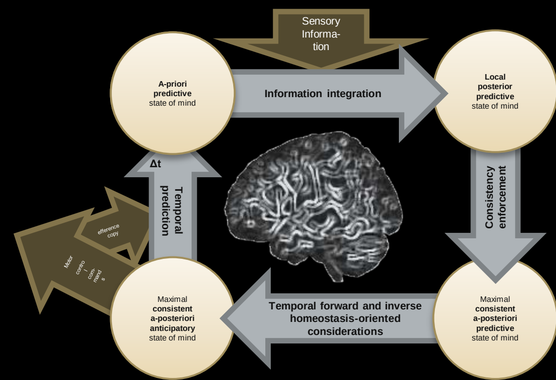
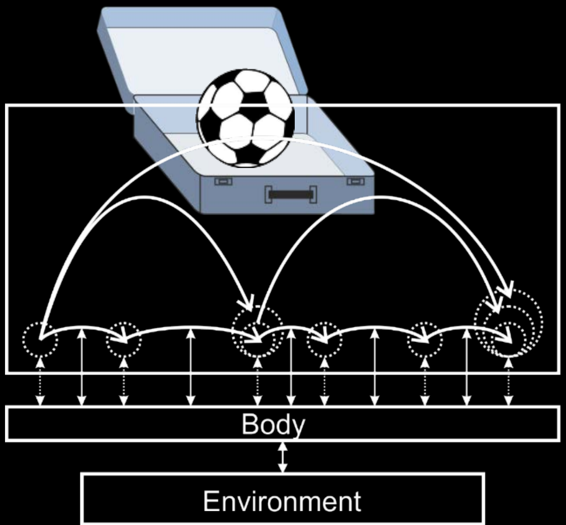
Chair of Cognitive Modeling
Department of Computer Science & Department of Psychology
Faculty of Science
University of Tübingen





An Integrative, Event-Predictive Theory of Cognition

Behavioral Evidence and Artificial Neural Network Models

Example 1: The Disappearing Hand Trick

(closely related to the Rubber Hand Illusion)

by Roger Newport, Helen Gilpin, & Catherine Preston

General Explanation of the Disappearing Hand Trick

- *Our brain attempts to*

  ***continuously** maintain a*

  ***consistent** postural “**image”** of*

  *our own **body’s** current state.*

  (body posture as well as
  its position and orientation relative to the outside environment)

Example 2: Levesque's Winograd Schema Challenge

(Levesque, 2011), The Winograd Schema Challenge

- Consider the following sentence:

  The ball fits into the suitcase,
  *because it is **large**.*

➢ Grammatical regularities lead to (slight) garden path effect:

  ➢ Pronoun is more likely to reference the subject, i.e., "the ball".

- Which leads to **surprise** and a revision of the pronoun referent model.

Butz, M. V. (2017). Which Structures Are Out There. In T. K. Metzinger & W. Wiese, T. K. Metzinger & W. Wiese (Eds.), *Philosophy and Predictive Processing*. Frankfurt am Main: MIND Group. Retrieved from http://predictive-mind.net/papers/which-structures-are-out-there

General Explanation of Sentence Comprehension

- *Our brain attempts to **continuously** construct a **consistent** semantic “image” of the described state of affairs.*

Butz, M. V. (2017). Which Structures Are Out There. In T. K. Metzinger & W. Wiese, T. K. Metzinger & W. Wiese (Eds.), *Philosophy and Predictive Processing*. Frankfurt am Main: MIND Group. Retrieved from http://predictive-mind.net/papers/which-structures-are-out-there

General Explanation for Both Examples

- Our brain attempts to continuously construct (on the fly) a **consistent postural / semantic “image”** of the perceived state of affairs.

- It predicts next sensory inputs (e.g. words, visual information about the hand) and is surprised when certain predictions are violated, attempting to revise the “image” accordingly.

In the examples:

1. Reaching for the other hand yields empty space – leading to the disappearing hand illusion and then quickly the revision of the postural image.
2. Binding of pronoun *it* yields a “**semantic model”** that indicates a reasoning inconsistency, thus requiring a revision.

Butz, M. V. (2017). Which Structures Are Out There. In T. K. Metzinger & W. Wiese, T. K. Metzinger & W. Wiese (Eds.), *Philosophy and Predictive Processing*. Frankfurt am Main: MIND Group. Retrieved from http://predictive-mind.net/papers/which-structures-are-out-there

Many Open Questions about the Details

- **What is a semantic image ?**
- **How is it constructed** by and within our brain ?
- **Which encodings** are involved ?
- How are the involved encodings
  dynamically (& selectively) **activated** ?
- How can these encodings be **learned** ?

Butz, M. V. (2016). Towards a Unified Sub-Symbolic Computational Theory of Cognition. *Frontiers in Psychology, 7*, 10.3389/fpsyg.2016.00925.
Butz, M. V. & Kutter, E. F. (2017). How the Mind Comes Into Being: Introducing Cognitive Science from a Functional and Computational Perspective. Oxford, UK: Oxford University Press.

Brain as a Generative / Predictive Model

(cf. e.g. Moshe Bar, Horace Barlow, Lawrence Barsalou, Karl Friston, Peter König, and many others…)

- The brain develops a **generative, predictive model** of the encountered environment in order to interact with it in an effective, goal-directed manner.

- The **free energy principle** allows the formalization of this development – including the involved behavior – but …

  - … the formalism **is overly general**.

  - **Structural, inductive biases –**
    that is, tendencies to develop certain encoding structures –
    must shape cognitive development further!

Butz, M. V. (2016). Towards a Unified Sub-Symbolic Computational Theory of Cognition. *Frontiers in Psychology, 7*, 10.3389/fpsyg.2016.00925.
Butz, M. V. & Kutter, E. F. (2017). How the Mind Comes Into Being: Introducing Cognitive Science from a Functional and Computational Perspective. Oxford, UK: Oxford University Press.

Types of Predictive Encodings & Inductive Biases

- At least 3 fundamental types of predictive encodings are distinguishable:
  - **Spatial**
    - **E.g.: relative spatial mappings of entities and frames of reference**
  - **Top-down**
    - **E.g.: Gestalt-related perceptual expectations**
  - **Temporal**
    - E.g.: Sensorimotor codes but also force-dependent codes

- **Significant free energy signal changes** lead to the encoding of
  - **Events**
    - ➢ **Active set of P.E.s**
    - ➢ **Predictive attractors with low residual error**
  - **Event boundary / event transition encodings**
    - ➢ **Predictions across event attractors**

Butz, M. V. (2016). Towards a Unified Sub-Symbolic Computational Theory of Cognition. *Frontiers in Psychology*, *7*, 10.3389/fpsyg.2016.00925.
Butz, M. V. & Kutter, E. F. (2017). How the Mind Comes Into Being: Introducing Cognitive Science from a Functional and Computational Perspective. Oxford, UK: Oxford University Press.

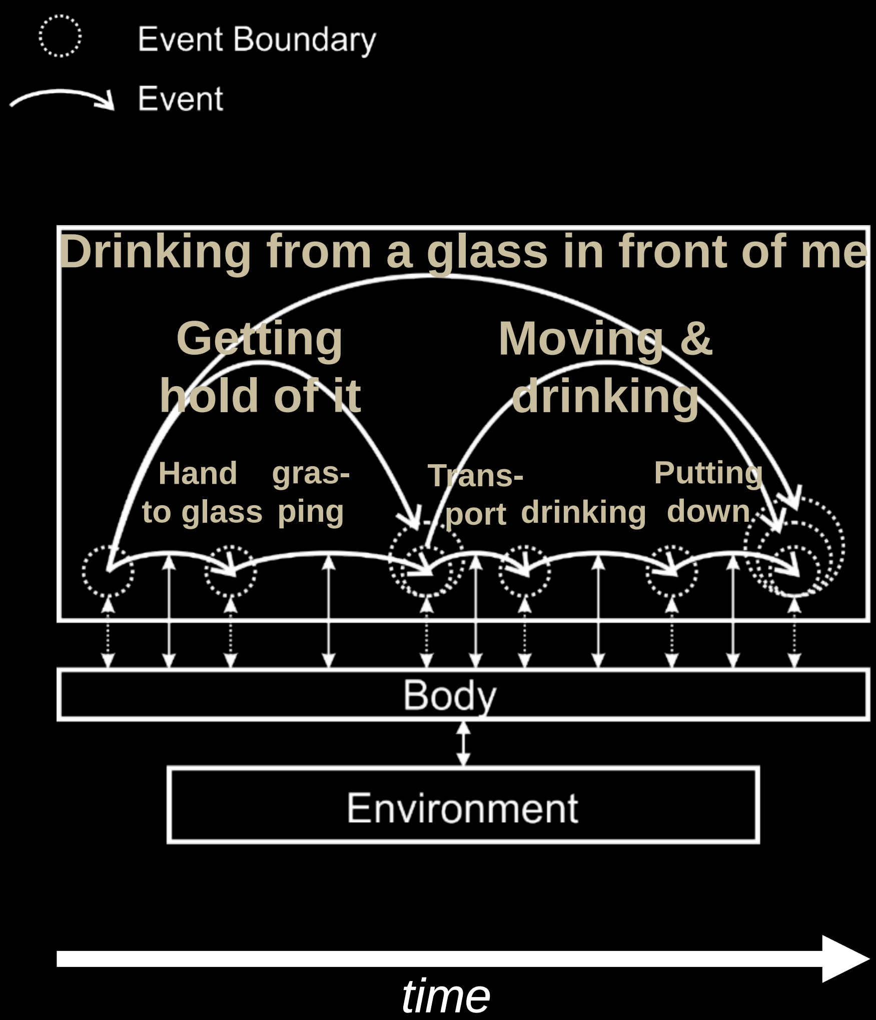
Event Schemata & Hierarchies

- E**vent-schemata** can be formed, which encode
  - **Preconditions** necessary to initiate an event;
  - **Final consequences** that are typically reached when the event ends;
  - The **event code** itself.

- **Hierarchically organized event encodings** enable
  - hierarchical, conceptual,
    goal-directed planning / reinforcement learning and behavioral control;
  - conceptual and hypothetical reasoning.

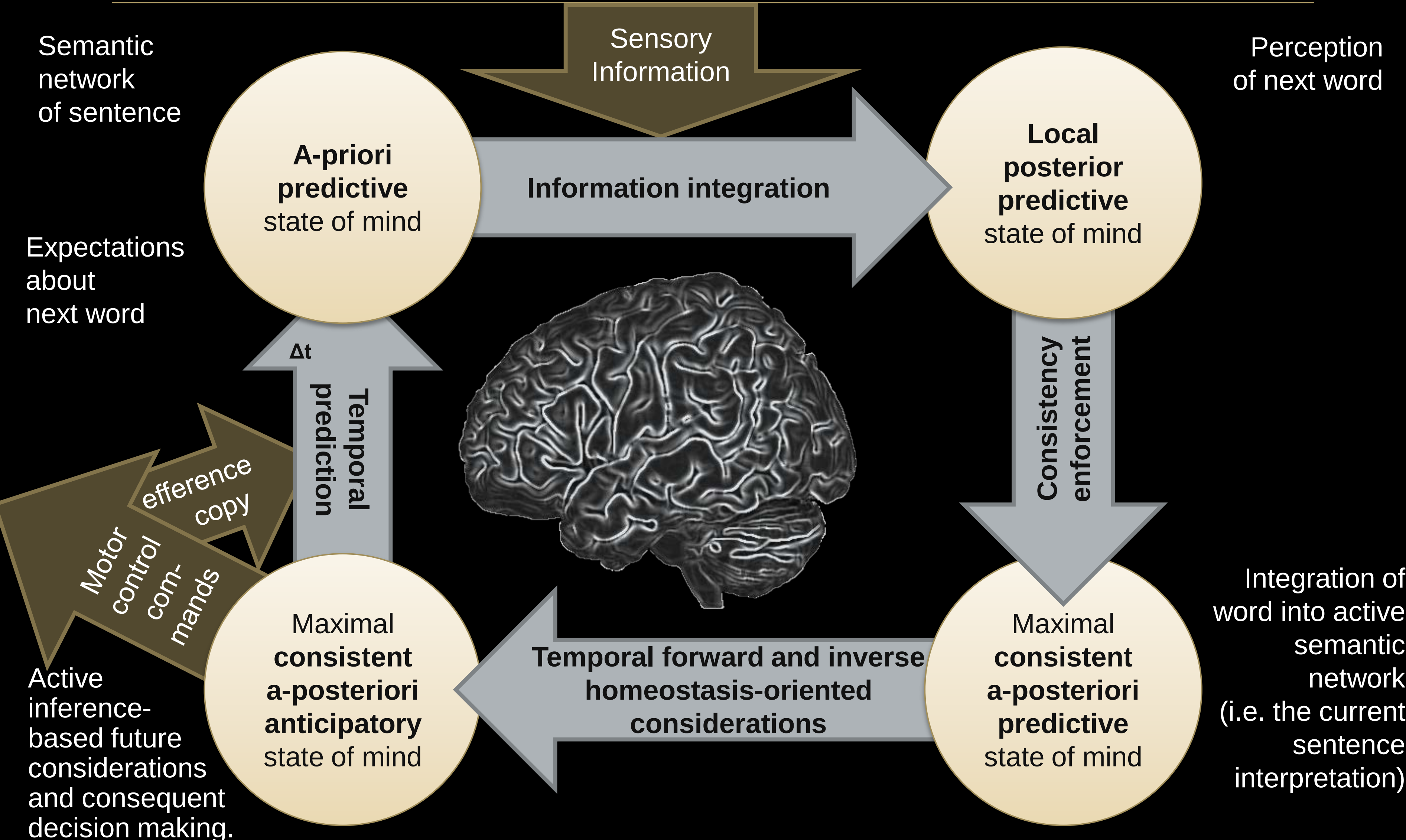
Butz, M. V. (2016). Towards a Unified Sub-Symbolic Computational Theory of Cognition. *Frontiers in Psychology, 7*, 10.3389/fpsyg.2016.00925.
Butz, M. V. & Kutter, E. F. (2017). How the Mind Comes Into Being: Introducing Cognitive Science from a Functional and Computational Perspective. Oxford, UK: Oxford University Press.

Nested Event Schemata Yield Hierarchical Structure



- Events
  - Predictive (probabilistic) encoding **network** of how (sensorimotor, -force, & more abstract) dynamics unfold over time.
- Event Boundaries
  - Conditional predictive encodings of event transitions.
- Event Hierarchy
  - Hierarchical / taxonomical structure of events, event boundaries and their typical interactions.

