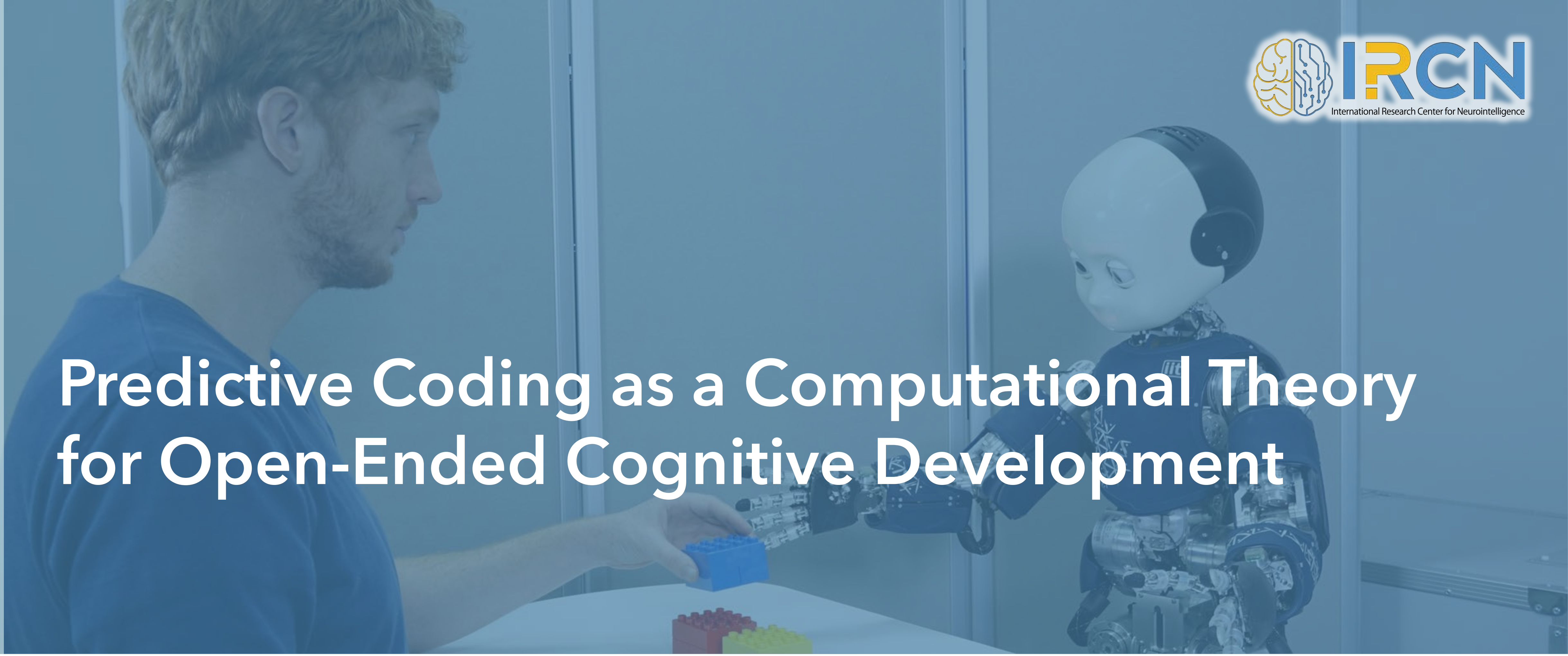


IRCN
International Research Center for Neurointelligence

Predictive Coding as a Computational Theory for Open-Ended Cognitive Development

Yukie Nagai

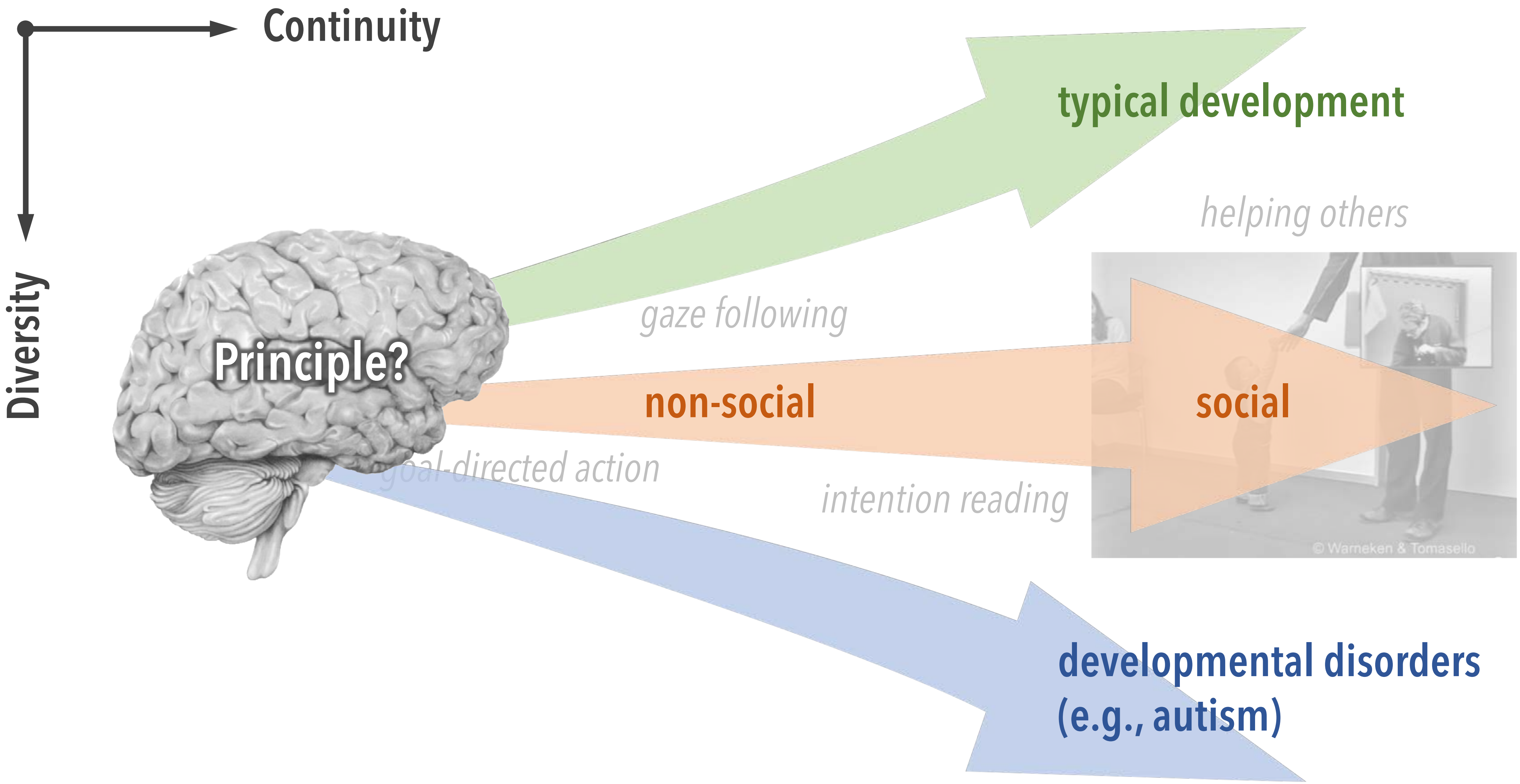
The University of Tokyo

IROS 2019 Workshop on Open-Ended Learning for Object Perception and Grasping: Current Successes and Future Challenges @ Macau, China, November 8, 2019

Altruistic Behavior by 14-month-old Infants

[Warneken & Tomasello, 2007]

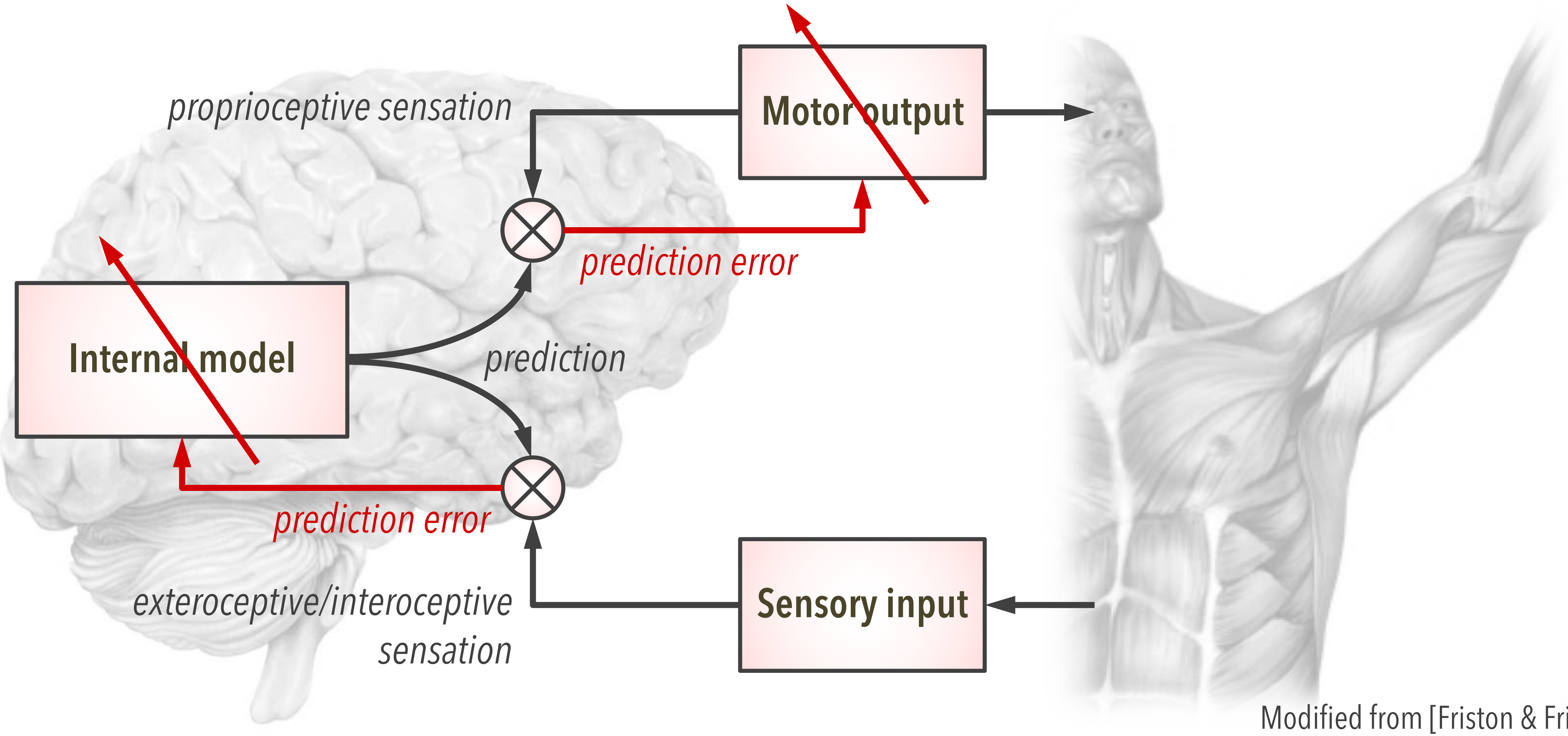
Two Important Aspects in Cognitive Development



