Texte

Active Exploration Mechanisms in Autonomous Learning and Development

A Robotic Modeling Perspective

Pierre-Yves Oudeyer

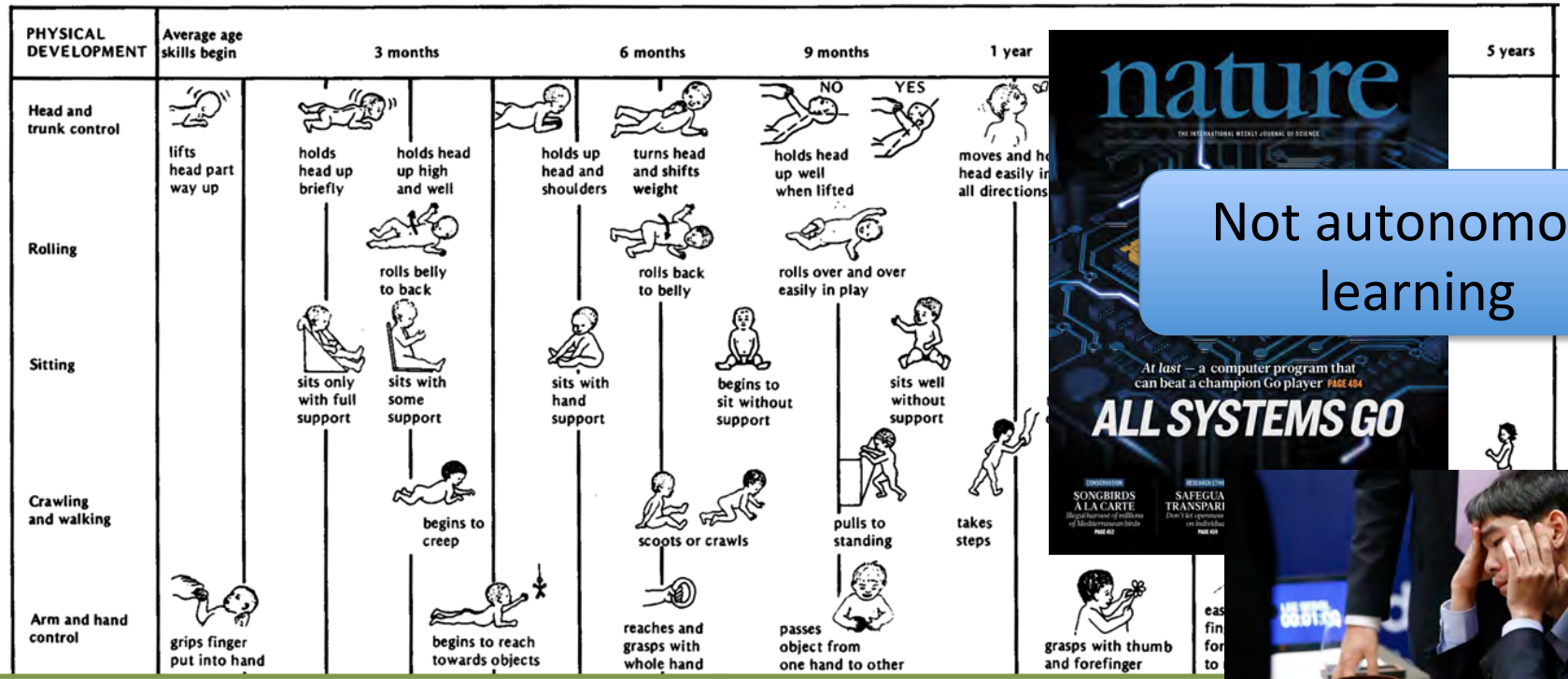
Project-Team INRIA-ENSTA-ParisTech FLOWERS

http://www.pyoudeyer.com

https://flowers.inria.fr

Twitter: @pyoudeyer

Autonomous Learning and Development in Human Infants



Not autonomous learning

- **How do developmental structures form?**
- **What is the role of structured learning curriculums?**
- **How do they enable autonomous learning?**

Team: ~20-25 people

- 4 Inria seniors:
  PY. Oudeyer, M. Lopes,
  D. Roy, A-L. Vollmer
- 3 Ensta ParisTech
- seniors:
  D. Filliat, F. Stulp,
  A. Gepperth
- 8-9 PhDs
- 3-5 engineers
- 1-3 postdocs

Cognitive sciences
models to understand better human development

Lifelong autonomous learning in **robotics and AI**

Applications in **educational technologies**

Many collaborations with researchers in

- Developmental psychology
- Neuroscience
- Robotics and AI
- Educational sciences

Exploration and guidance mechanisms

Intrinsic motivation, active learning curiosity

- Cognitive science
- Robotics/AI
- Applications in education

Body morphology and growth

- Cognitive science
- Robotics/AI
- Applications in education

Interactive learning, imitation

- Cognitive science
- Robotics/AI
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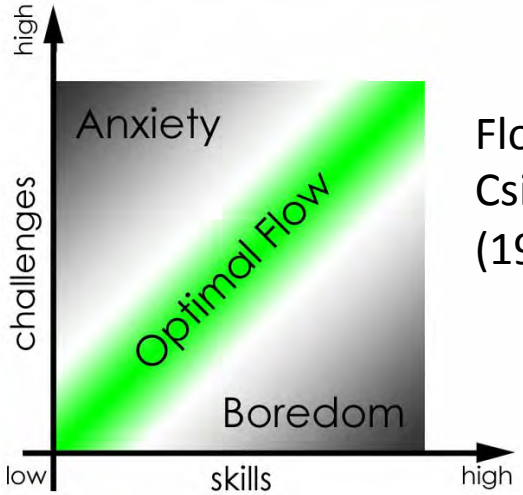
Spontaneous active exploration

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

Intrinsic motivation, curiosity and active learning



Flow theory
Csikszentmihalyi
(1996)

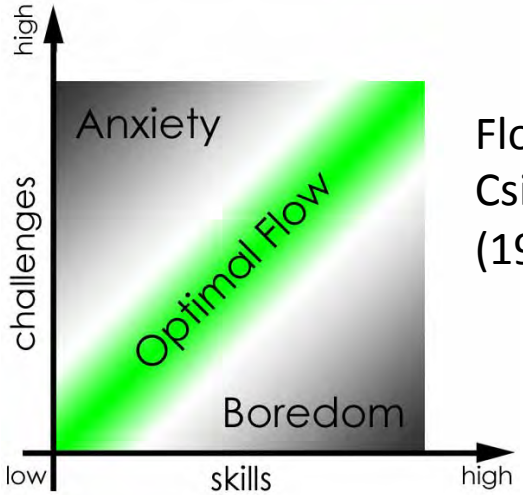
➔ Intrinsic drive to reduce uncertainty, and to experiencing novelty, surprise, cognitive dissonance, challenge, incongruences, …

➔ Optimal interest = optimal difficulty = neither trivial nor too difficult challenges

Berlyne (1960), White (1960), Kagan (1972), Csikszentmihalyi (1996), (Kidd et al., 2012), …

See review in (Oudeyer et al., 2016)