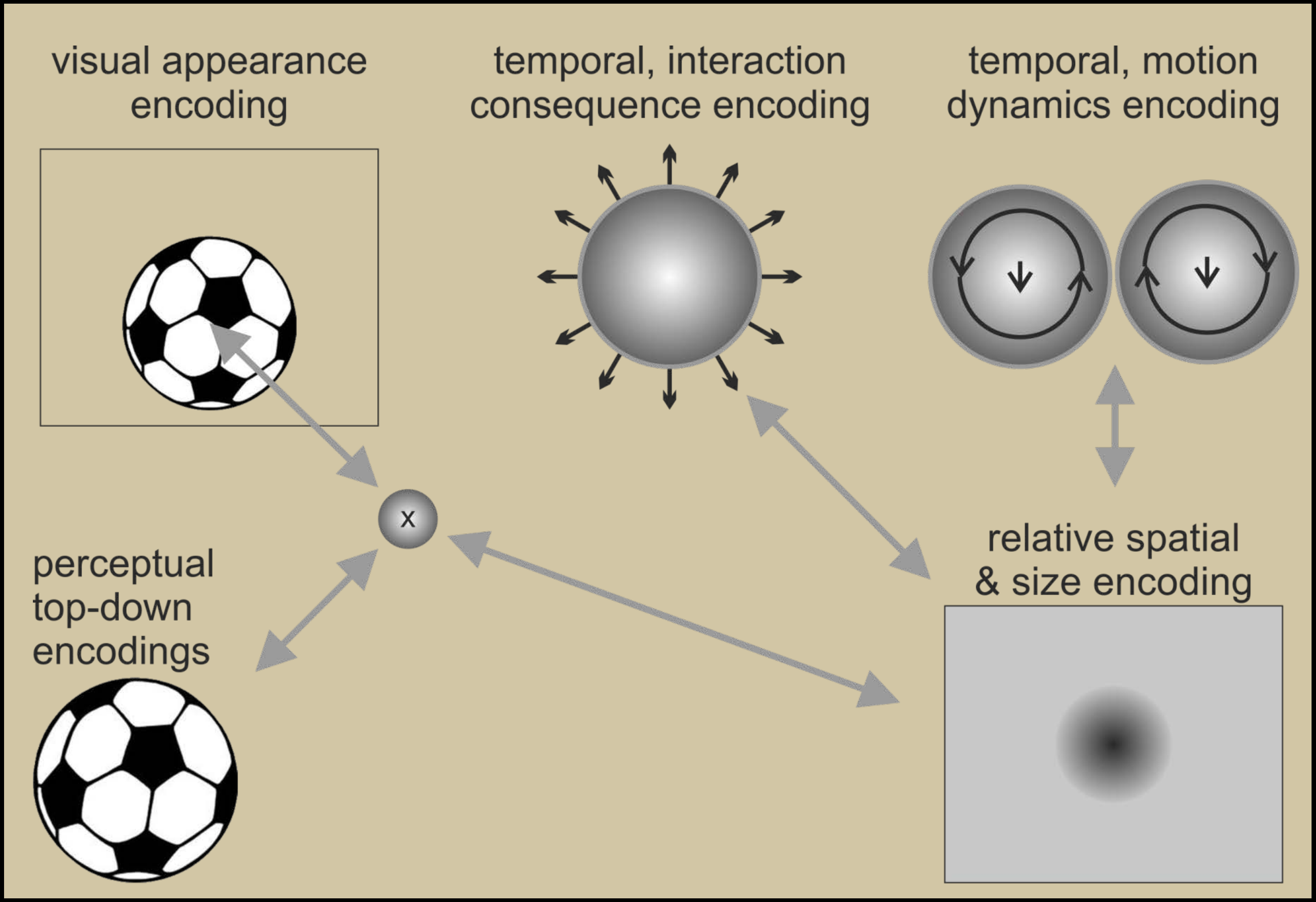
Unfolding Predictive & Active Inferences



Butz, M. V. (2016). Towards a Unified Sub-Symbolic Computational Theory of Cognition. *Frontiers in Psychology*, *7*, 10.3389/fpsyg.2016.00925.
Butz, M. V. & Kutter, E. F. (2017). How the Mind Comes Into Being: Introducing Cognitive Science from a Functional and Computational Perspective. Oxford, UK: Oxford University Press.

“The ball fits into the suitcase, because it is large.”

The ball …



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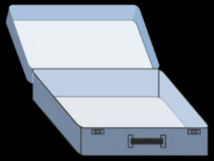
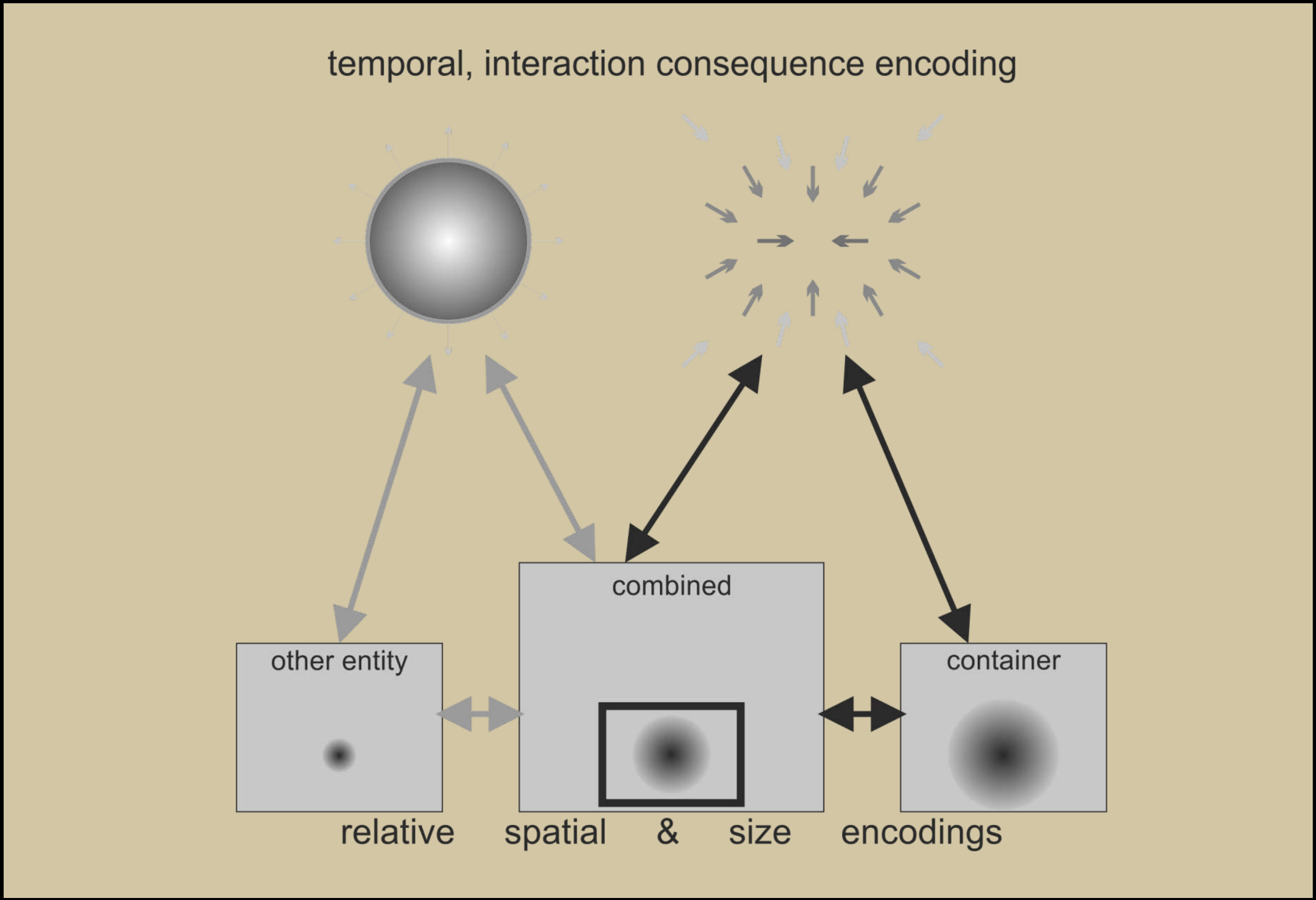
“The ball fits into the suitcase, because it is large.”

… fits into …





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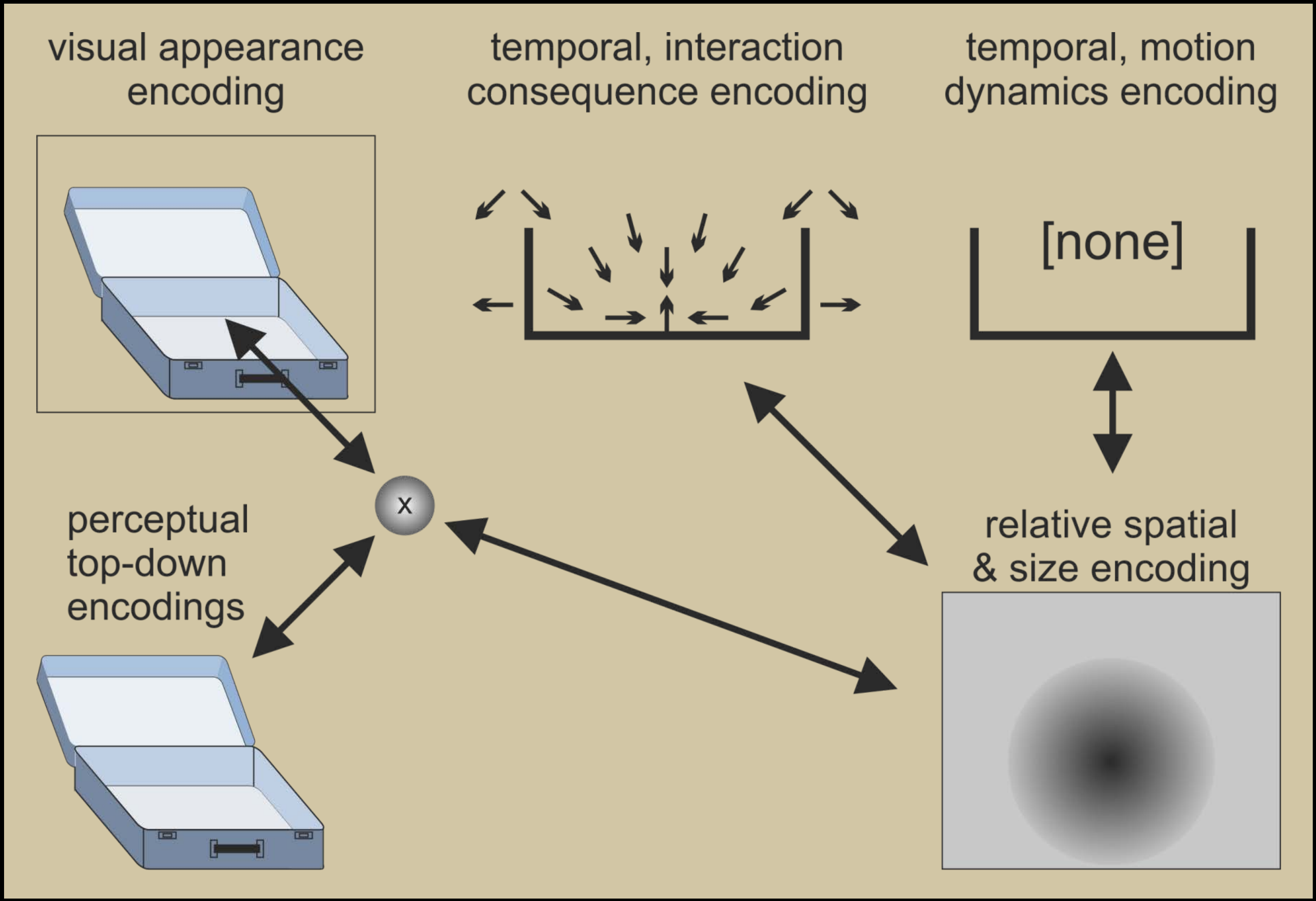
"The ball fits into the suitcase, because it is large."

… the suitcase



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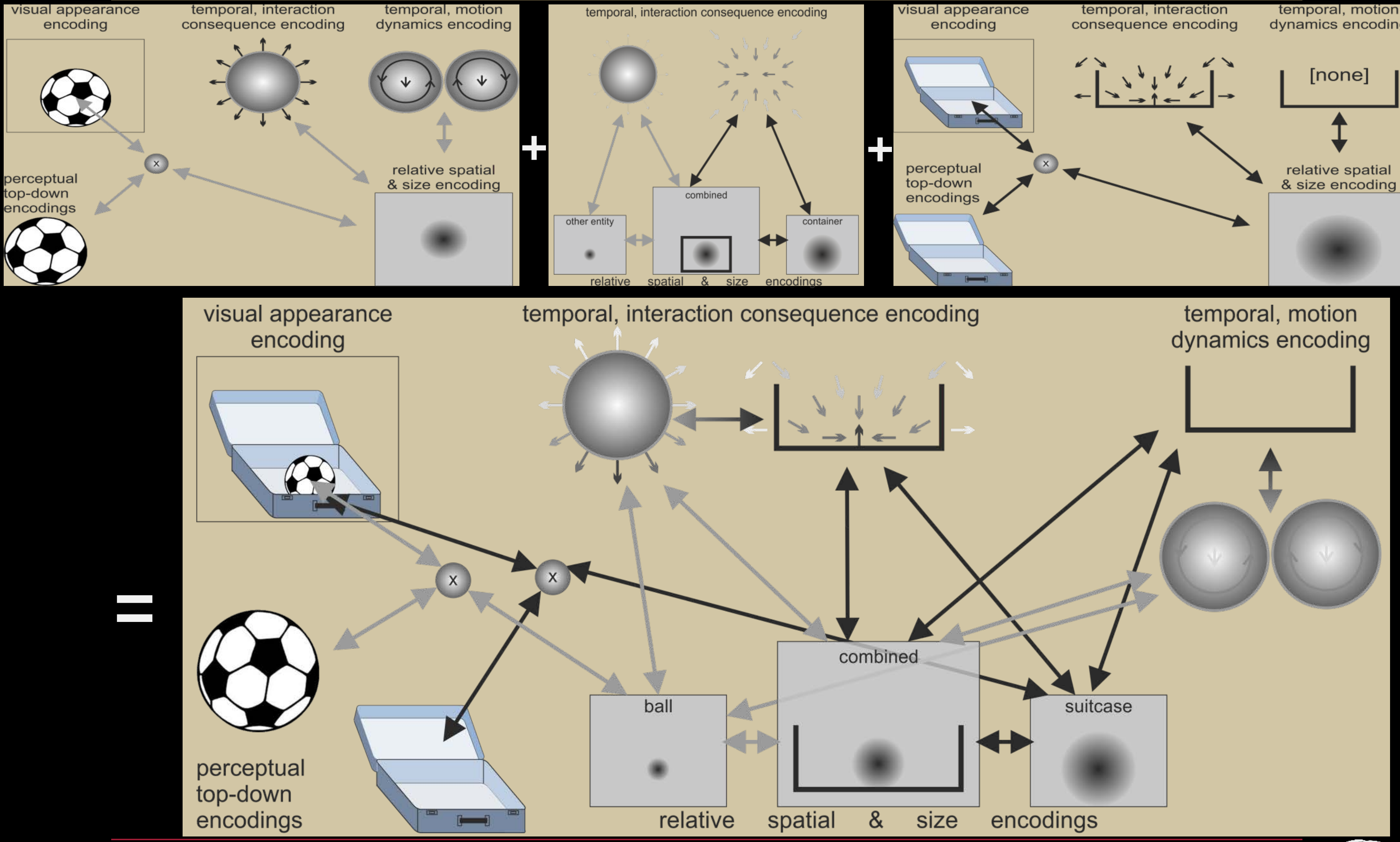
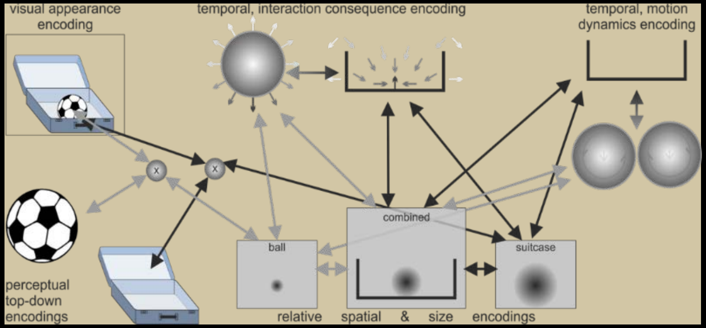
“The ball … fits into … the suitcase.”



