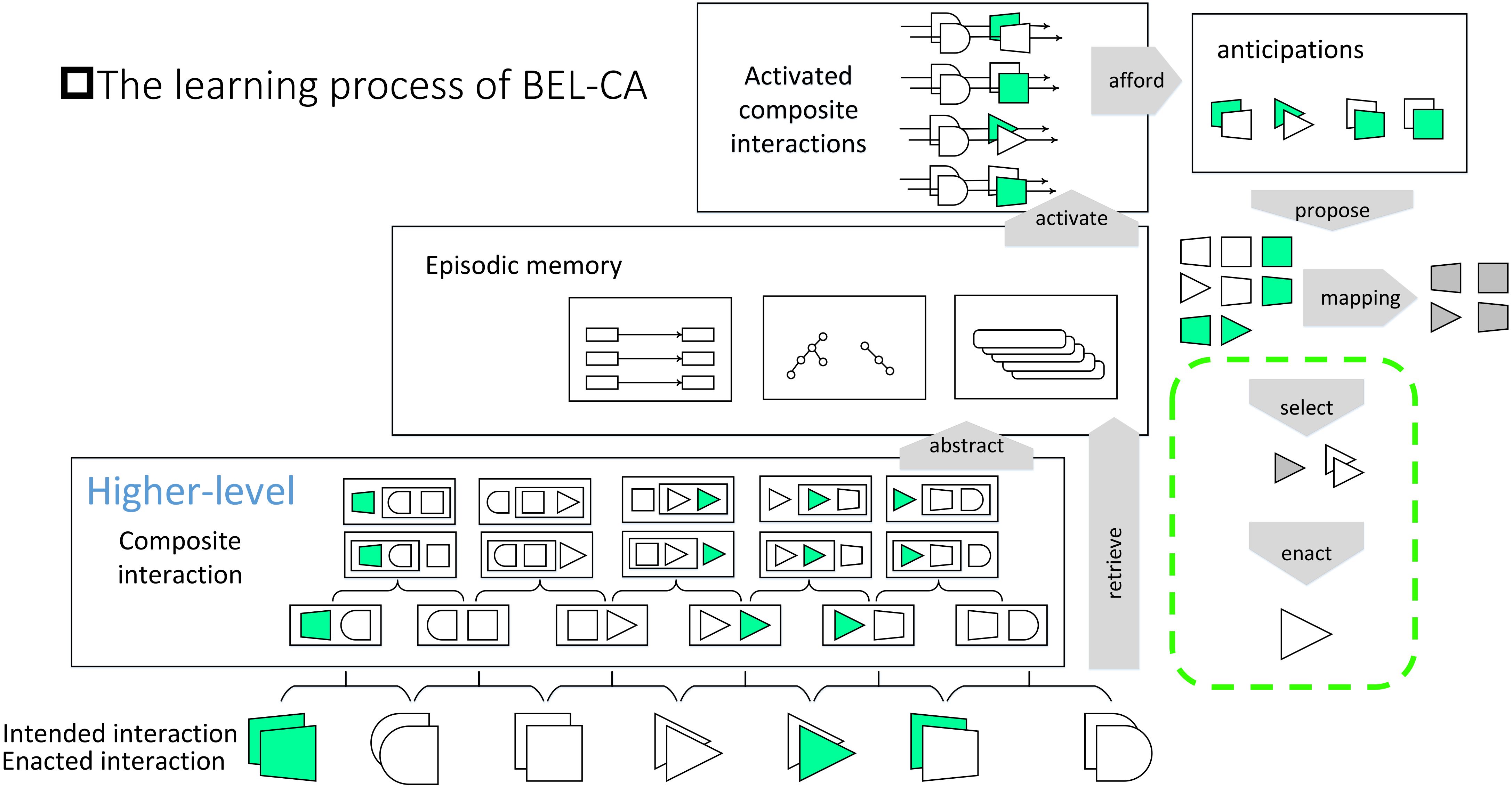
Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

- The learning process of BEL-CA



Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

- The learning process of BEL-CA



Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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The selection and enaction of intended interaction

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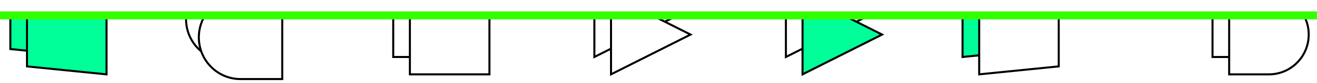
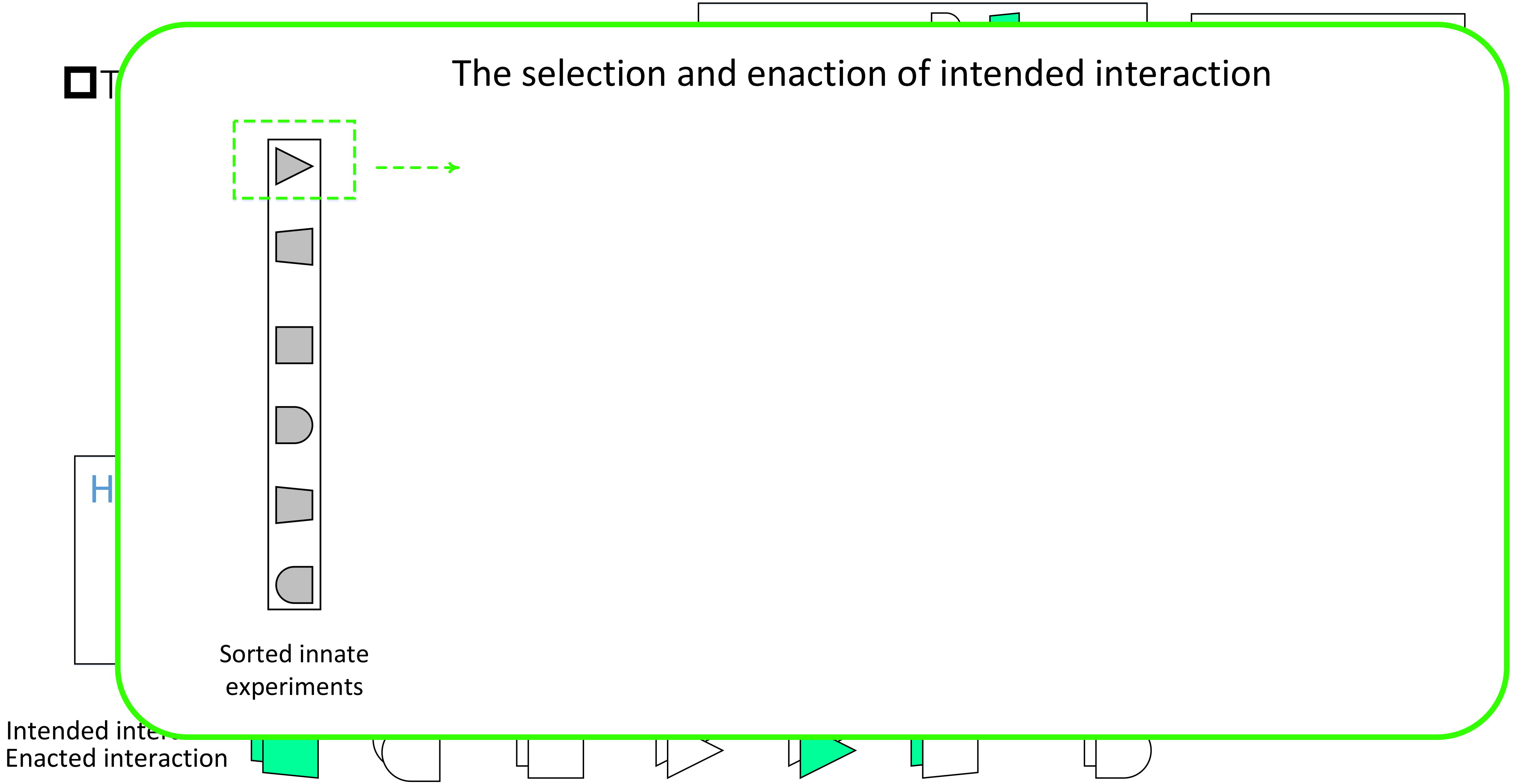
Intended inte
Enacted interaction



Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)



Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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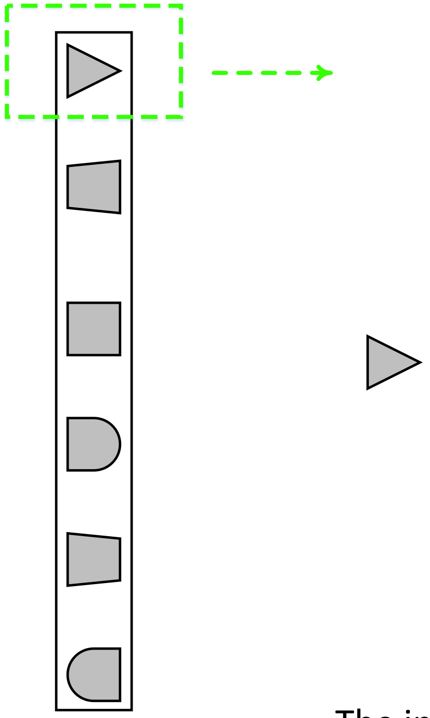

Sorted innate experiments

The innate experiment with the biggest proclivity

Intended inte

Enacted interaction

Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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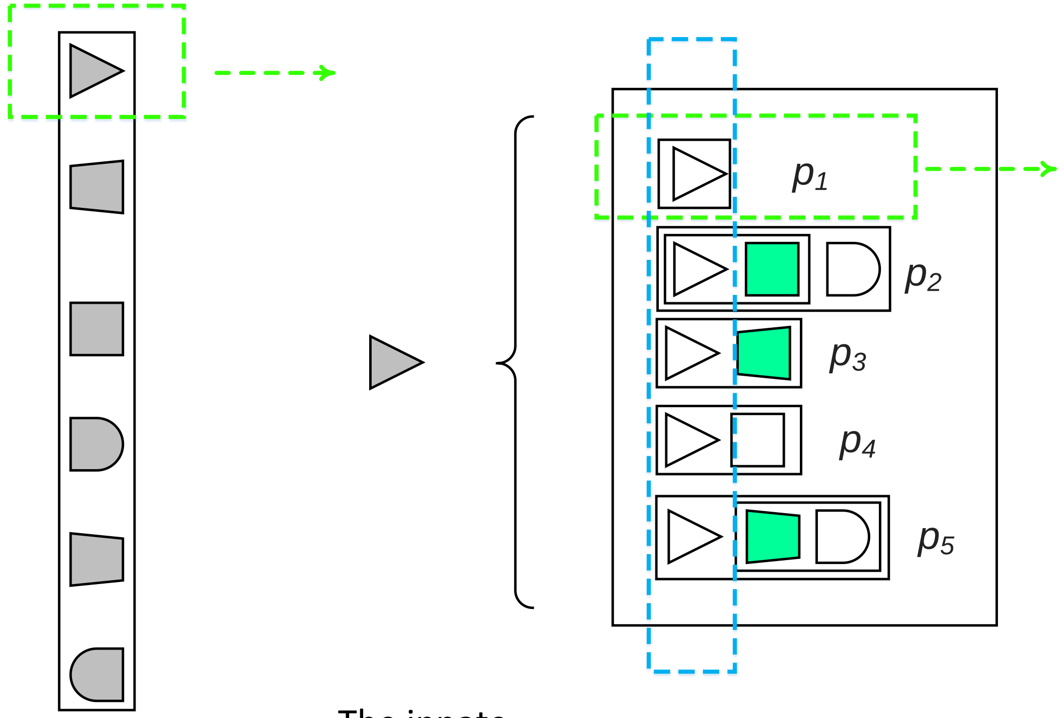
The selection and enaction of intended interaction



Intended inte
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Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

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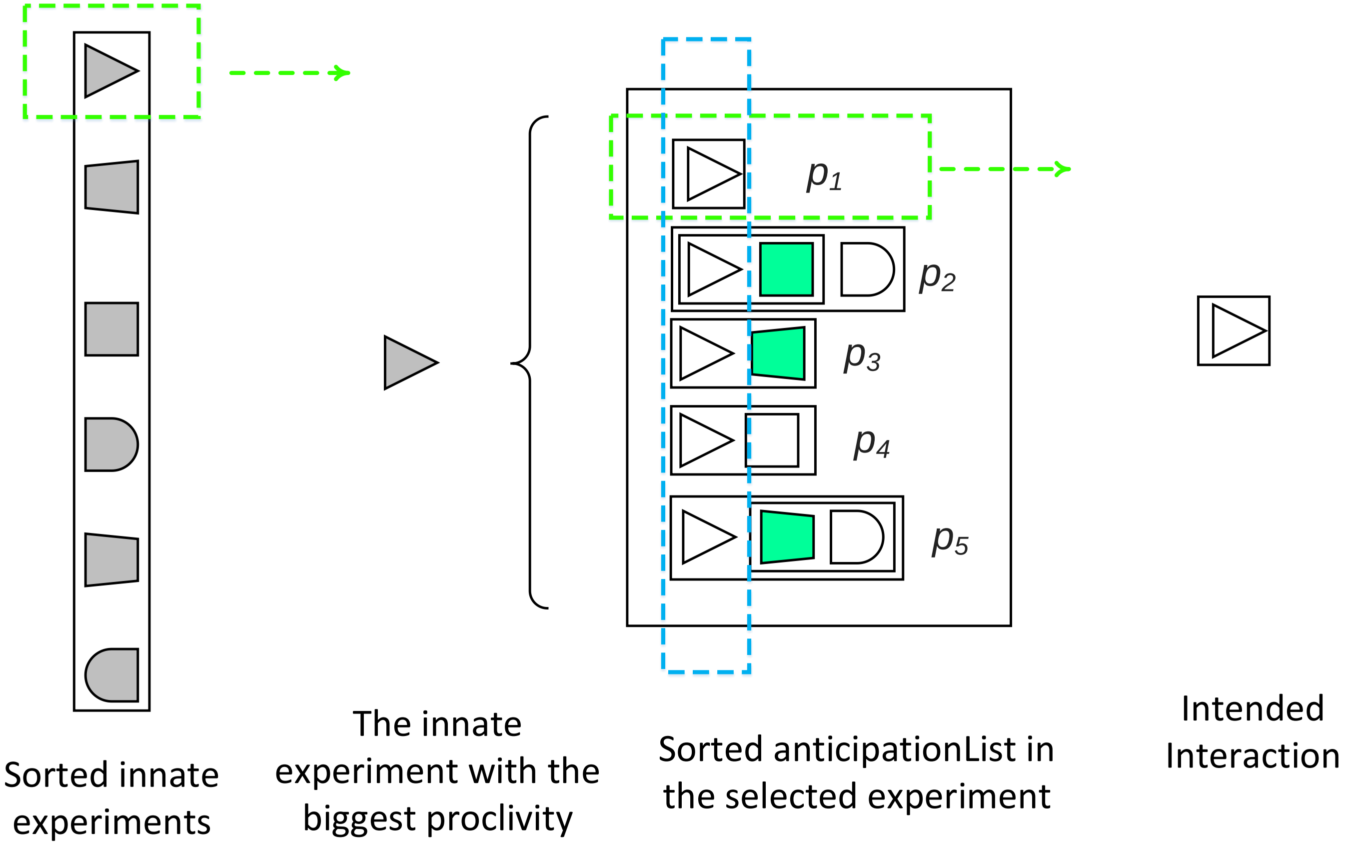
The selection and enaction of intended interaction



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Intended inte

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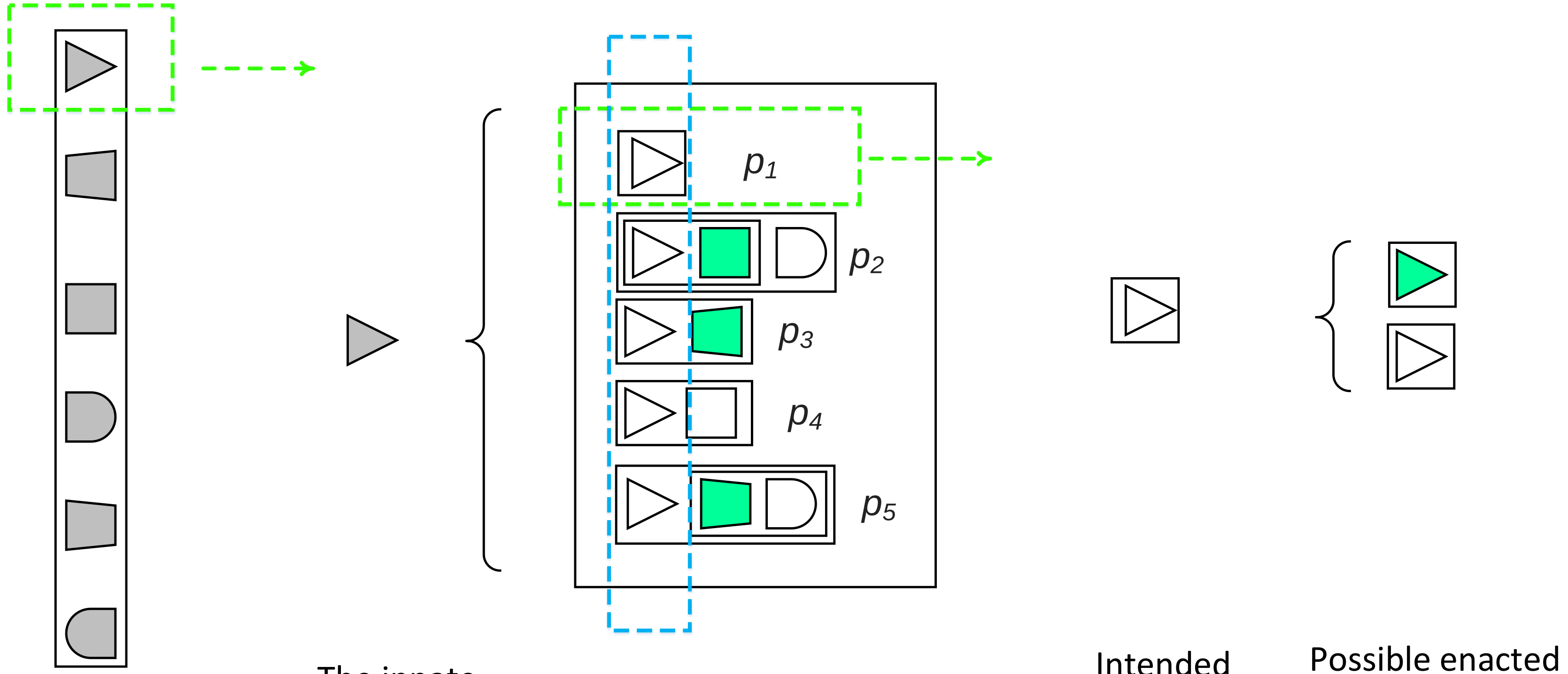
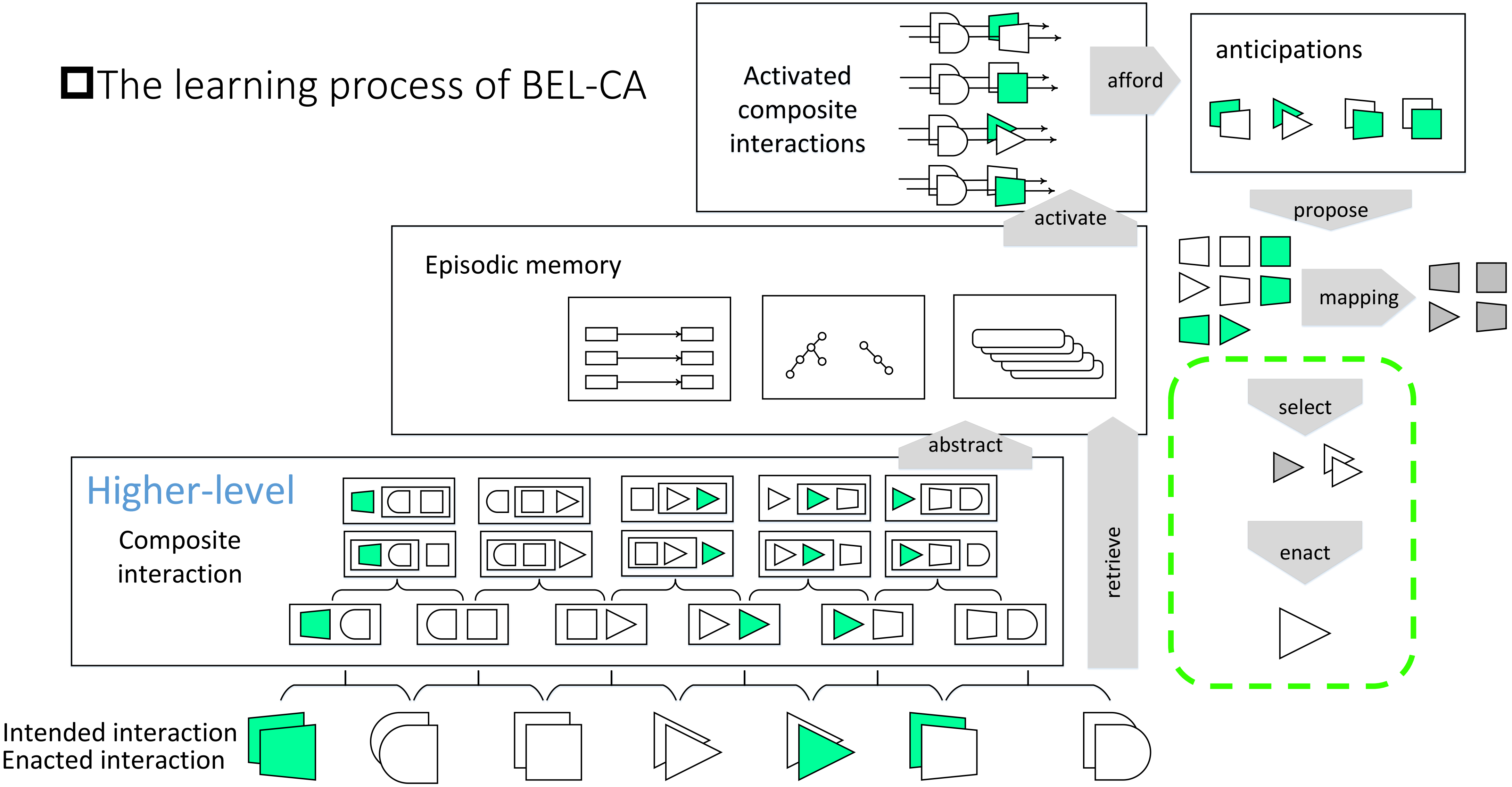