Predictive Coding: A Principle of Human Brain

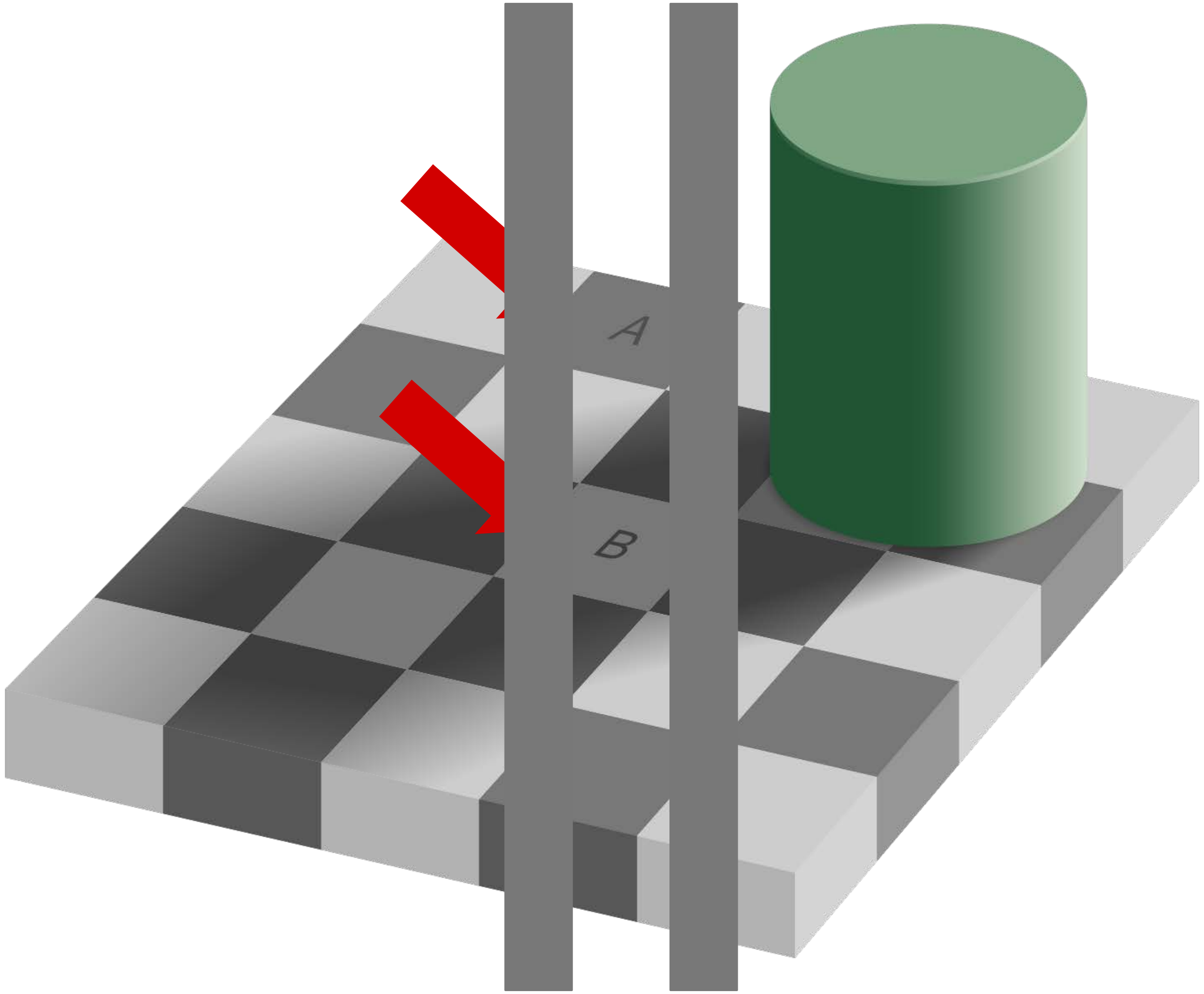
[Friston et al., 2006; Friston, 2010; Clark, 2013]

- The human brain perceives the world (i.e., perceptual inference) and acts on the world (i.e., active inference) so as to minimize prediction errors.



Modified from [Friston & Frith, 2015]

Optical Illusion Generated by Predictive Brain



Which area is lighter, A or B?

A = B

Cognitive Development Based on Predictive Learning

[Nagai, Phil Trans B 2019]

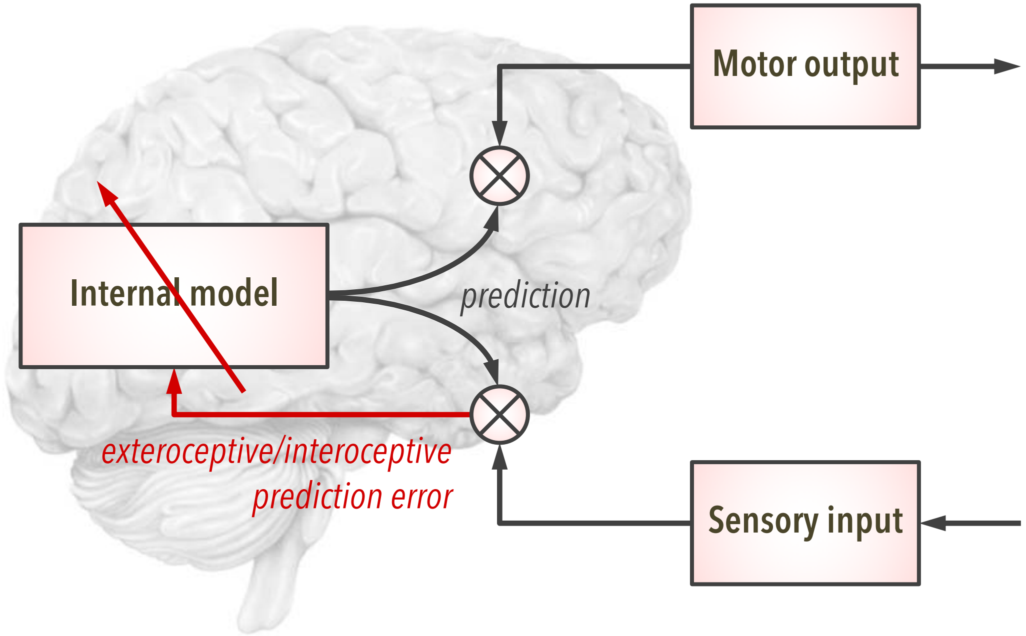
- Infants acquire various cognitive abilities through learning to minimize prediction errors:

(a) *Updating the internal model* through own sensorimotor experiences

– Non-social (i.e., self-oriented) behaviors

(b) *Generating actions* to alter sensory signals

– Proto-social (i.e., other-oriented) behaviors



Cognitive Development Based on Predictive Learning

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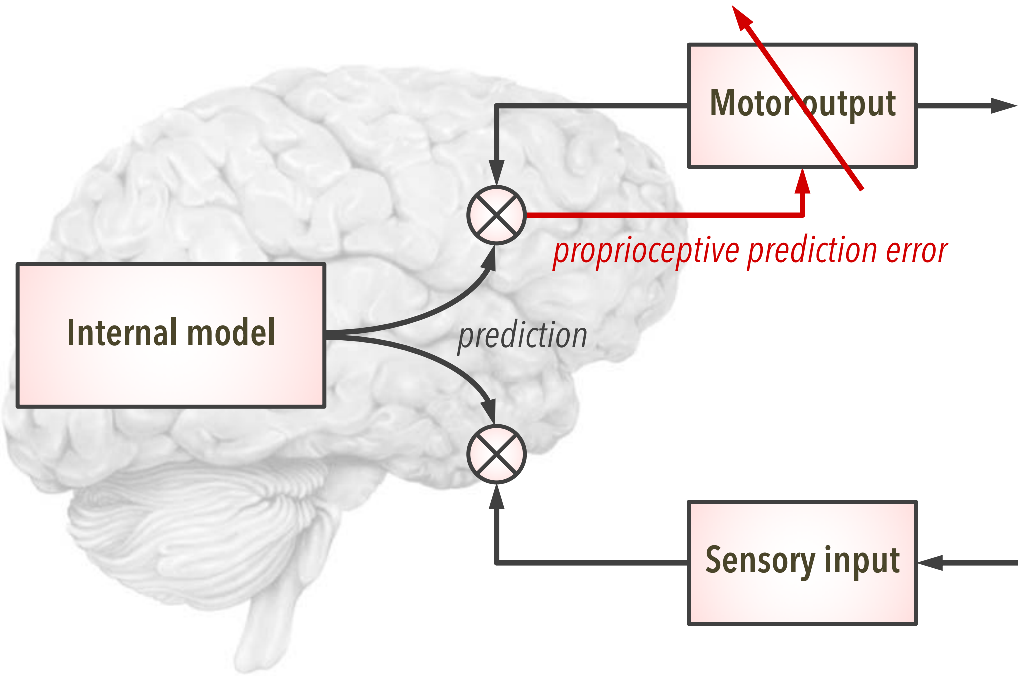
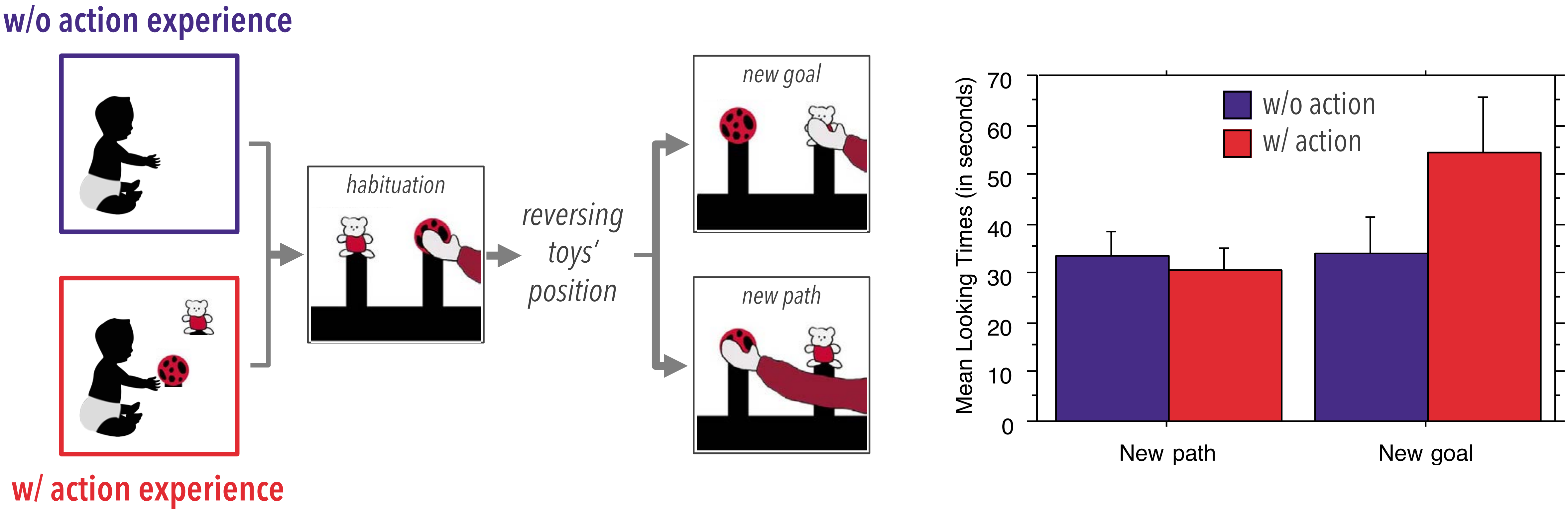