Intrinsic motivation, curiosity and active learning



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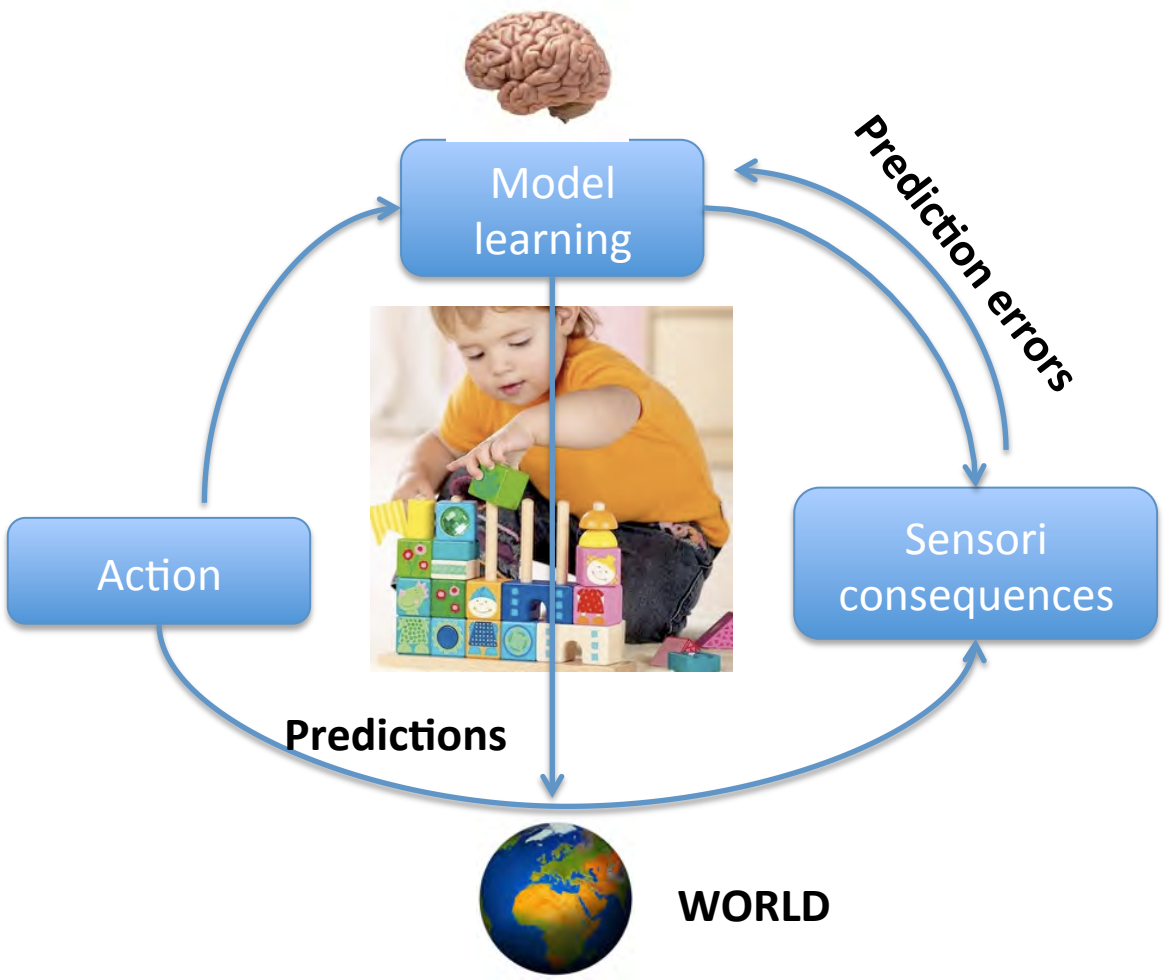
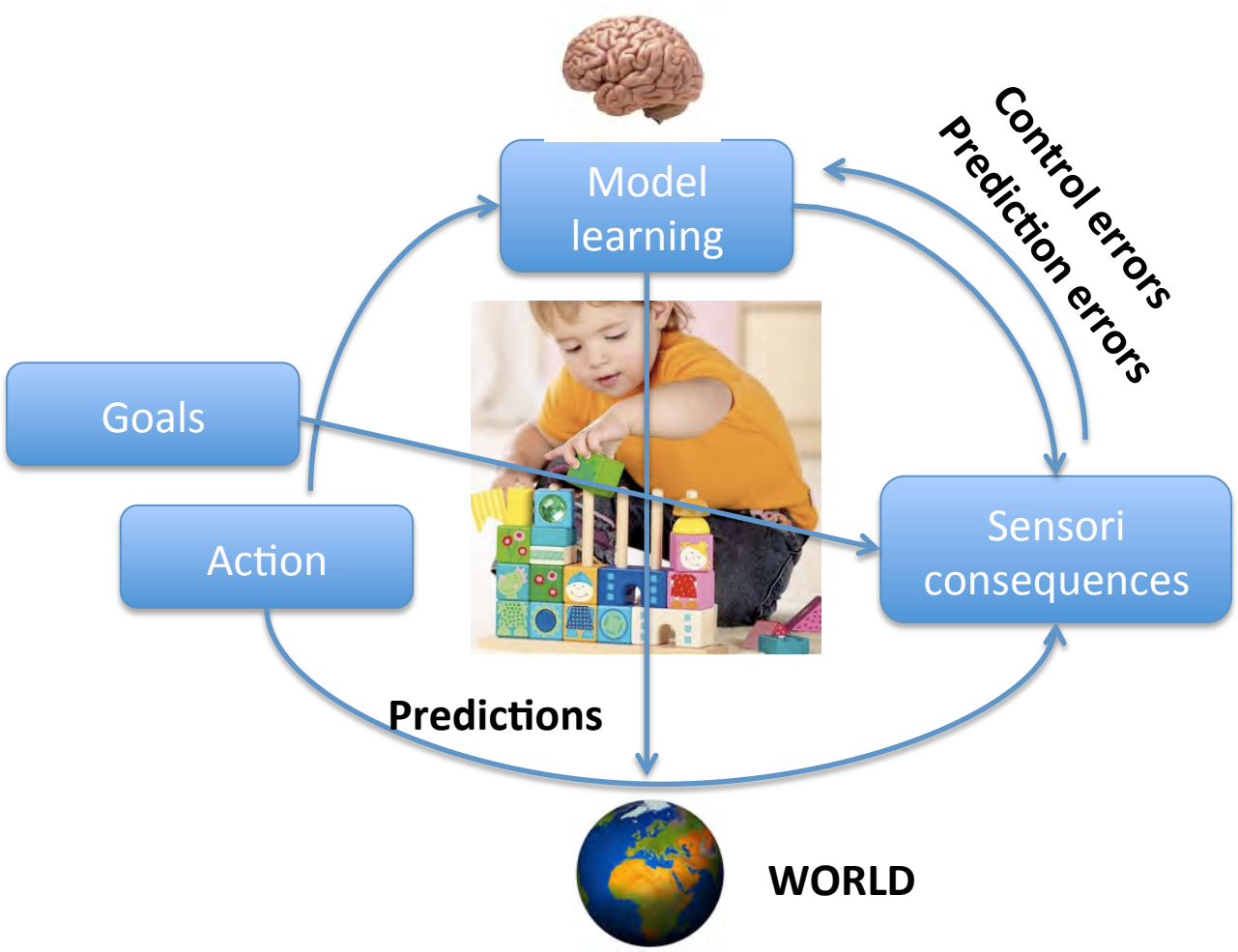
Contribution of Flowers lab and colleagues in the last 10 years:
Development of **a unified formal and theoretical framework**
in psychology and neuroscience

(Frontiers in Neuroscience 2007; IEEE TEC 2007; Trends in Cognitive Science, Nov. 2013; Progress in Brain Research, 2016; Frontiers in Neuroscience, 2014; Scientific Reports, 2016; PNAS, in press)