Intended inte
Enacted interaction

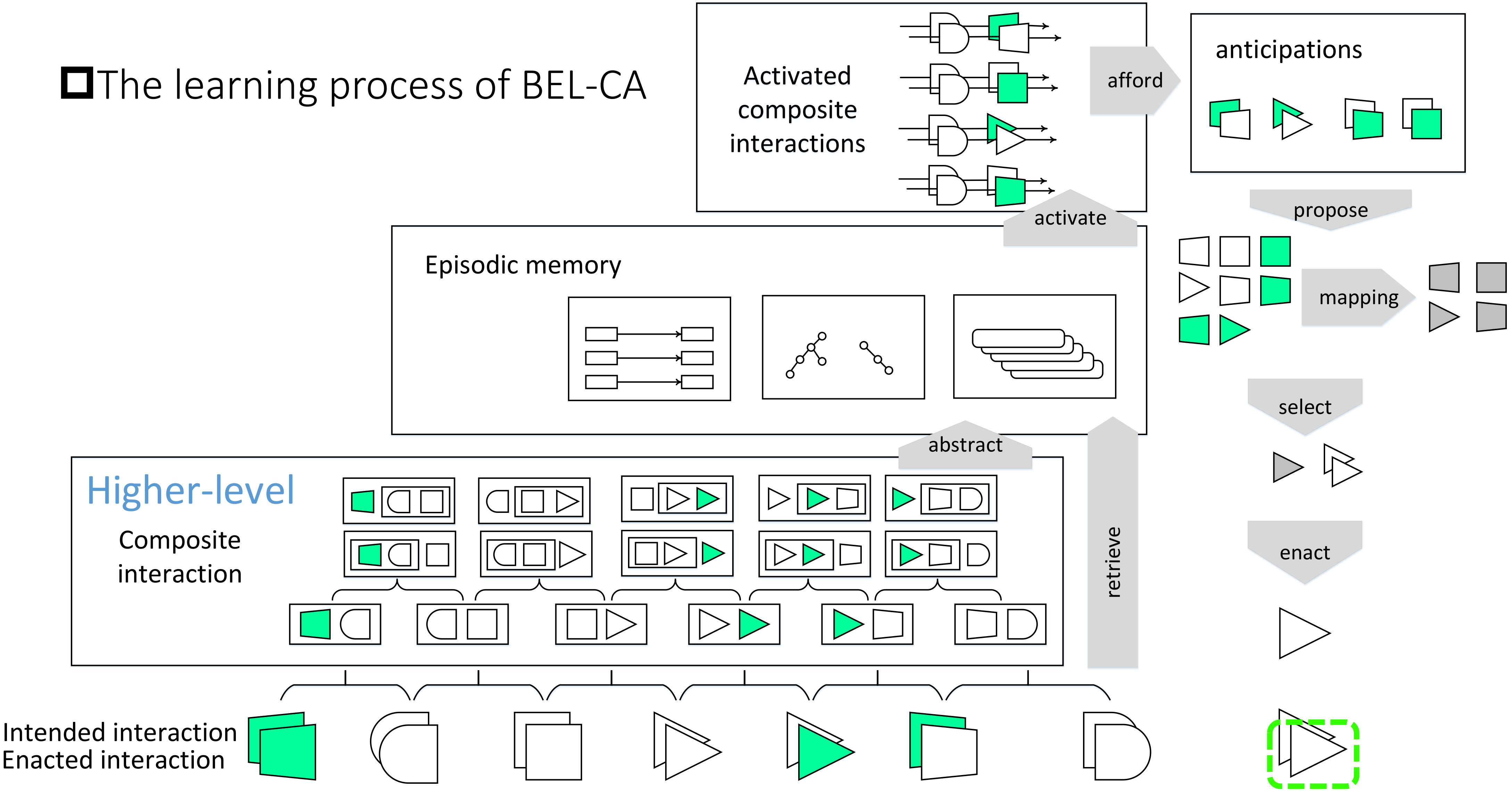
Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

- The learning process of BEL-CA



Contribution 3: Bottom-up hiErarchical sequential Learning in CCA (BEL-CA)

- The learning process of BEL-CA



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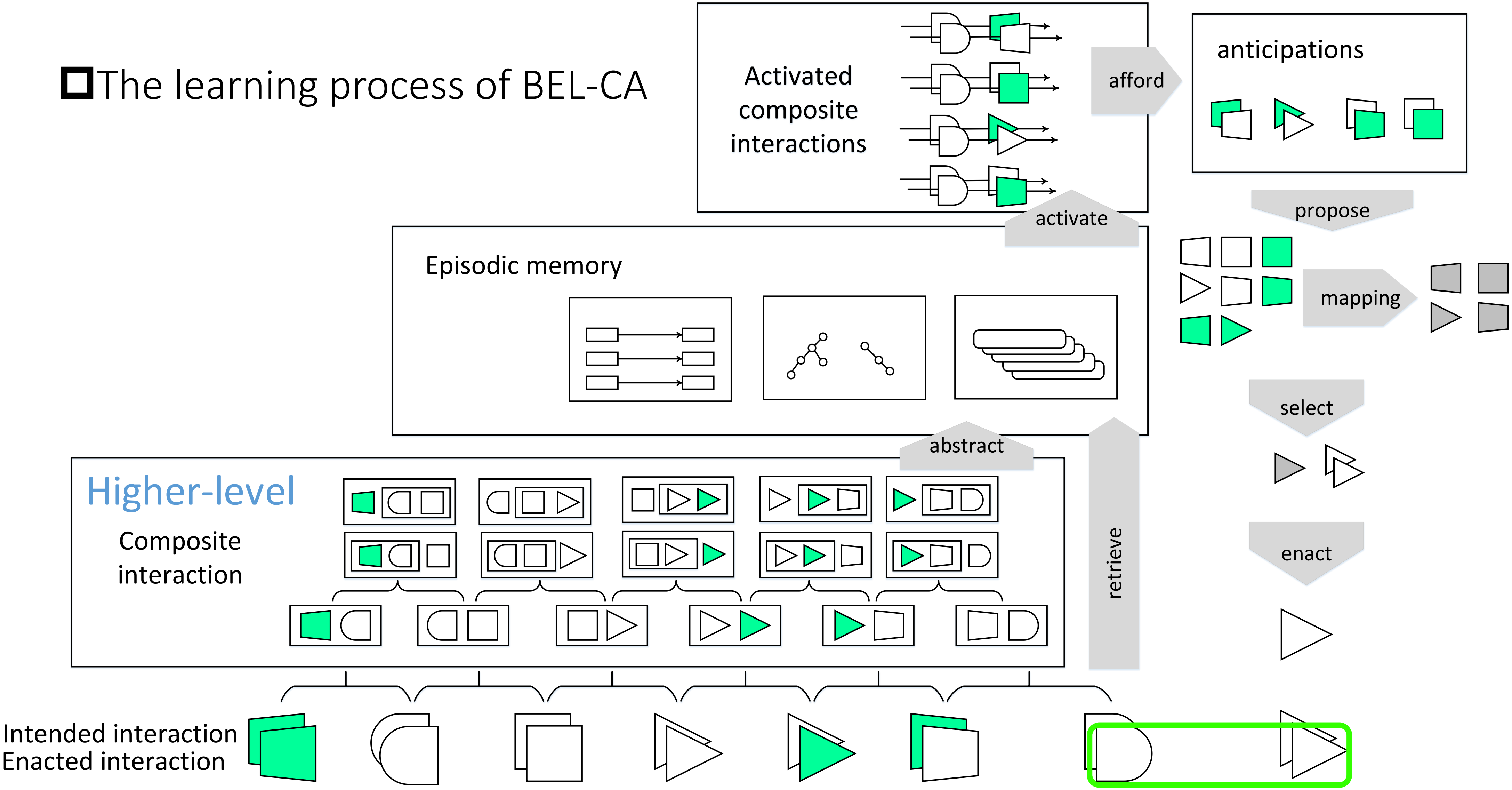

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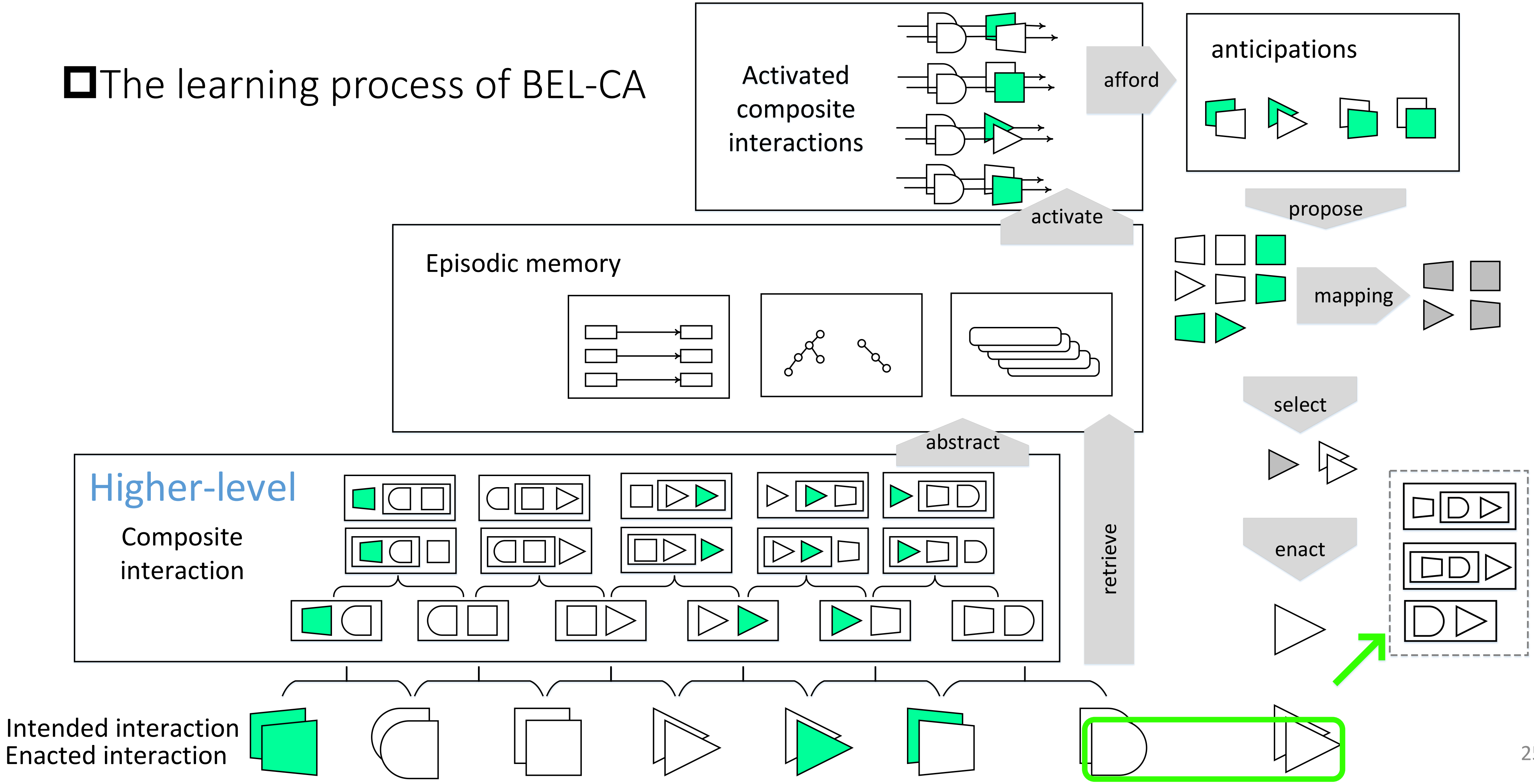

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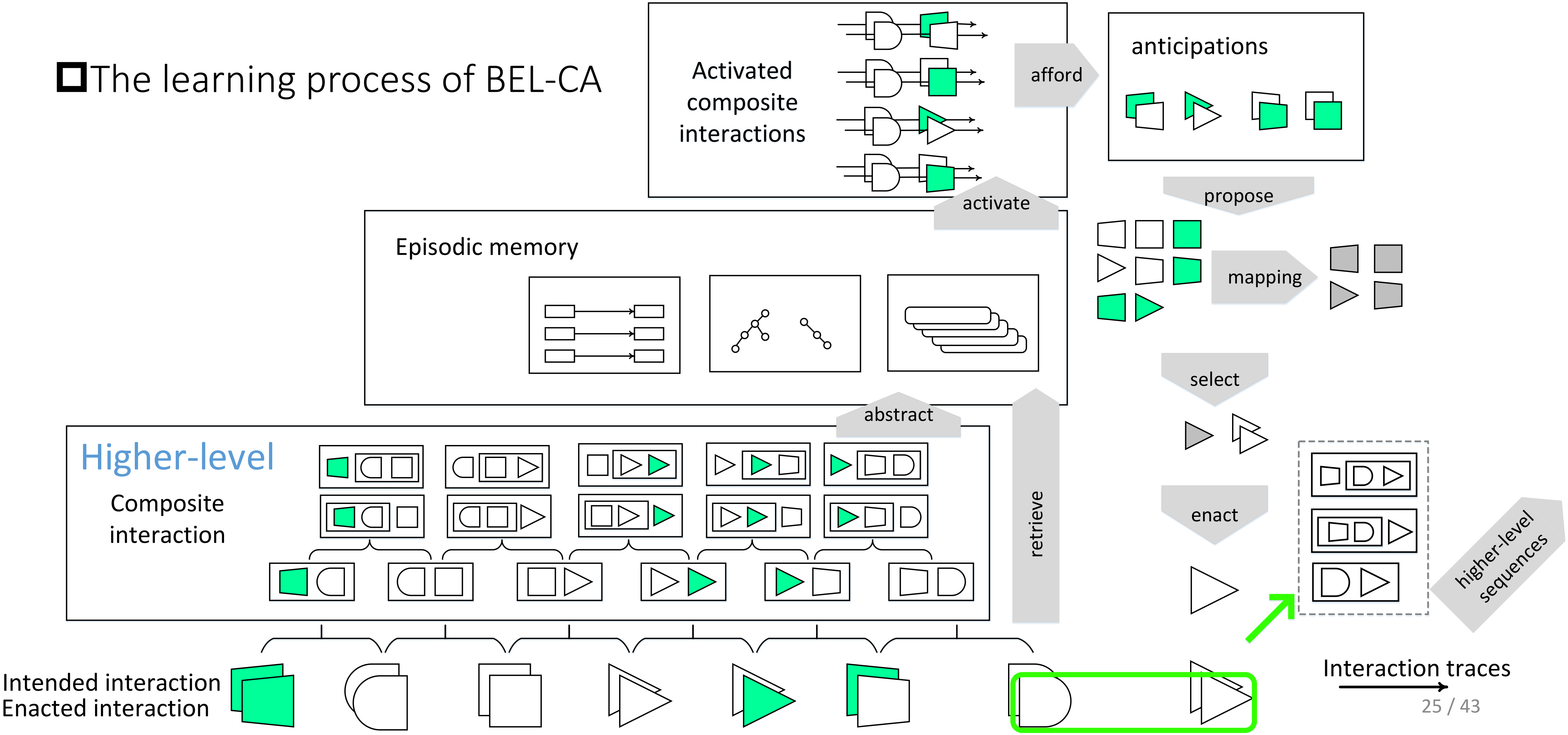
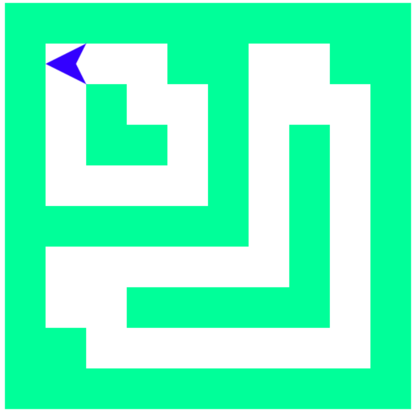
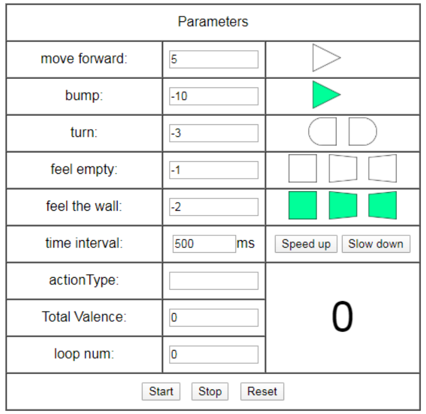
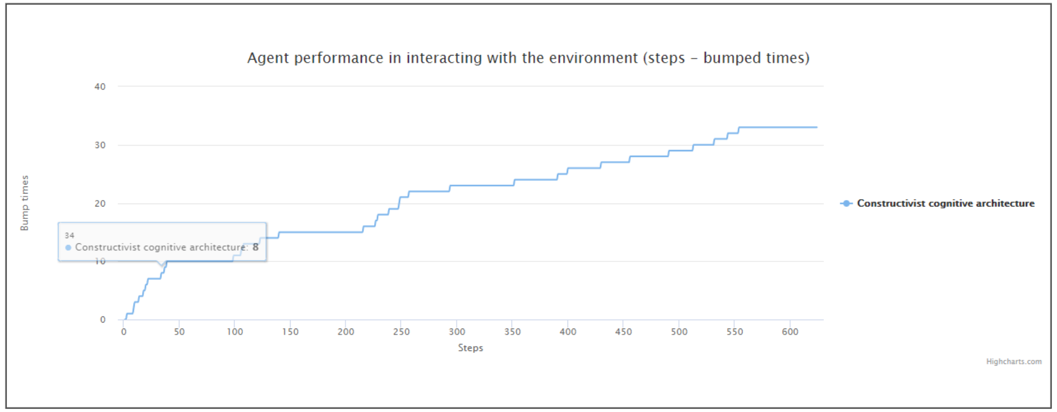


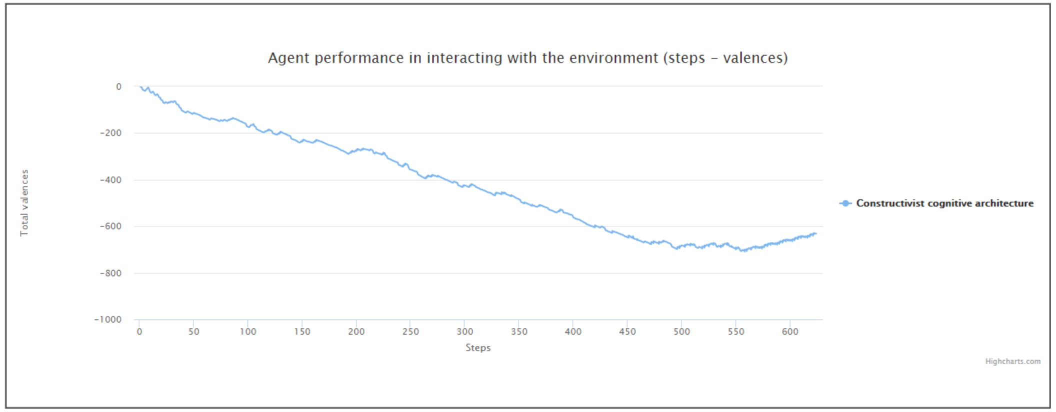
Contribution 4: Methodology and experimental scenario with GAIT

☐ Generating and Analyzing Interaction Traces toolkit (GAIT)



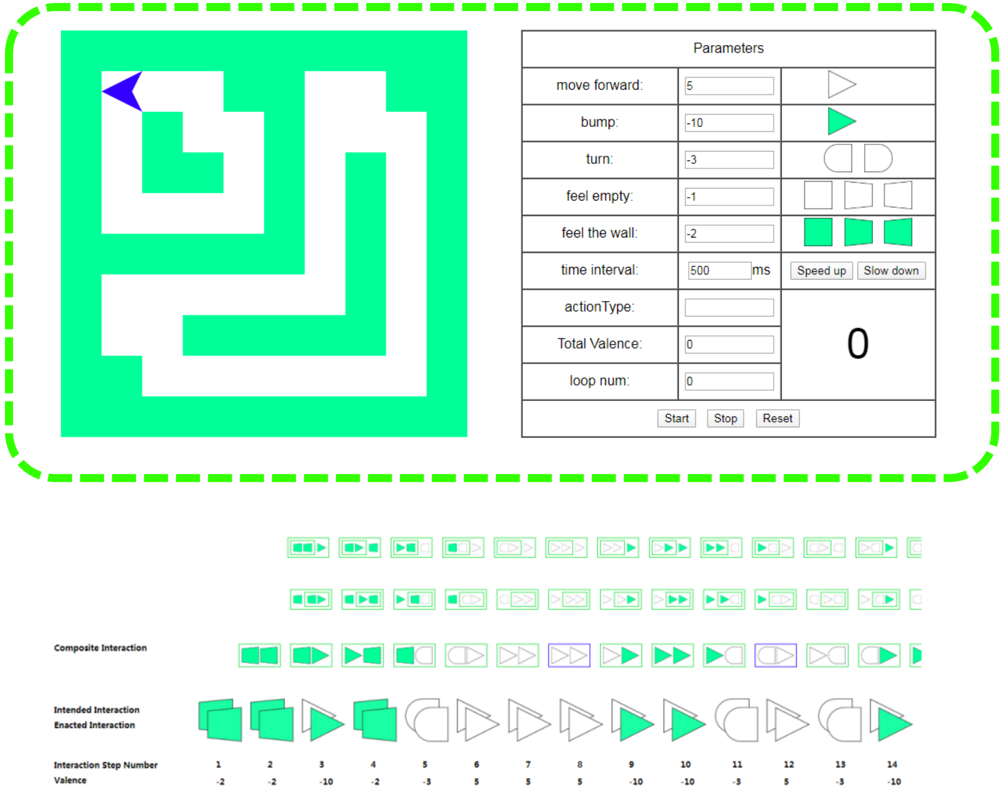


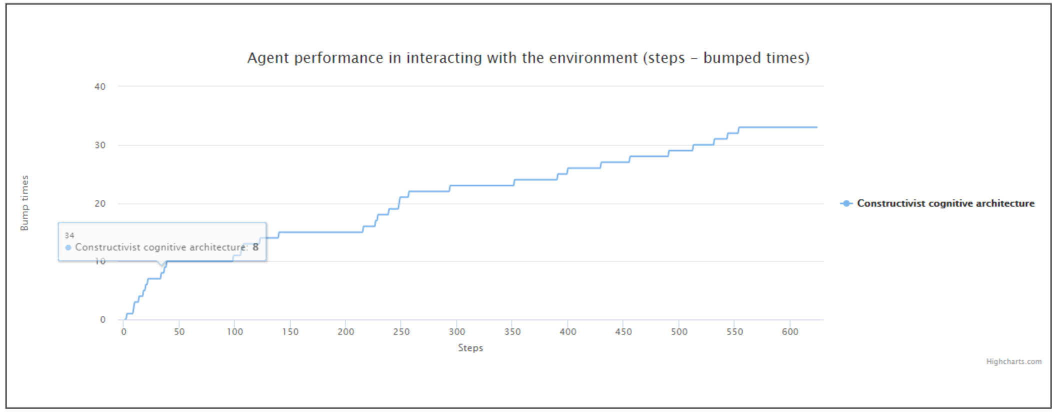


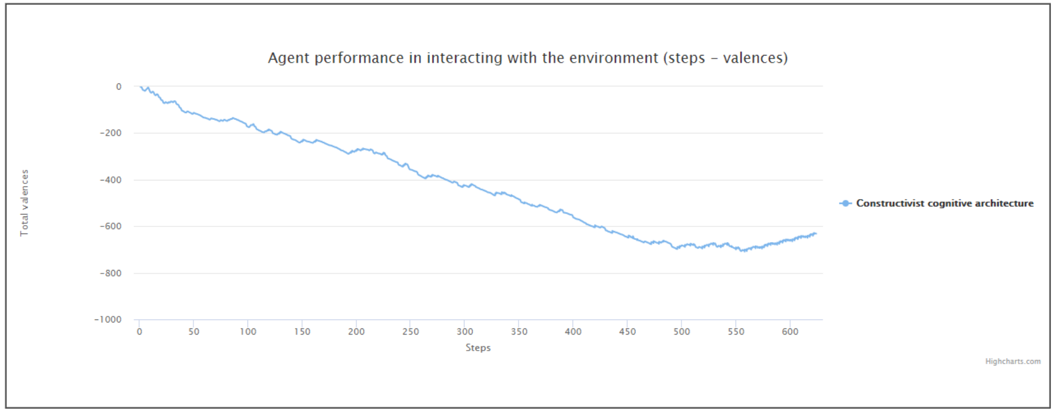


Contribution 4: Methodology and experimental scenario with GAIT

- Generating and Analyzing Interaction Traces toolkit (GAIT)