Open-Ended Cognitive Development in Robots

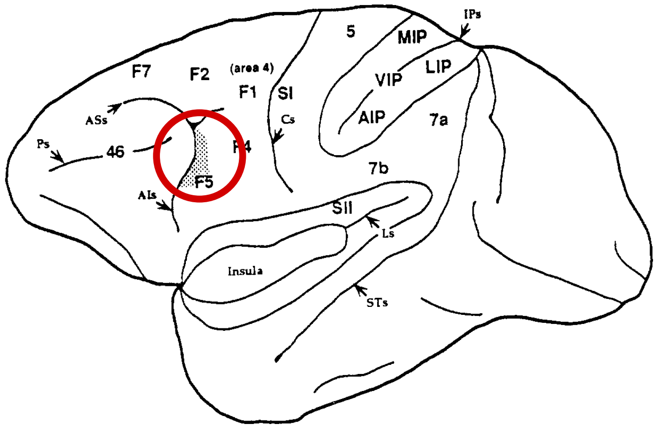
Action Production Facilitates Action Perception in Infants

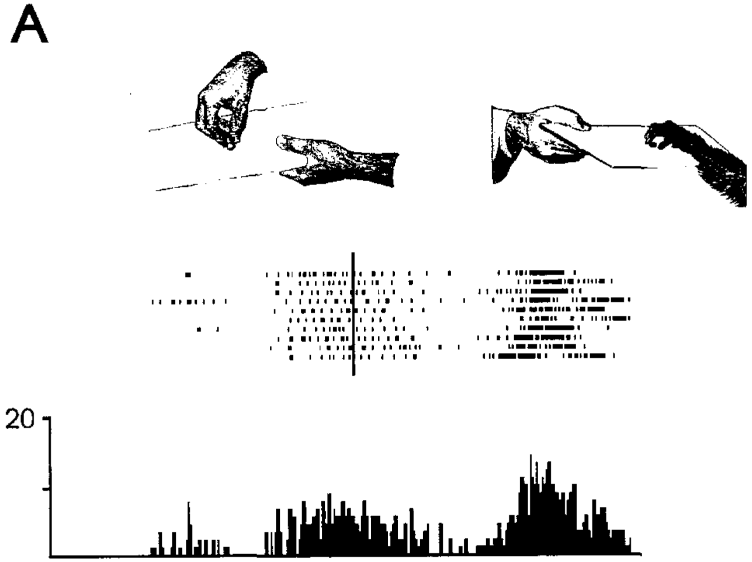
[Sommerville et al., 2005; Gerson & Woodward, 2014]

- 3-month-old infants detect the *goal-directed structure of others' actions* only when they were given experiences of *generating the same actions*.

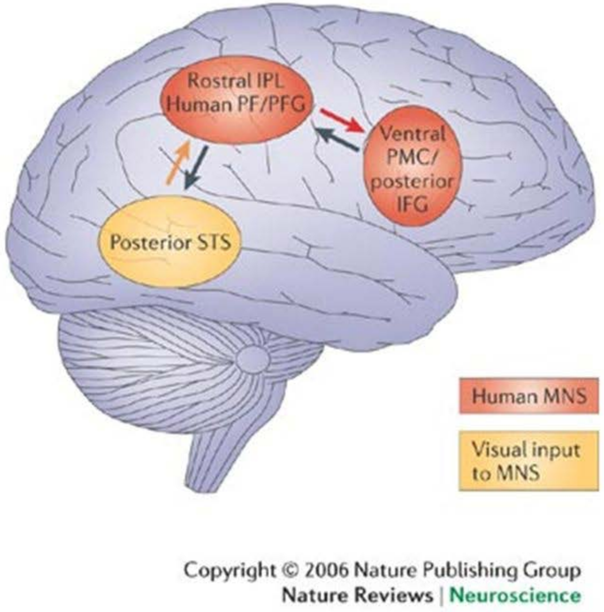


Mirror Neurons [Rizzolatti et al., 1996; 2001]





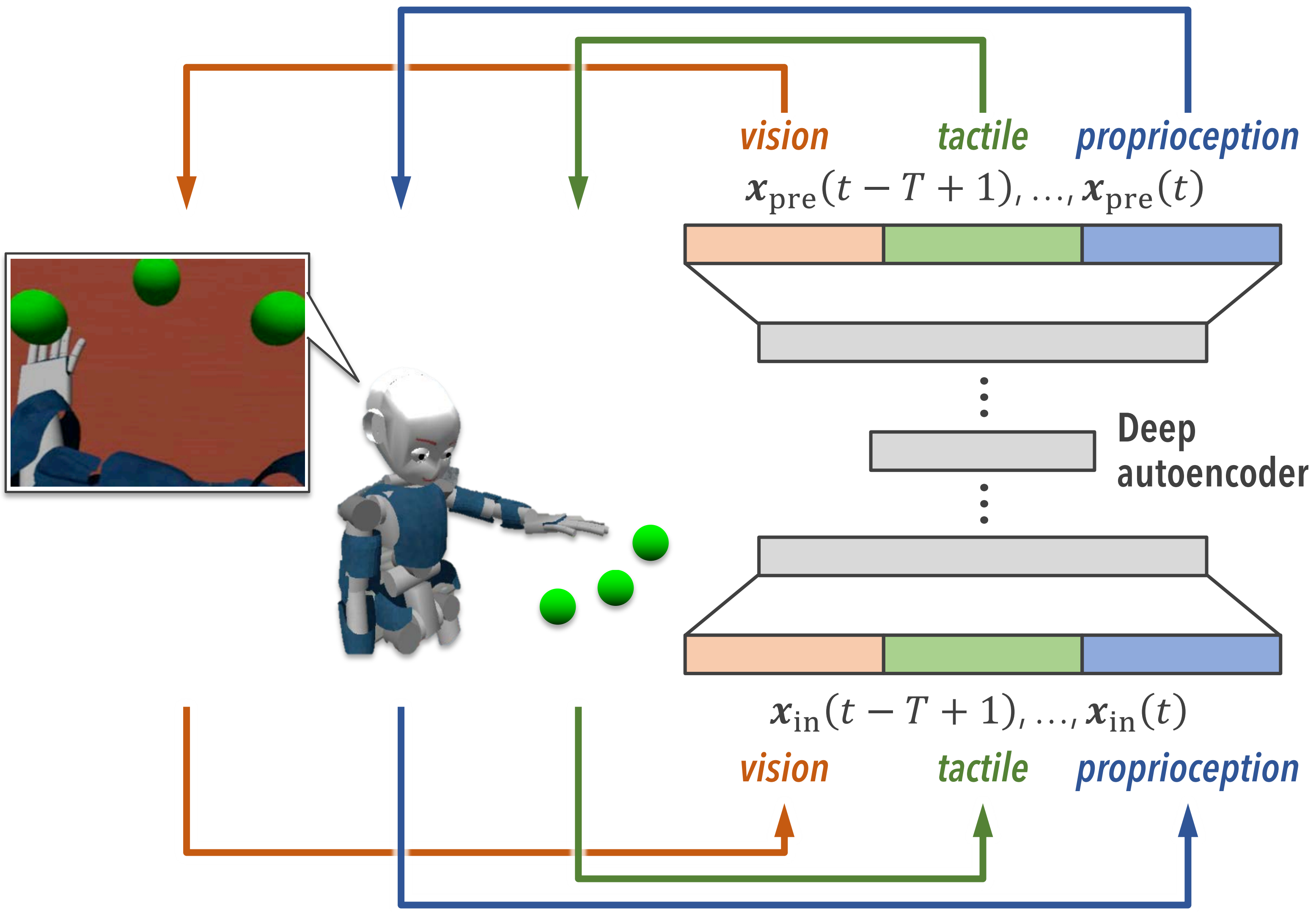
[Rizzolatti et al., 1996]



[Iacoboni & Dapretto, 2006]

- Originally found in monkey's premotor cortex
- Discharge both:
  - when *executing* own actions
  - when *observing* the same action performed by other individuals
- Understand others' action and intention based on self's motor representation