Butz, M. V. (2017). Which Structures Are Out There. In T. K. Metzinger & W. Wiese, T. K. Metzinger & W. Wiese (Eds.), *Philosophy and Predictive Processing*. Frankfurt am Main: MIND Group. Retrieved from http://predictive-mind.net/papers/which-structures-are-out-there

“The ball fits into the suitcase, because it is large.”

“The ball fits into the suitcase....”



“… because it is large.”

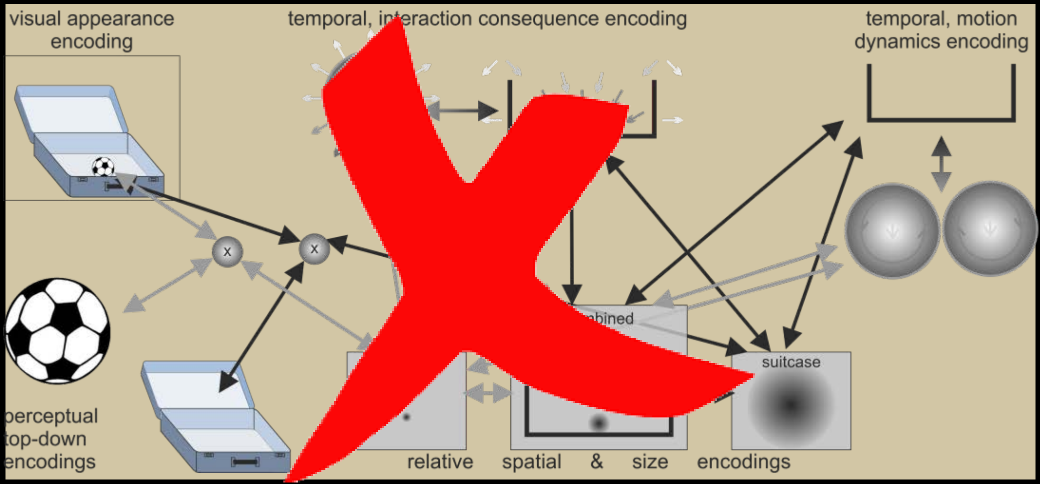
This implies:

“Was it small, then the first part of the sentence would be false.”

➢ **Counterfactual reasoning.**

“… because **the ball** is large?”

➢ “Was the ball small, the ball would still fit.



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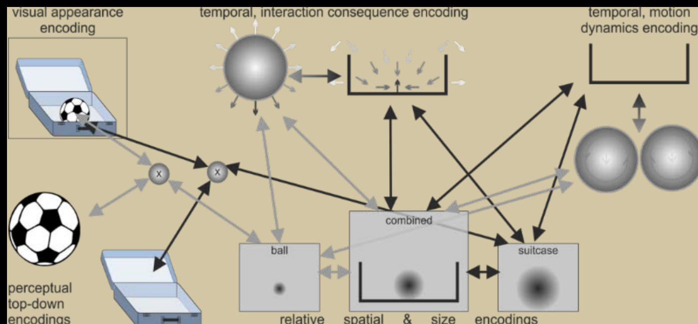
“The ball fits into the suitcase, because it is large.”

“The ball fits into the suitcase....”



“… because it is large.”

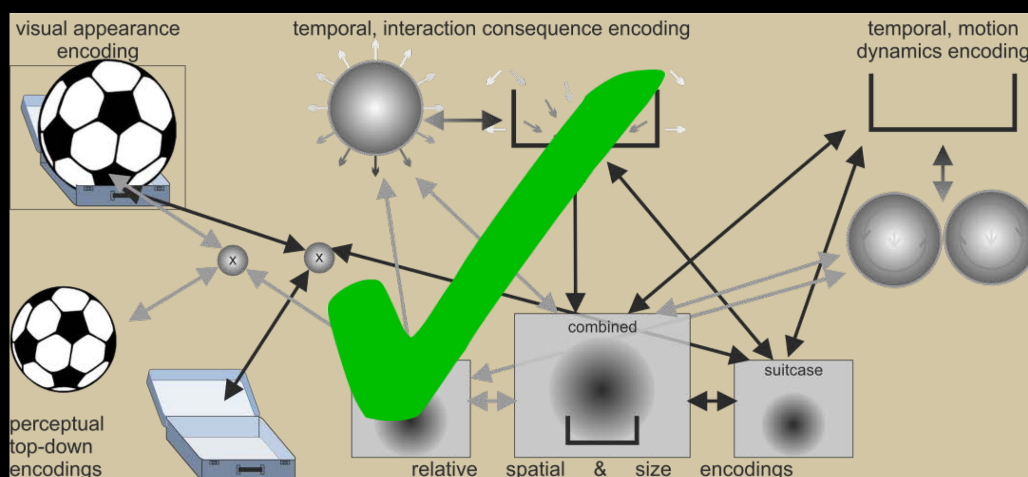
This implies:

“Was it small, then the first part of the sentence would be false.”

➢ **Counterfactual reasoning.**

“… because the **suitcase** is large?”

➢ “Was the suitcase small, the ball would NOT fit.”



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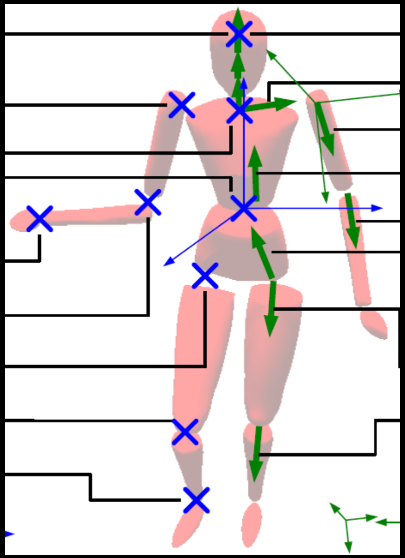
Neuro-Computational Cognitive Models

… and some psychological experiments.

1. **Event Dynamics**
2. **Inference of and within Events**
3. **Event Boundary Anticipation**
4. **Event Schemata: Segmentation and Inference**

1. Event Dynamics
2. Inference of and within Events
3. Event Boundary Anticipation
4. Event Schemata: Segmentation and Inference



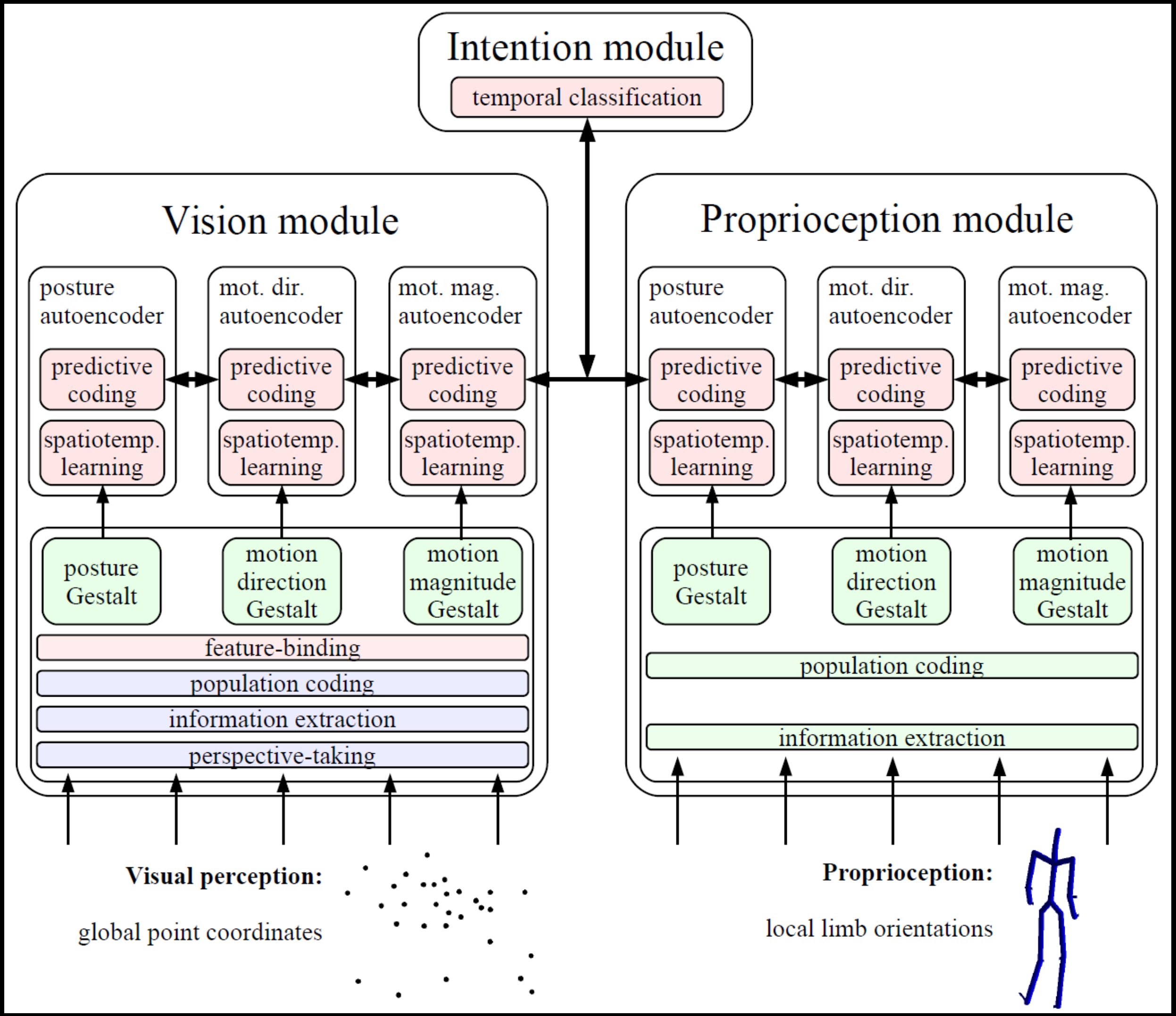
Learning to Infer Biological Motion Events

A Perspective Taking, Gestalt Inference, & Mirror Neuron Model

INFERENCE OF BIOLOGICAL MOTION

Schrodt, F. (2018). PhD dissertation.
Schrodt, F., & Butz, M. V. (2016). Just Imagine! Learning to Emulate and Infer Actions with a Stochastic Generative Architecture. *Frontiers in Robotics and AI*. doi:10.3389/frobt.2016.00005

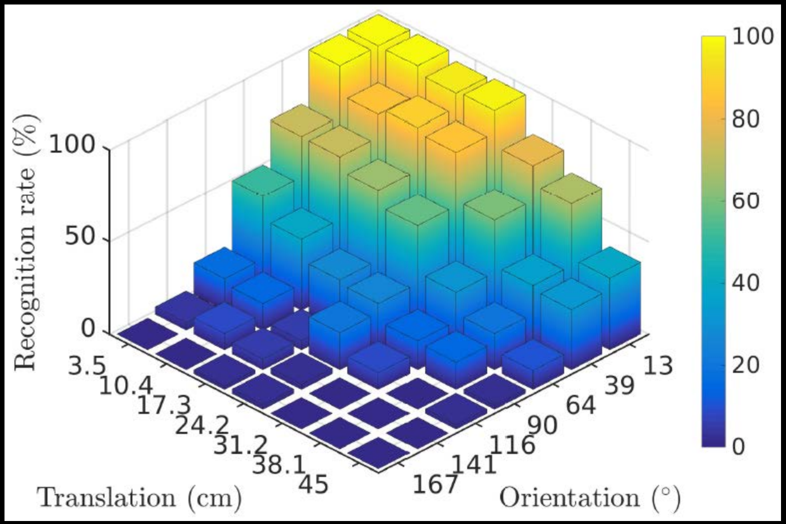
An ANN of Biological Motion Inference

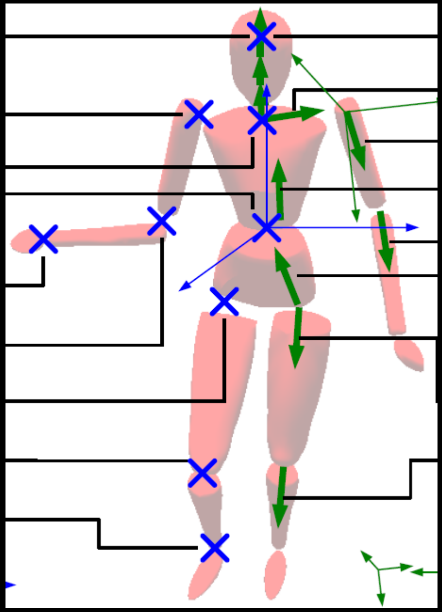


- “Intention module” clusters types of motion via a supervised temporal autoencoder
- Spatiotemporal autoencoders predict cluster-interdependencies and dynamics over time
- Top-down predictive autoencoders yield biological motion clusters
- Separation into posture, motion direction, & -magnitude Gestalt encodings
- Perspective- & focus-relative encodings

Schrodt, F. (2018). PhD dissertation.