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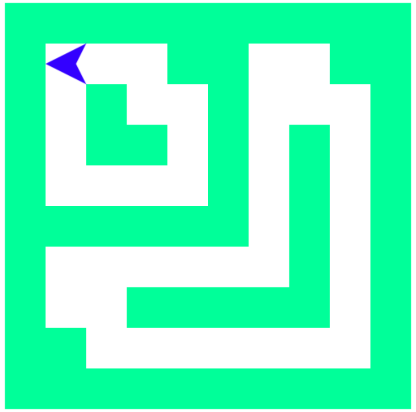
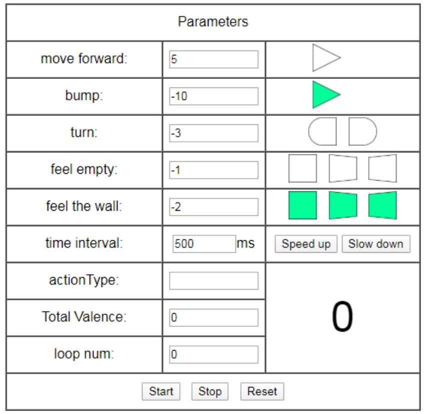
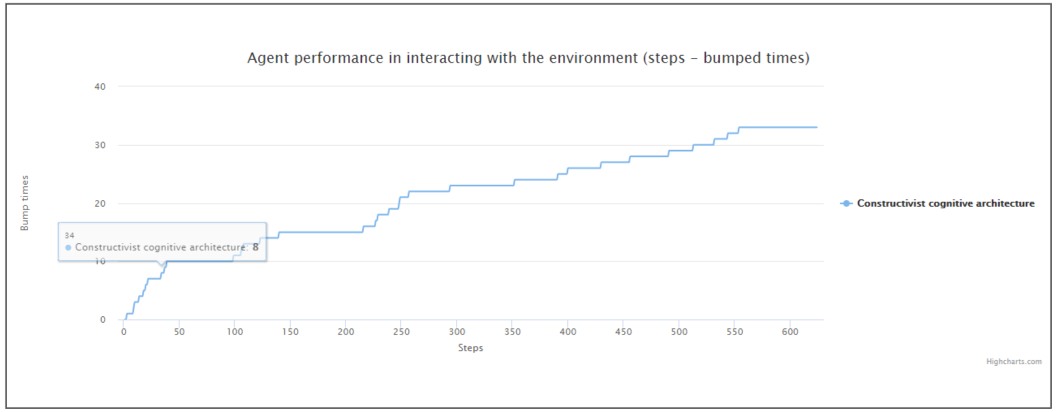
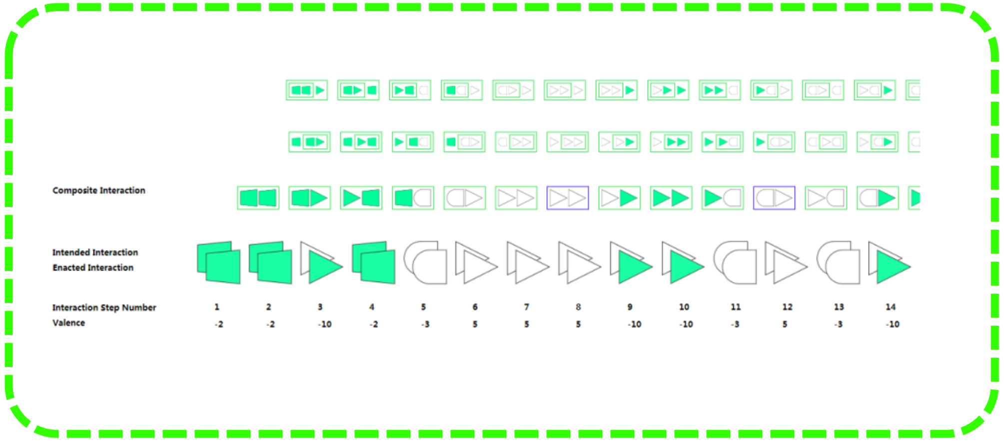
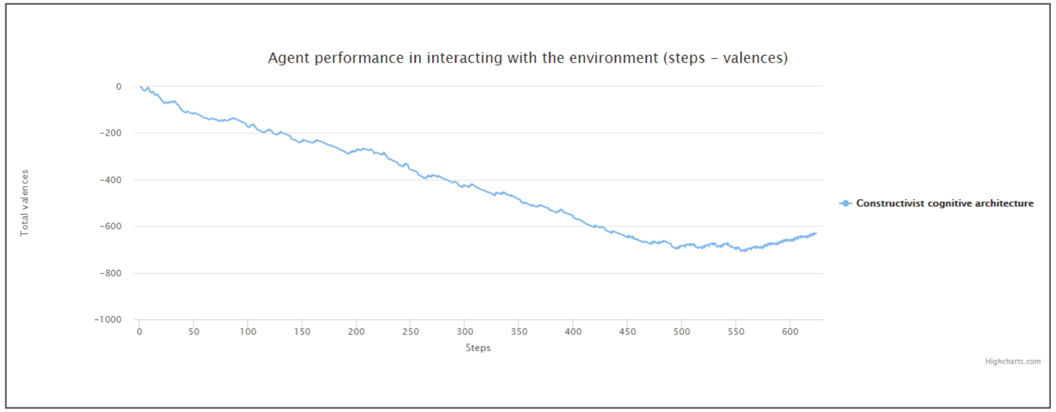




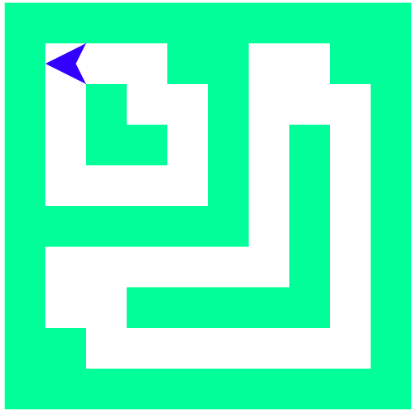


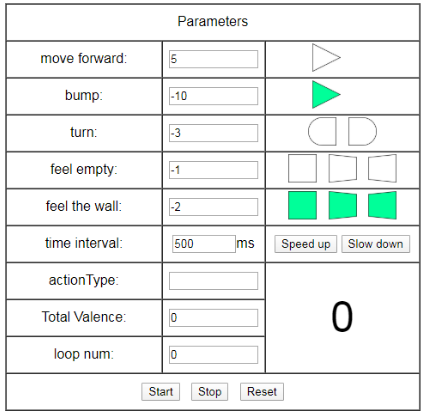


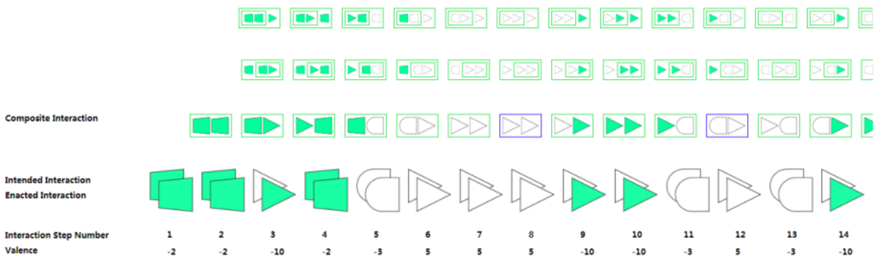


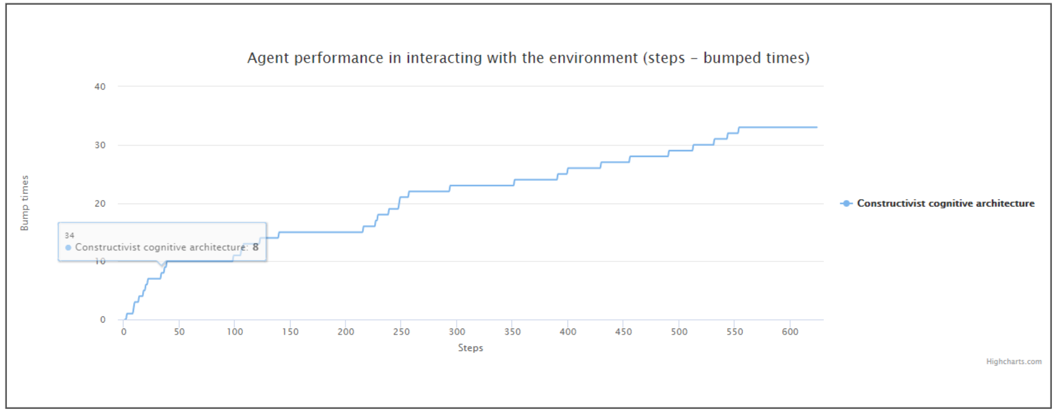
Contribution 4: Methodology and experimental scenario with GAIT

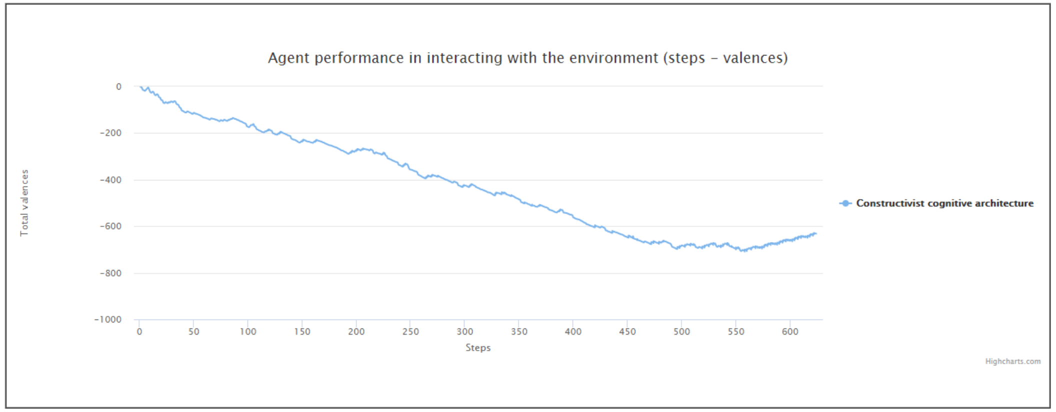
Generating and Analyzing Interaction Traces toolkit (GAIT)





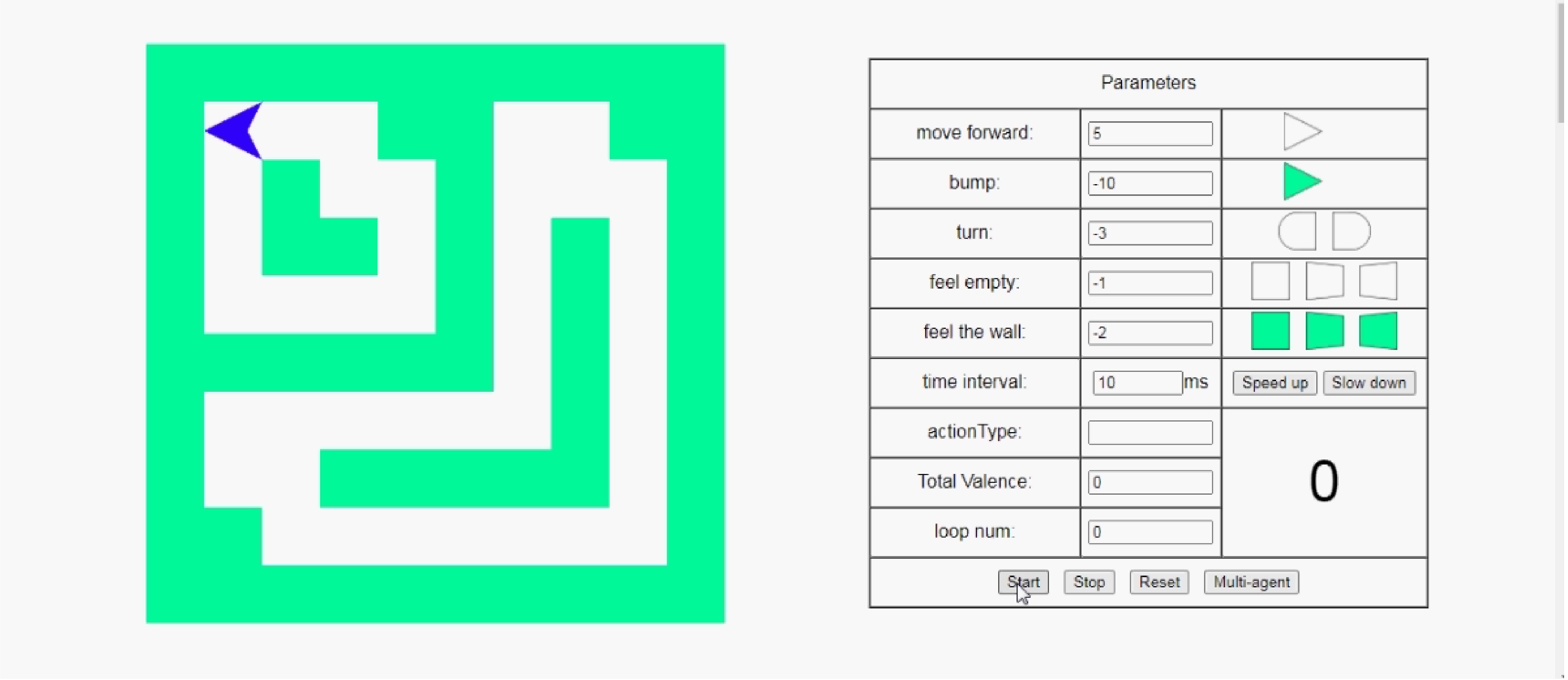






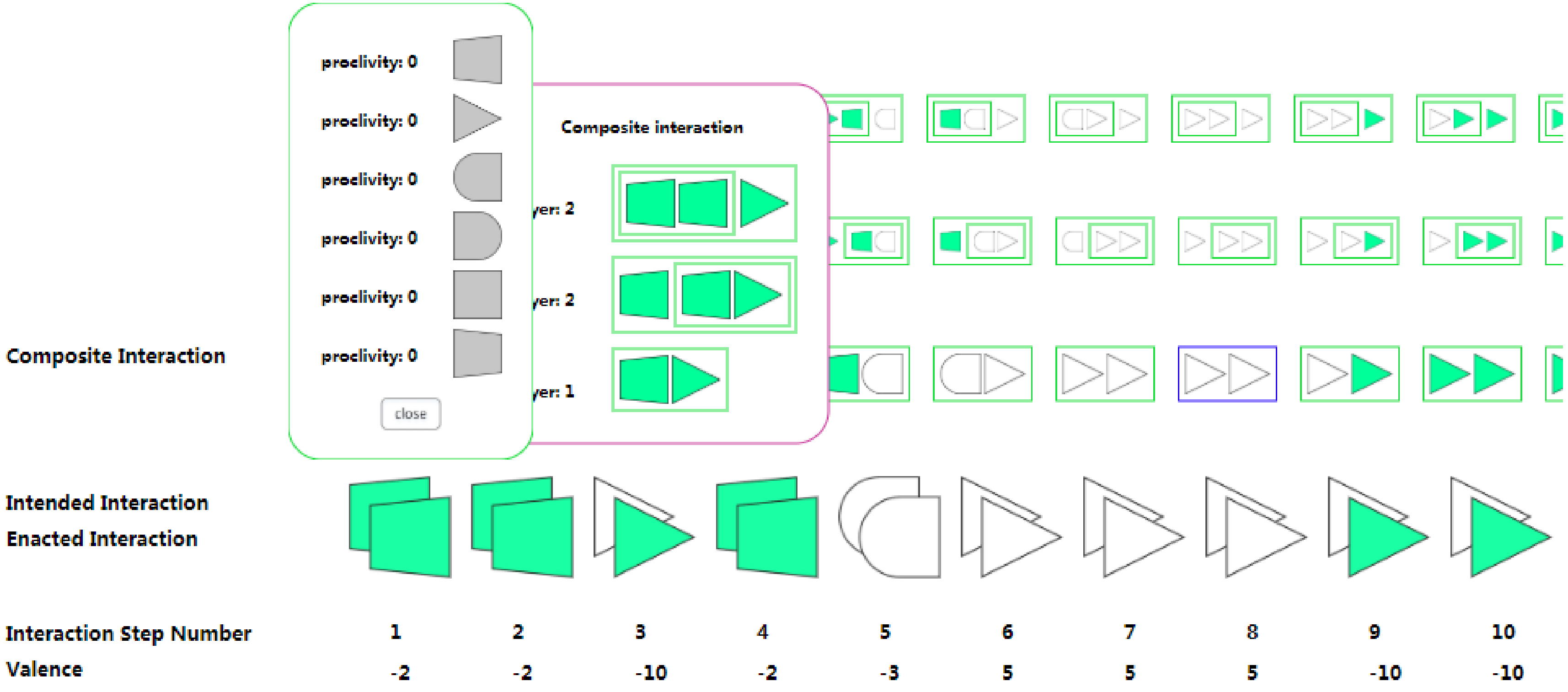
Contribution 4: Methodology and experimental scenario with GAIT

- The agent's performance in GAIT



Contribution 4: Methodology and experimental scenario with GAIT

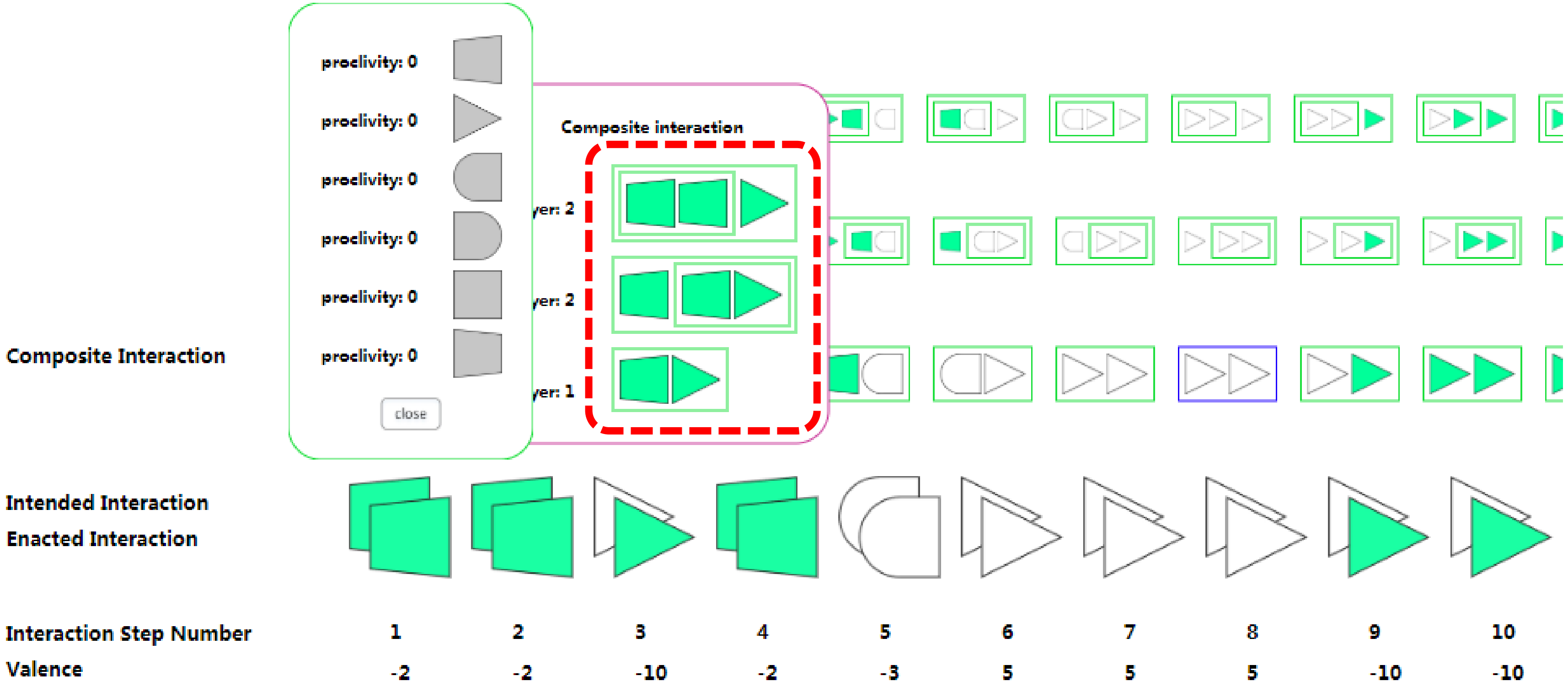
- Interaction traces analysis



The first interactions and the construction of composite interactions.