Predictive Learning for Action Production and Perception

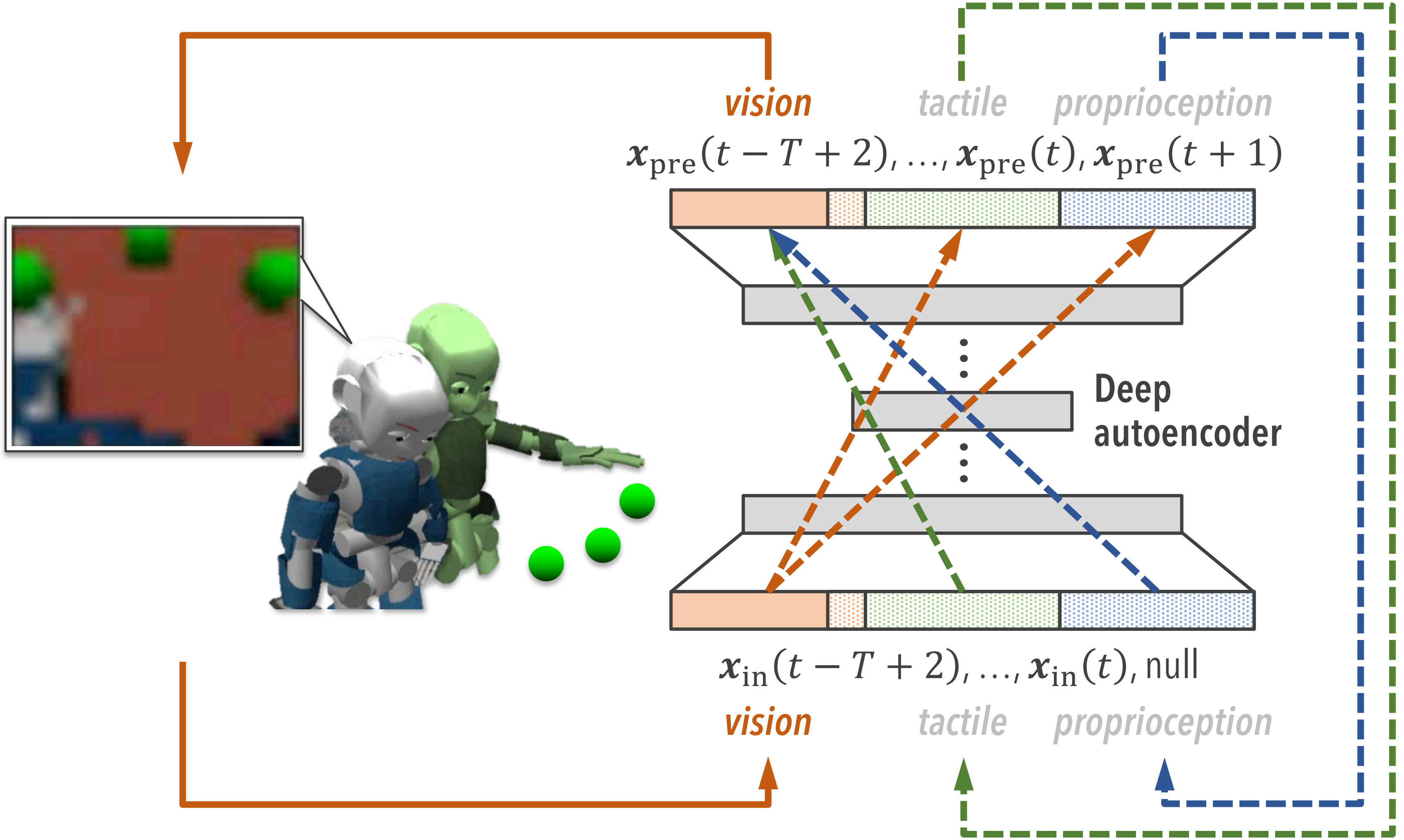


Action production:

- Predictive learning (i.e., minimizing $\|x_{in} - x_{pre}\|$) to associate *visual*, *tactile*, and *proprioceptive* signals

[Copete, Nagai, & Asada, ICDL-EpiRob 2016]

Predictive Learning for Action Production and Perception



Action production:

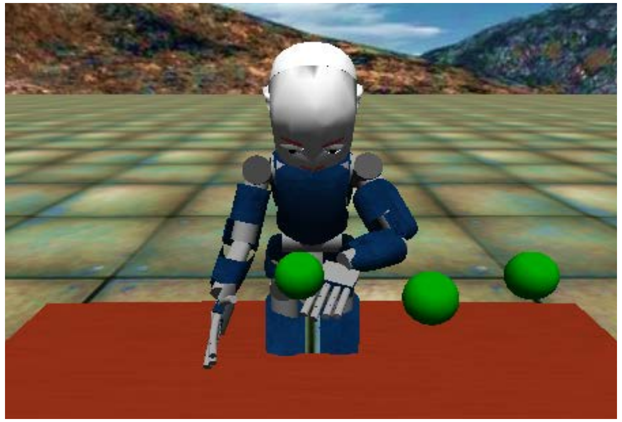
- Predictive learning (i.e., minimizing $\|\boldsymbol{x}_{\mathrm{in}} - \boldsymbol{x}_{\mathrm{pre}}\|$) to associate *visual*, *tactile*, and *proprioceptive* signals

Action perception:

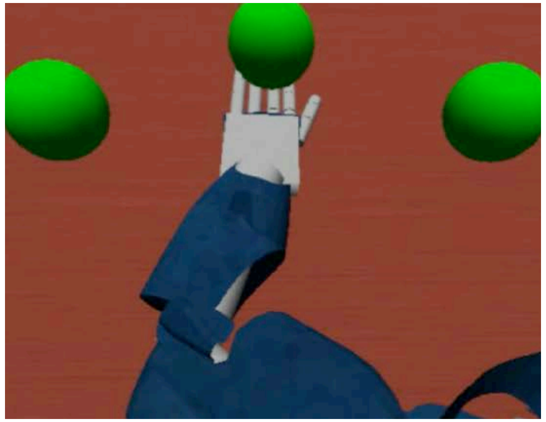
- *Visual* action prediction facilitated by imaginary *tactile* and *proprioceptive* signals

[Copete, Nagai, & Asada, ICDL-EpiRob 2016]

Result 1: Prediction of Observed Action



Actual image



Predicted image

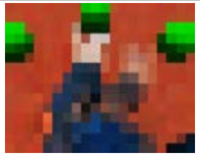
Input/output signals

- Vision: camera image (30 dim)
- Tactile: on/off (3 dim)
- Proprioception: joint angles of the arm (4 dim)

… for $T = 30$ steps

Assumption

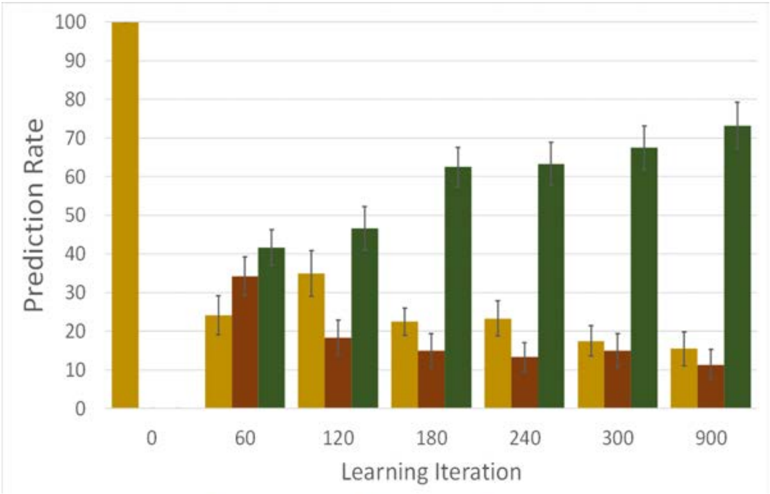
- Shared viewpoint between self and other

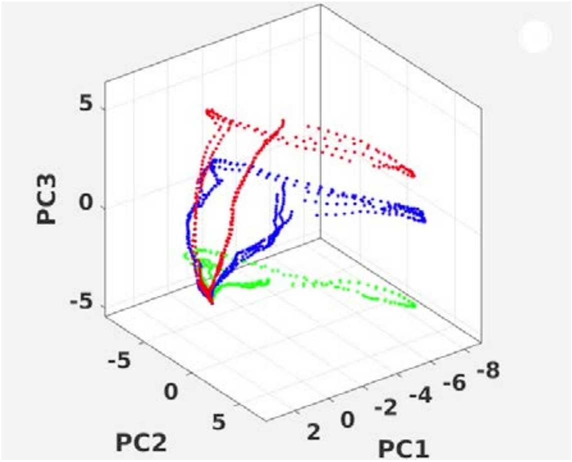
Predicted image	Classification of prediction
	Correct goal
	Incorrect goal
	No goal

[Copete, Nagai, & Asada, ICDL-EpiRob 2016]

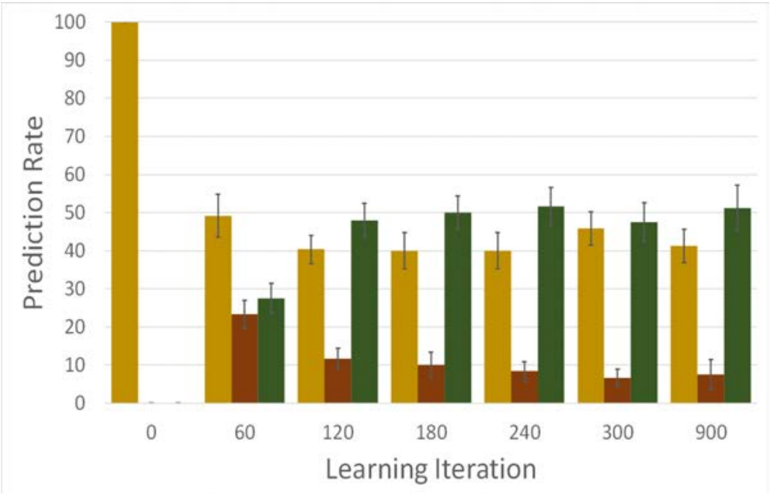
Result 2: Prediction Accuracy Improved by Action Generation