Predictive brain framework: Exploring to learn world models



Predictive brain framework: Exploring to learn world models

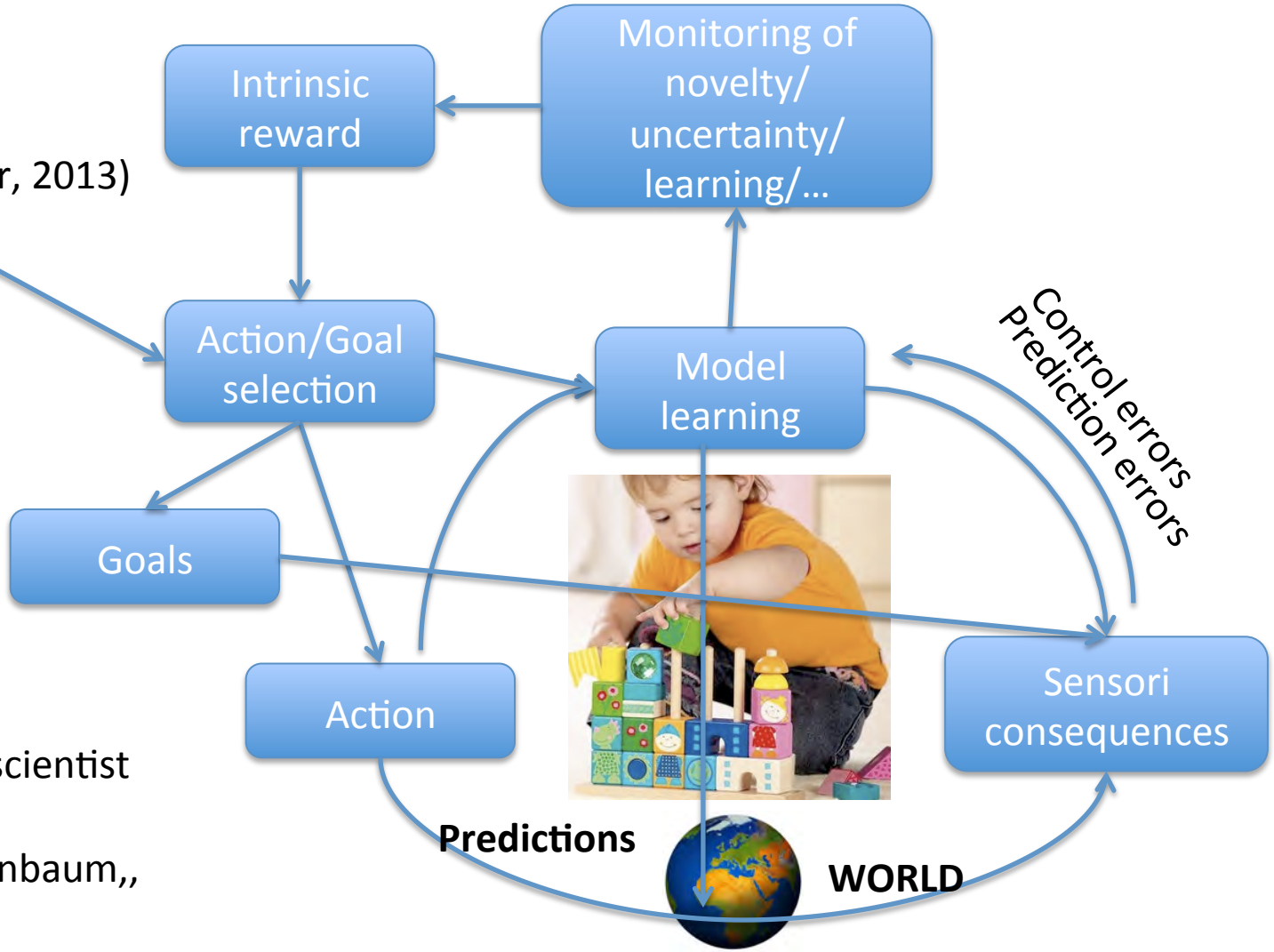


The active exploration system

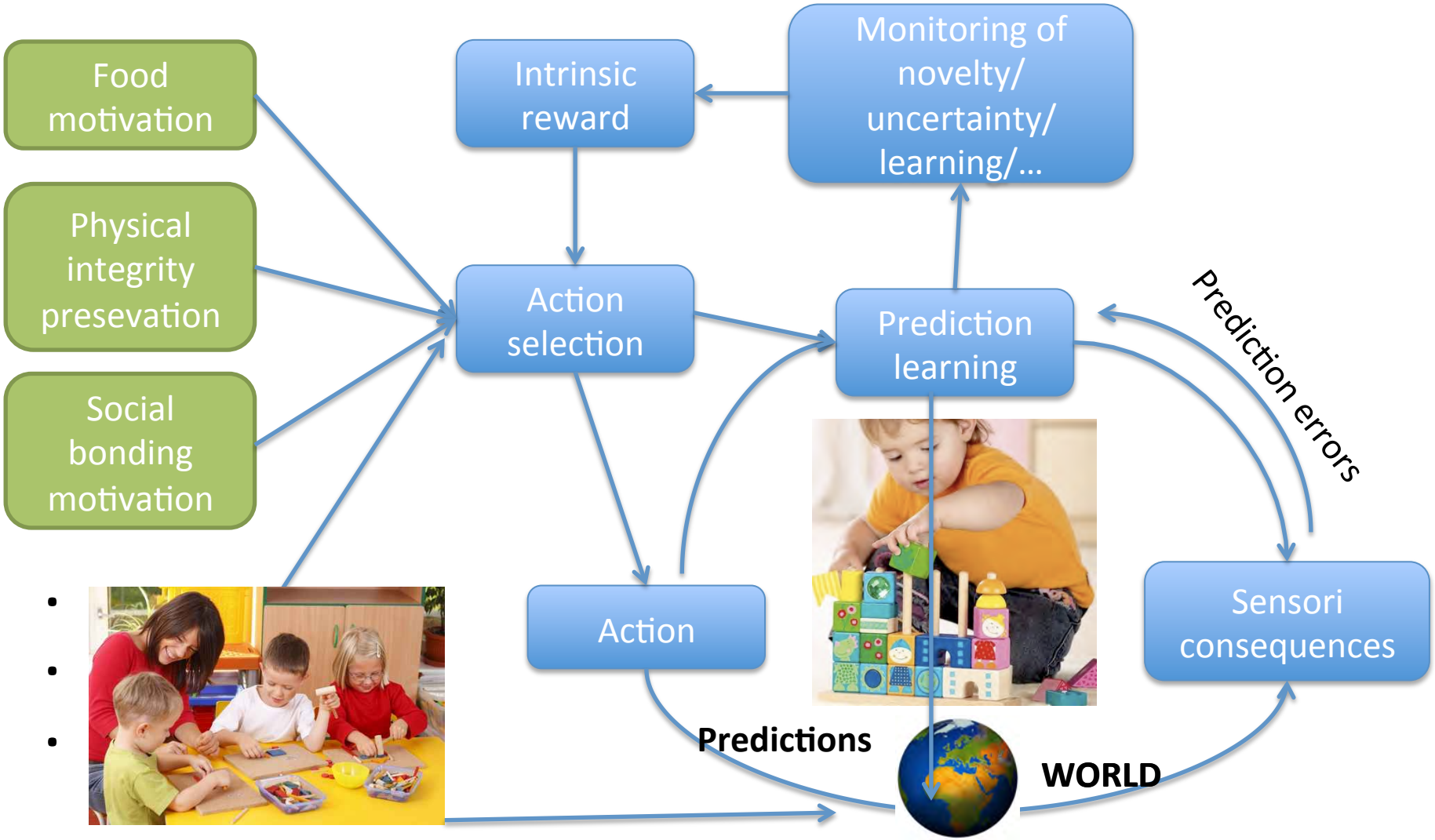
(Baranes and Oudeyer, 2013)

(Oudeyer et al., 2016;
Gottlieb et al., 2013;
Friston, 2012;
Barto et al., 2004;
Oudeyer et al., 2007;
Schmidhuber, 1991)

Also related to
Child as a (Bayesian) scientist hypothesis
(Shulz, Gopnick, Tenenbaum,,
…)

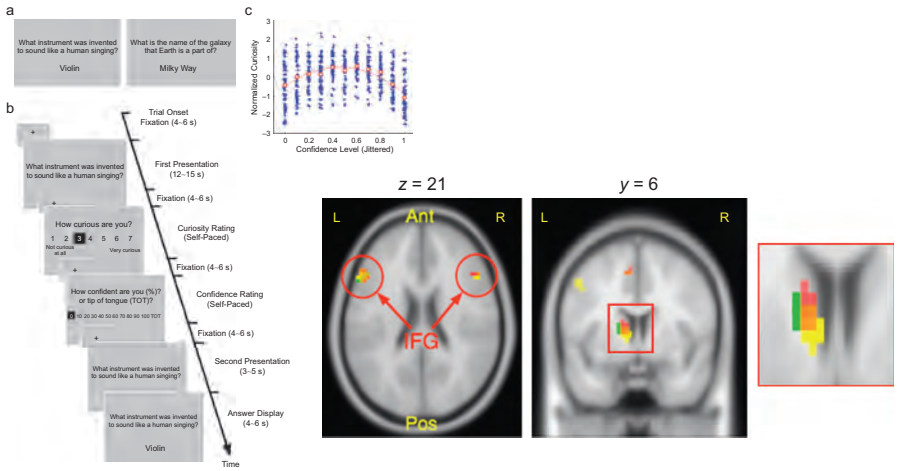


Interaction with other motivations and learning mechanism



Curiosity in experimental studies

Attention driven by **surprising external stimuli**
in **short time scales**



- Perceptual curiosity e.g. Stahl and Feigenson, 2015
- Epistemic curiosity e.g. Kang et al., 2009; Gruber et al., 2014