Contribution 4: Methodology and experimental scenario with GAIT

Interaction traces analysis



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Contribution 4: Methodology and experimental scenario with GAIT

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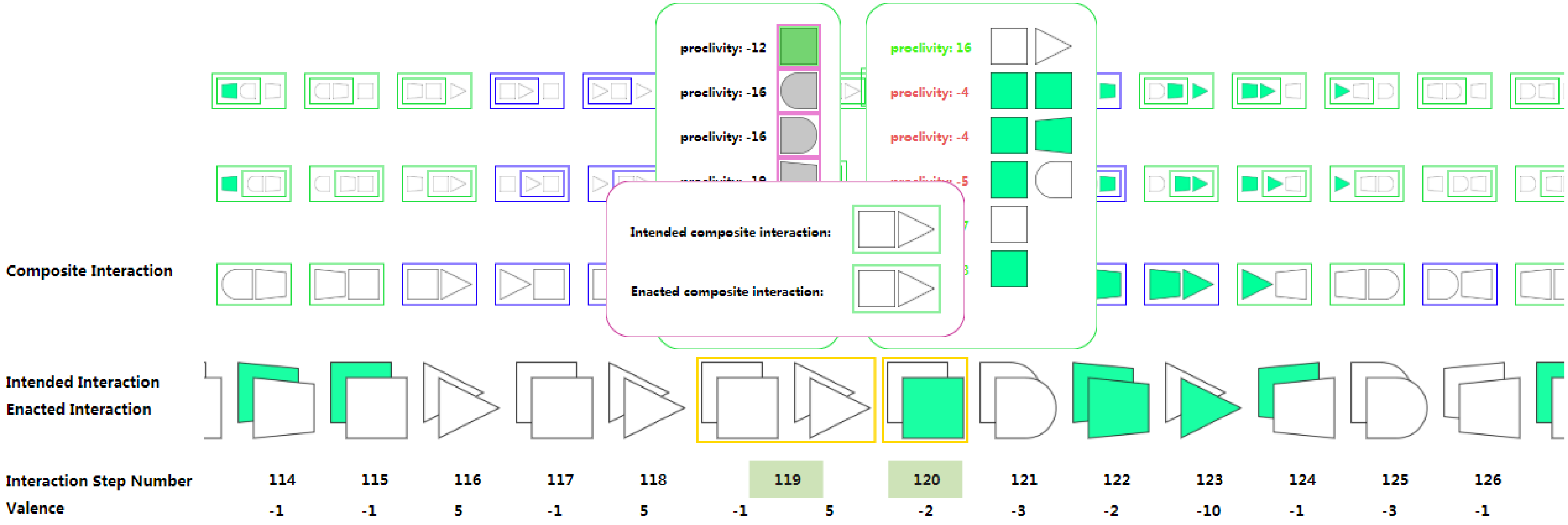
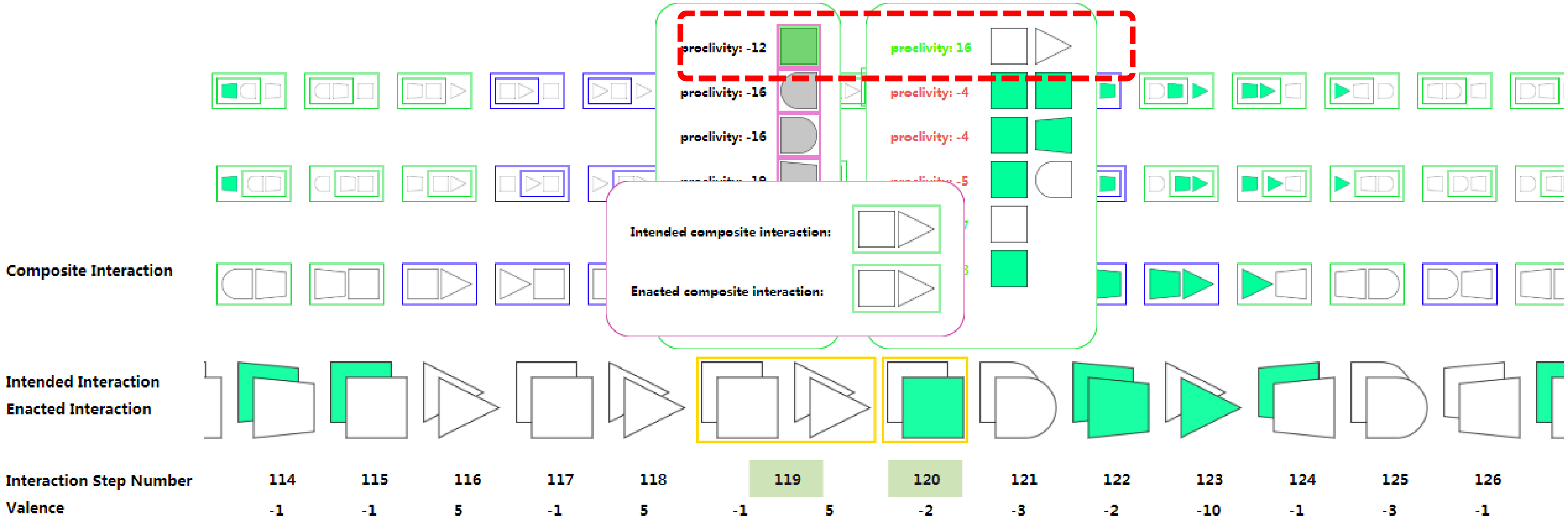


The agent successfully enacts composite interaction and constructs higher-level composite interaction

Contribution 4: Methodology and experimental scenario with GAIT

Interaction traces analysis



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Contribution 4: Methodology and experimental scenario with GAIT

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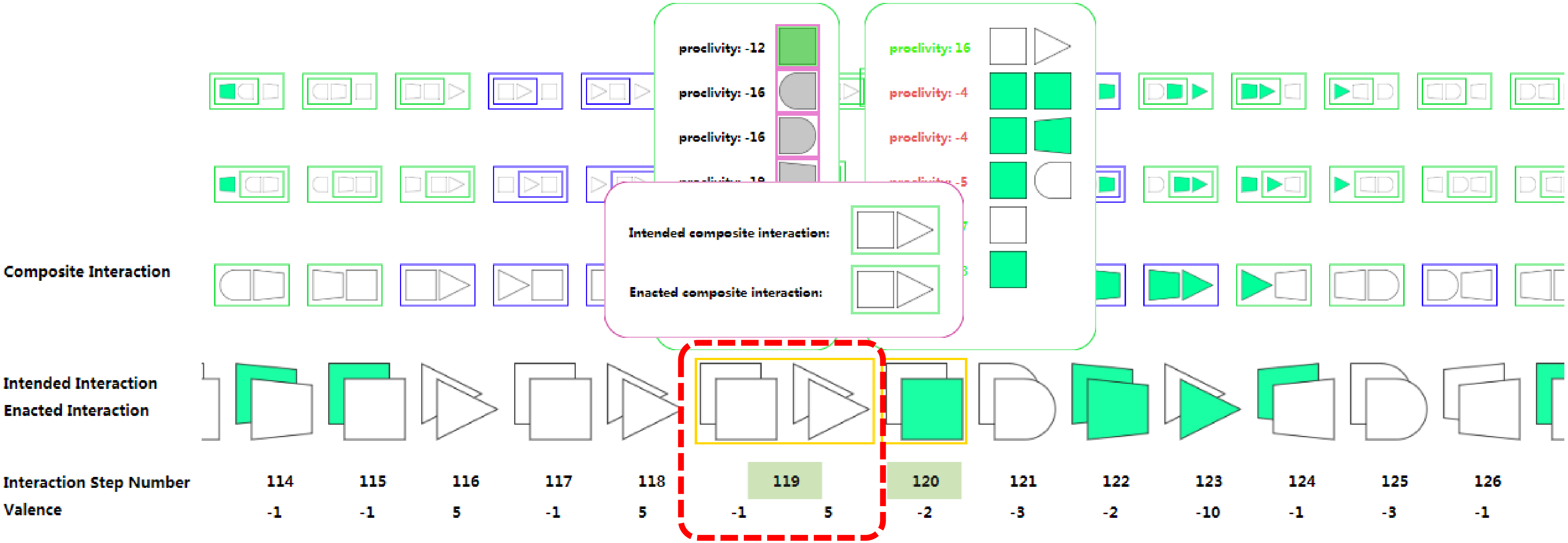

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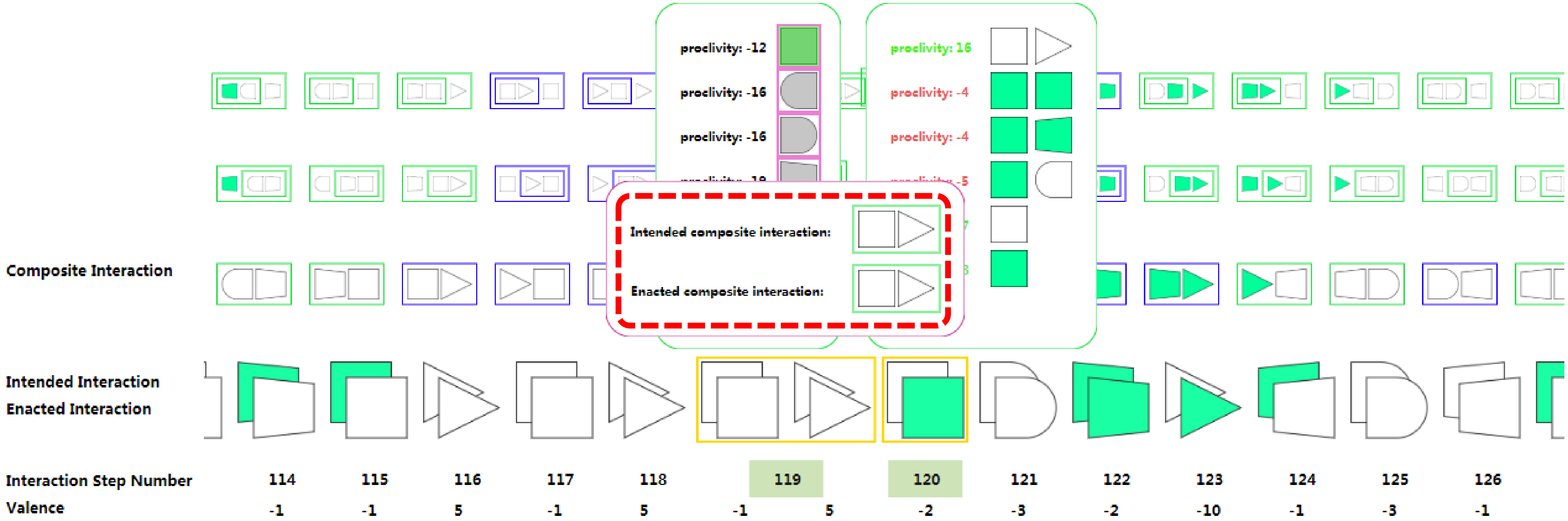
Contribution 4: Methodology and experimental scenario with GAIT

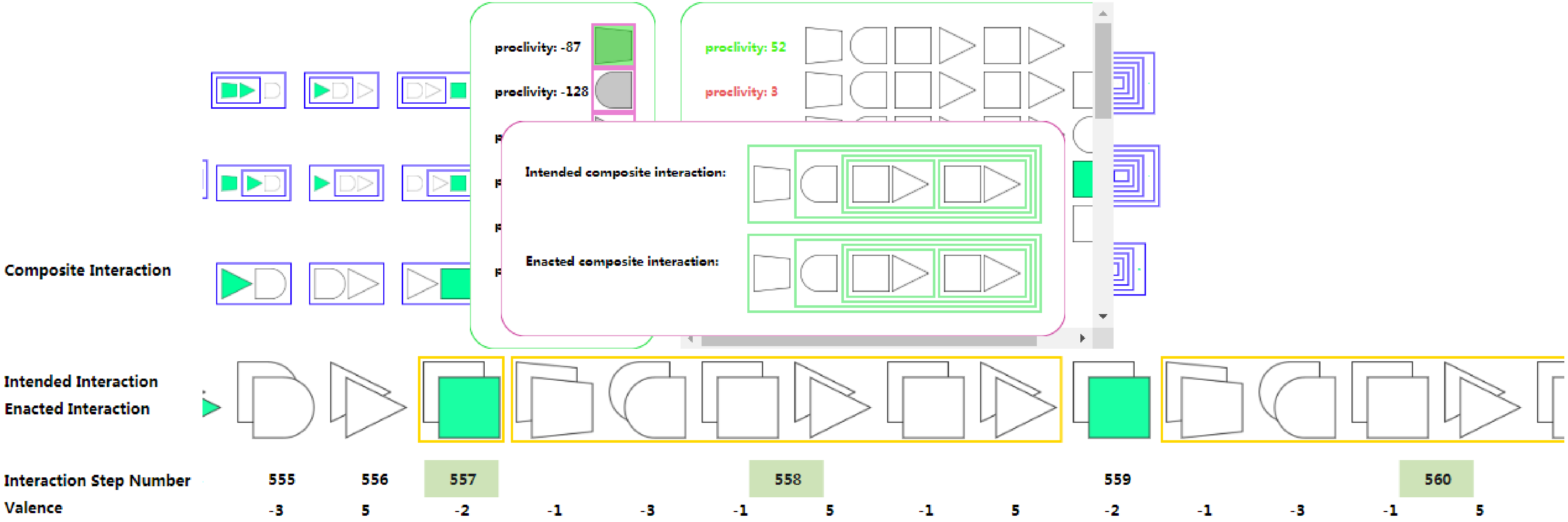
☐ Interaction traces analysis



The agent successfully enacts composite interaction and constructs higher-level composite interaction

Contribution 4: Methodology and experimental scenario with GAIT

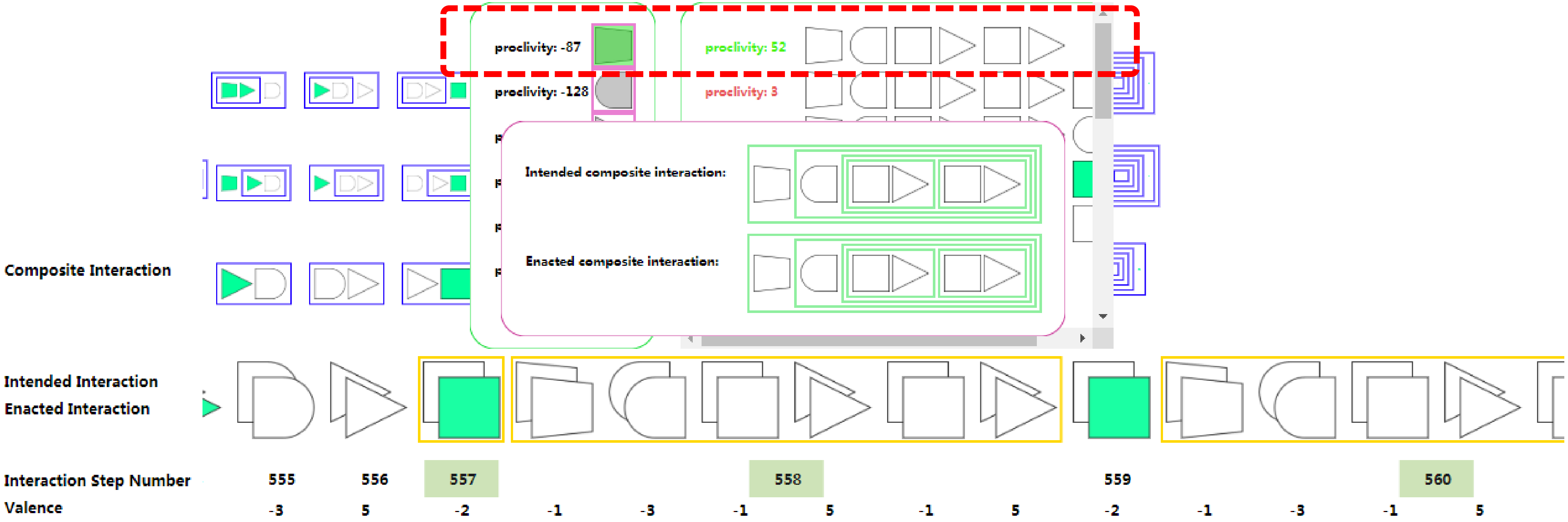
- Interaction traces analysis



Enacting complicated composite interaction.

Contribution 4: Methodology and experimental scenario with GAIT

- Interaction traces analysis



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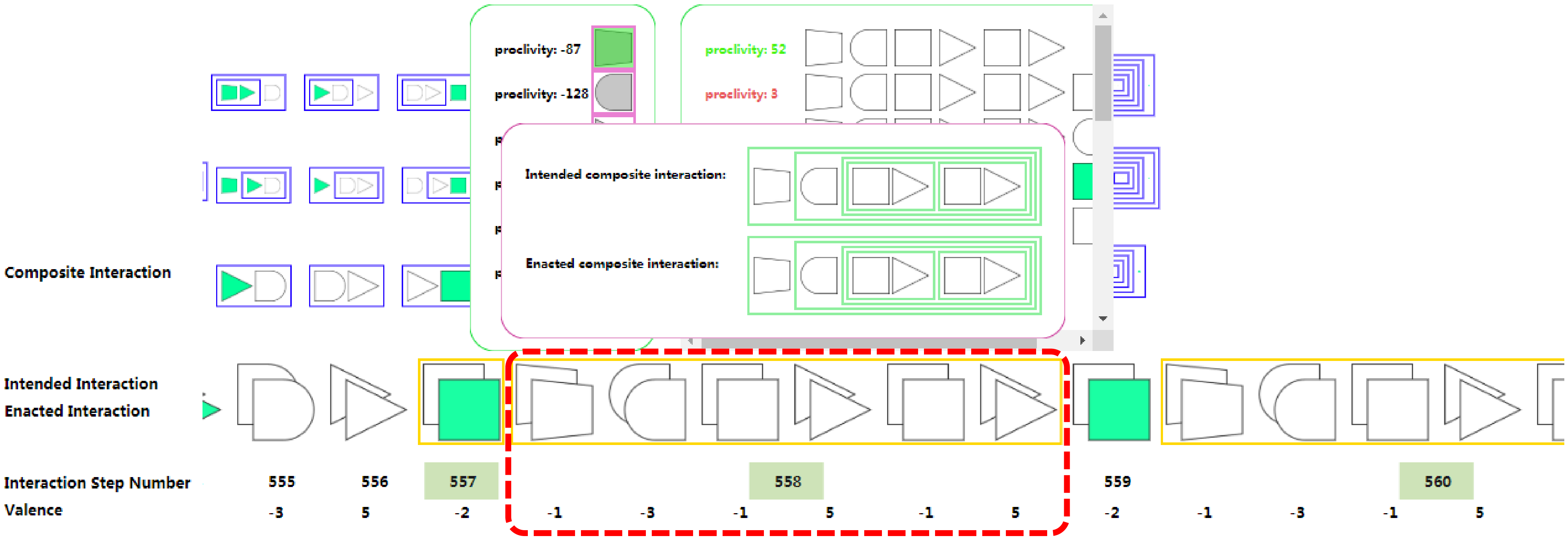

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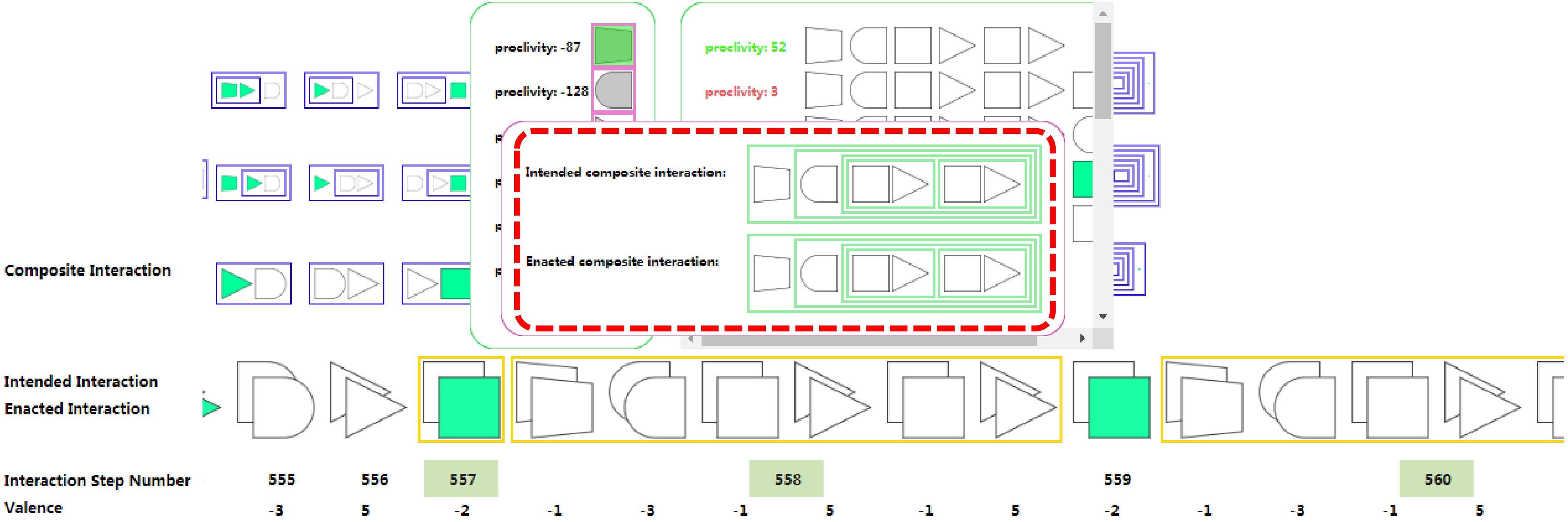
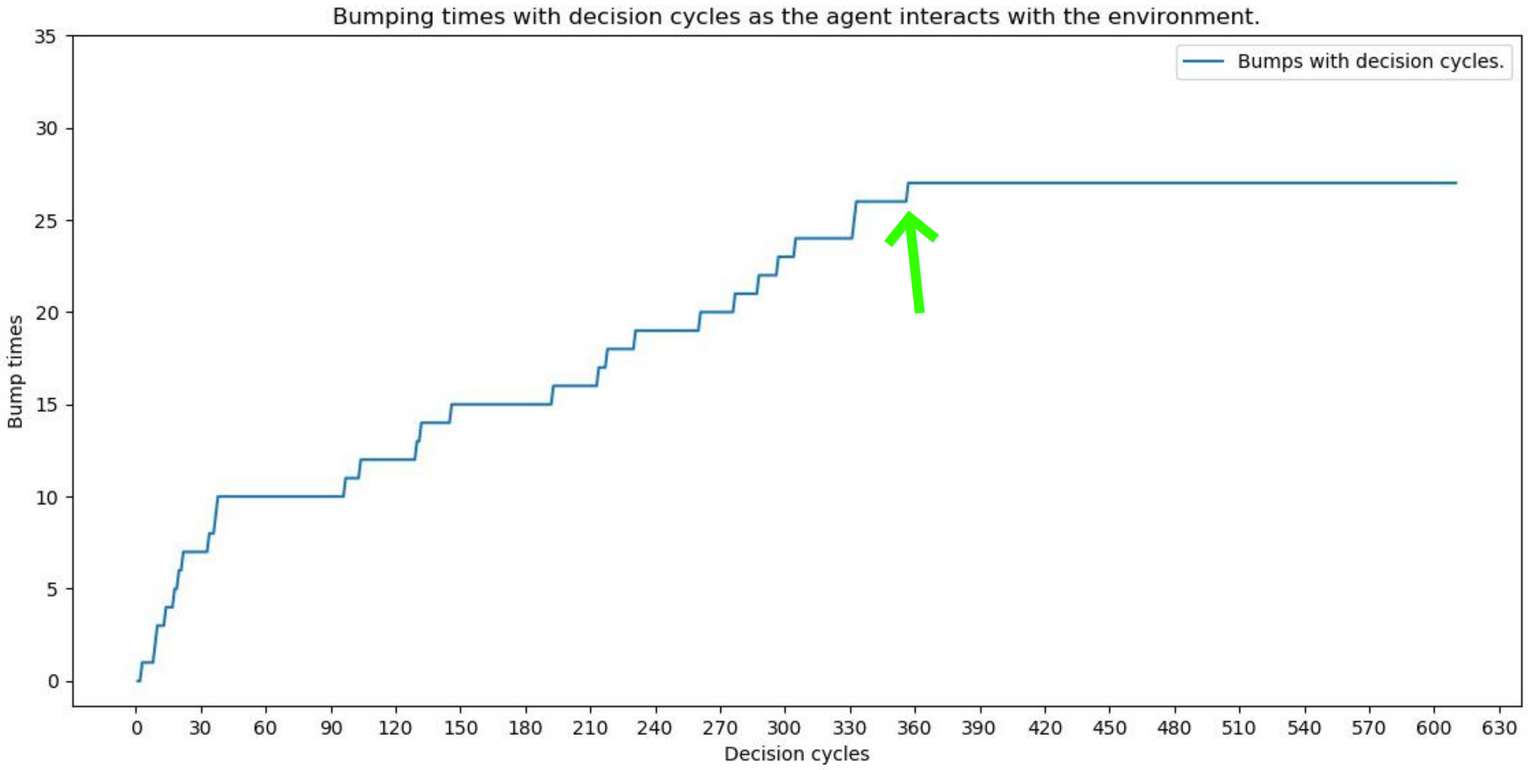


Enacting complicated composite interaction.