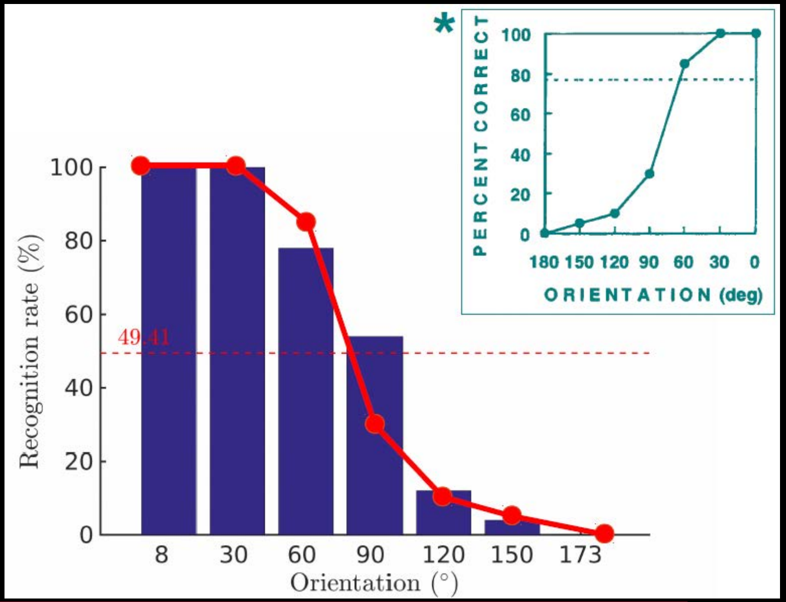
Generative ANN Model Evaluation





Trained on 3 types of motions
- 15 Location features
- 16 limb orientation features

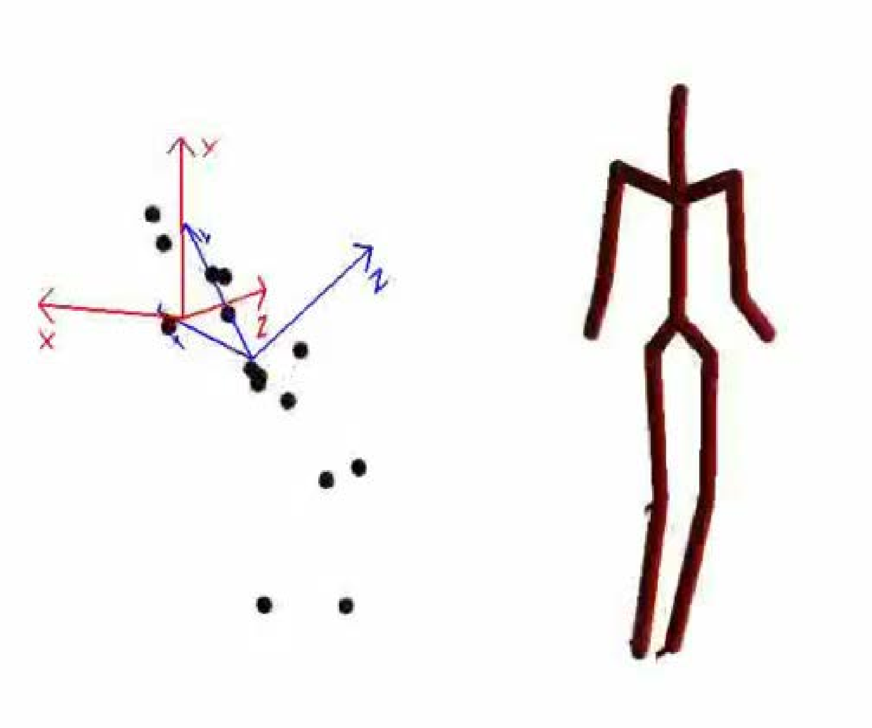
Tested on location input only
- Other motion data of the same 3 types
- 15 distractors during testing
- Random assignment of location feature inputs.
  - Right bottom: Comparison with human data published in Pavlova & Sokolov (2000, Perception & Psychophysics)



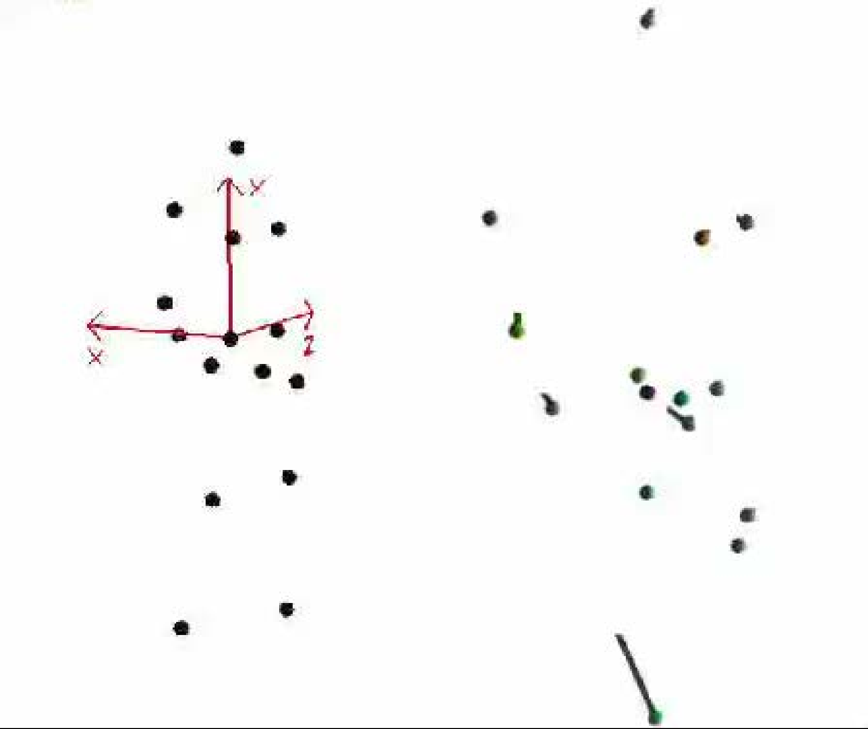
Schrodt, F. (2018). PhD dissertation.

Exemplar Model Capabilities

Inference of Perspective & Type of Motion (Color Code)



Inference of Gestalt & Proprioceptive Resonance



Stimulus and FORs vs. **Model Expectation**
(1/5 speed)

Stimulus and FORs vs. **Model Expectation**
(1/5 speed)

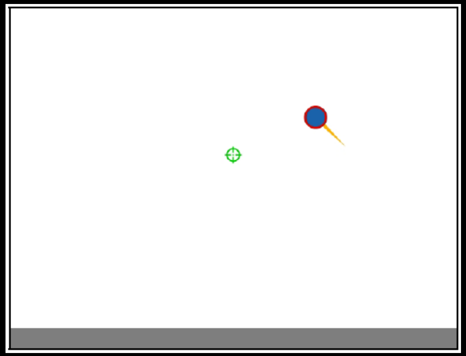
Sensorimotor forward model used for control

NEURAL ACTIVE-INFERENCE-BASED IMAGINING AND CONTROL

Sebastian Otte, Theresa Schmitt, Karl Friston, & Martin V. Butz (2017). Inferring adaptive goal-directed behavior within recurrent neural networks. *ICANN 2017*.

The RNN Model

"Rocket" scenario



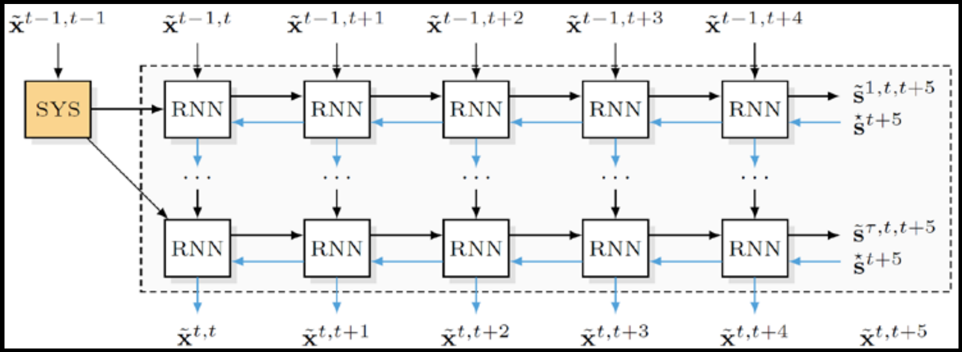
- Recurrent neural network architecture (LSTM) learns a sensorimotor forward model.
- **Scenario**: A "rocket" with simulated gravity and two thrust motors
- Input to the LSTM:
  - Current location of rocket and current motor activity
- Output of the LSTM:
  - Resulting velocity and next location of rocket
- During training:
  - Training samples of somewhat systematic random explorations
- During testing:
  - Active inference-based motor control derivation

Sebastian Otte, Theresa Schmitt, Karl Friston, & Martin V. Butz (2017). Inferring adaptive goal-directed behavior within recurrent neural networks. *ICANN 2017*.

Controlling a Glider

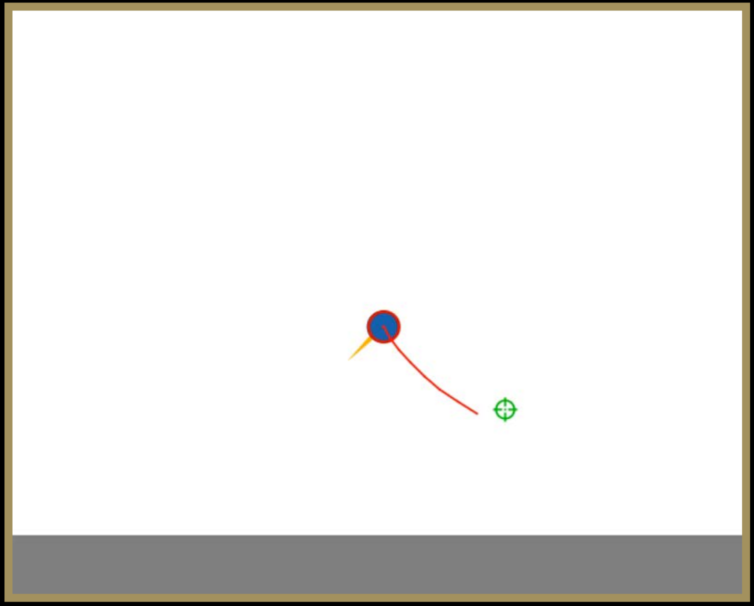
(Otte, Schmitt, Friston, & Butz, ICANN 2017)

- Learning a sensorimotor forward model with an RNN (LSTM)



- Control via active inference:
  - Attempting to reach goal state $\boldsymbol{M_G}$
  - Inferring policy π by maximizing expected Q_τ over expected future model states $\boldsymbol{M_\tau}$ and observations $\boldsymbol{o_\tau}$.

$$
\begin{aligned}
&Q_\tau(\pi, s_t) = \\
&-D_{KL}[P(\boldsymbol{o_\tau}|\boldsymbol{M_\tau})||P(\boldsymbol{o_\tau}|\boldsymbol{M_G})] \\
&-E_\pi\left[H\left(P(\boldsymbol{o_\tau}|\boldsymbol{M_\tau})\right)\right]
\end{aligned}
$$



Sebastian Otte, Theresa Schmitt, Karl Friston, & Martin V. Butz (2017). Inferring adaptive goal-directed behavior within recurrent neural networks. *ICANN 2017*.

1. Event Dynamics
2. b) Inference of and within Events
3. Event Boundary Anticipation
4. Event Schemata: Segmentation and Inference

Concurrent Event Inference and Goal-Directed Control

REPRISE: A RETROSPECTIVE & PROSPECTIVE INFERENCE SCHEME

Martin V. Butz, David Bilkey, Alistair Knott, & Sebastian Otte (in press). REPRISE: A Retrospective and Prospective Inference Scheme. CogSci 2018.

The Setup

- Recurrent neural network architecture (LSTM) learns a sensorimotor forward model.
  - ➢ **With dedicated, stable hidden state event indicator neurons**

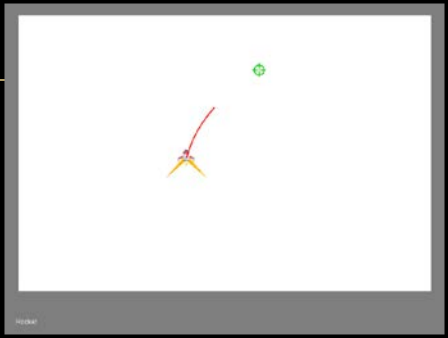
- **3 - “Event” Scenario**:
  1. “Rocket” simulation (2 thrust directions, inertia gravity)
  2. Stepper simulation (4 combinable directional step motions, no inertia)
  3. Glider simulation (4 thrust directions, inertia)

- Input to the LSTM:
  - Current location of the “vehicle” and current motor activity
- Output of the LSTM:
  - Resulting motion of rocket

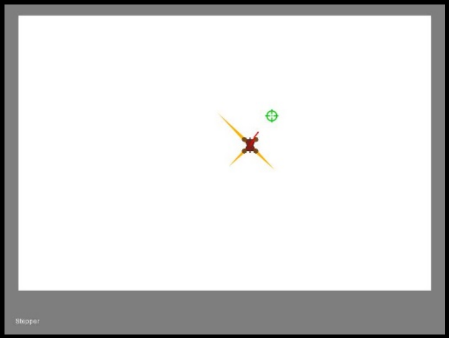
- During training:
  - Switching between three vehicles.
  - Switch triggers
    1. Retrospective (stable) hidden state inference
    2. BPTT learning

- During testing:
  - Retrospection: hidden state inference
  - Prospection: Active inference-based motor control derivation

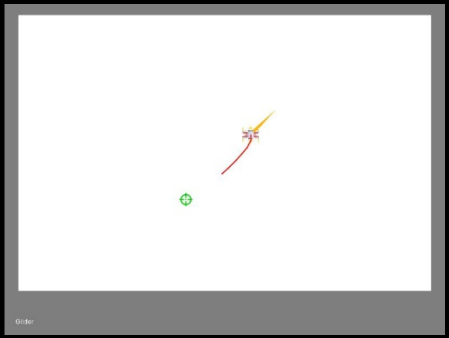
“Rocket” event



“Stepper” event



“Glider” event



Martin V. Butz, David Bilkey, Alistair Knott, & Sebastian Otte (in press). REPRISE: A Retrospective and Prospective Inference Scheme. CogSci 2018.