- Study impact on memorization/learning
- Neural correlates (also in monkeys, e.g. Waelti et al., 2001; Gottlieb et al., 2013)
- Behavioral correlates (e.g. eye movements, Baranes et al., 2015)

Spontaneous exploration:

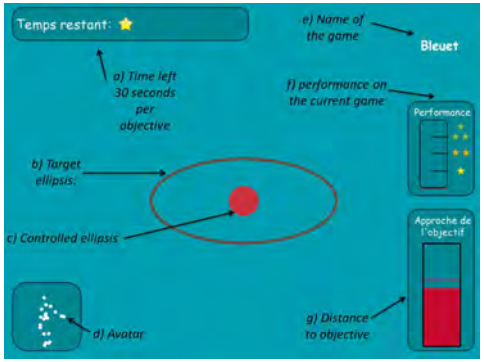
Beyond visual attention towards
external stimuli,
Beyond surprise,
Beyond short-time scales:

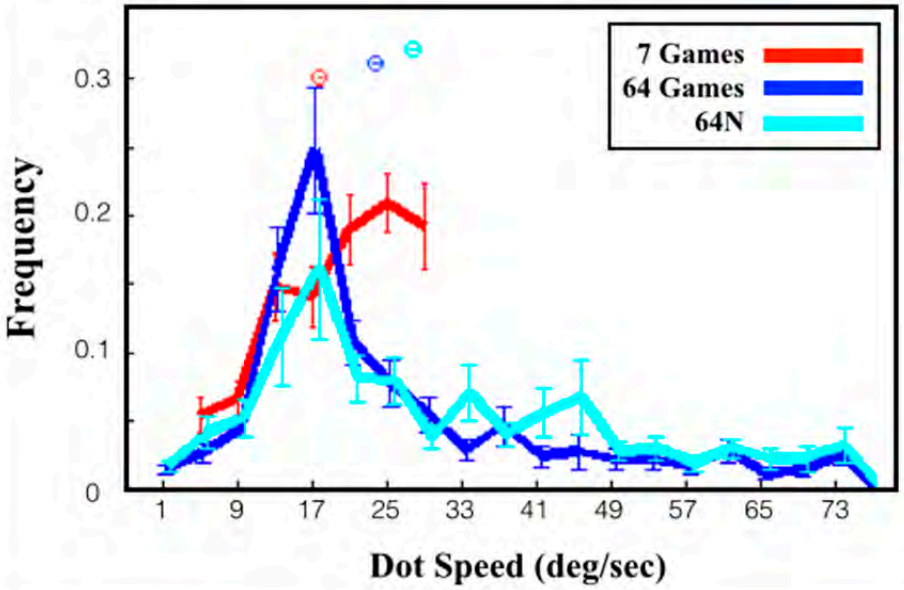
Open questions
in psychology and neuroscience

(1) Beyond visual attention towards external stimuli

➔ *What kind of choices can be made during active exploration? (interestingness of* ***what****?)*

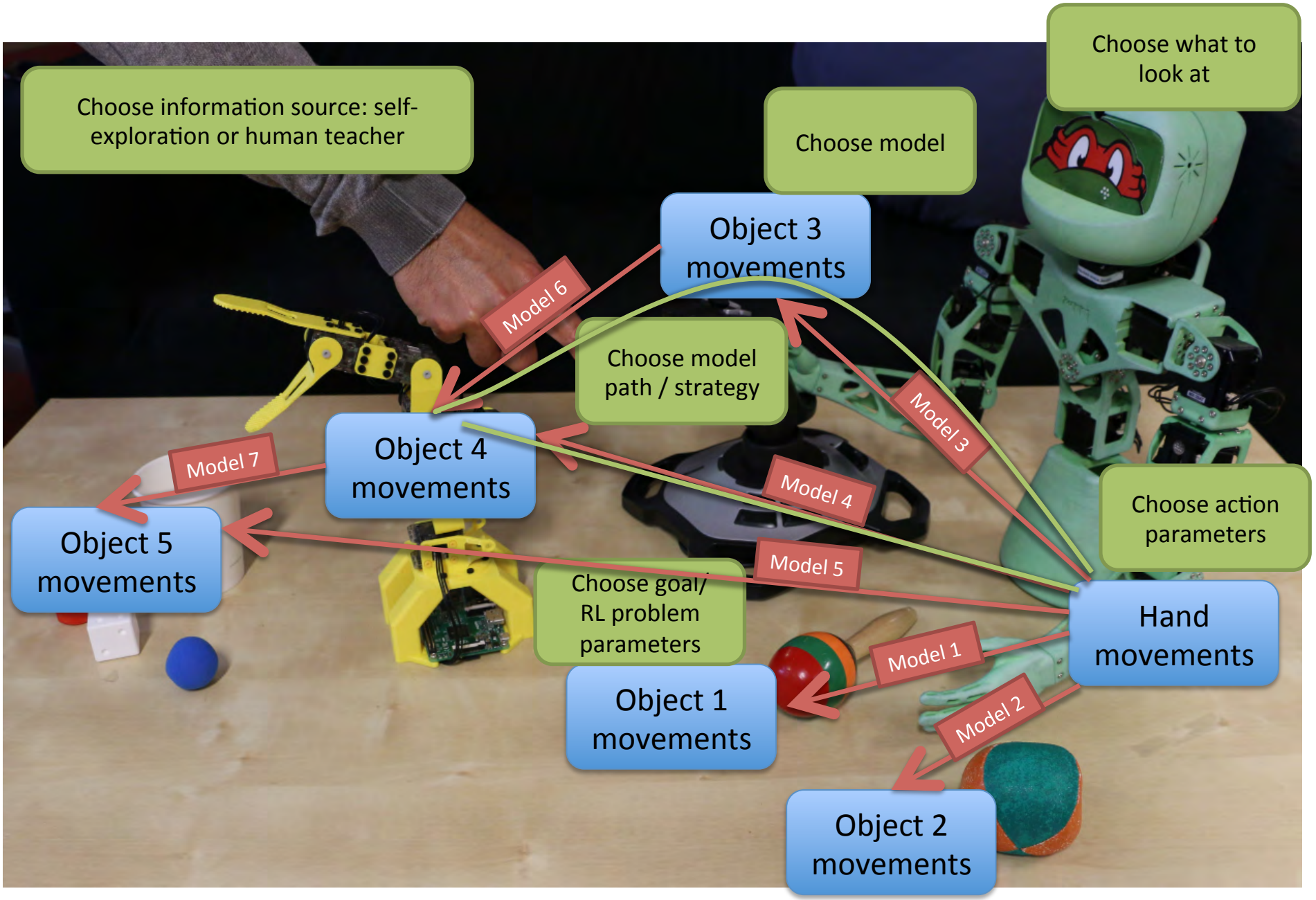
Intrinsically motivated exploration of sensori*motor* activities