Contribution 4: Methodology and experimental scenario with GAIT

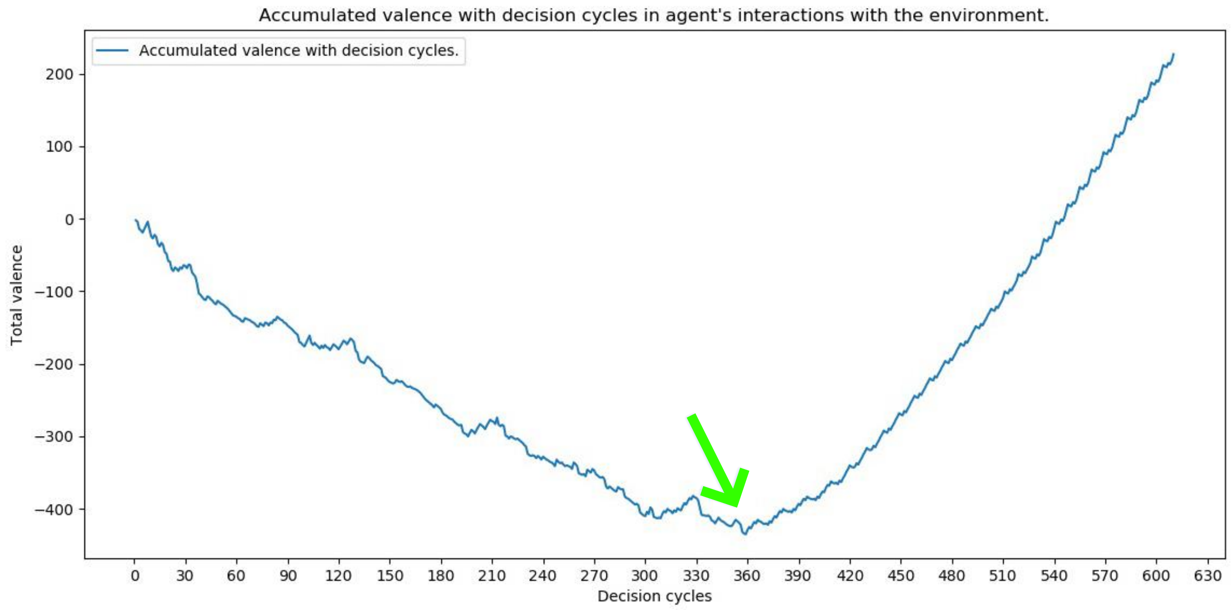
The results: Bump times with the interaction step



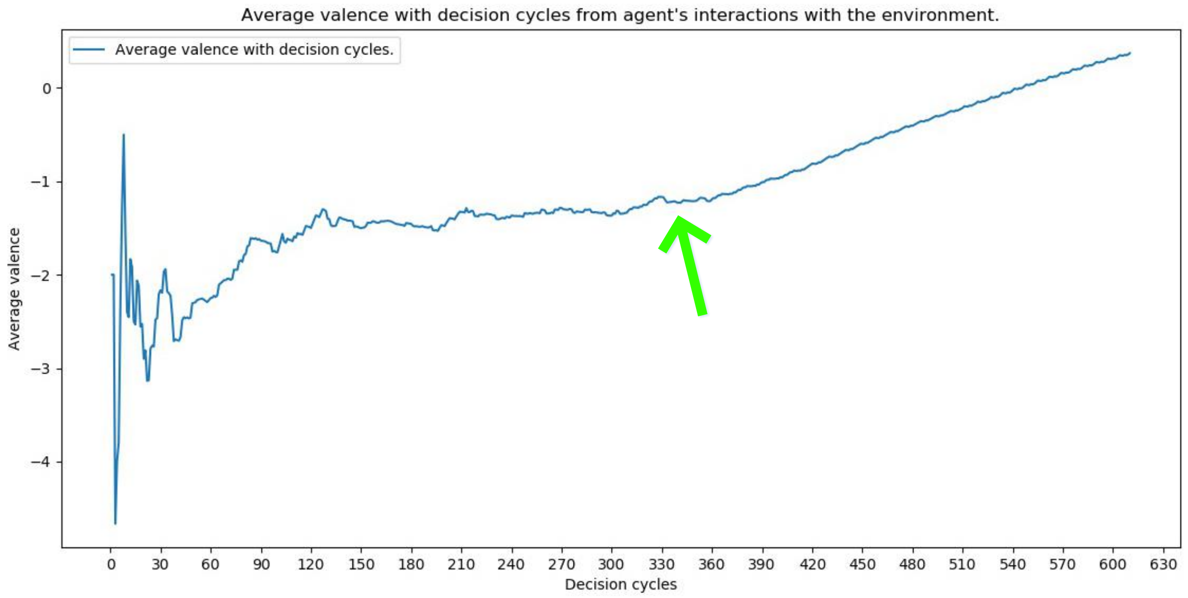
Bump times with decision cycles as agent interacts with the environment.

Contribution 4: Methodology and experimental scenario with GAIT

The results: Accumulated valence and the average valence



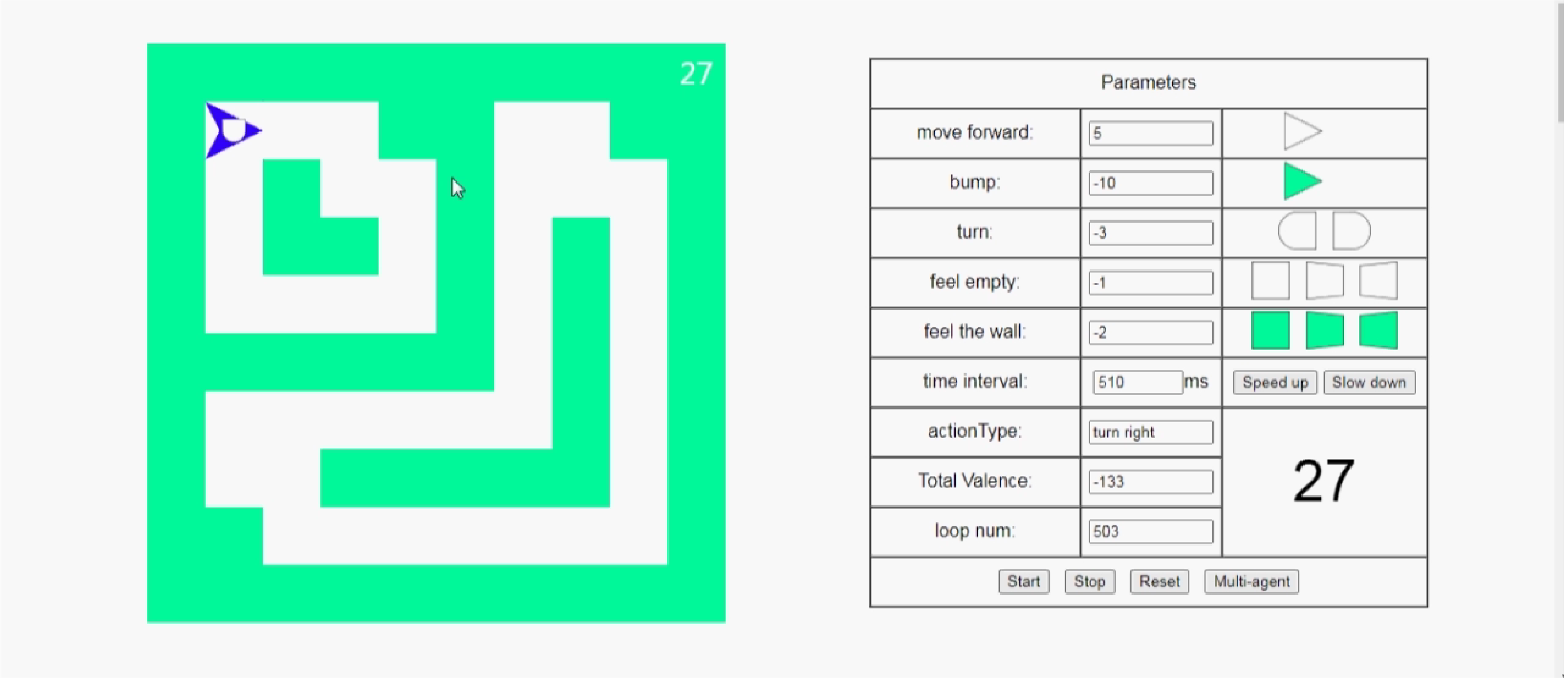
The accumulated valence with decision cycles in agent's interactions with the environment.



The average valence with decision cycles in agent's interactions with the environment.

Contribution 4: Methodology and experimental scenario with GAIT

- The agent's performance in the changed environment



Contribution 4: Methodology and experimental scenario with GAIT

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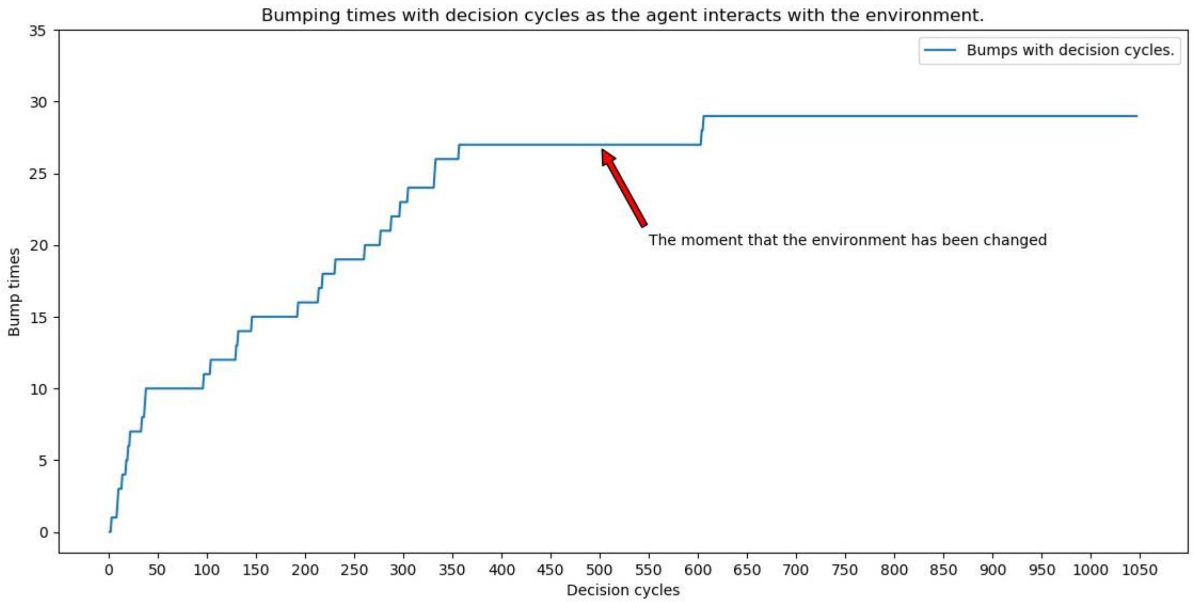
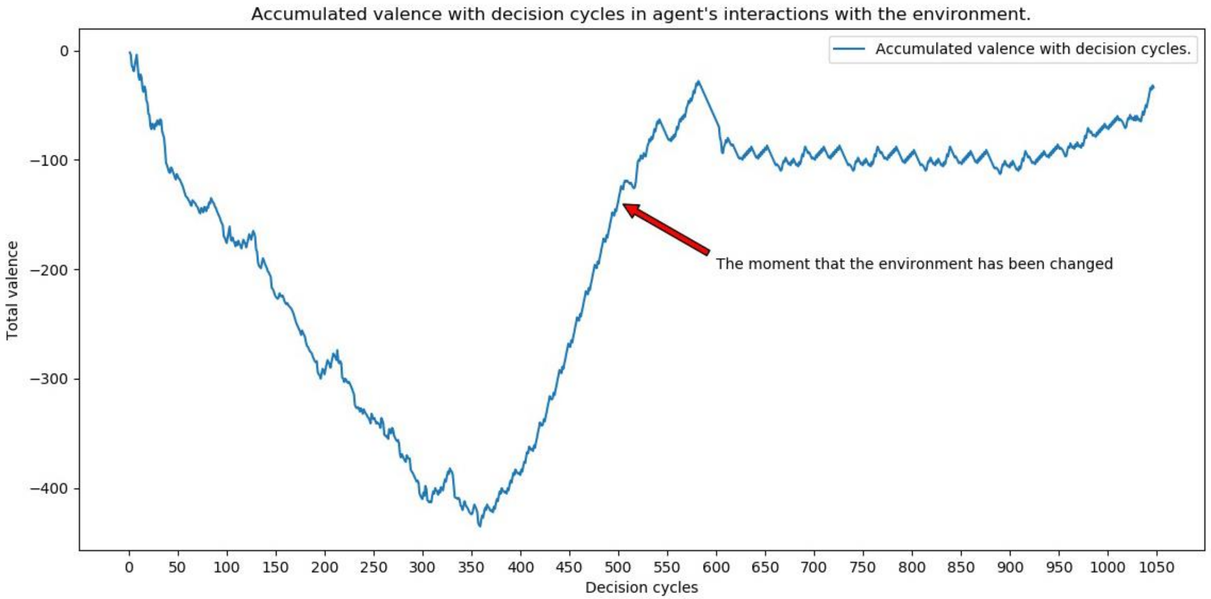


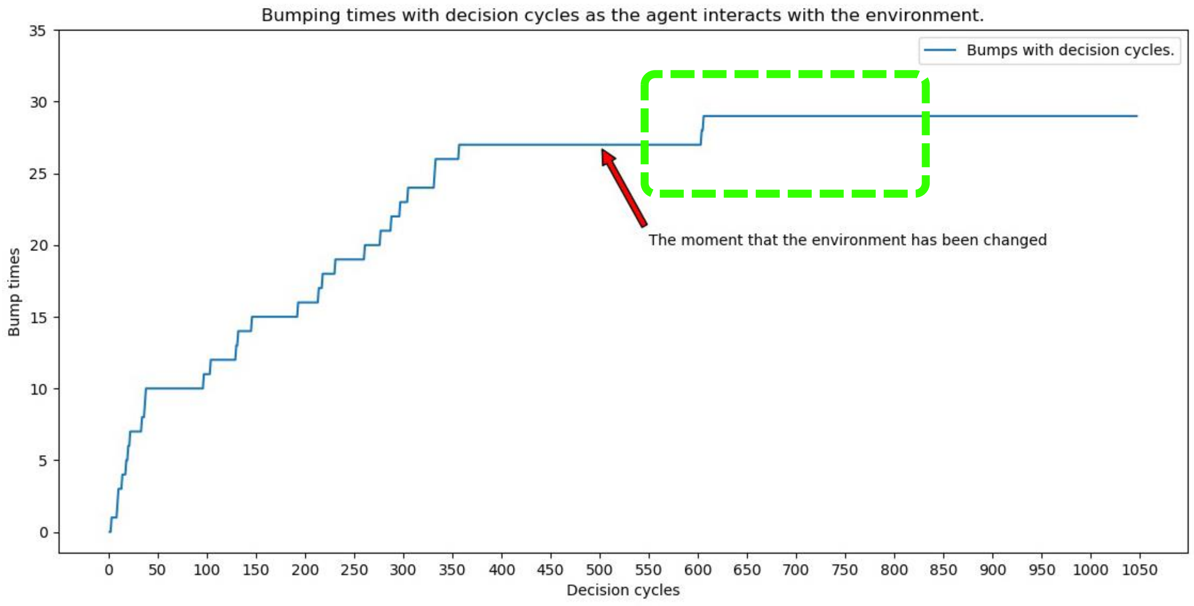
The bumps with decision cycles in the changed environment



The accumulated valence with decision cycles in the changed environment.

Contribution 4: Methodology and experimental scenario with GAIT

- The agent's performance in the changed environment



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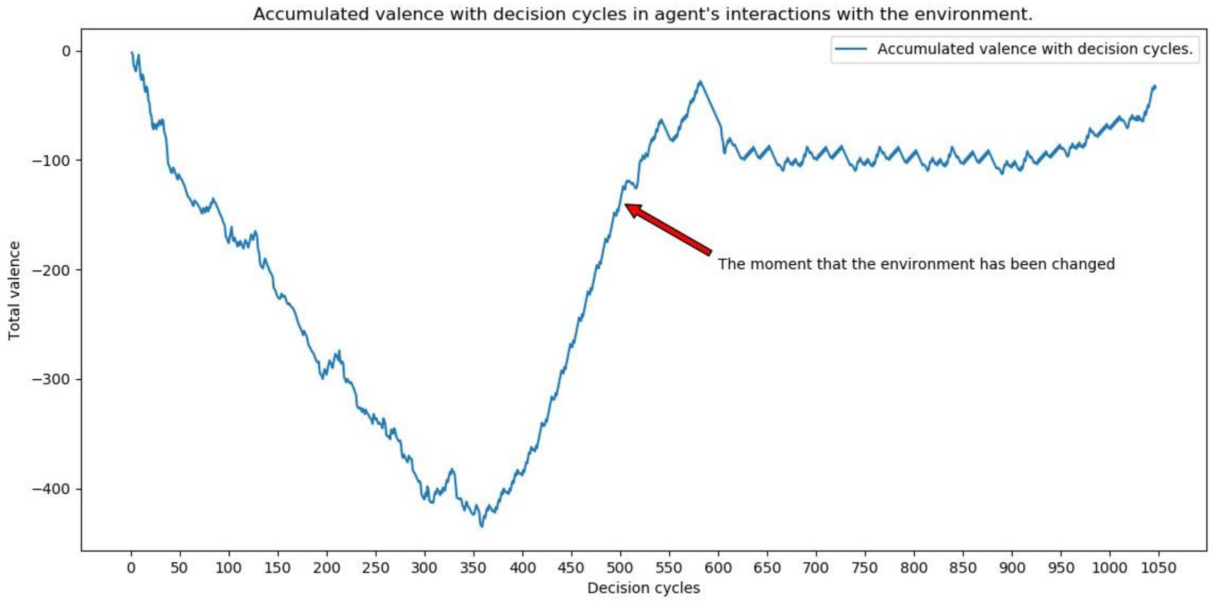
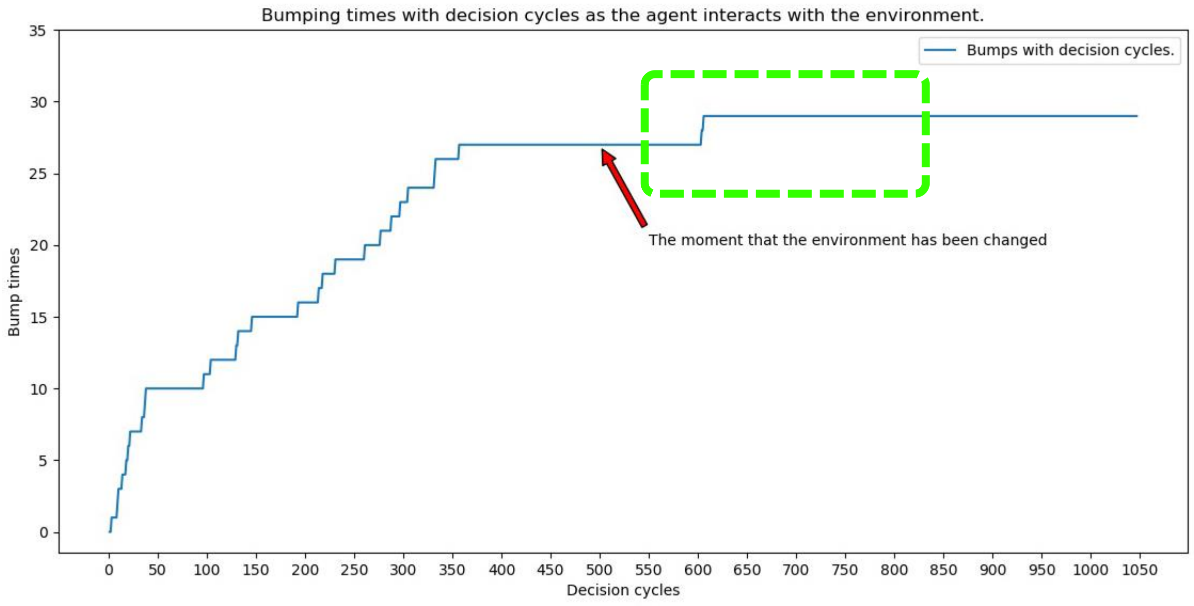


The accumulated valence with decision cycles in the changed environment.