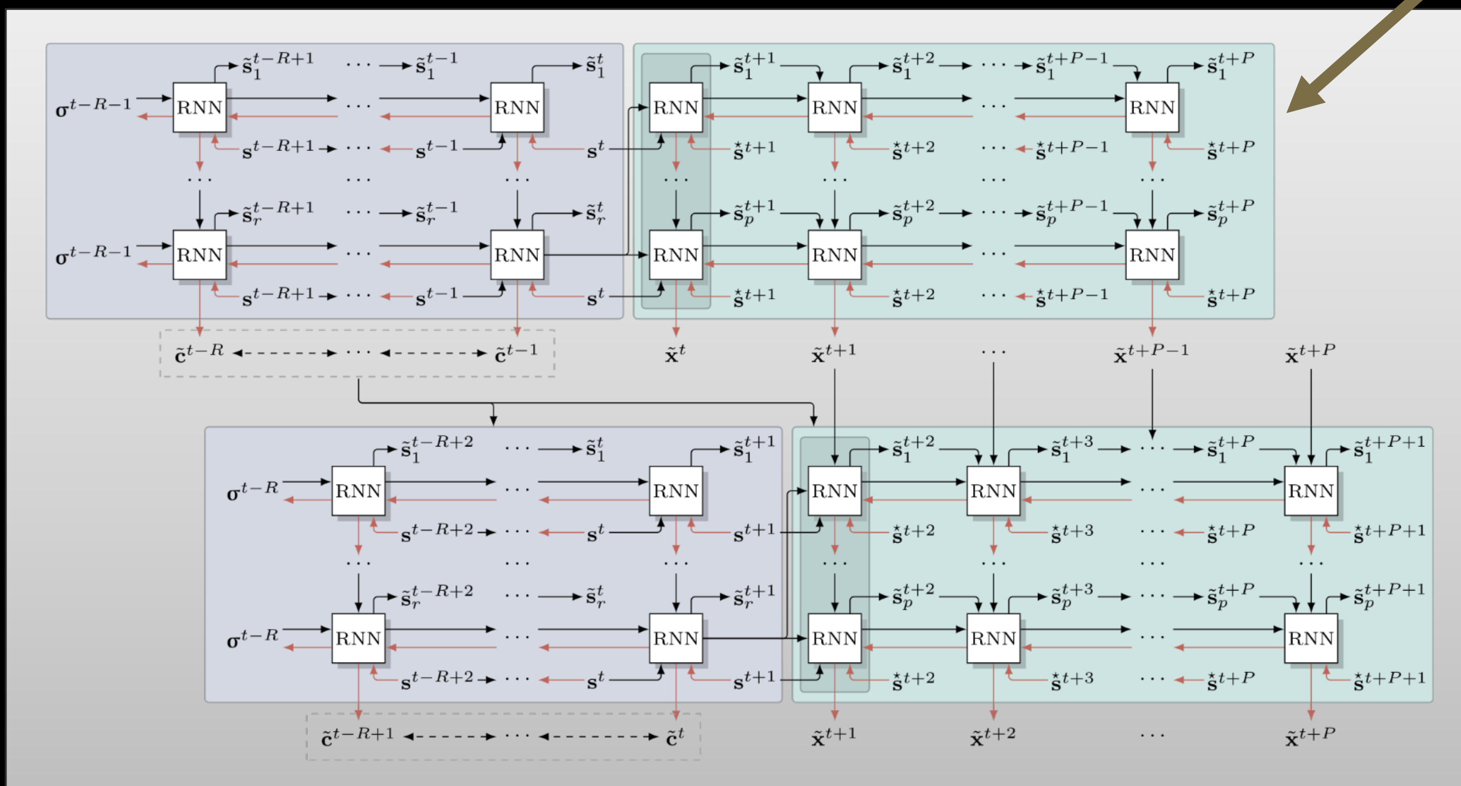
REPRISE: Retro- and Prospective Inference Dynamics

Retrospection (hidden state & event inference)

Predictive Current State

Prospection (active motor inference)

GOAL



Martin V. Butz, David Bilkey, Alistair Knott, & Sebastian Otte (in press). REPRISE: A Retrospective and Prospective Inference Scheme. CogSci 2018.

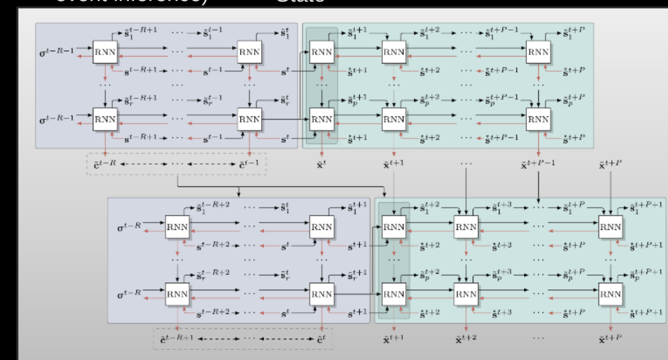
REPRISE Performance

Training

Retrospection (hidden state & event inference)

Predictive Current State

Random motor commands



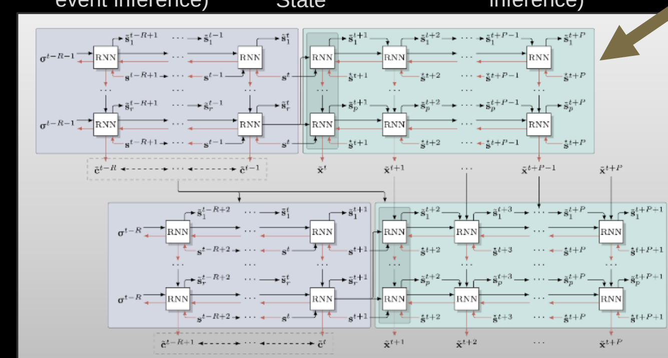
Testing

Retrospection (hidden state & event inference)

Predictive Current State

Prospection (active motor inference)

GOAL



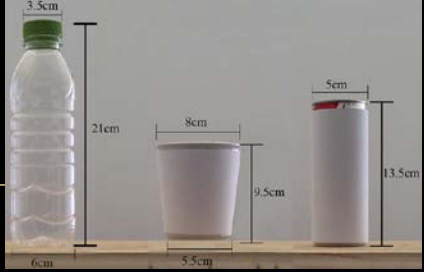
Martin V. Butz, David Bilkey, Alistair Knott, & Sebastian Otte (in press). REPRISE: A Retrospective and Prospective Inference Scheme. CogSci 2018.

Goal-Oriented Object Interactions

ANTICIPATING UPCOMING EVENT BOUNDARIES

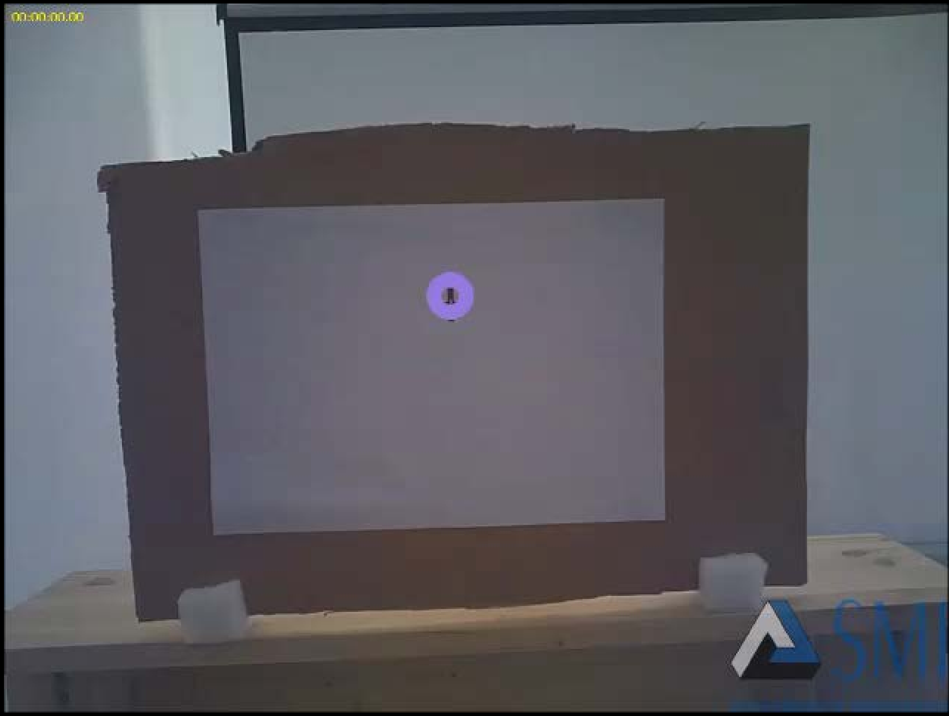
Belardinelli, A. & Butz, M. V. (2013). Gaze strategies in object identification and manipulation. *Annual Conference on Cognitive Science (CogSci 2013),* 1875-1880.
Belardinelli, A., Herbort, O., & Butz, M. V. (2015). Goal-oriented gaze strategies afforded by object interaction. *Vision Research, 106*, 47–57.
Belardinelli, A., Stepper, M. Y., & Butz, M. V. (2016). It's in the eyes: Planning precise manual actions before execution. *Journal of Vision, 16(1),* 18. doi:10.1167/16.1.18
Belardinelli, A., Barabas, M., Himmelbach, M., & Butz, M. V. (2016). Anticipatory eye fixations reveal tool knowledge for tool interaction. *Experimental Brain Research, 234*, 2415–2431.

Videos of Typical Trial Interactions



Task:
Grasp & *Drink* from object

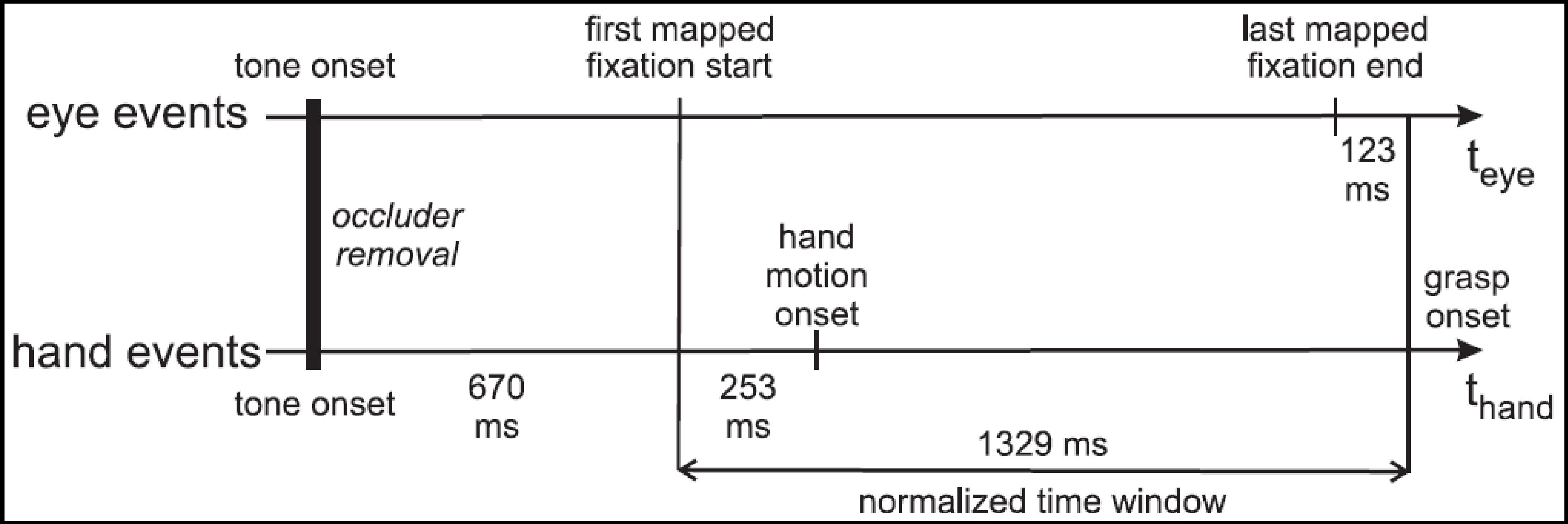
Task:
Grasp & *Handover* object



Belardinelli, A., Stepper, M. Y., & Butz, M. V. (2016). It's in the eyes: Planning precise manual actions before execution. *Journal of Vision, 16(1)*, 18. doi:10.1167/16.1.18

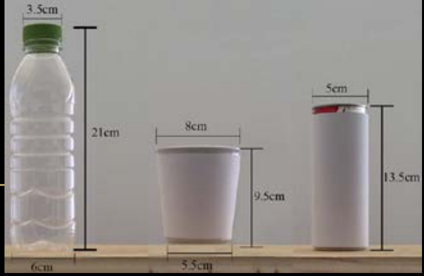
Time Course of the Average Trial

- Note the normalized time window from the first mapped fixation until grasp onset.