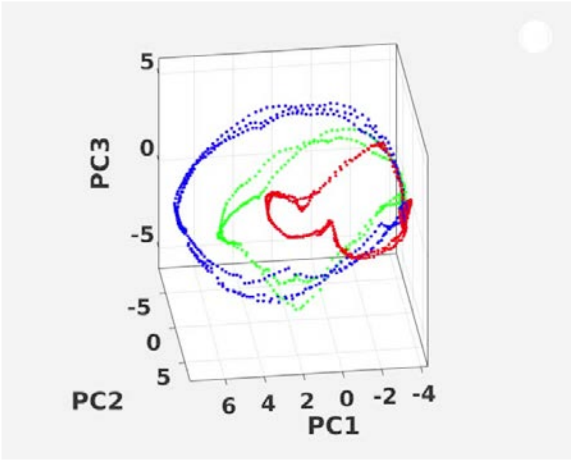
Learning through action generation





… action observation





Correct goal

Incorrect goal

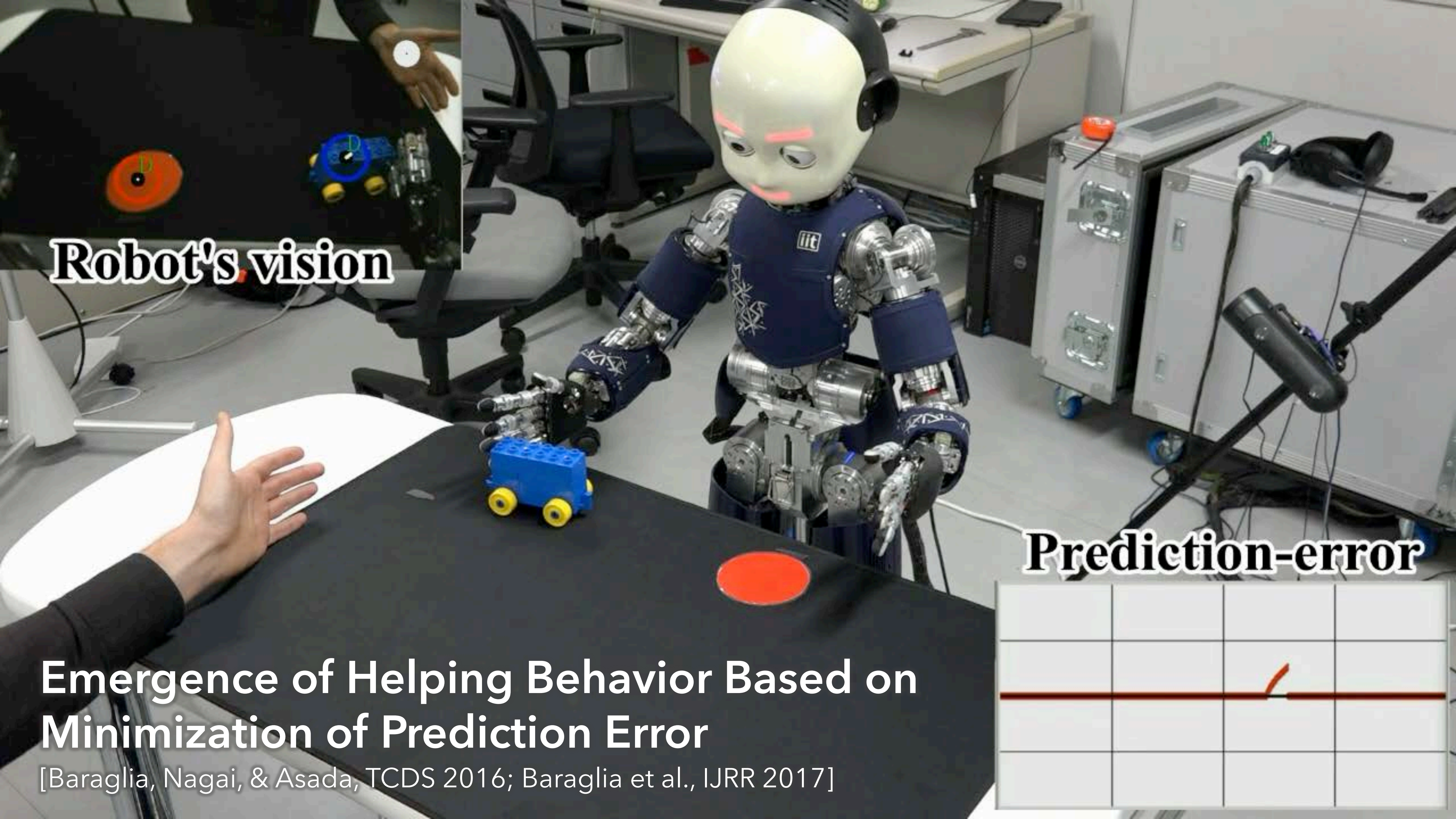
No goal

Reaching for left

Reaching for center

Reaching for right

[Copete, Nagai, & Asada, ICDL-EpiRob 2016]



Emergence of Helping Behavior Based on Minimization of Prediction Error

[Baraglia, Nagai, & Asada, TCDS 2016; Baraglia et al., IJRR 2017]

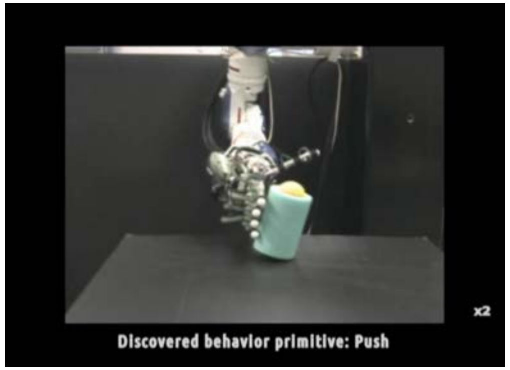
Prof. Emre Ugur

Prof. Erhan Oztop

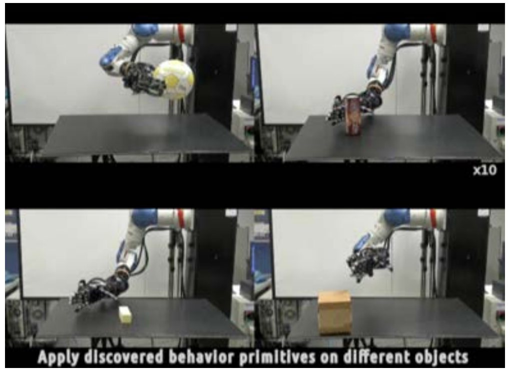
Open-Ended Affordance Learning in Robots

https://www.youtube.com/watch?v=8vNxjwt2AqY

Staged Development of Robot Skills



1. Discovery of behavior primitives
   – A robot equipped with reflexes learns to discover behavior primitives by exploring its parameter space.

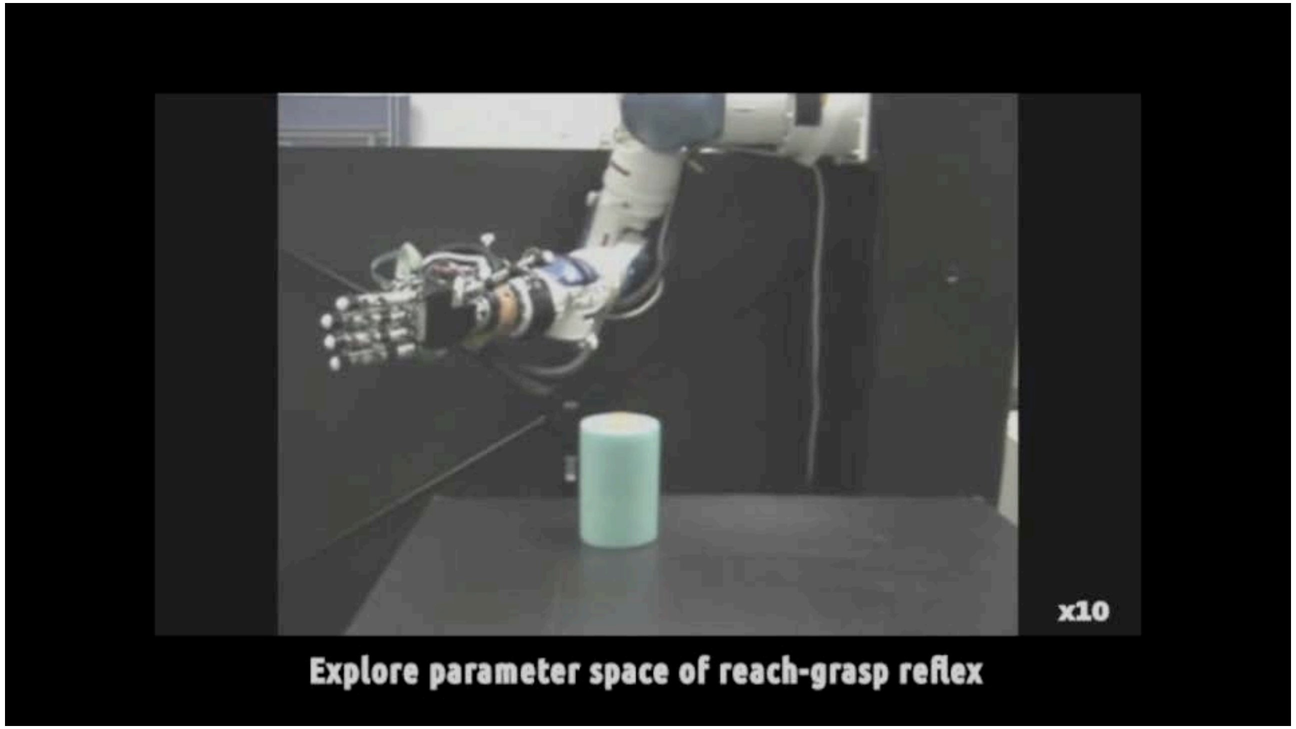


2. Affordance learning
   – The robot executes the discovered behavior primitives on different objects and learns the cause-and-effect relationship (i.e., affordance).

3. Imitation learning through social interaction
   – The robot imitates actions presented by tutors by exploiting learned affordances.