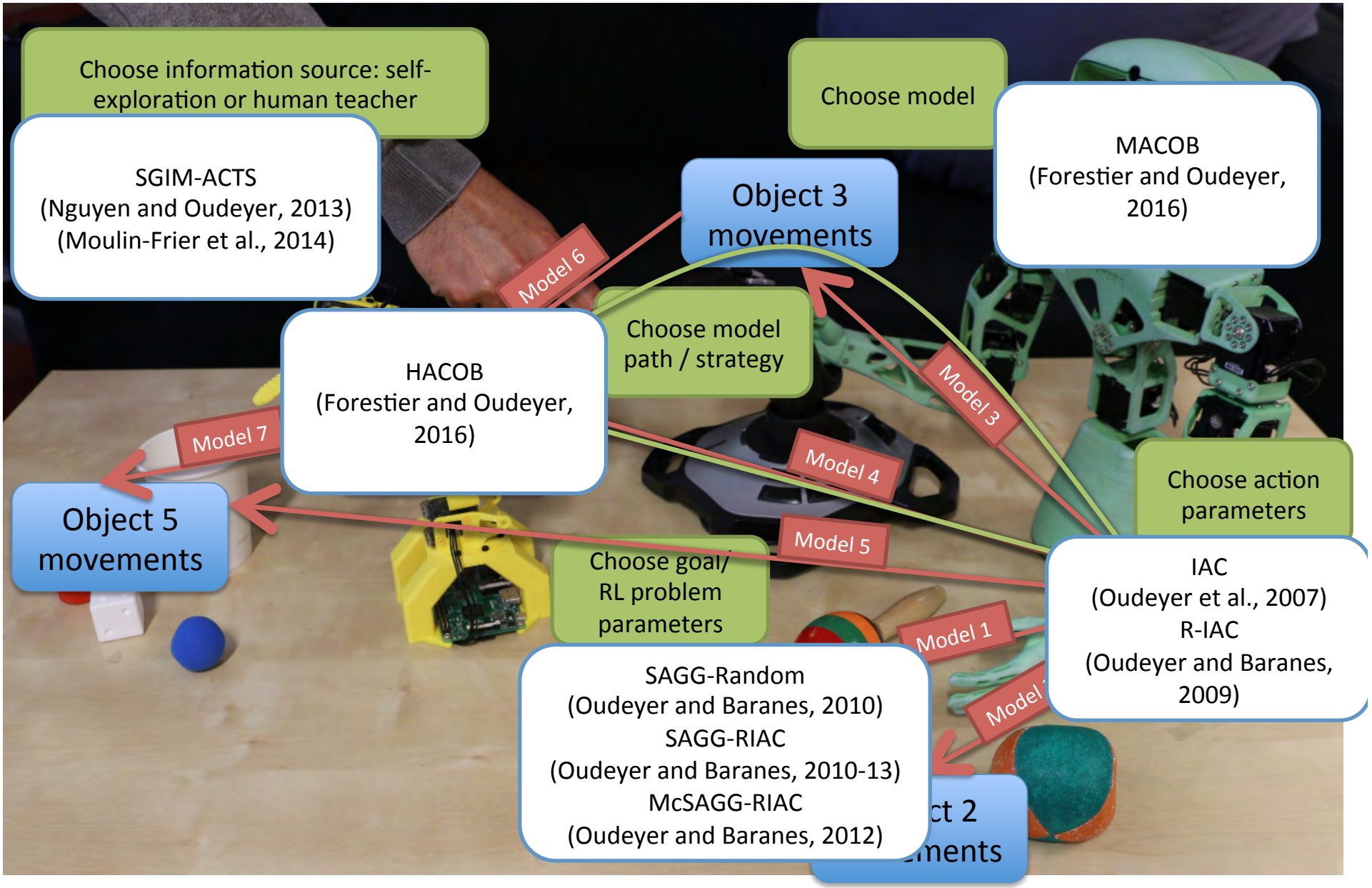
(Frontiers in Neuroscience, 2014; ICDL-Epirob 2014;
See also Scientific Reports, 2016; PNAS, in press)

The choice spaces in curiosity-driven exploration



Hierarchical **strategic learning** algorithms

(Lopes and Oudeyer, 2012; Nguyen and Oudeyer, 2013)



(1) Beyond « surprise »: *what are the features of interestingness?*

- High novelty/high complexity?
- (Bayesian ?) Surprise? (Itti and Baldi)
- Knowledge gap, cognitive dissonance? (Kagan, Festinger, Lowenstein)
- Intermediate novelty, intermediate complexity? (Berlyne, Kidd)
- Intermediate challenge? (White, Csikszentmihalyi)
- Free energy? (Friston)
- **Learning progress, improvement of prediction errors? (Oudeyer et al., Schmidhuber)**

All these measures can be mathematically modelled and compared in computational and robotic experiments
(Oudeyer, Gottlieb and Lopes, 2016)

frontiers
IN NEUROROBOTICS

What is intrinsic motivation? A typology of computational approaches

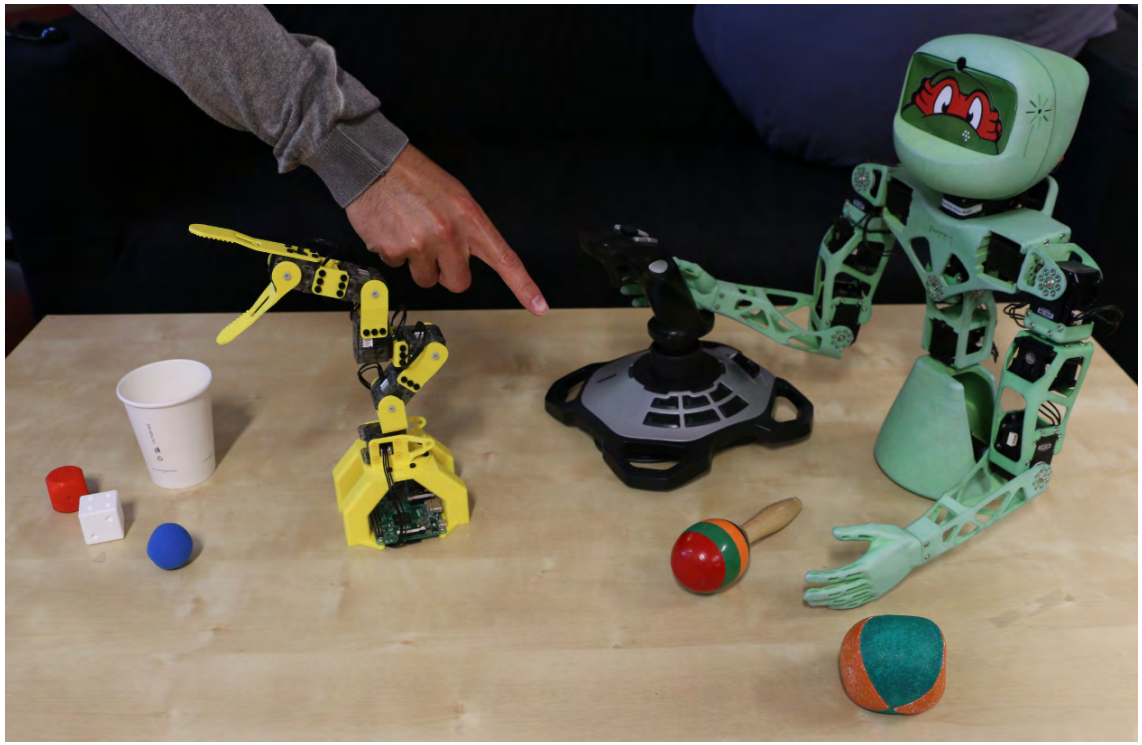
Pierre-Yves Oudeyer[1,2,*] **and Frederic Kaplan**[3]

					Homeostatic (-) vs Heterostatic (+)	Motivation	Exploration potential	Organization potential	Computational cost	Existing models
Internal	Intrinsic	Adaptive	Knowledge-based	Information theoretic	+	UM	**	*	**	**
						IGM	***	***	**	**
						DSM	**	**	**	*
					–	DFM	*	**	**	*
				Predictive	+	NM	**	*	*	***
					–	ILNM	**	**	*	**
					+	LPM	***	***	**	**
						SM	**	**	**	*
					–	FM	*	**	**	**
			Competence-based		+	IM	**	*	**	*
						CPM	***	***	**	*
					–	CM	*	**	**	*
		Fixed	Morphological		–	SyncM	*	**	**	**
						StabM	*	**	*	**
					+	VarM	**	*	*	*
	Extrinsic				–	SocM	/	/	*	***
					–	EnerM	/	/	*	***

Figure 7. This table presents all the models discussed in this paper and the families to which they belong. *For each model we give a rough estimation of its exploration potential (how likely such a motivation can lead to exploratory and investigation behaviours) and of its organization potential (how likely such a motivation can lead to a structured and organized behaviour). We also estimate the computational cost and number of computational models existing so far for each of the categories.*

Active curiosity-driven exploration as a means to learn models of the world dynamics/ affordances?

➔ Searching for maximal novelty or uncertainty or entropy will not be efficient at all!