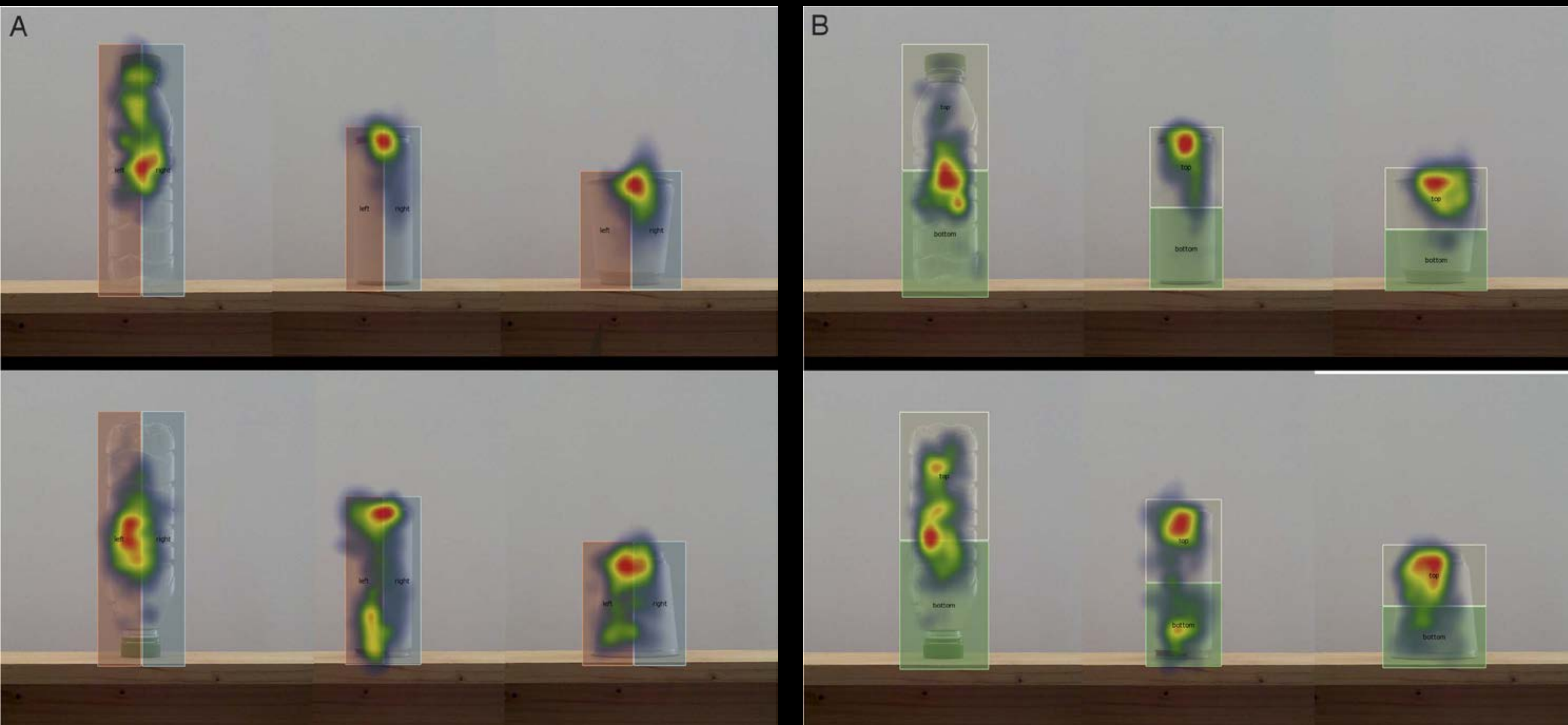
Belardinelli, A., Stepper, M. Y., & Butz, M. V. (2016). It's in the eyes: Planning precise manual actions before execution. *Journal of Vision, 16(1)*, 18. doi:10.1167/16.1.18

Heat maps until object grasp: Objects are fixated in the light of the final event



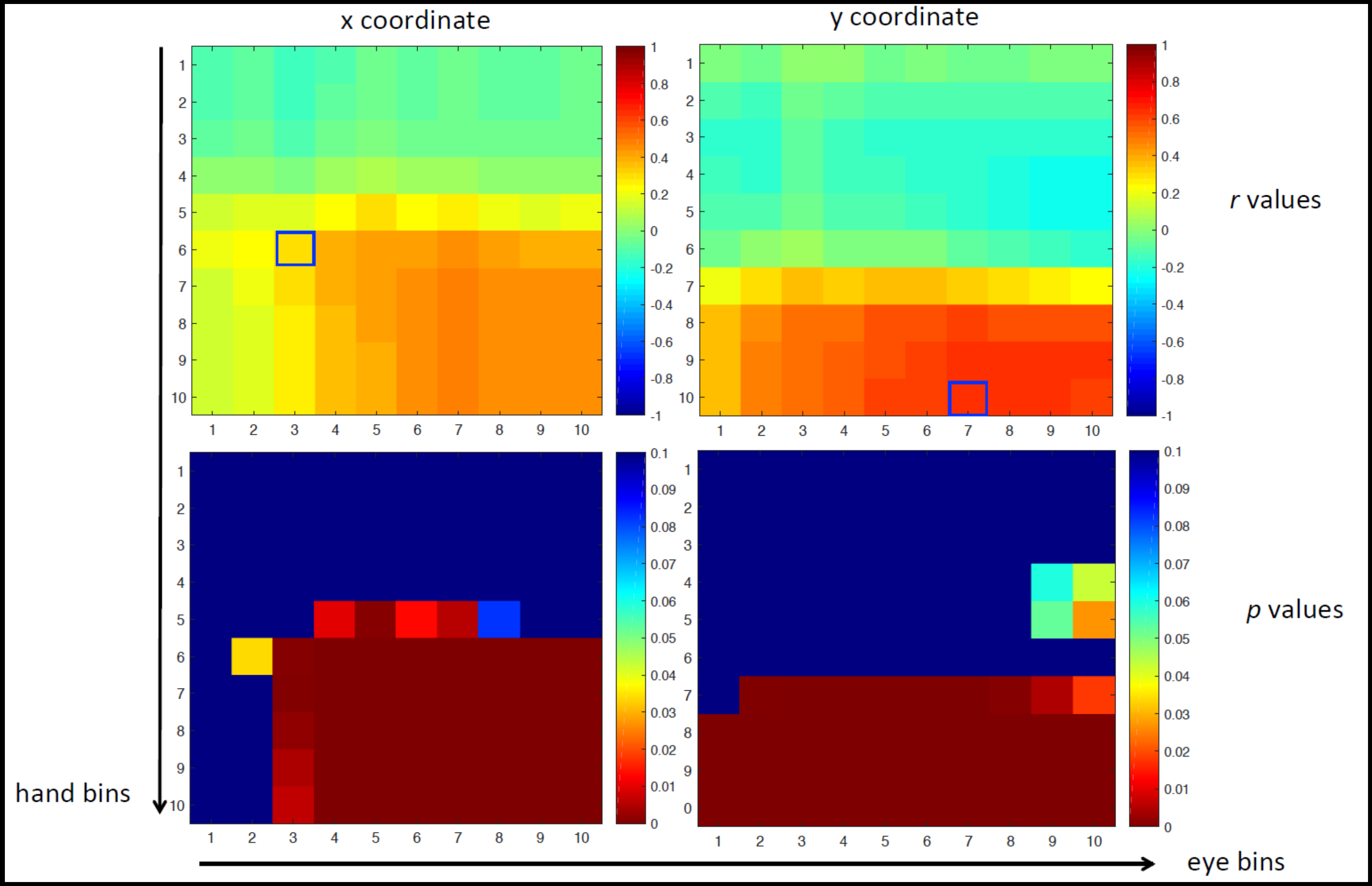
Task:
Grasp & drink from object

Task:
Grasp and hand over object



Belardinelli, A., Stepper, M. Y., & Butz, M. V. (2016). It's in the eyes: Planning precise manual actions before execution. *Journal of Vision, 16(1)*, 18. doi:10.1167/16.1.18

Anticipatory Eye Behavior – Time Course



Belardinelli, A., Stepper, M. Y., & Butz, M. V. (2016). It's in the eyes: Planning precise manual actions before execution. *Journal of Vision, 16(1)*, 18. doi:10.1167/16.1.18

- Manual peripersonal space maps into the future

ANTICIPATING BODILY STATES AT FUTURE EVENT BOUNDARY

Belardinelli, A., Lohmann, J., Farnè, A., & Butz, M. V. (2018). Mental space maps into the future. *Cognition, 176*, 65–73. doi:10.1016/j.cognition.2018.03.007

Event-Predictive Encodings in Action

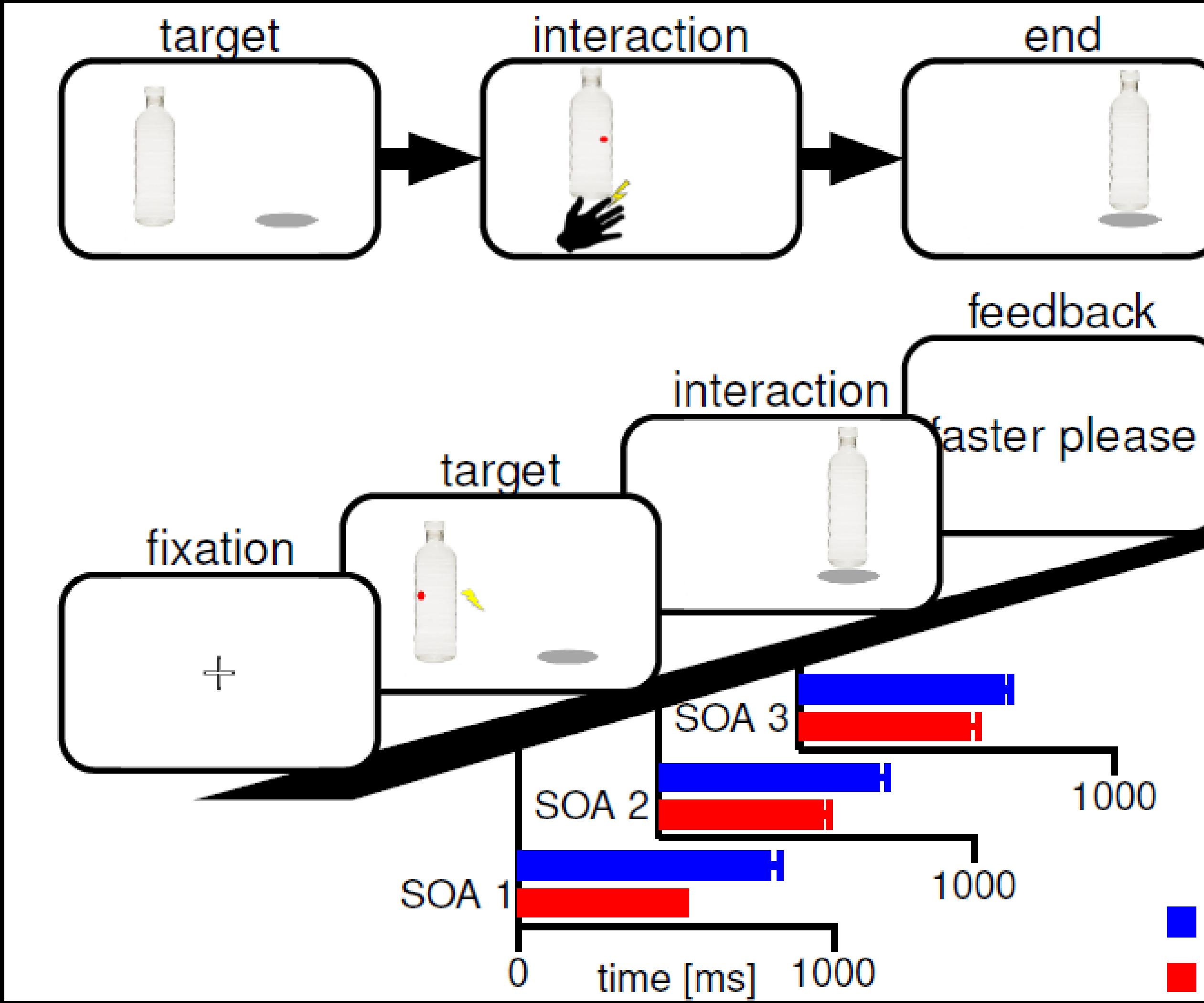
- Focus:
  - Manual interactions with objects
  - Peripersonal space around the hand
    - ➢ Known to integrate multiple sensory information sources.
    - ➢ Surrounds hand / face and other body parts.
    - ➢ Can be modified via tool usage.

- Dual task paradigm with
  1. Expected cross-modal congruency
     - ➢ Does a light flash close to FUTURE FINGER POSITIONS influence the detection of vibrotactile stimulations of the respective fingers?

  2. Task-oriented object interaction
     - ➢ Transport an object to the right and place it upright

Belardinelli, A., Lohmann, J., Farnè, A., & Butz, M. V. (2018). Mental space maps into the future. *Cognition, 176*, 65–73. doi:10.1016/j.cognition.2018.03.007

Event-Predictive Encodings in Action – Trial Schedule



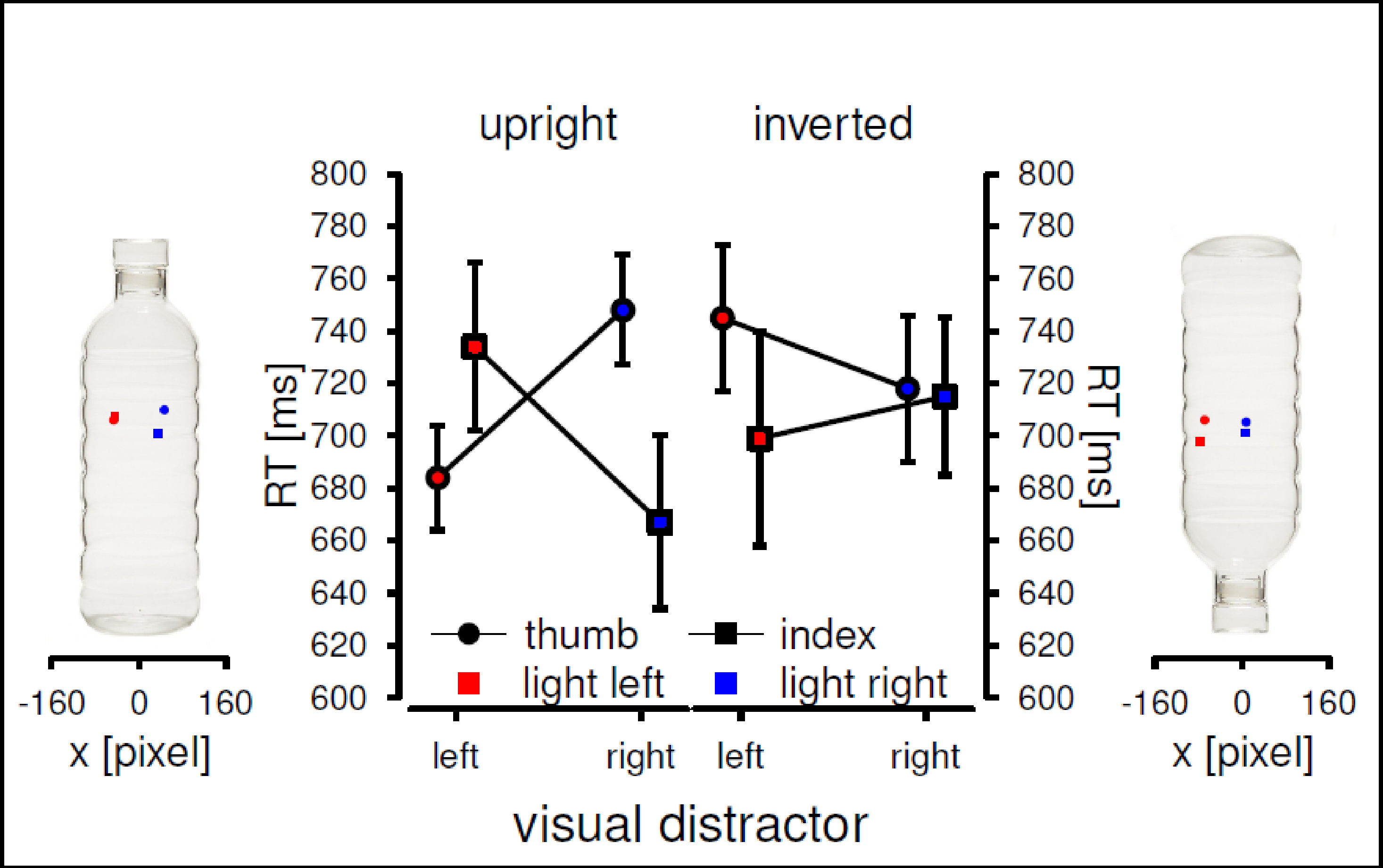
SOAs:
1. 200ms after visual onset
2. Upon motion onset
3. 200ms after motion onset

Belardinelli, A., Lohmann, J., Farnè, A., & Butz, M. V. (2018). Mental space maps into the future. *Cognition, 176*, 65–73. doi:10.1016/j.cognition.2018.03.007

Cross-Modal Congruency Effect

- Vibration detection response time is influenced by the visual distractor in anticipation of future hand posture (finger locations).