[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

Stage 1: Discovery of Behavior Primitives



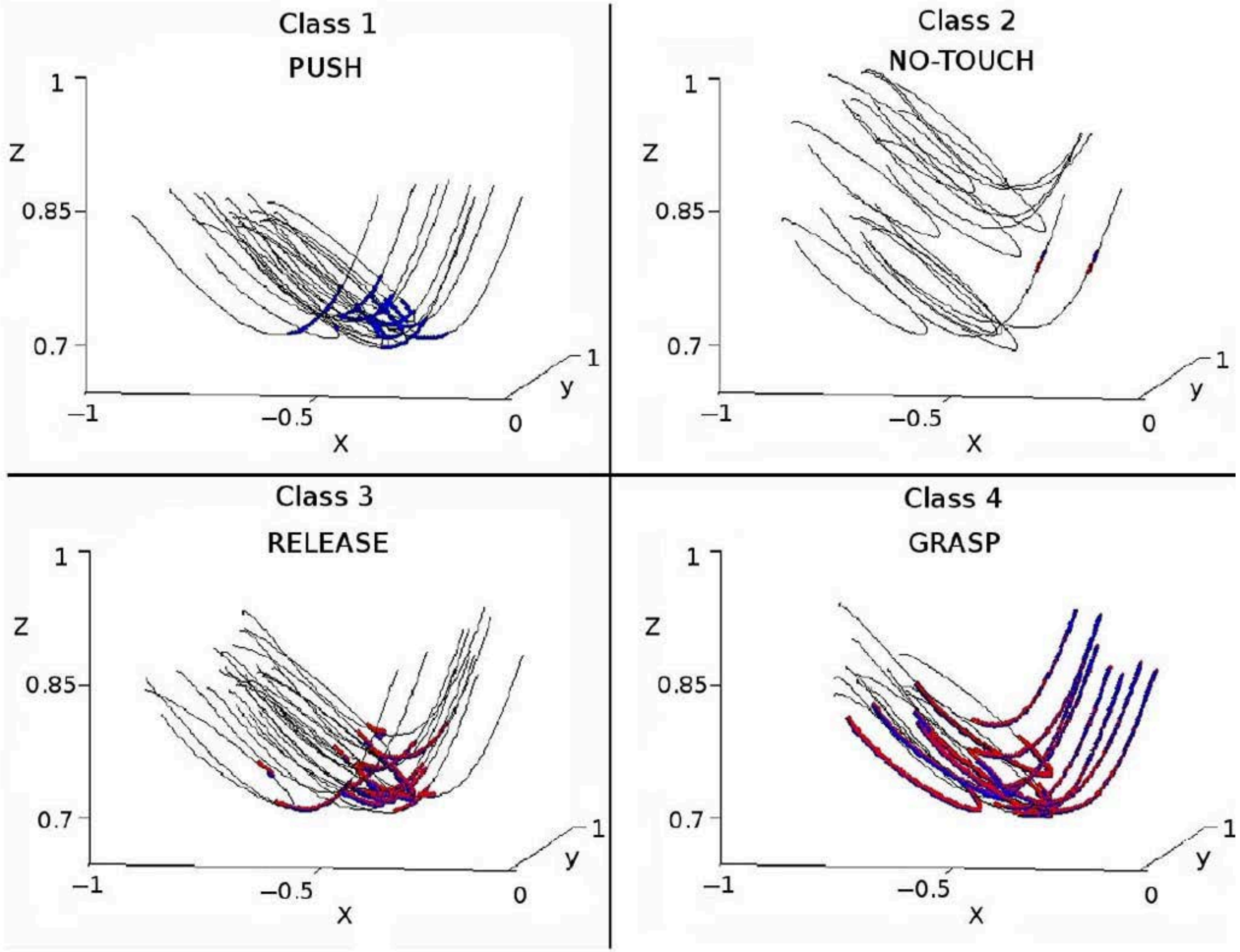
- Inherent reflex behaviors (swiping and grasping) are executed on an object using different parameters:
  - Target position
  - Initial and end positions of the hand
  - Open and close states of the hand

- Behavior primitives $\boldsymbol{b}_i$ are discovered based on the similarity of the tactile profile $\boldsymbol{T}_{\mathrm{traj}}$:

$$\{C_i\}_{i=1}^{I} \leftarrow \mathrm{X-means}\left(\left\{\boldsymbol{T}_{\mathrm{traj}}^{j}\right\}_{j=1}^{N}\right)$$

[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

Result 1: Behavior Primitives Discovered through Explorations



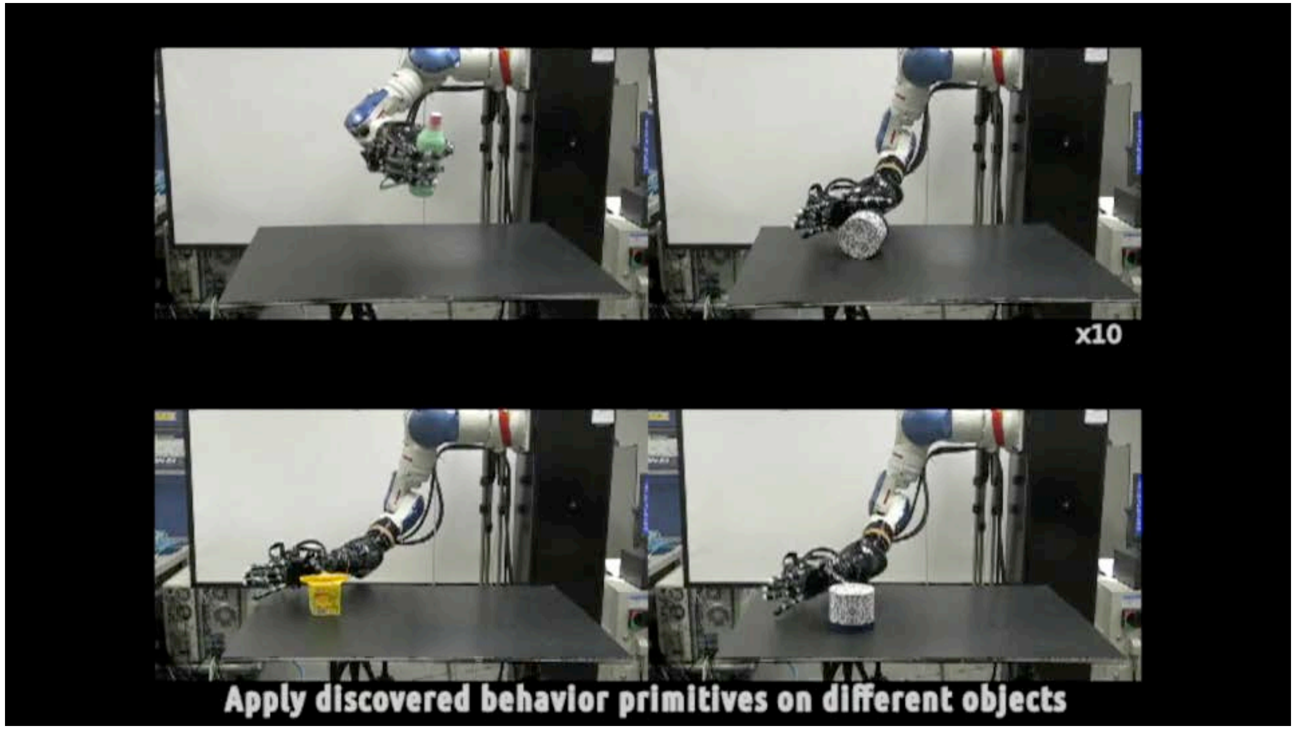
Four primitives:

- Push: temporary touch of fingers
- No-touch: no touch
- Release: temporary activation of fingers and palm
- Grasp: activation of fingers and palm until final position

hand trajectories
finger touch
palm touch

[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

Stage 2: Affordance Learning



- Affordances $\langle \boldsymbol{f}_{\text{init}}, b_i, \boldsymbol{f}_{\text{effect}} \rangle$ are acquired by executing the behavior primitives b_i on different objects with different features $\boldsymbol{f}$ (e.g., size, position, etc.):

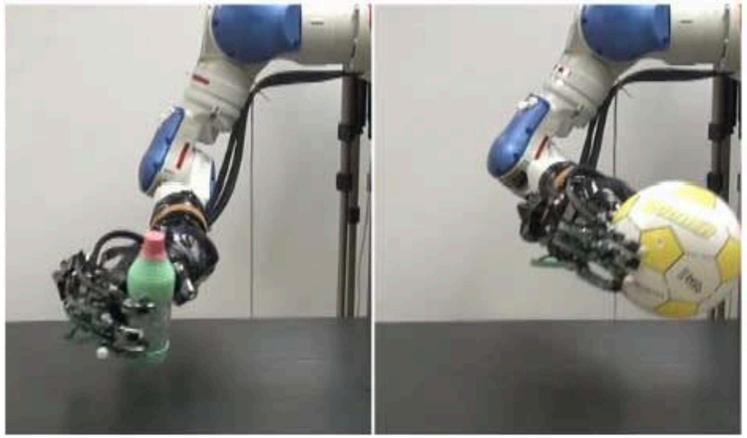
$$\langle \boldsymbol{f}_{\text{init}}, b_i, \boldsymbol{f}_{\text{effect}} \rangle$$
$$\text{where } \boldsymbol{f}_{\text{effect}} = \boldsymbol{f}_{\text{end}} - \boldsymbol{f}_{\text{init}}$$

- Effects $\boldsymbol{f}_{\text{effect}}$ are learned to be predicted by further exploring b_i with different end positions:

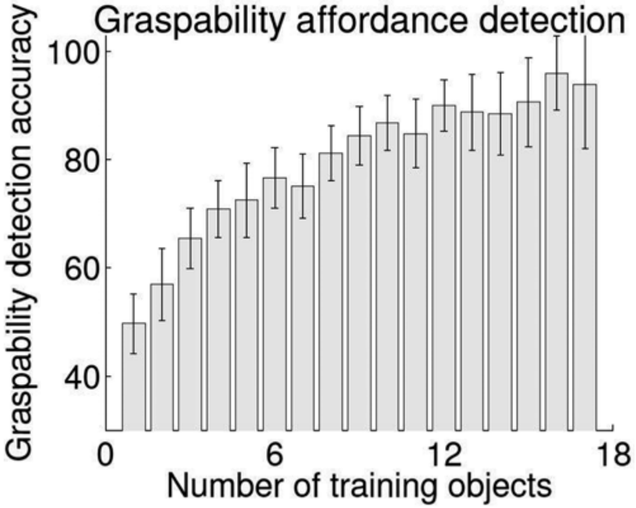
$$\langle \boldsymbol{f}_{\text{init}}, b_i \rangle \rightarrow \boldsymbol{f}_{\text{effect}}(\boldsymbol{f}_{\text{end}})$$