Contribution 4: Methodology and experimental scenario with GAIT

- The agent's performance in the changed environment



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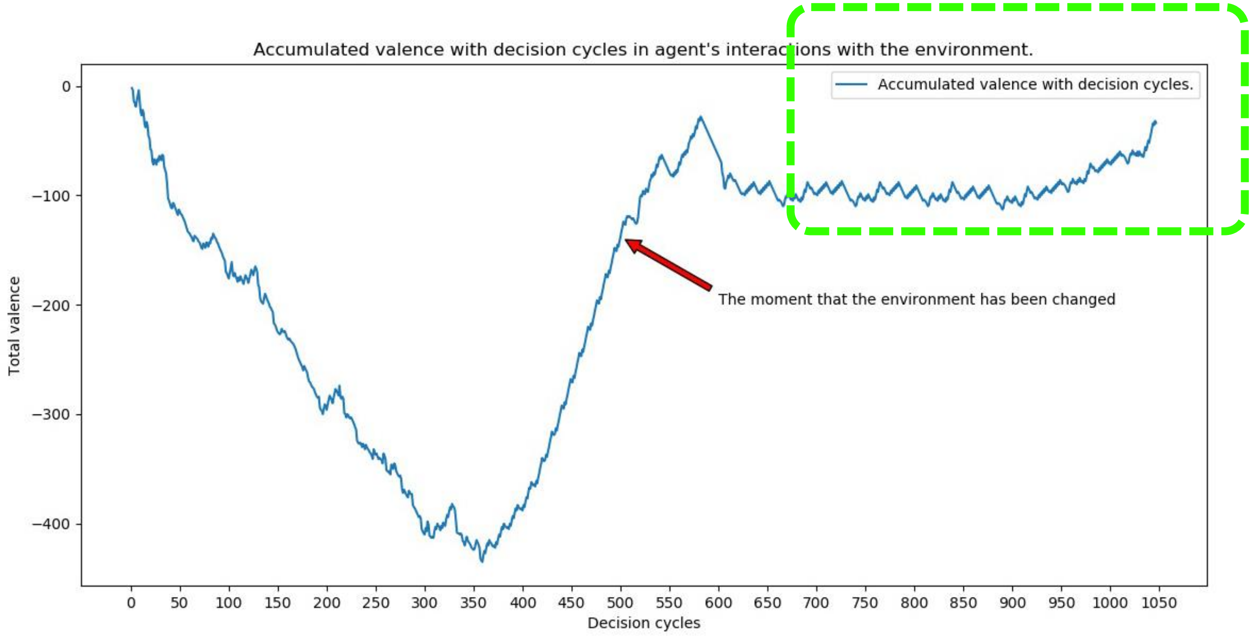
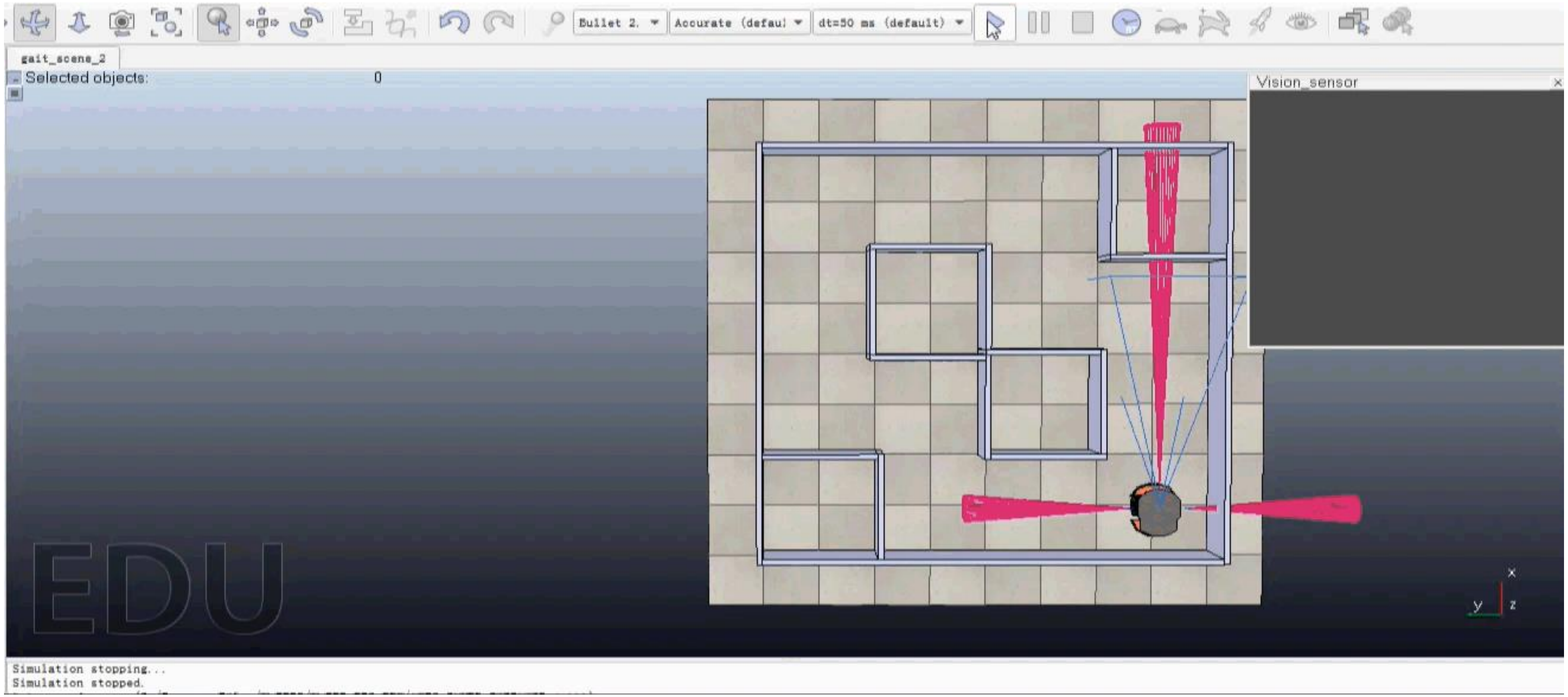


The accumulated valence with decision cycles in the changed environment.

Contribution 4: Methodology and experimental scenario with GAIT

- The performance of a self-motivated robot with BEL-CA and GAIT



Comparison with related works

Criteria	CCA	Reinforcement learning	Trace-Based Reasoning	Soar	Autonomous learning (robotics)
Theoretical framework	Constructivism	Behaviorism	Symbolic logicist	Cognitivism	Behaviorism
Mechanism	Sequential learning	Value iteration	Traces reasoning	Multiple mechanisms	Structured behavioral learning
Input/output	Enacted interaction / Intended interaction	Observation/Action	+	Perception/action	Actuators/sensors
Reward	Intrinsic (inward)	Extrinsic	+	Extrinsic	Intrinsic/Extrinsic
Goal	Self-motivated	Goal-directed	+	Goal-directed	Goal-directed
Perception	internally constructed	Function of the environment	+	From the environment	From the environment
knowledge representation	No endowed nor supplied	+	Encoded by the designer	+	Afforded by the designer
Cycle	Starts from the agent	Starts from environment	+	Starts from environment	Starts from environment

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Input/output	Enacted interaction / Intended interaction	Observation/Action	+	Perception/action	Actuators/sensors
Reward	Intrinsic (inward)	Extrinsic	+	Extrinsic	Intrinsic/Extrinsic
Goal	Self-motivated	Goal-directed	+	Goal-directed	Goal-directed
Perception	internally constructed	Function of the environment	+	From the environment	From the environment
knowledge representation	No endowed nor supplied	+	Encoded by the designer	+	Afforded by the designer
Cycle	Starts from the agent	Starts from environment	+	Starts from environment	Starts from environment

Comparison with related works

Criteria	CCA	Reinforcement learning	Trace-Based Reasoning	Soar	Autonomous learning (robotics)
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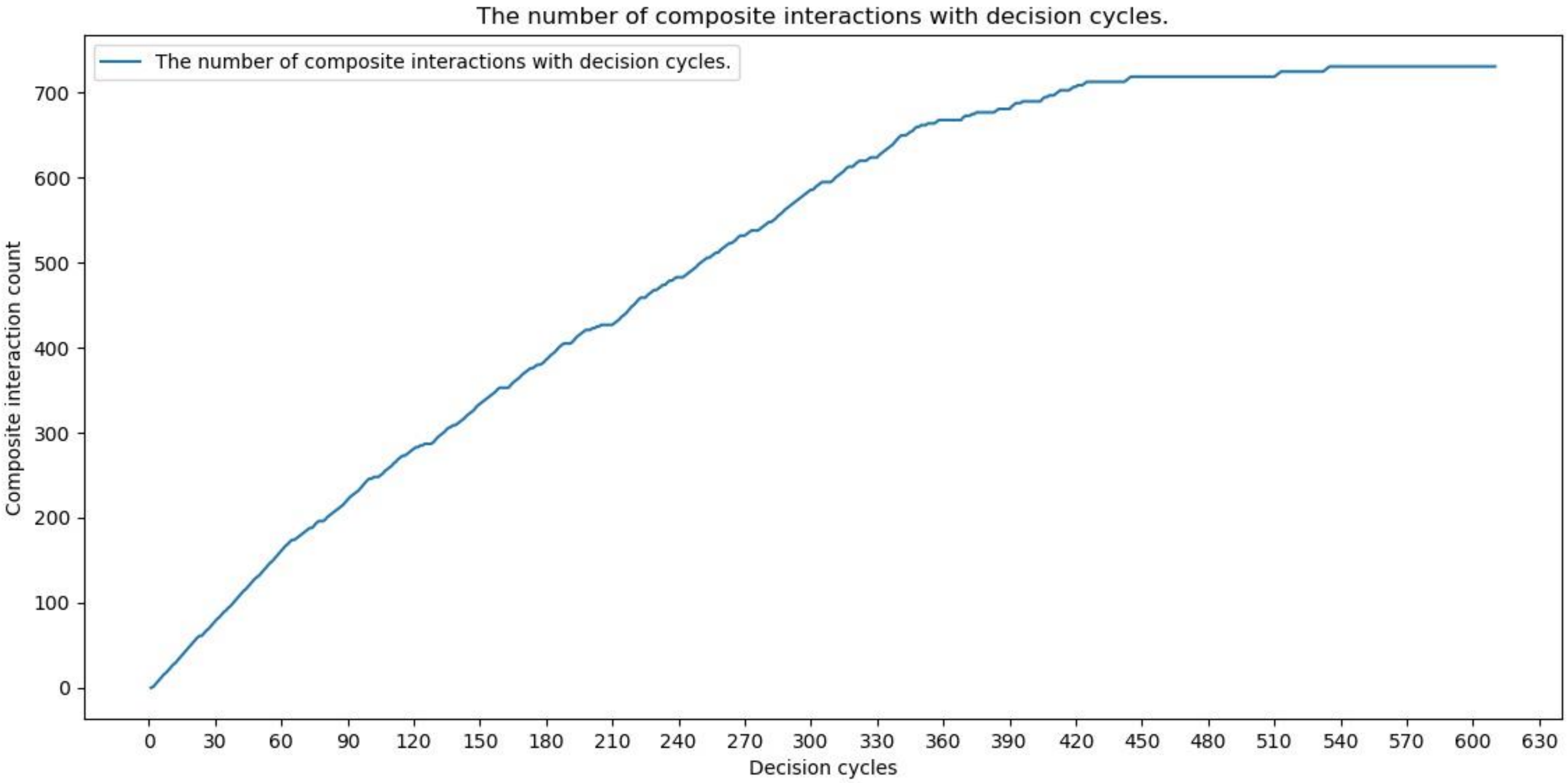

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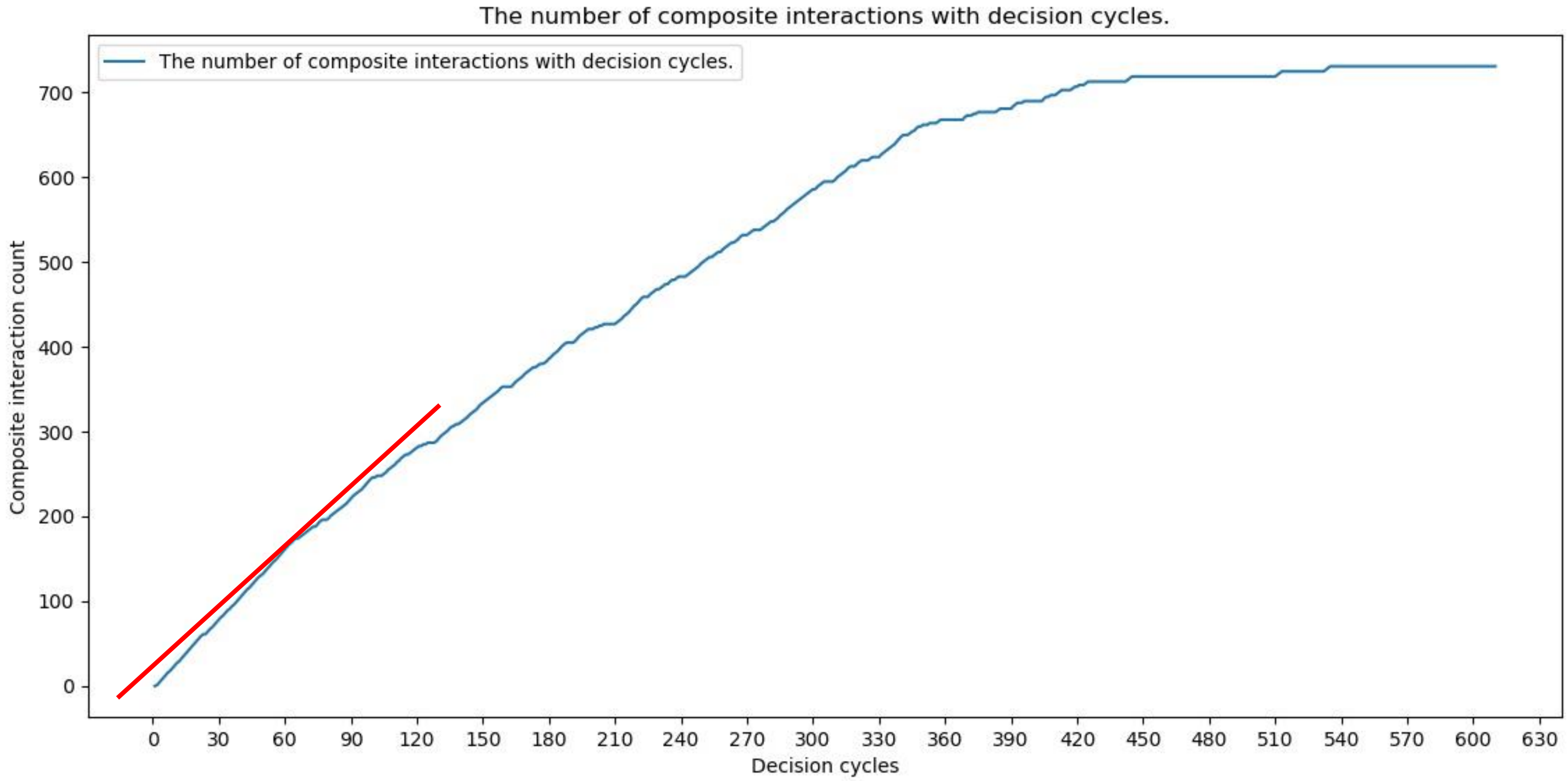

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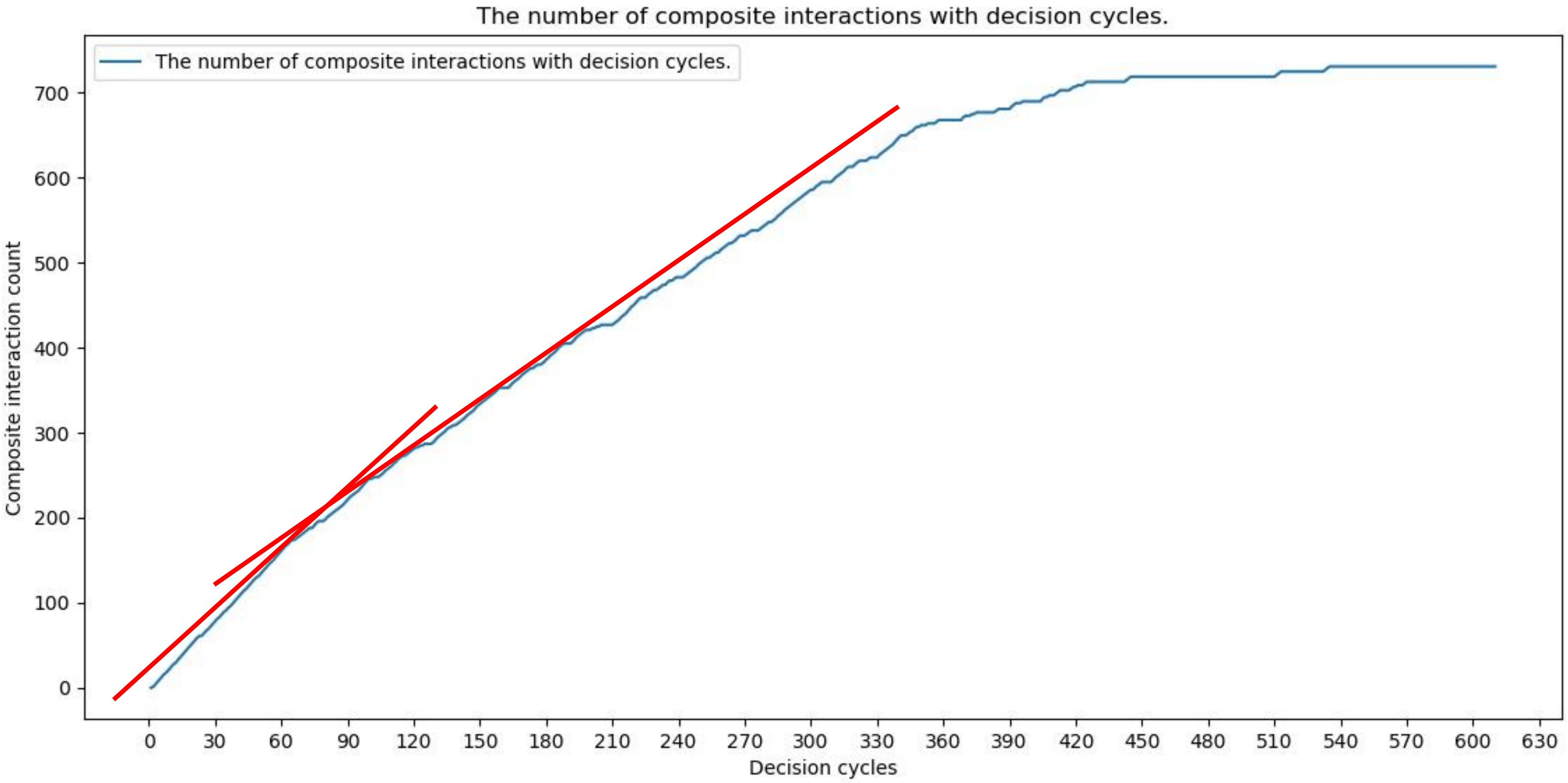

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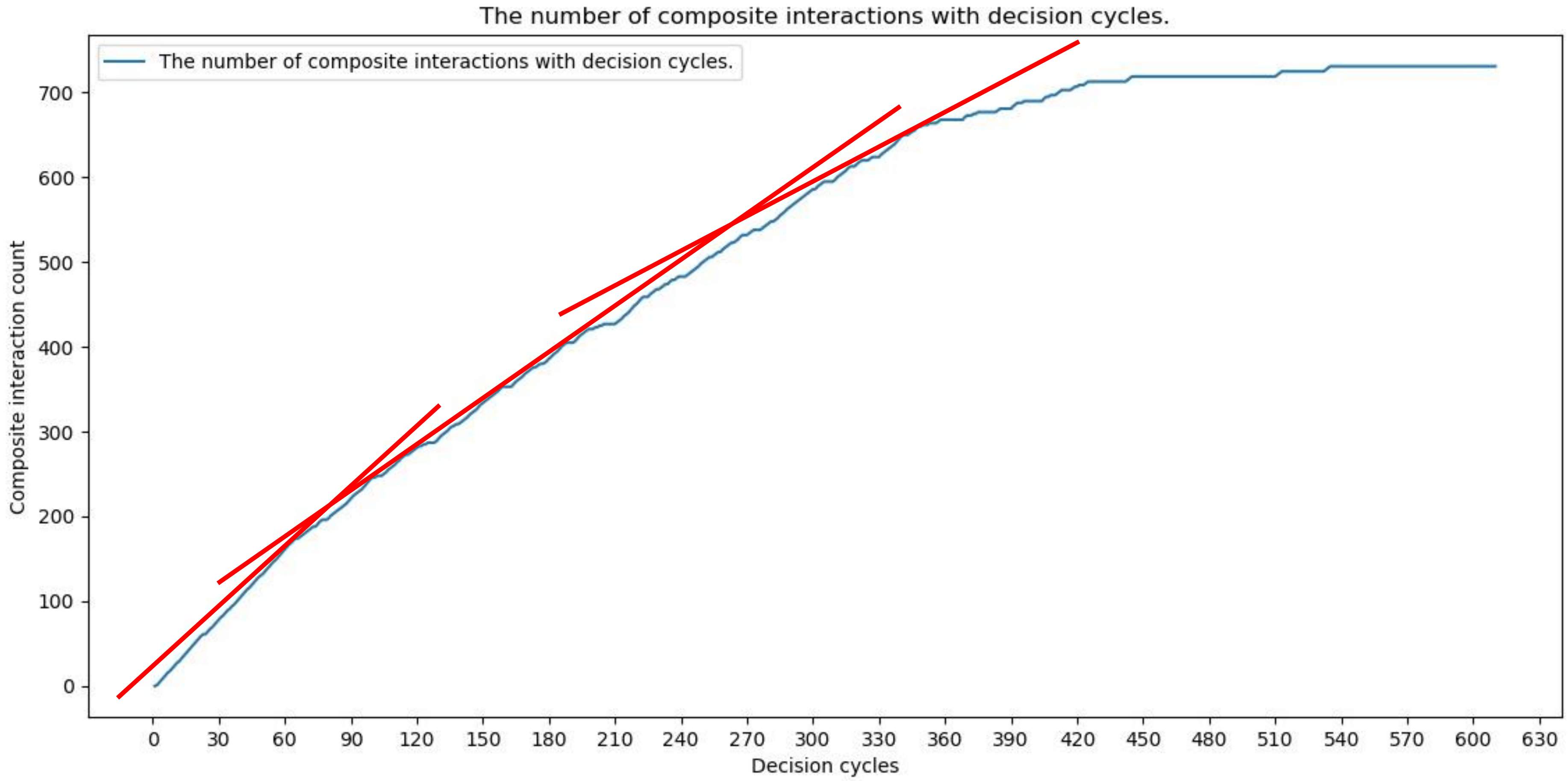