  (data shown is averaged over all three SOAs.)



Belardinelli, A., Lohmann, J., Farnè, A., & Butz, M. V. (2018). Mental space maps into the future. *Cognition, 176*, 65–73. doi:10.1016/j.cognition.2018.03.007

1. Event Dynamics
2. Inference of and within Events
3. Event Boundary Anticipation
4. **a) Event segmentation and active inference**

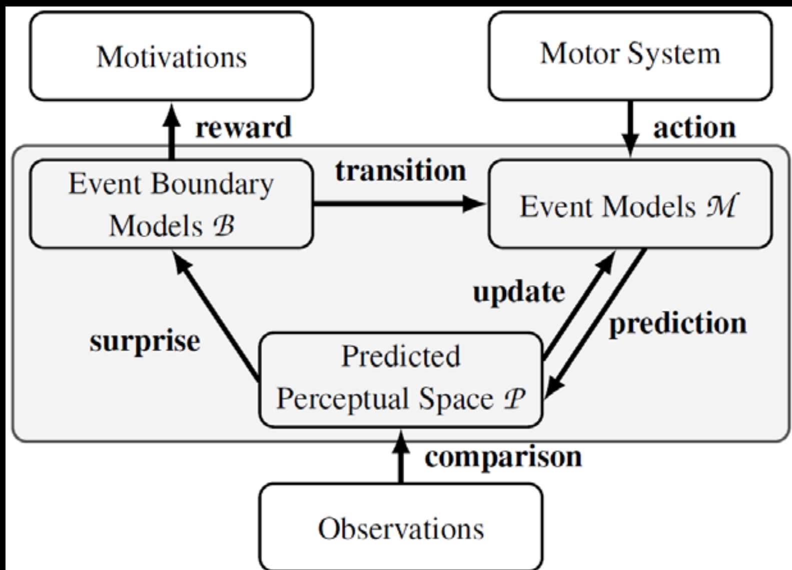
A computational model of event & event transition detection, abstraction, and planning via free-energy based (active) inference

LEARNING EVENT TAXONOMIES FROM SENSORIMOTOR EXPERIENCES

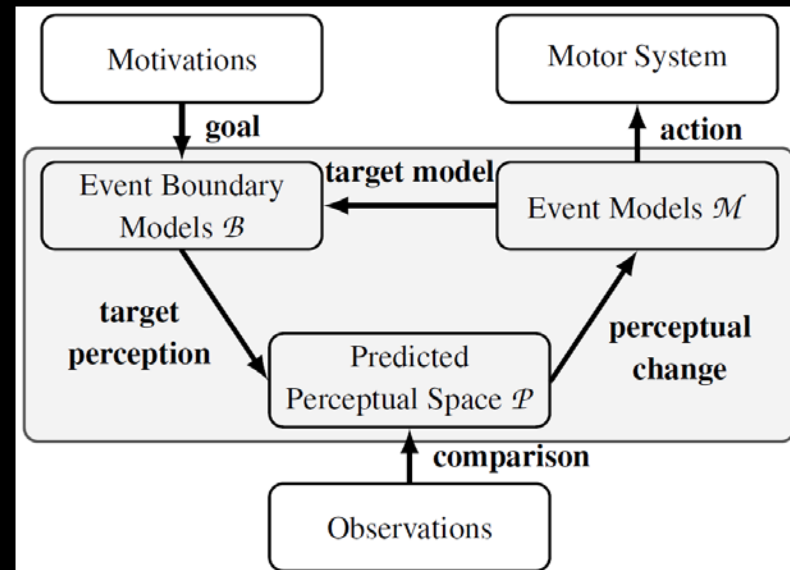
Gumbsch, C., Kneissler, J., & Butz, M. V. (2016). Learning behavior-grounded rvent segmentations. Proceedings of the 38th Annual Meeting of the Cognitive Science Society (pp. 1787–1792). Austin, TX: Cognitive Science Society.
Gumbsch, C., Otte, S., & Butz, M. V. (2017). A computational model for the dynamical learning of event taxonomies. Proceedings of the 39th Annual Meeting of the Cognitive Science Society (pp. 452–457). London, UK: Cognitive Science Society.
Gumbsch, C. (2018). Master dissertation.

Computational Model of Event Processing and Inference

Predictive processing & learning



Hierarchical, active-inference-based goal-directed behavior

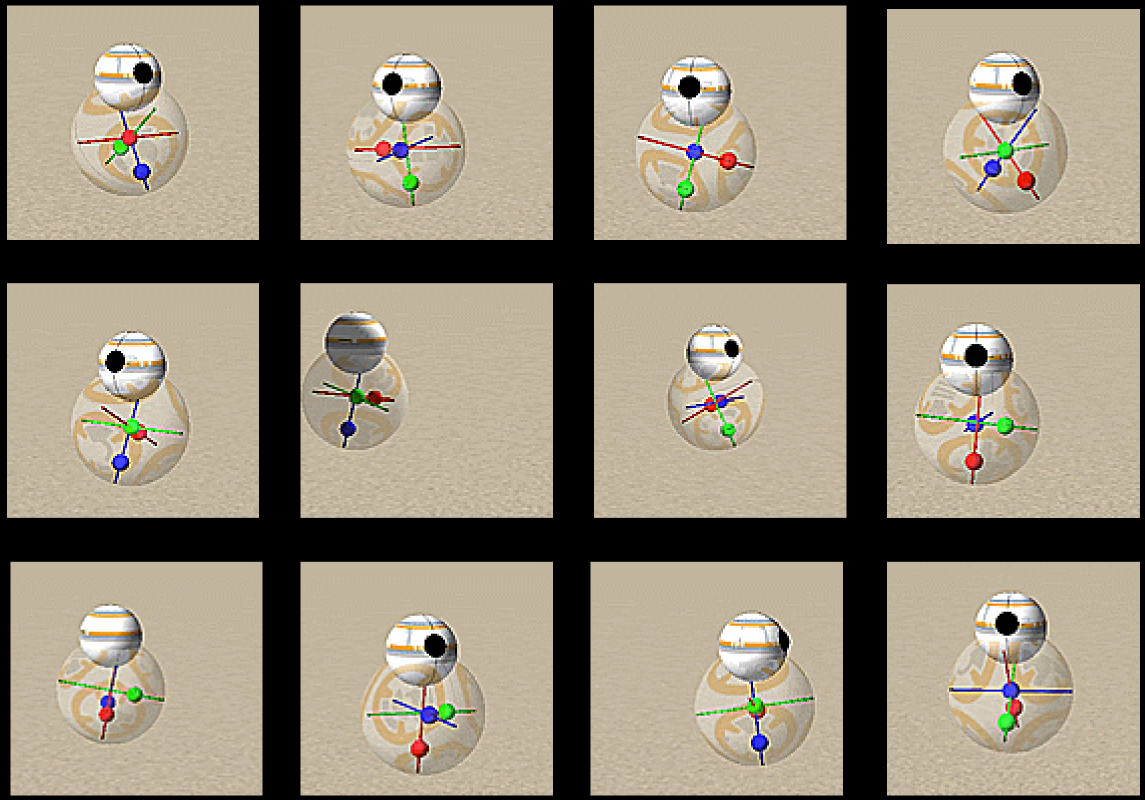


- **Event Models** are sensorimotor forward models
- **Event Boundary Models** are multivariate Gaussians
- **Predictive Perceptual Space** yields information fusion and imaginations
- **Motivations** selectively activate EBMs to reach anticipated reward
- **Motor system** executes motor commands and provides efference copies
- **Observations** yield relative locations of hand, mouth, and object, as well as object properties.

Gumbsch, C., Otte, S., & Butz, M. V. (2017). A computational model for the dynamical learning of event taxonomies. Proceedings of the 39th Annual Meeting of the Cognitive Science Society (pp. 452–457). London, UK: Cognitive Science Society.

Learned Behavioral Events

- Starting with Differential Extrinsic Plasticity control
  (Ralf Der & Georg Martius)



Gumbsch, C. (2018). Master dissertation.

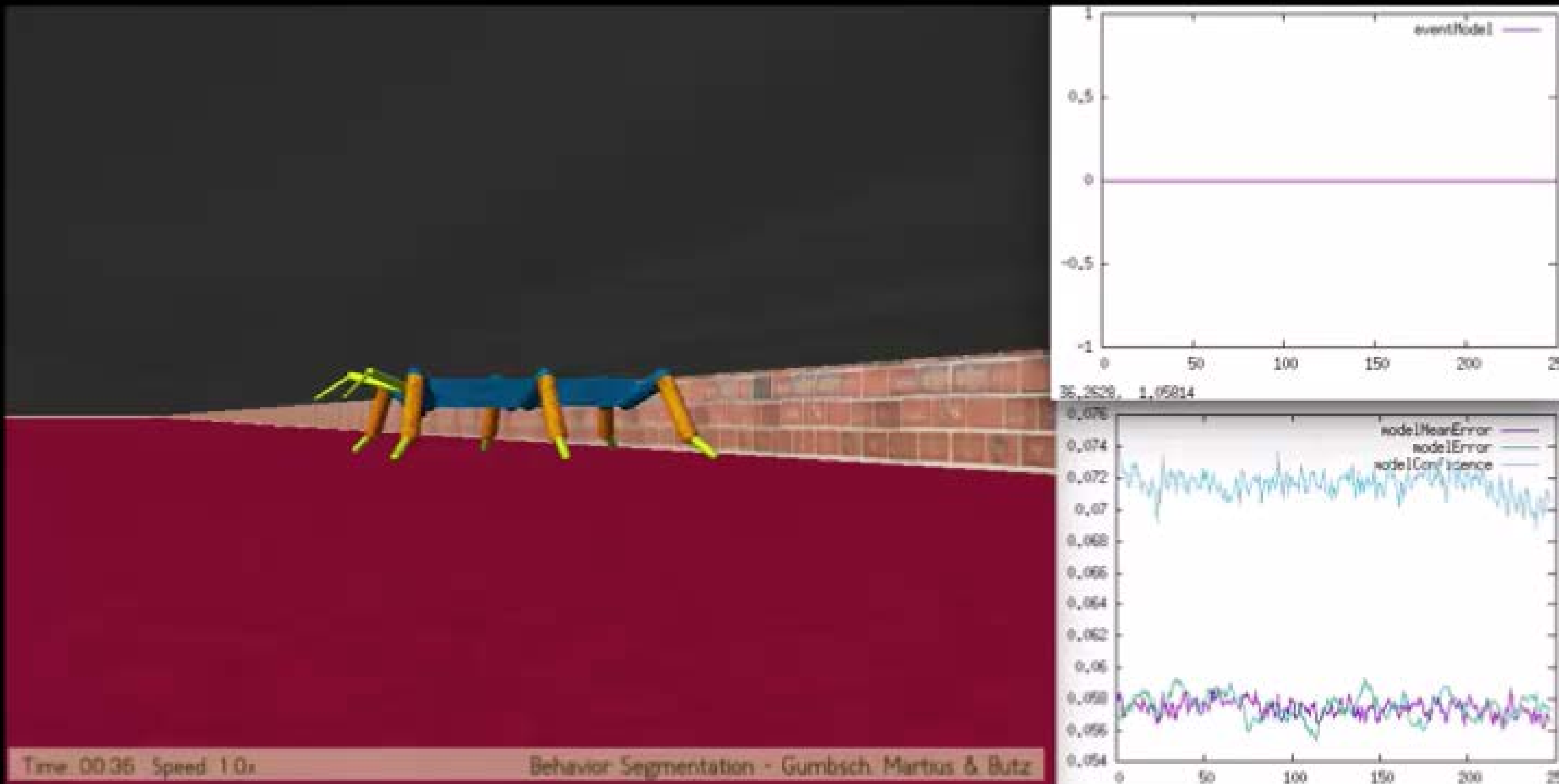
Goal-Directed Event-Predictive Control

Reaching Goals

Collecting & Transporting Objects

Gumbsch, C. (2018). Master dissertation.