The Learning Progress hypothesis

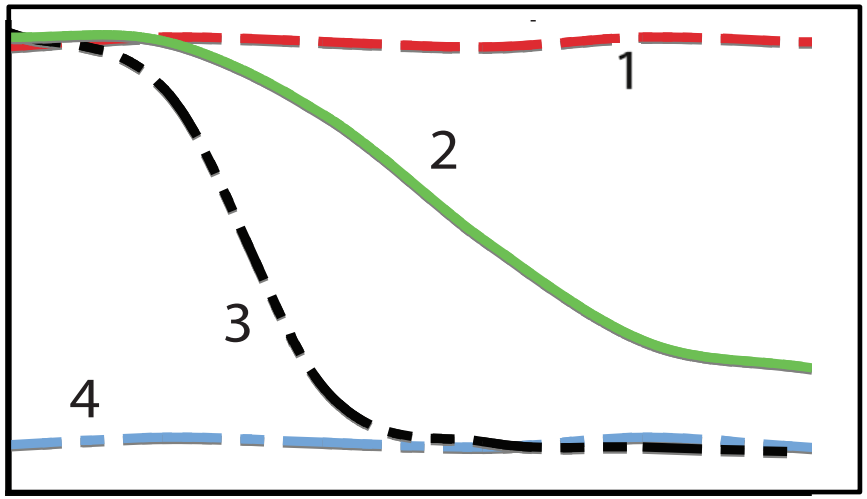
➔ Explore tasks that currently maximize empirical learning progress

(Oudeyer et al., 2004; 2007;
Gottlieb et al., 2013;
Oudeyer et al., 2016)

➔ Optimal active learning of multiple tasks with concace learning curves
in the Strategic Student Learning framework (Lopes and Oudeyer, 2012)

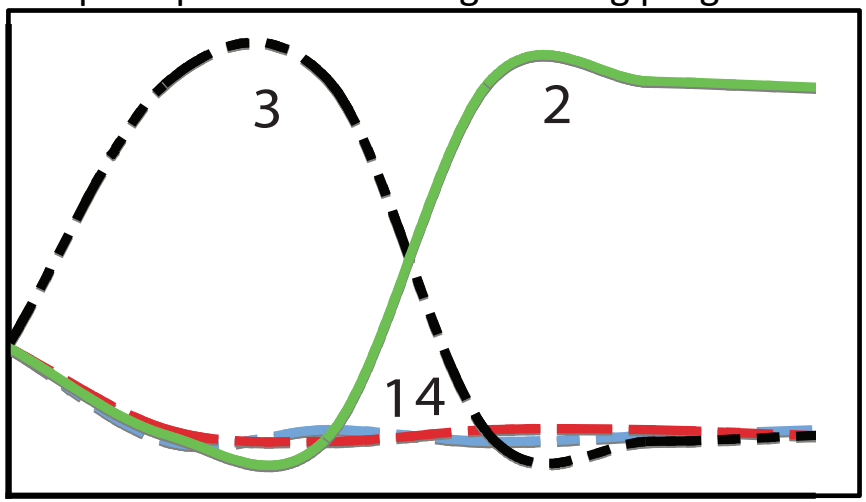
➔ This achieves **automated and intrinsically motivated curriculum learning** of multiple tasks and/or models (Oudeyer et al., 2007; Oudeyer and Baranes, 2013; Forestier et al., 2016)

Errors in prediction in 4 activities



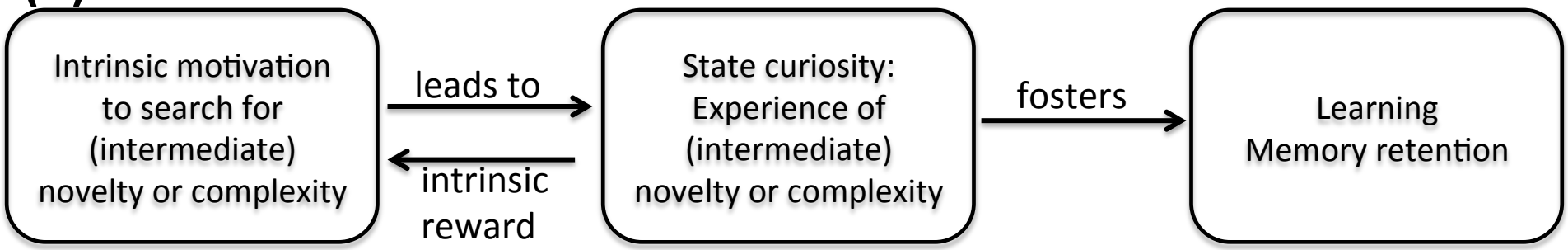
time

% of time spent in each activity based on the principle of maximizing learning progress



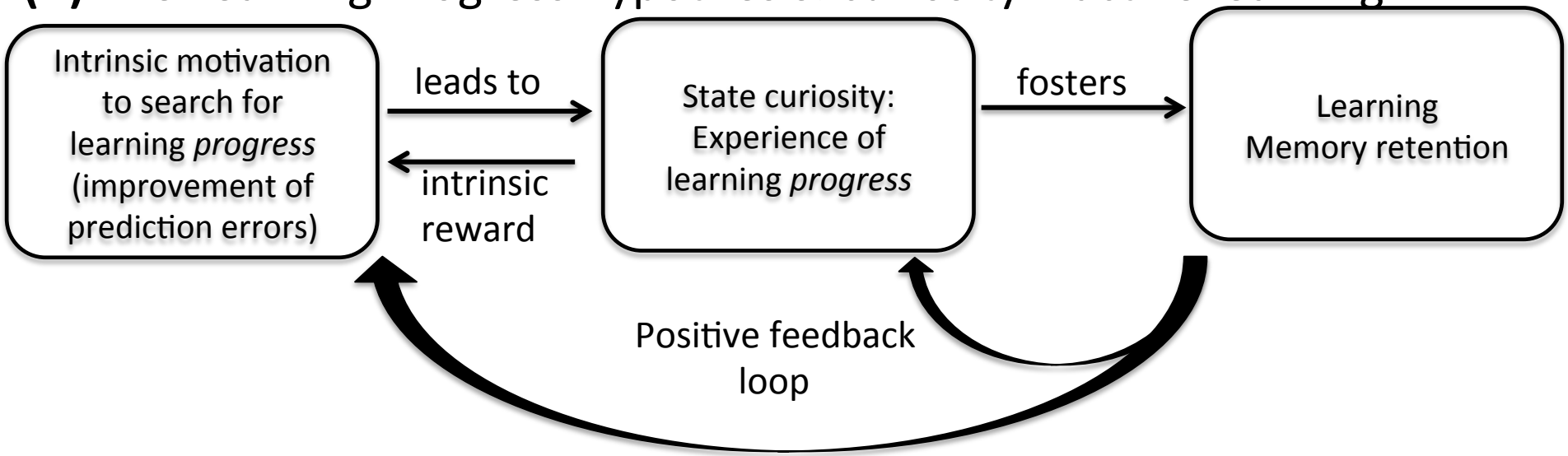
time

(A)



(Walti et al., 2001; Kang et al., 2009; Gruber et al., 2014; Stahl and Feigenson , 2015)

(B) The Learning Progress hypothesis: curiosity = active learning

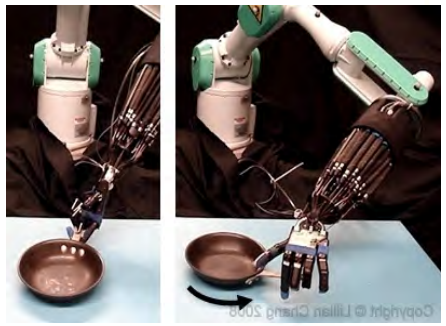


(Oudeyer et al., 2007; Oudeyer, Gottlieb, Lopes, 2016)