[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

Result 2: Affordance and Effect Prediction



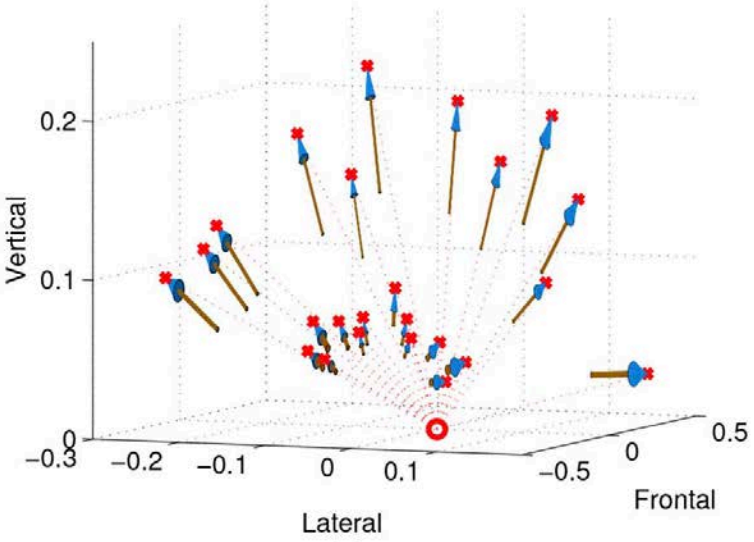
Graspability



Three affordances:

- Pushability
- Rollability
- Graspability

Predicted effects (object position) with different grasps



Effect predictions:

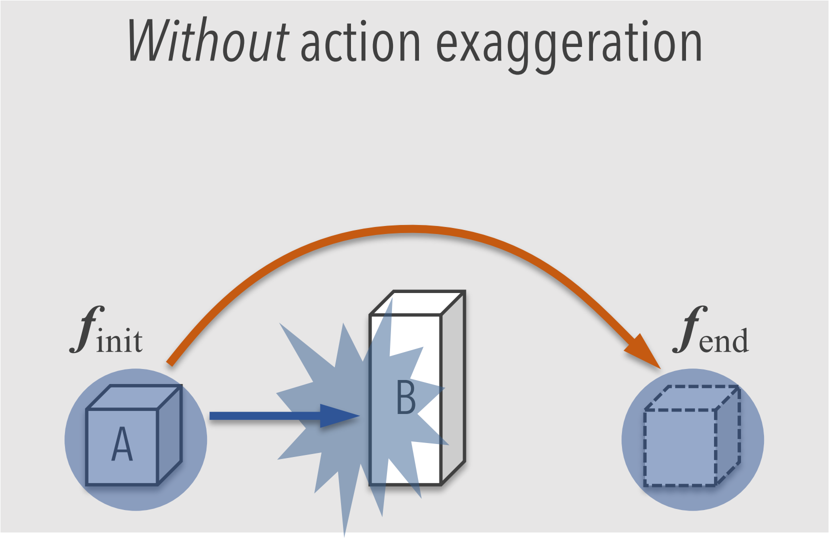
- Effects $\boldsymbol{f}_{\text{effect}}$ (e.g., object position) is properly predicted based on acquired affordances.

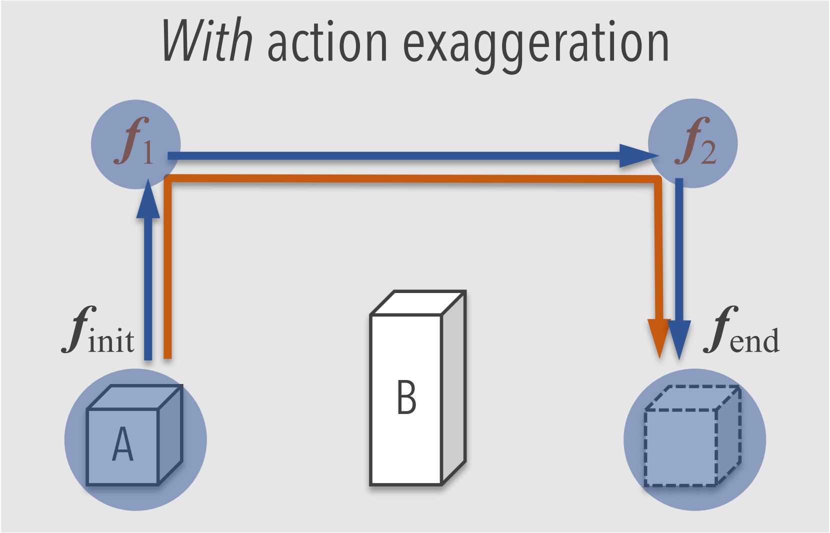
[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

Stage 3: Imitation Learning through Social Interaction

- Affordances involving multiple objects are learned through social interaction using the acquired single-object affordances.
- Sub-goals (i.e., $\boldsymbol{f}_{\text{init}}, \dots, \boldsymbol{f}_n, \dots, \boldsymbol{f}_{\text{end}}$) to be imitated are extracted based on single-object affordances.

ex.) Affordances acquired by the robot
- Pushability
- Rollability
- Graspability



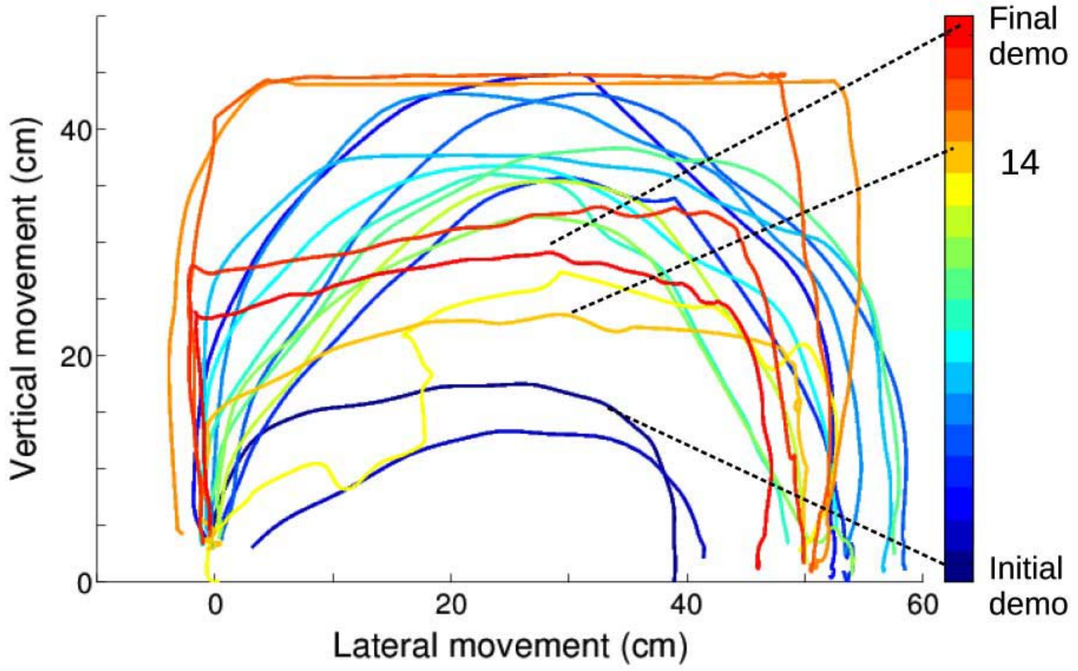


[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

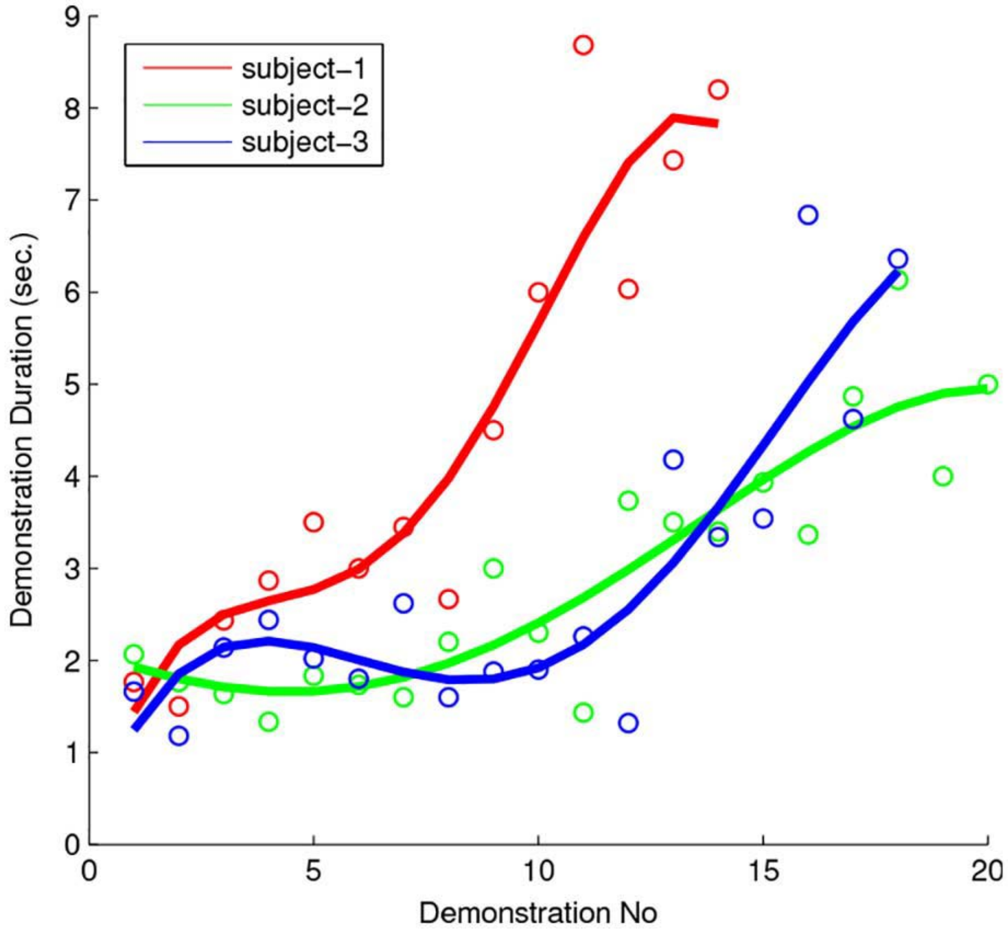
Finally, tutor displays motionese enabling successful imitation