Hexapod
Inferring Event Boundaries and Event Schemata



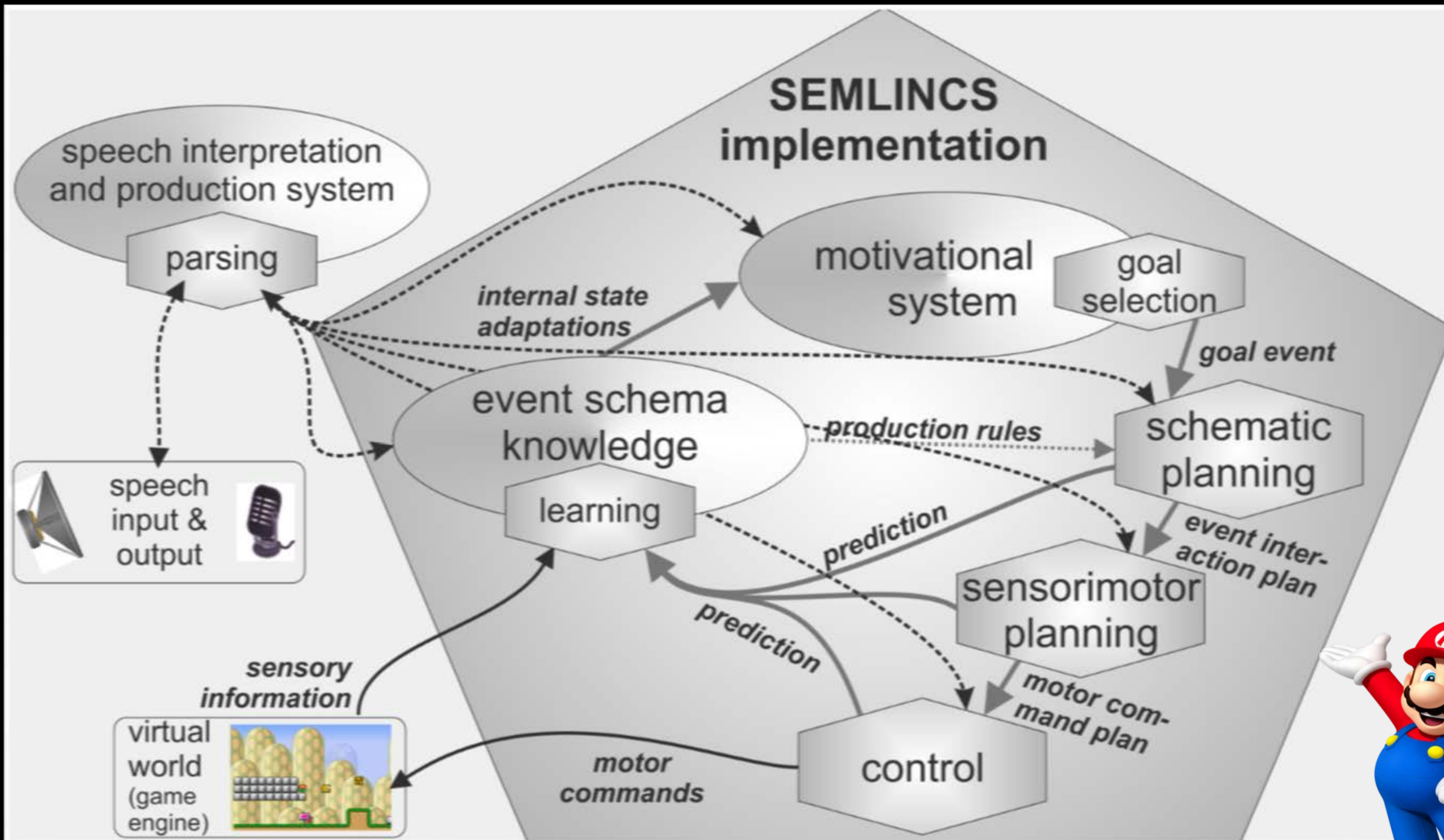
Gumbsch, C. (2018). Master dissertation.

1. Event Dynamics
2. Inference of and within Events
3. Event Boundary Anticipation
4. **b) Event schemata, motivations & language inference**

- A Mario clone to explore the learning of event schema rules and the link to language.

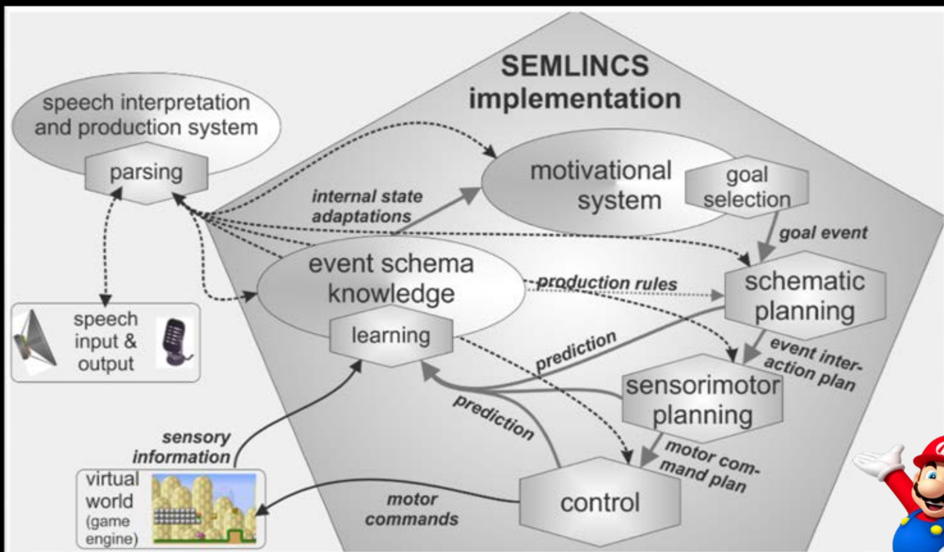
EVENT-ORIENTED ABSTRACTIONS TOWARDS LANGUAGE COMPREHENSION

Mario's Brain – SEMLINCS Architecture



Schrodt, F., Kneissler, J., Ehrenfeld, S., & Butz, M. V. (2017). Mario becomes cognitive. *Topics in Cognitive Science, 9(2)*, 343–373. doi:10.1111/tops.12252

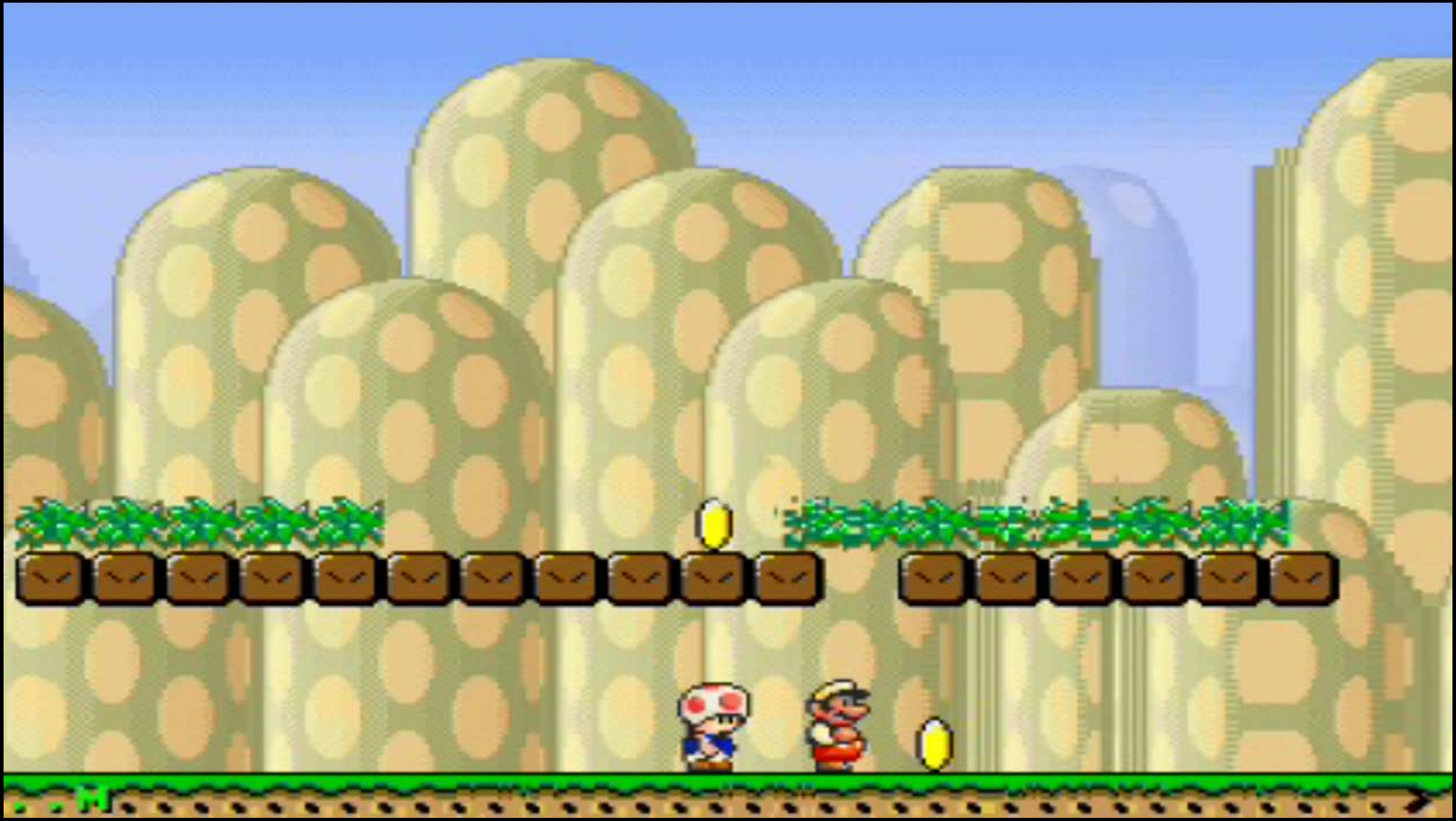
Main Features of SEMLINCS Architecture



- **Motivational system**
  - Based on homeostatic variables;
  - Allows the autonomous selection of goals.
- **Event schema knowledge** in the form of condition-action-effect rules…
  - ... is learned from surprising event signals (e.g. disappearing object);
  - … allows temporal forward predictions and inverse planning on a conceptual level.
- Planning:
  - **Sensorimotor planning** is currently hard-coded (A*) relying on game engine (simulator)
  - **Schematic planning** relies on event schema rule knowledge (i.e. production rules)
- **Speech interface** enables
  - querying and manipulating:
    - Event schema knowledge
    - Goal selection
    - Motivational system state
    - Current motor commands.
  - autonomously agreeing on (sequential) joint action plans.

Schrodt, F., Kneissler, J., Ehrenfeld, S., & Butz, M. V. (2017). Mario becomes cognitive. *Topics in Cognitive Science, 9*(2), 343–373. doi:10.1111/tops.12252

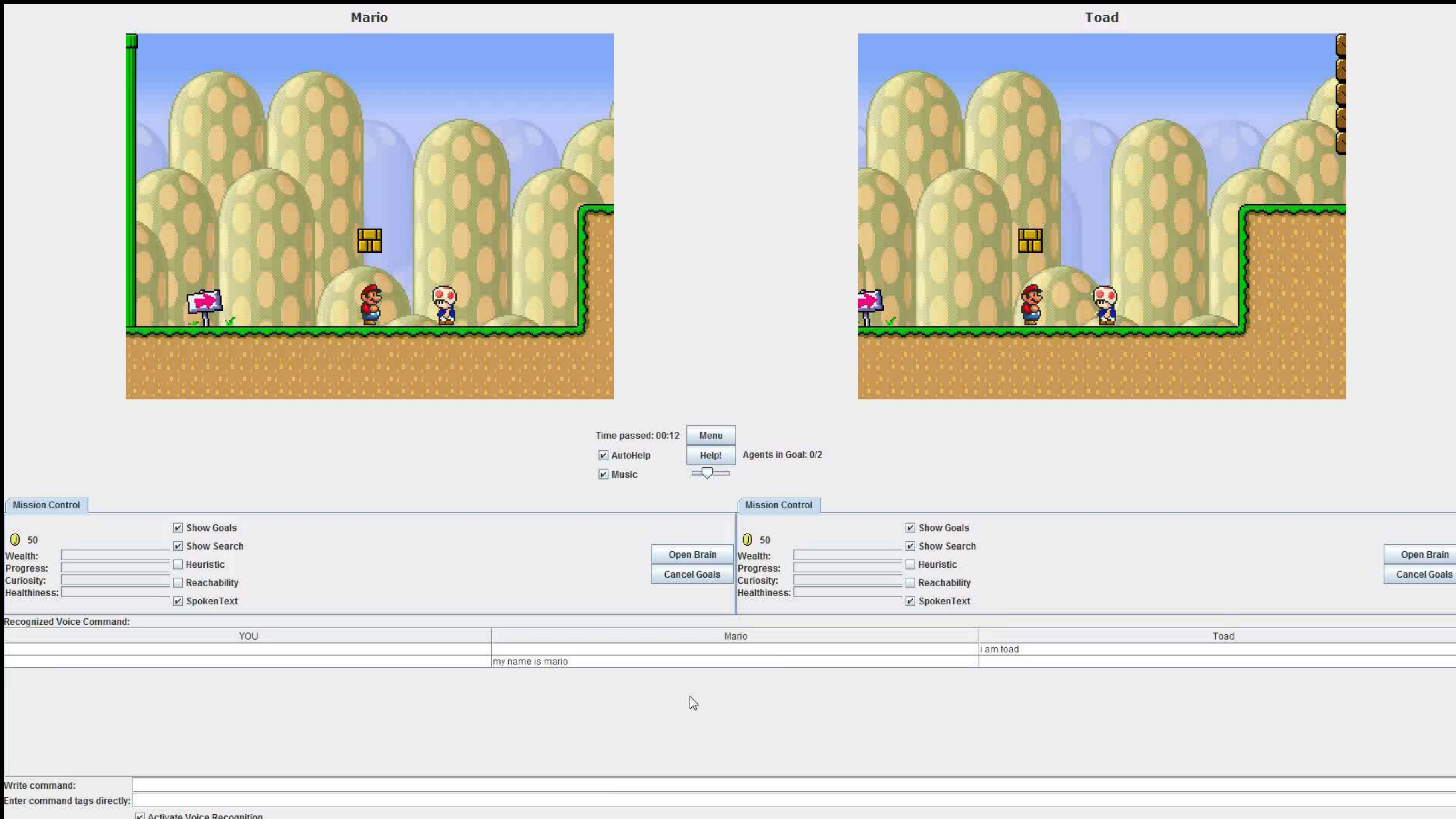
Example 1: Learning from Object Interaction Events and Observations



Schrodt, F., Kneissler, J., Ehrenfeld, S., & Butz, M. V. (2017). Mario becomes cognitive. *Topics in Cognitive Science, 9(2*), 343–373. doi:10.1111/tops.12252

➢ “Mario Becomes Social!” video available online on YouTube.

Example 2: Coordinating Plans



Schrodt, F., Röhm, Y., & Butz, M. V. (2017). An Event-Schematic, Cooperative, Cognitive Architecture Plays Super Mario. In *Proceedings of EUCognition 2016: Cognitive Robot Architectures* (pp. 10–15).

(Many) Open Challenges

For ANN-based neuro-cognitive models…

- More complex
- More real
- Optimizing motion primitives
- Episodic memory
- Emergent linkage to linguistic structure
- Conceptual abstractions beyond sensorimotor behaviors