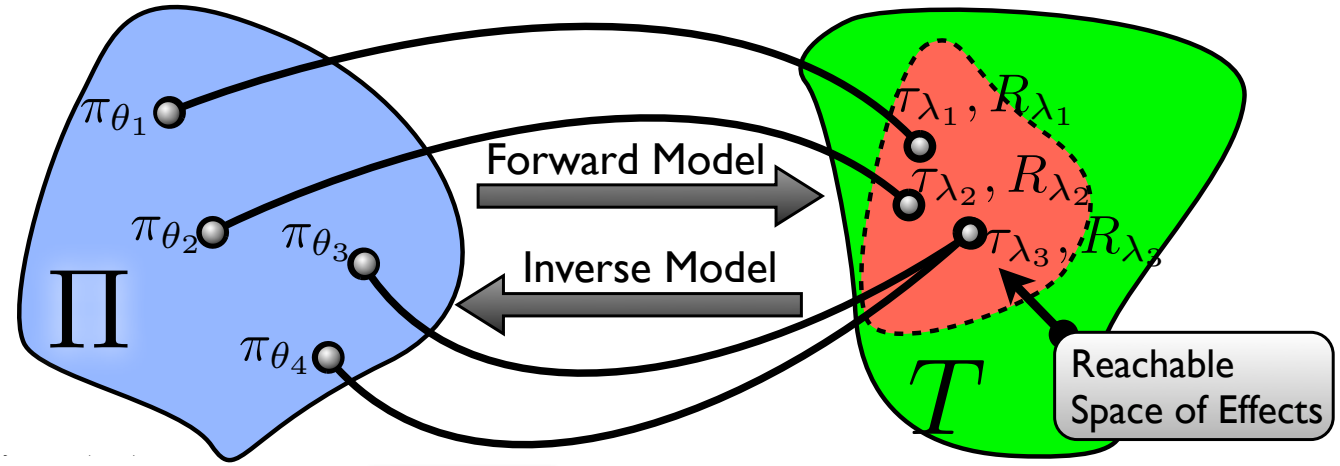
Examples of model architectures

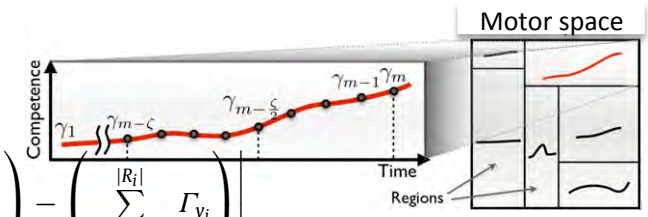
Curiosity-driven active **Motor Exploration**

(active selection of parameterized motor programs)



(Context, Movement)
→
Effect

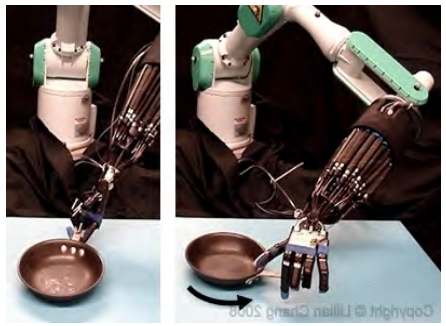




$$interest_i = \frac{\left| \left(\sum_{j=|R_i|-\zeta}^{|R_i|-\frac{\zeta}{2}} \Gamma_{y_j} \right) - \left(\sum_{j=|R_i|-\frac{\zeta}{2}}^{|R_i|} \Gamma_{y_j} \right) \right|}{\zeta}$$

Cost function for driving motor exploration = generating dynamically a learning curriculum

Curiosity-driven active **Goal Exploration**

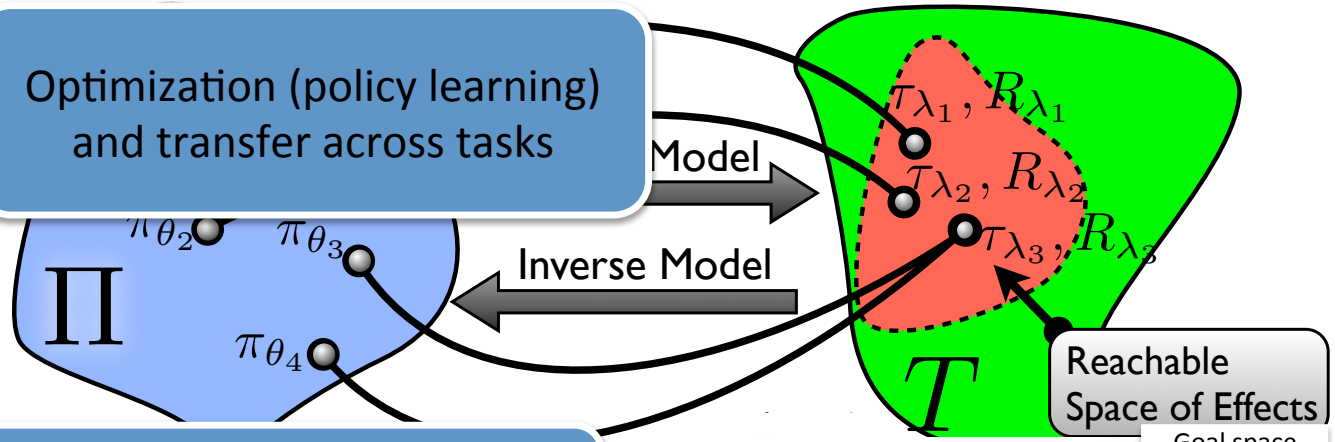


(Context, Movement)
→
Effect

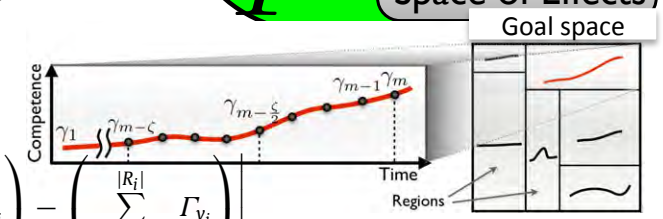
(active selection of parameterized RL problems)

Space of Controllers **Task Space = Space of Effects**

Optimization (policy learning) and transfer across tasks



Constraints over optimization and transfer (e.g. maturation)



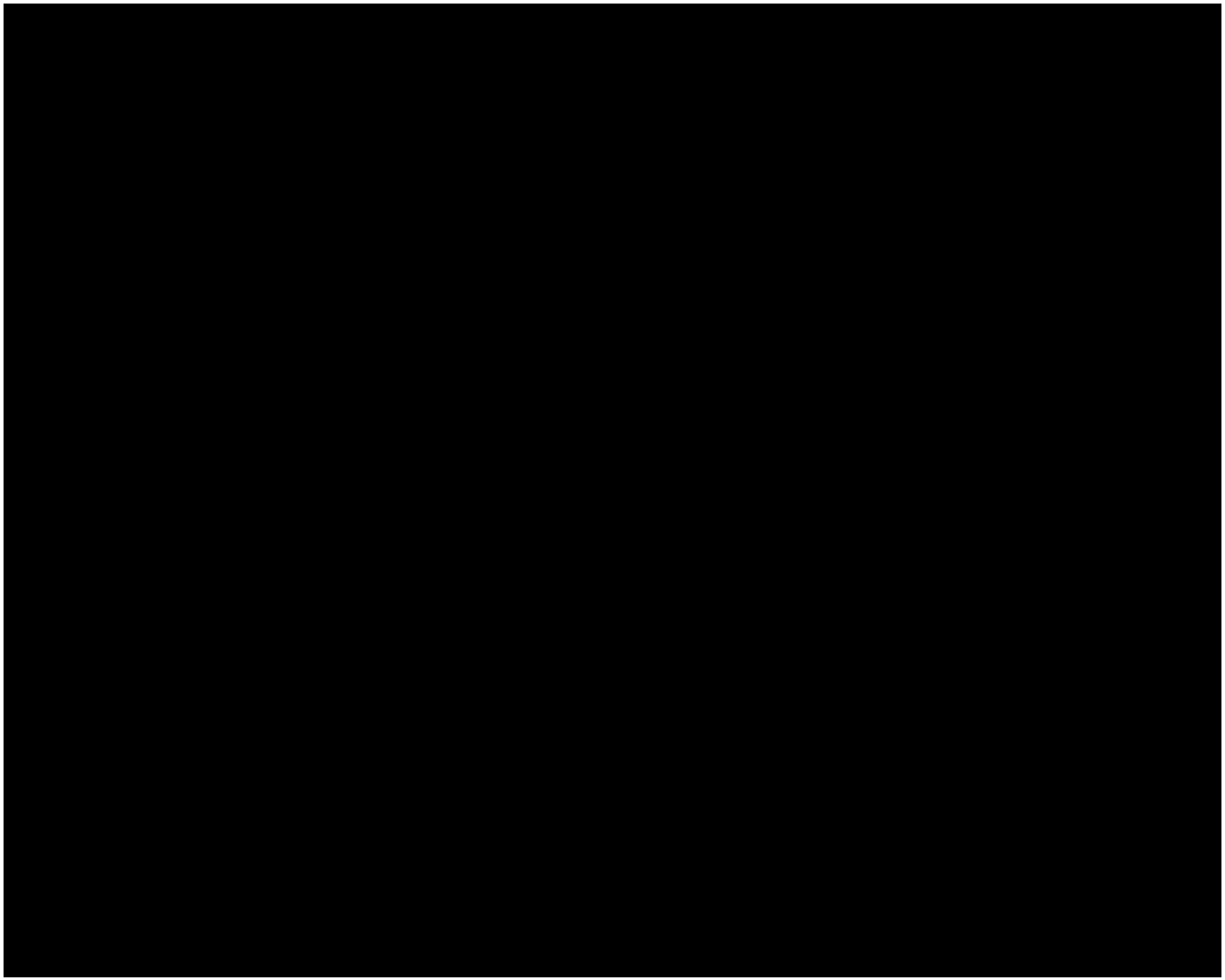
$$interest_i = \frac{\left| \left(\sum_{j=|R_i|-\zeta}^{|R_i|-\frac{\zeta}{2}} \Gamma_{y_j} \right) - \left(\sum_{j=|R_i|-\frac{\zeta}{2}}^{|R_i|} \Gamma_{y_j} \right) \right|}{\zeta}$$

Cost function for driving multi-task exploration
= generating dynamically a learning curriculum

(5) Do short-term curiosity-driven exploration mechanisms have consequences on **long term organization of learning**?