Result 3: Impact of Social Interaction on Demonstrations

- Roundabout ratio: *lower* → *higher*

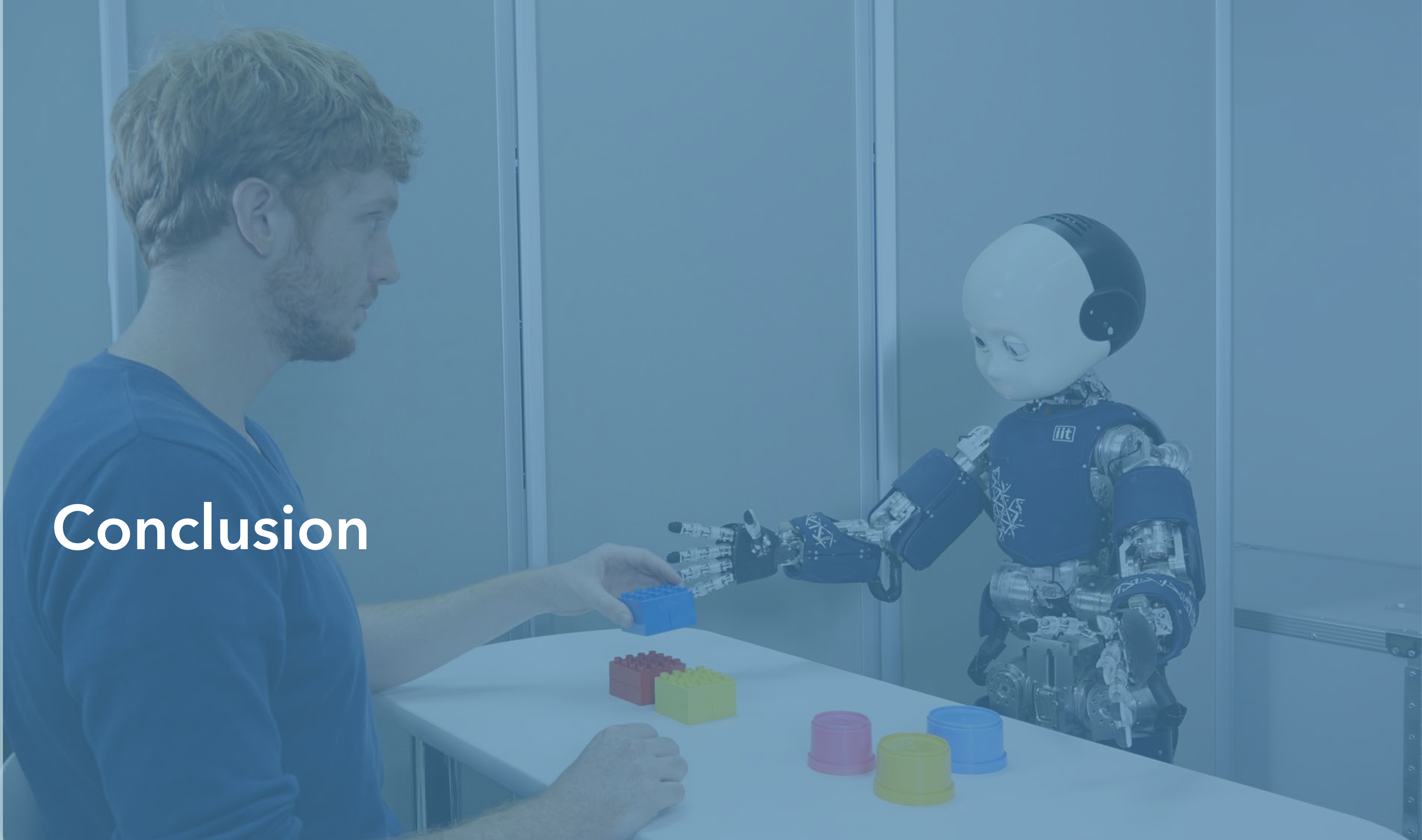


- Duration of demonstration: *shorter* → *longer*



[Ugur, Nagai, Sahin, & Oztop, IEEE TAMD 2015]

Conclusion



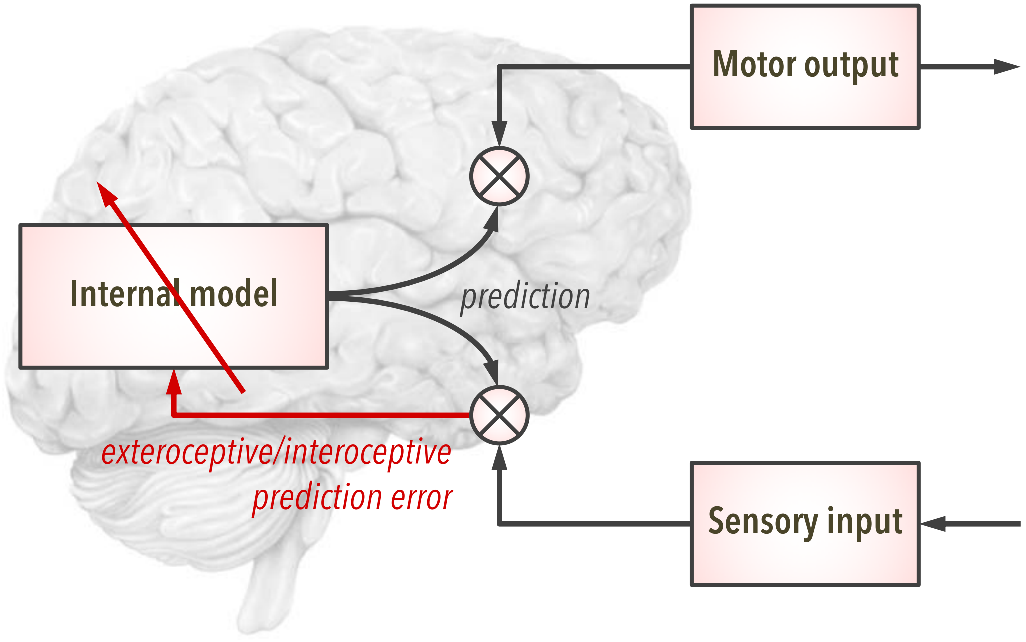
Cognitive Development Based on Predictive Learning

[Nagai, Phil Trans B 2019]

- Infants acquire various cognitive abilities through learning to minimize prediction errors:

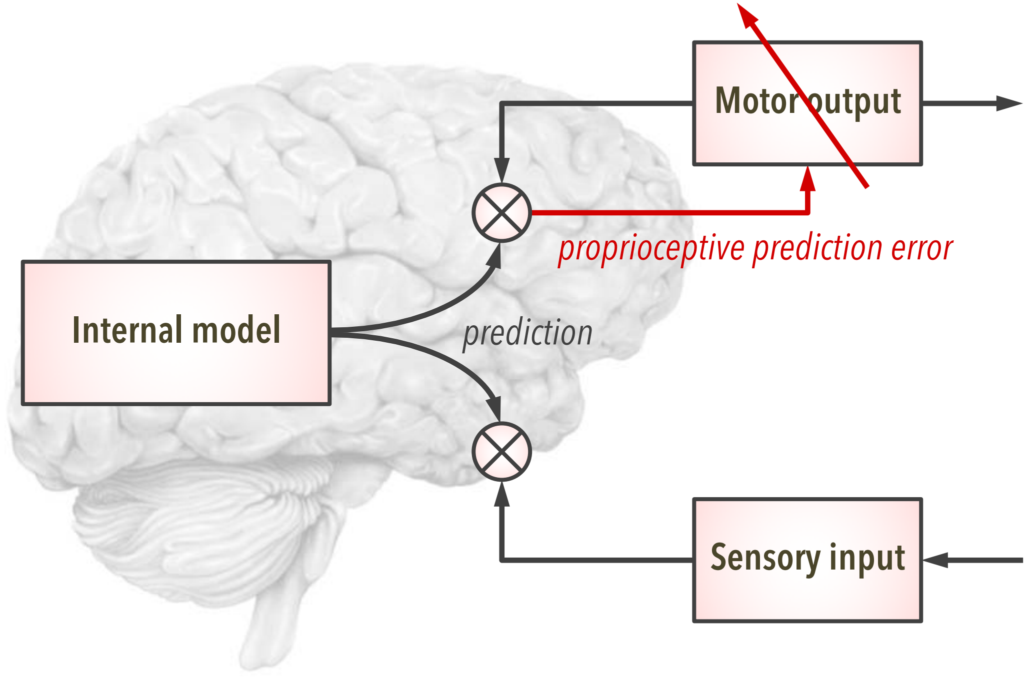
(a) *Updating the internal model* through own sensorimotor experiences

– Non-social (i.e., self-oriented) behaviors



(b) *Generating actions* to alter sensory signals

– Proto-social (i.e., other-oriented) behaviors



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Review

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One contribution of 17 to a theme issue ‘From social brains to social robots: applying

Predictive learning: its key role in early cognitive development

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What is a fundamental ability for cognitive development? Although many researchers have been addressing this question, no shared understanding has been acquired yet. We propose that predictive learning of sensorimotor signals plays a key role in early cognitive development. The human brain is known to represent sensorimotor signals in a predictive manner, i.e. it attempts to minimize prediction error between incoming sensory signals and top–down prediction. We extend this view and suggest that two mechanisms for minimizing prediction error lead to the development of cognitive abilities during early infancy. The first mechanism is to update an immature predictor. The predictor must be trained through sensorimotor experiences because it does not inherently have prediction ability. The second mechanism is to execute an action anticipated by the predictor. Interacting with other individuals often increases prediction error, which can be minimized by executing one’s own action corresponding to others’ action. Our experiments using robotic systems

Thank you!

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- Kyoichiro Kobayashi (-2019.03)

Bogazici University

- Emre Ugur

Ozyegin University

- Erhan Oztop

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