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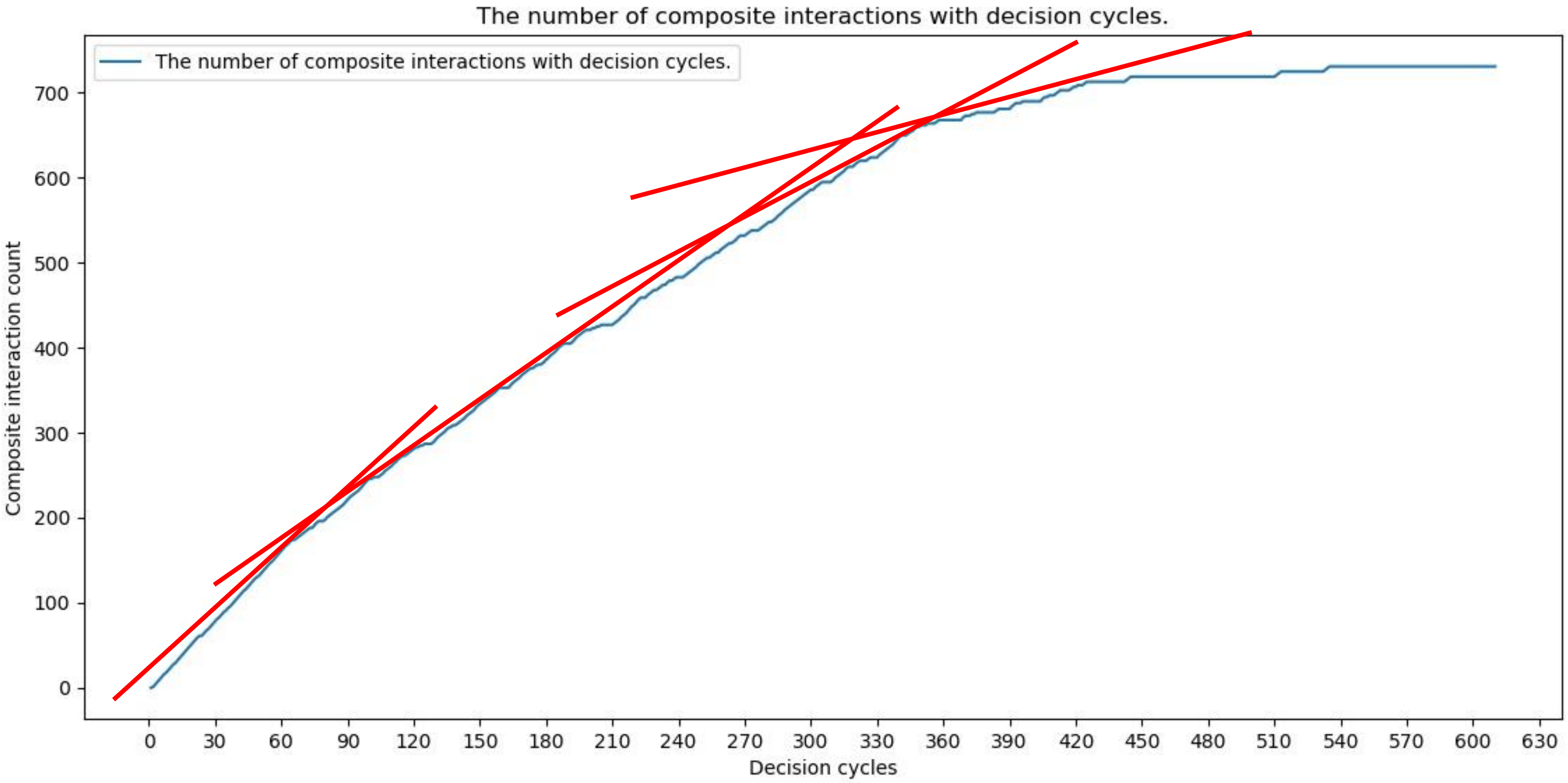

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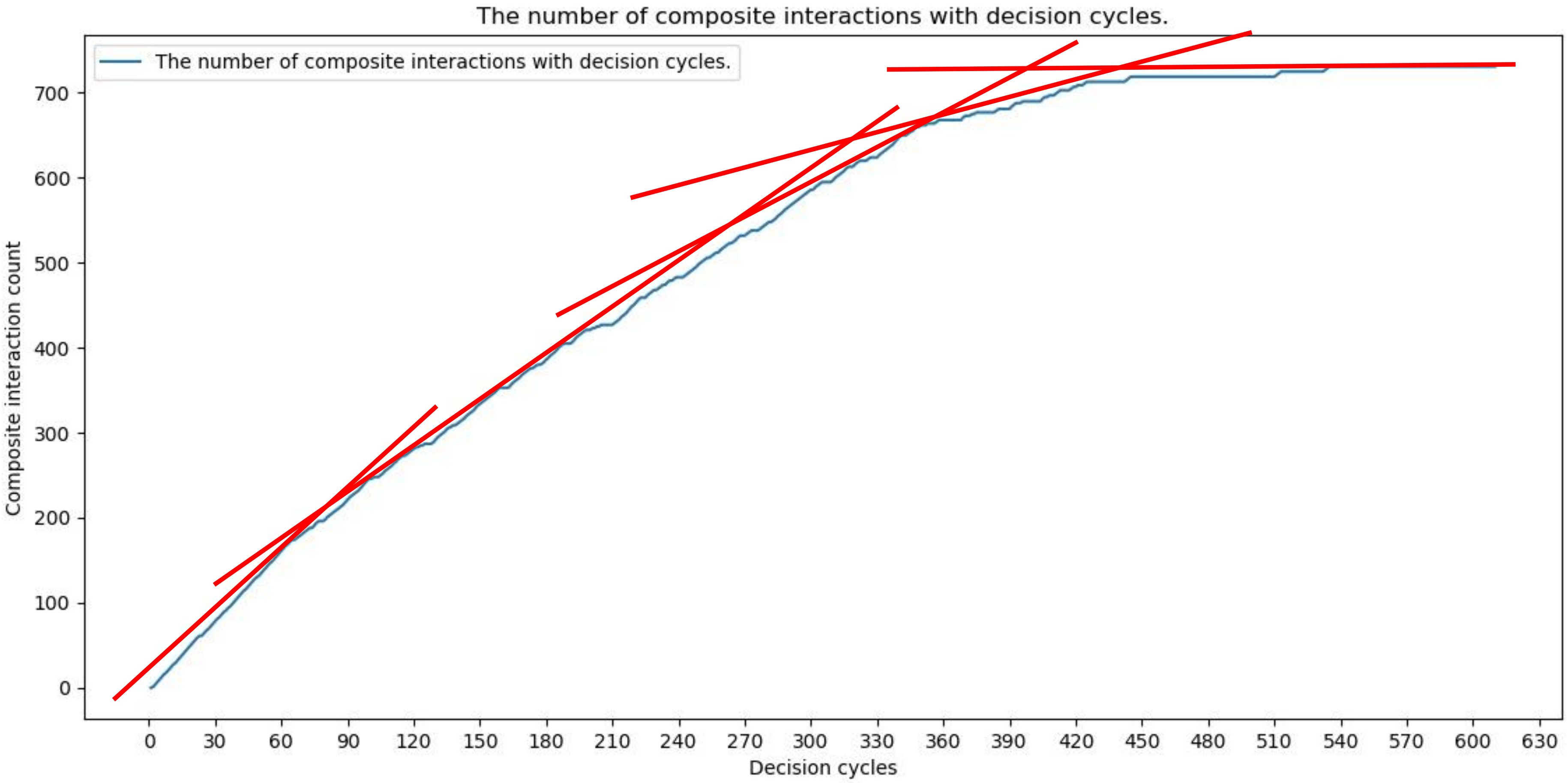

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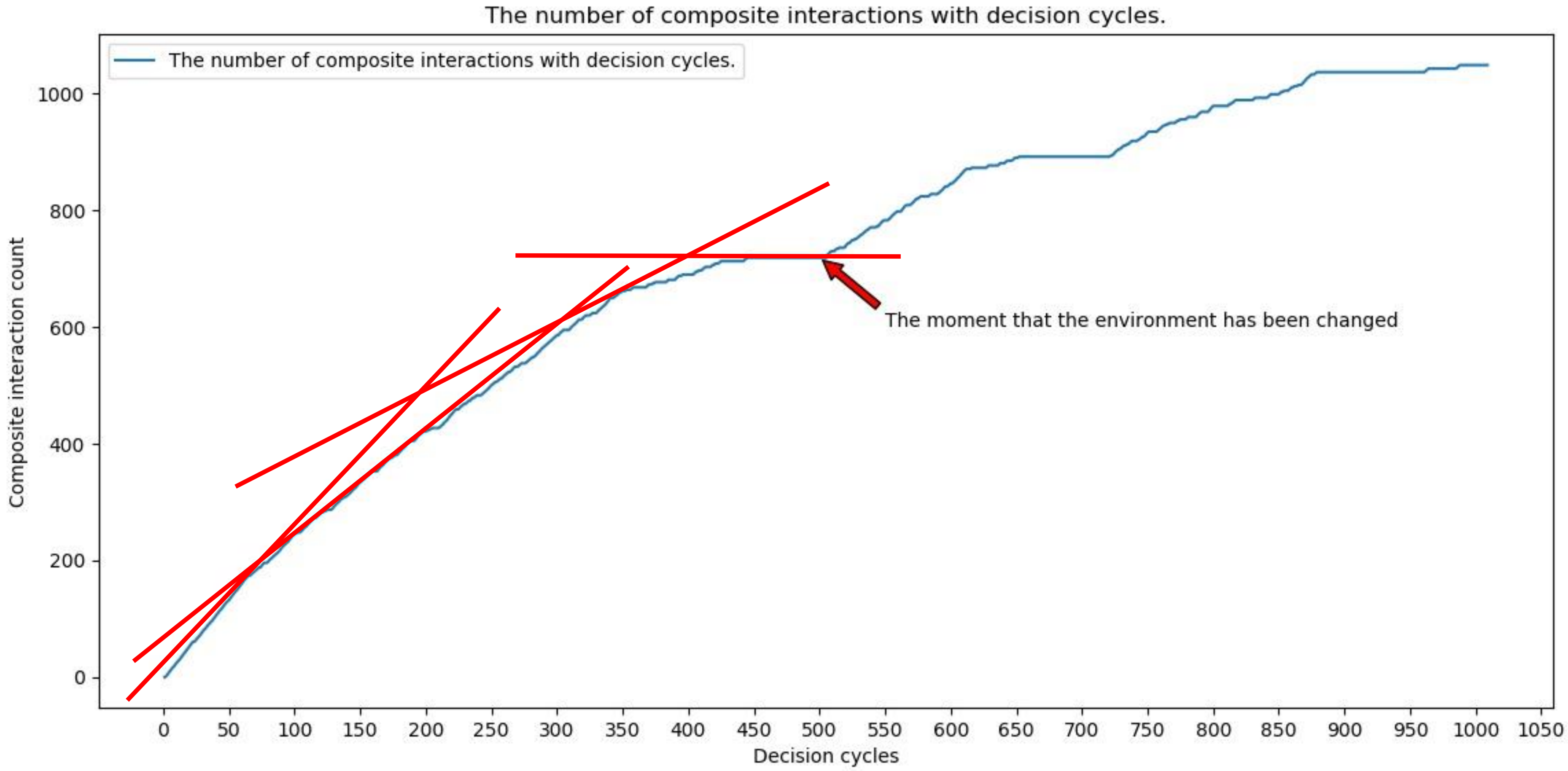

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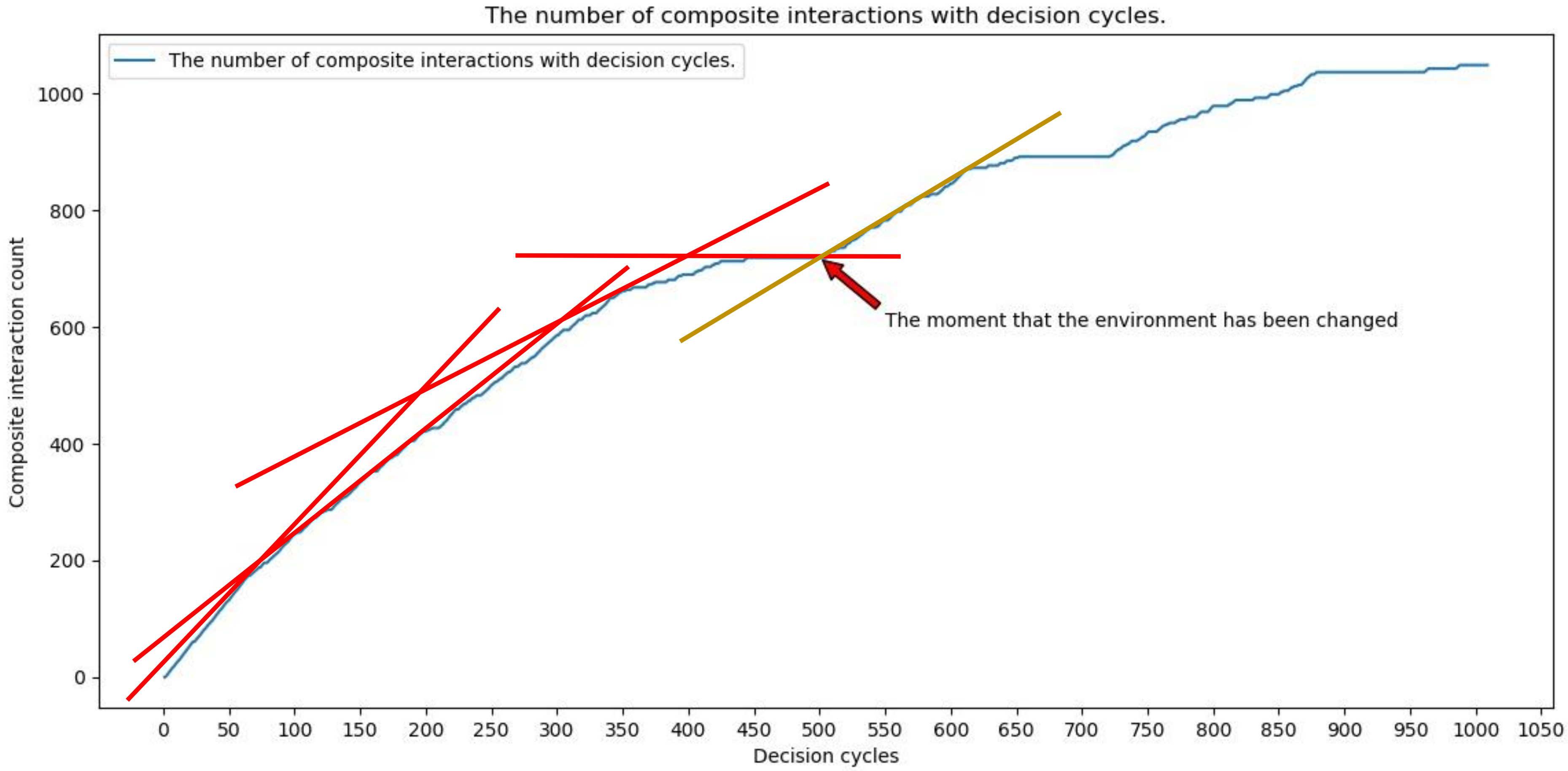

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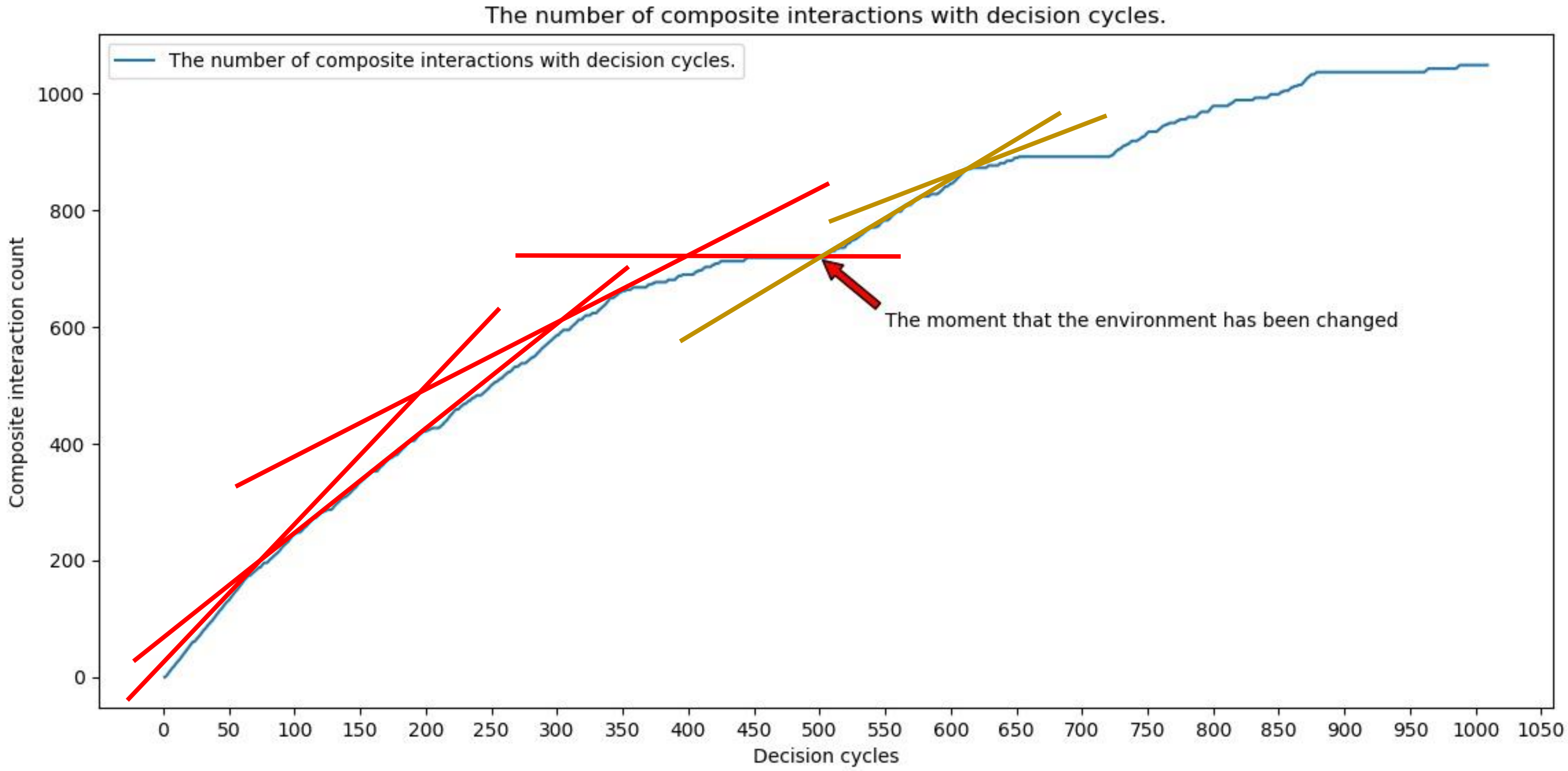

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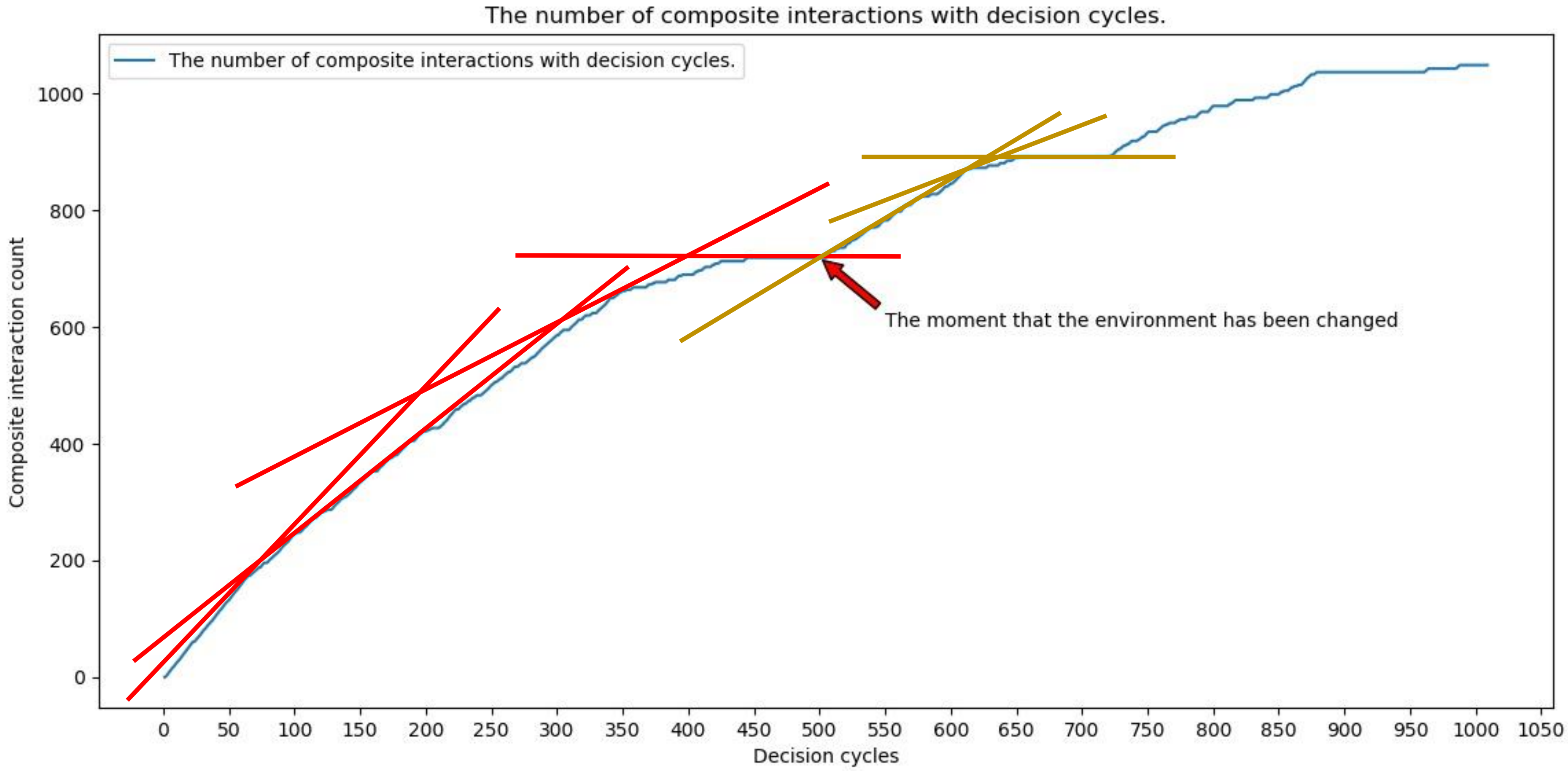

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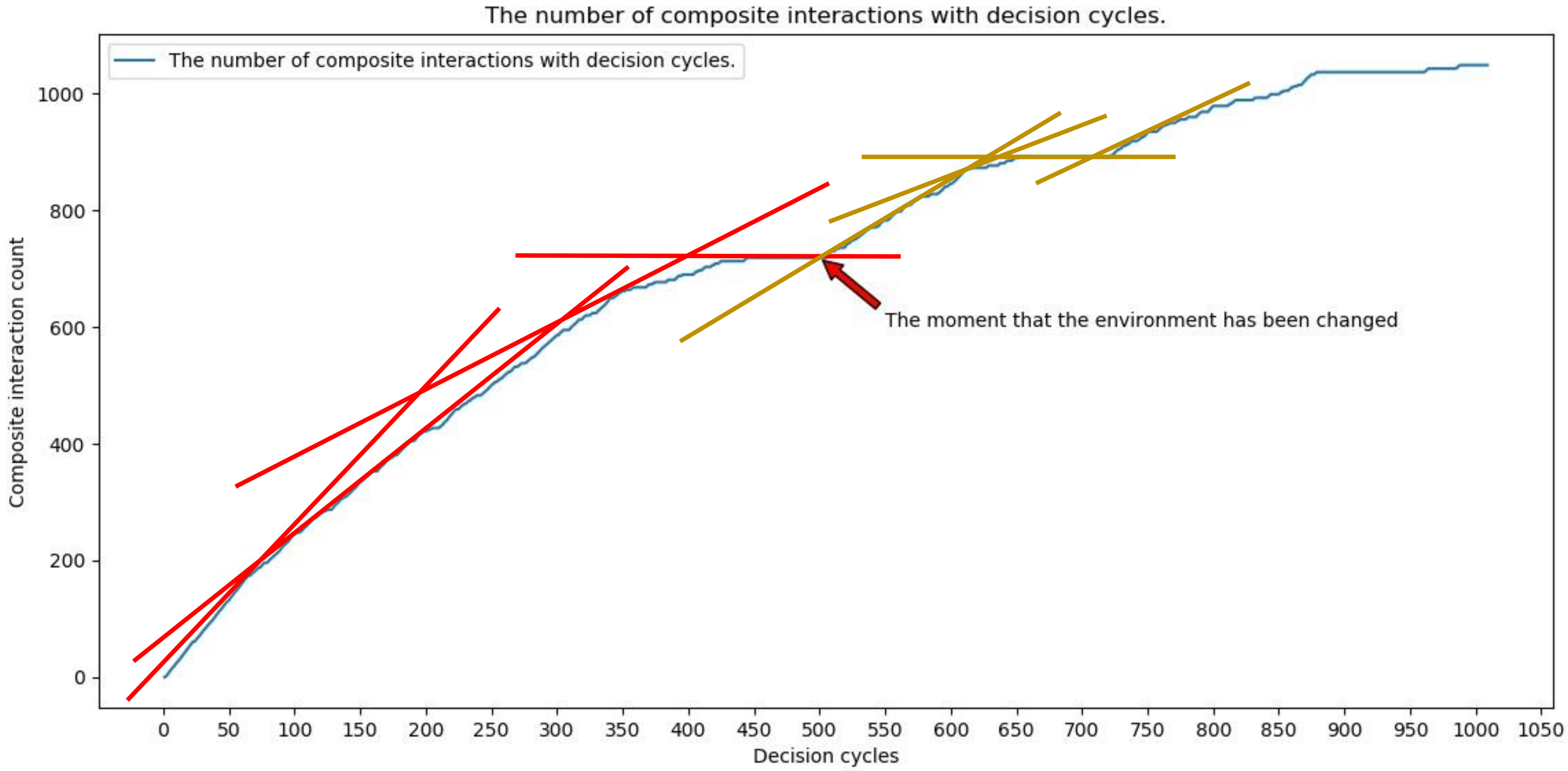

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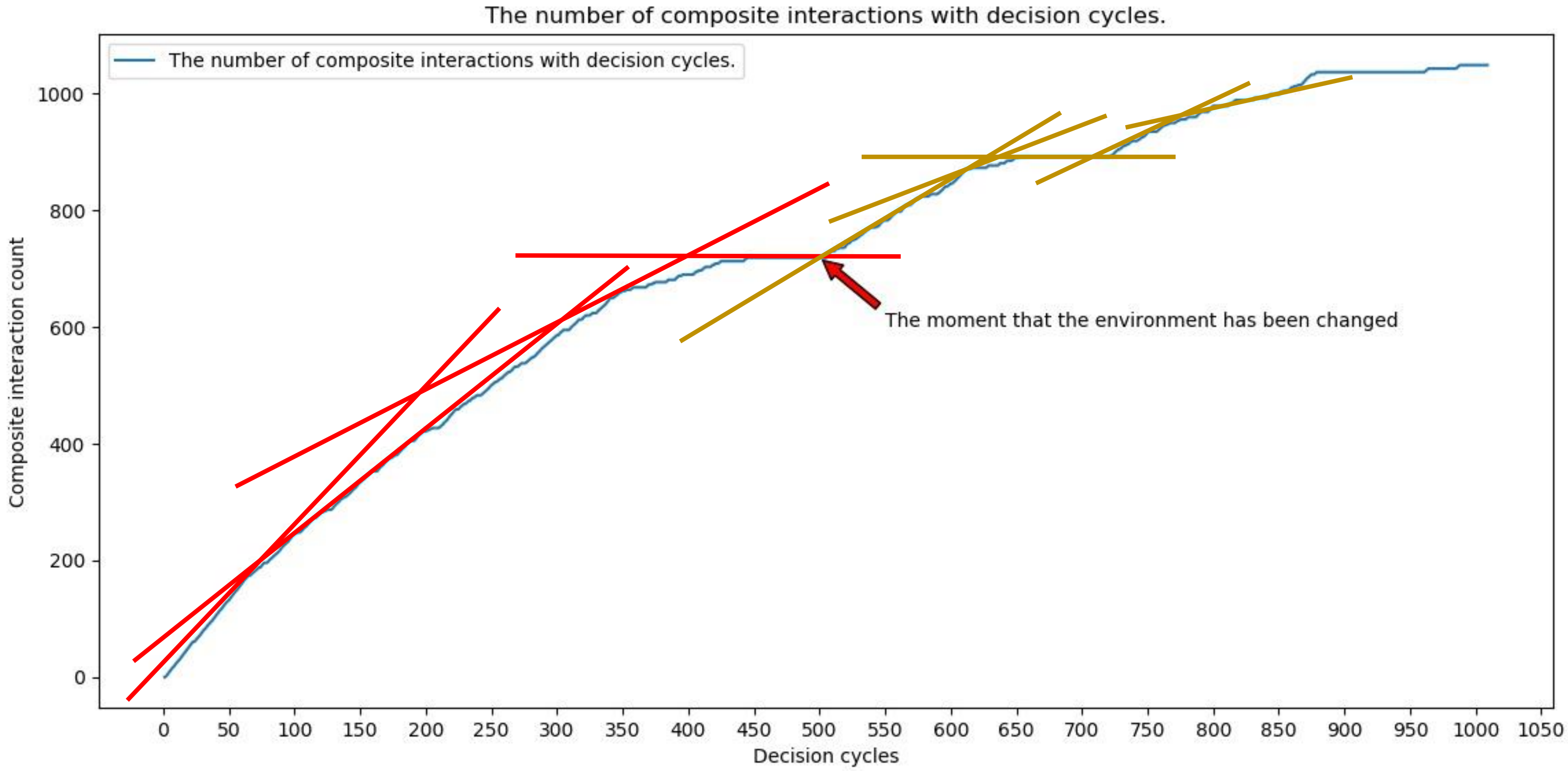

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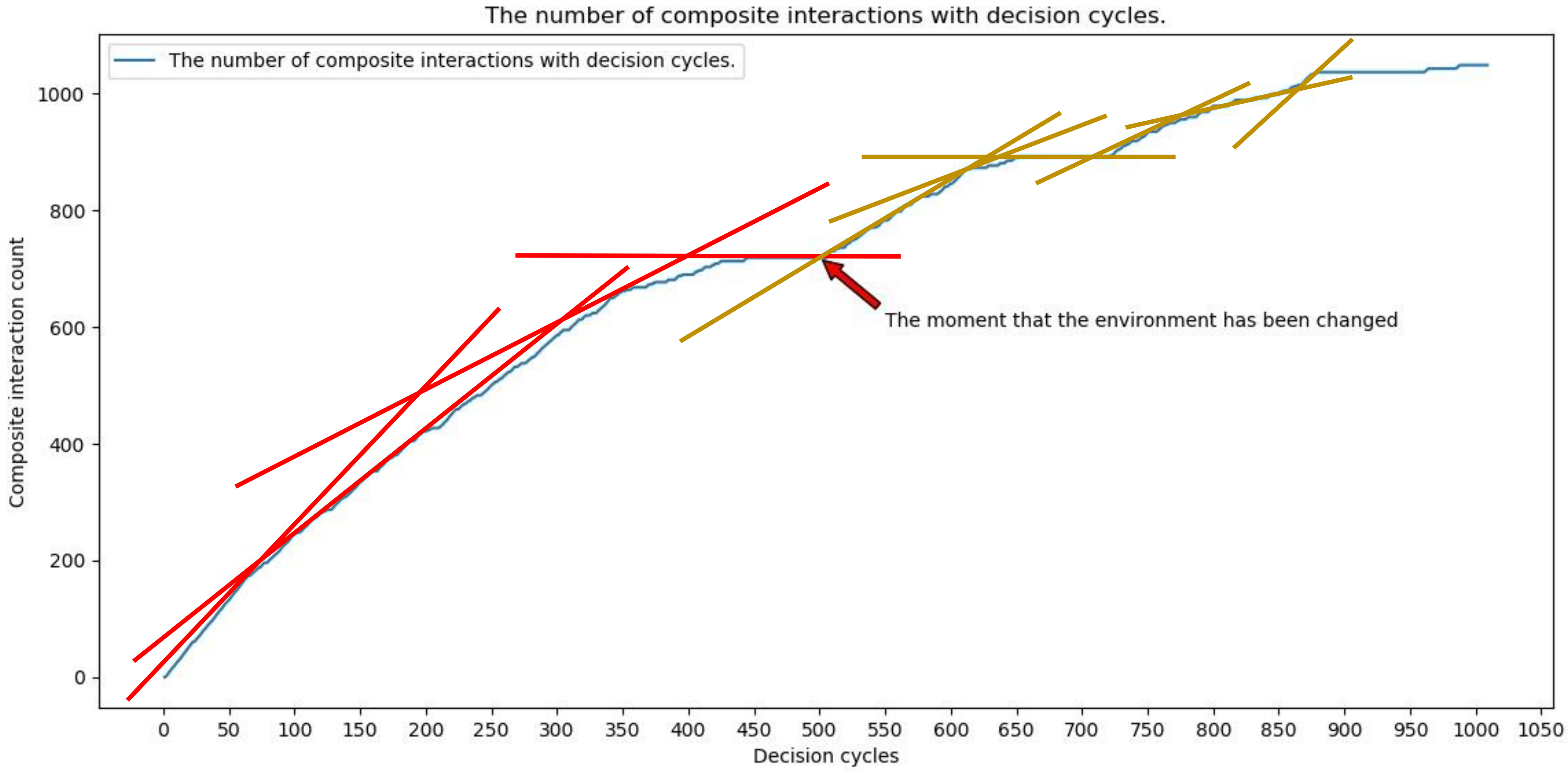

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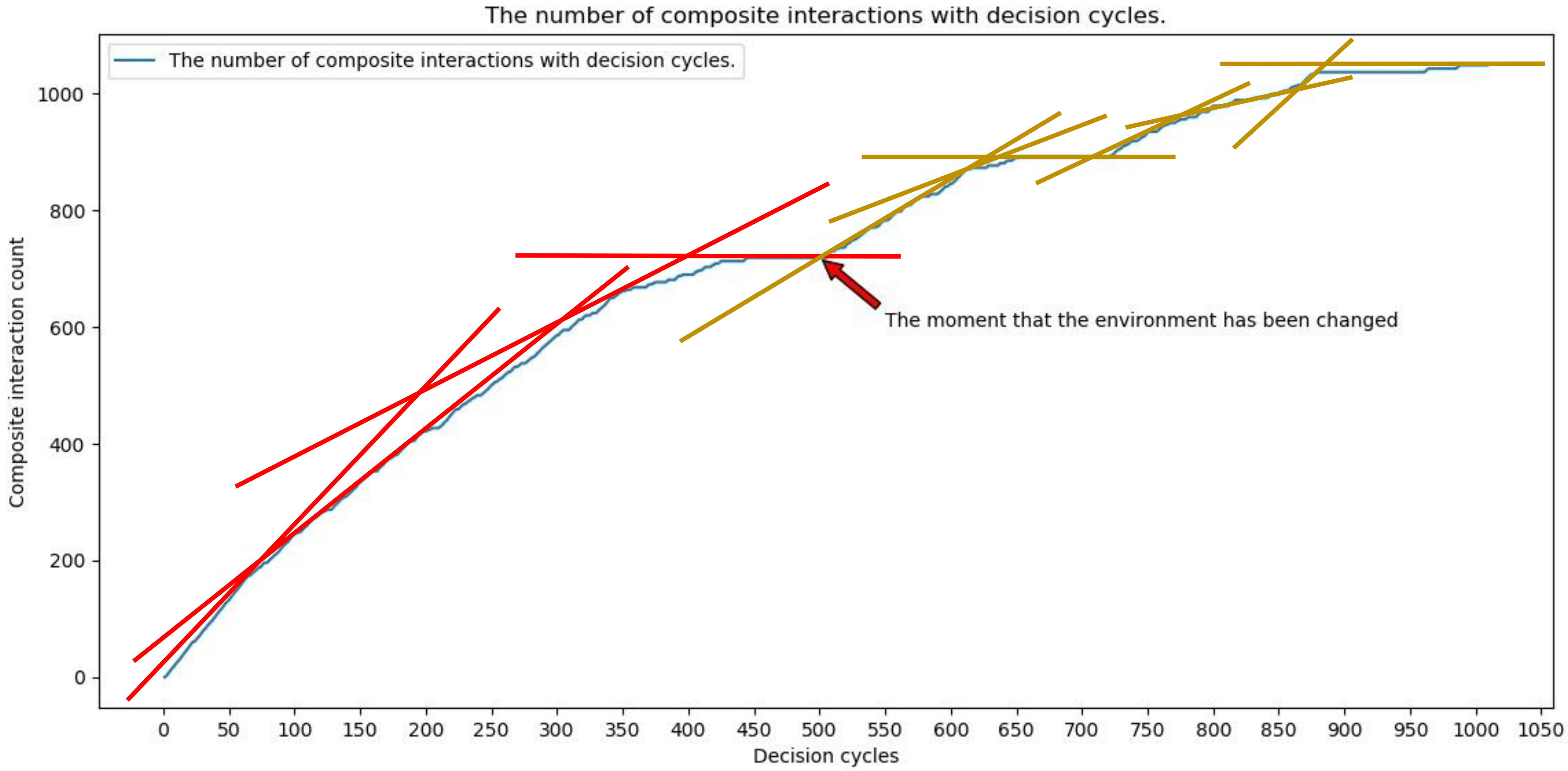


Discussion

☐ How to obtain a optimal set of valences for primitive interactions?

The Combinatorial Optimization Problem

Methods	Mechanism	Characteristic	Related works
Manually select from experience	Randomly select one set in the approximate range and try them.	Small combination space.	+
Brute-force Algorithm	Search optimal set from all possibilities of combinations	Small combination space with simple scenarios.	Lin 2009; Fellows et al. 2012; Bernstein 2005
Monte Carlo Algorithm	Select the global optimal from random local optimal	Massive combination space with complex scenarios.	Gutjahr 2003; Rubinstein and Kroese 2013; Sabar and Kendall 2015;.

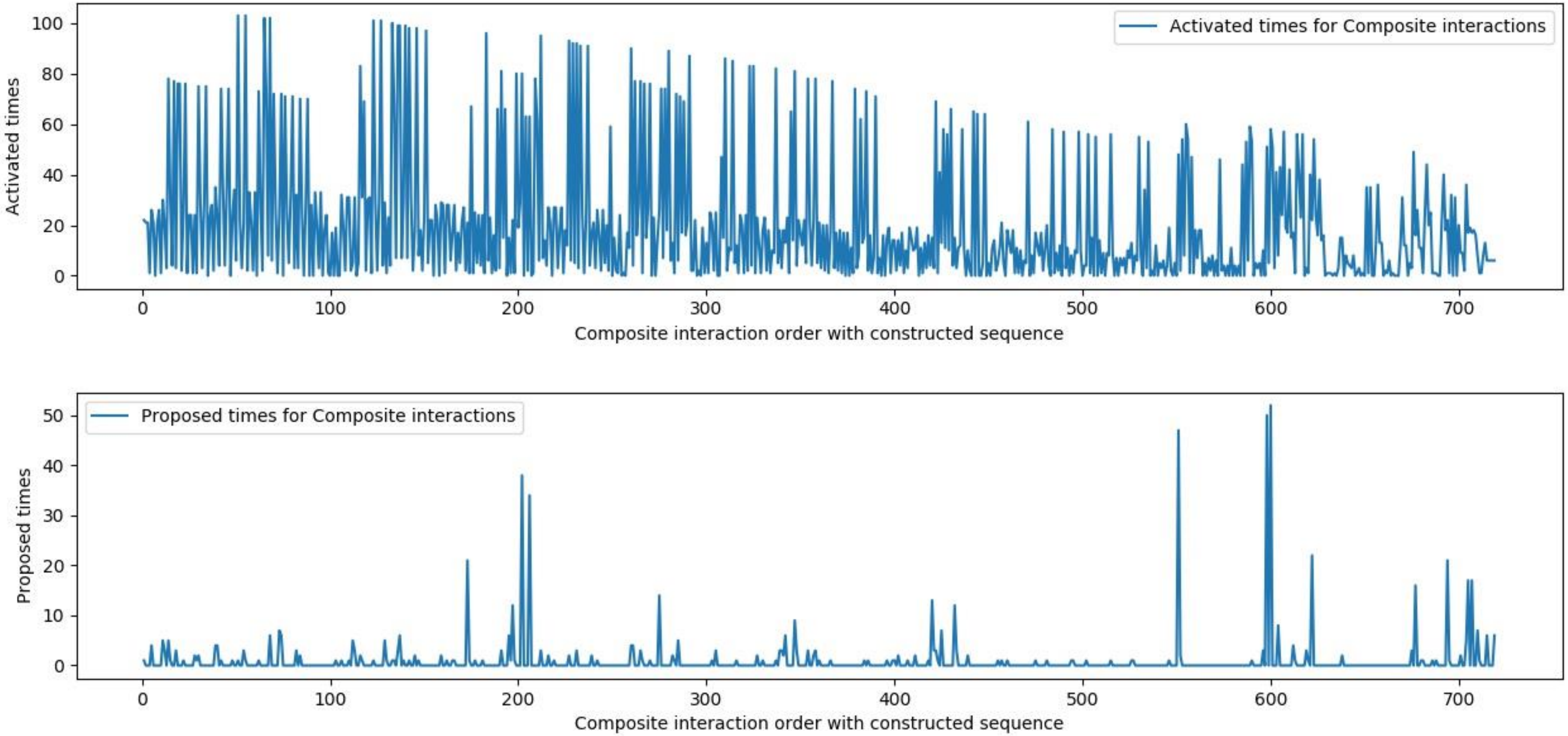
Conclusion

- The constructivist cognitive architecture.
  - Self-motivated agent makes sense of interactions.
  - Knowledge construct of the world (environment + itself).
  - Acquirement capabilities of self-adaption and flexibility.
- The demonstrations.
  - CCA's ability to discover and learn regularities of interaction.
  - Constructing causal perception between phenomena.
  - Bottom-up hierarchical sequential learning.
- The toolkit of GAIT.
- Self-motivated robots on multiple platforms.

Limitations

- The CCA relies upon too many hard-coded function, some of these functions should be autonomously constructed from agent's interaction experience.
- In each decision cycle, the agent needs to retrospect all previous learned composite interactions to retrieve the whole memory in each decision cycle.
- In terms of scalability, the growth of composite interaction depends on agent's complexity and the usage rate of the composite interactions needs to be improved.

Limitations



The activated and proposed times of composite interactions

Perspectives

- **Optimizing our model and upgrading the toolkit.** An experience-based predictive model could be used in the selection mechanism for better proposing anticipations for the agent to interact with the environment.
- **The reorganization of memories from interactions.** With caching temporary behavioral patterns that could improve the learning efficiency and eliminating composite interactions that probably will be not used in the future.
- **Higher-level abstraction mechanisms** endow the agent has capabilities to adapt to different interaction scenarios and generate behaviors flexibly.
- **Acquiring the capability of exploration.** With changed environments, the agent should not persist in following the generated behaviors in each interaction. Instead, acquiring novel behaviors by exploring unfamiliar parts in the environment.

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https://xuejianyong.github.io/

Publications

- **Xue, Jianyong**, Olivier L. Georgeon, and Salima Hassas. "A Constructivist Approach and Tool for Autonomous Agent Bottom-up Sequential Learning." *International Journal of Educational and Pedagogical Sciences* 14.10 (2020): 886-894.
- Georgeon, Olivier L., Paul Robertson, and **Jianyong Xue**. "Generating Natural Behaviors using Constructivist Algorithms." *International Workshop on Self-Supervised Learning*. PMLR, 2020.
- **XUE, Jianyong**, GEORGEON, Olivier L., et GILLERMIN, Mathieu. Causality Reconstruction by an Autonomous Agent. In : *Biologically Inspired Cognitive Architectures Meeting*. Springer, Cham, 2018. p. 347-354.
- **XUE, Jianyong**, WU, Kehe, et ZHOU, Yan. A risk analysis and prediction model of electric GIS based on deep learning. *International Journal of Computational Science and Engineering*, 2019, vol. 18, no 1, p. 39-43.

Merci