(= how intrinsic motivation can self-organize curriculum learning?)

The Playground Experiments



(Oudeyer et al., IEEE Trans. EC 2007; Oudeyer and Smith, 2016)

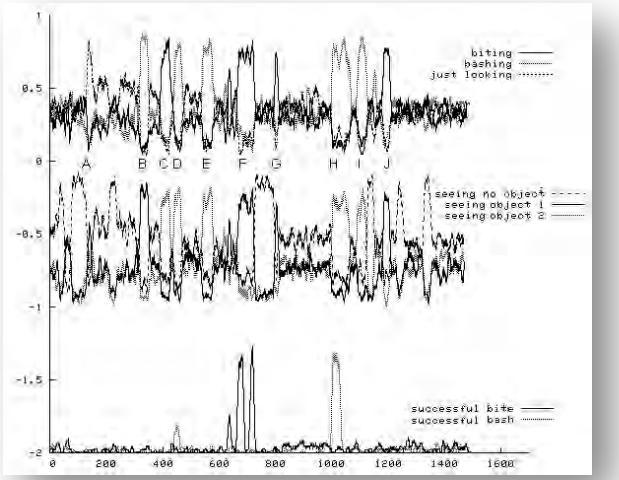
https://www.youtube.com/watch?v=uAoNzHjzzys

Autonomous acquisition of skill repertoires

Functions:

- Autonomous learning of novel affordances and skills, e.g. object manipulation, before they are needed for external needs
- Self-organization of developmental trajectories, bootstrapping of communication

➔ Developmental and evolutionary consequences



TOPICS
TOPICS IN COGNITIVE SCIENCE

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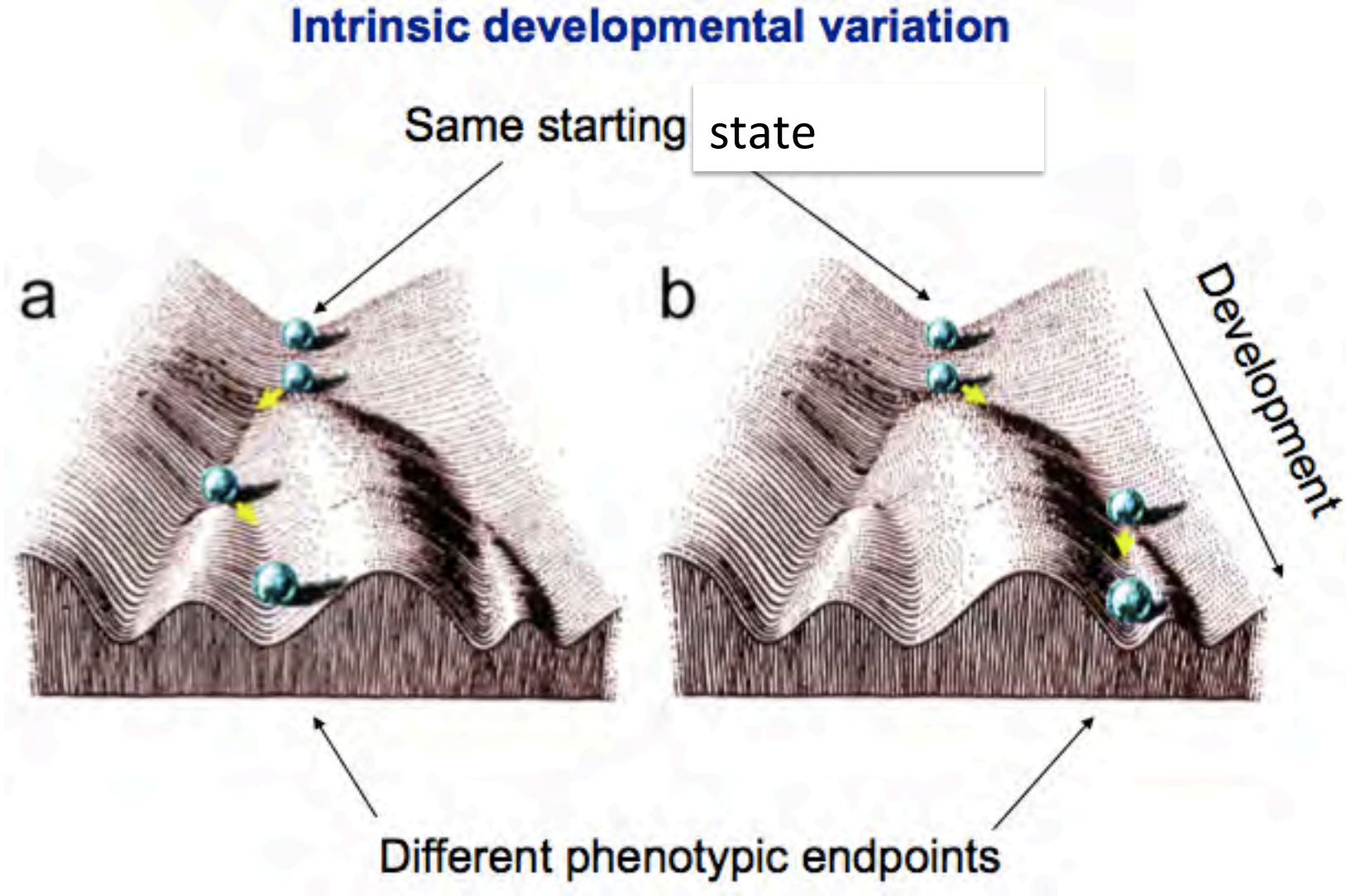
DOI: 10.1111/tops.12196

How Evolution May Work Through Curiosity-Driven Developmental Process

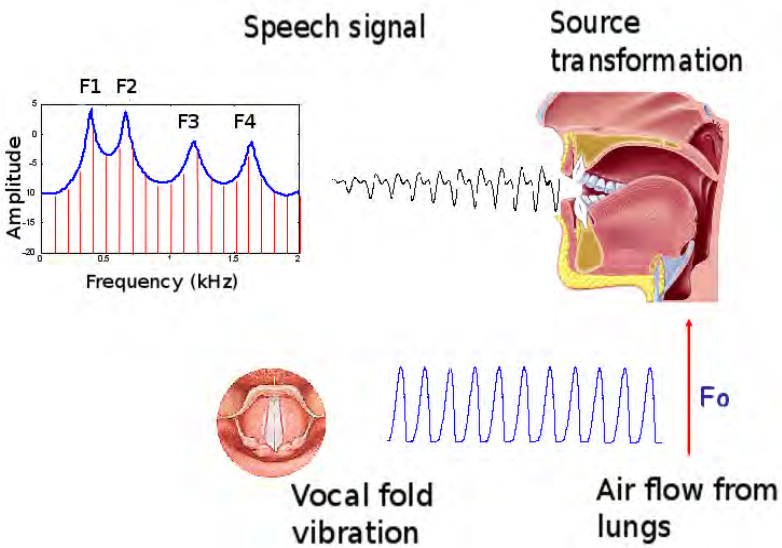
Pierre-Yves Oudeyer,[a] Linda B. Smith[b]

Regularities and diversity in developmental trajectories

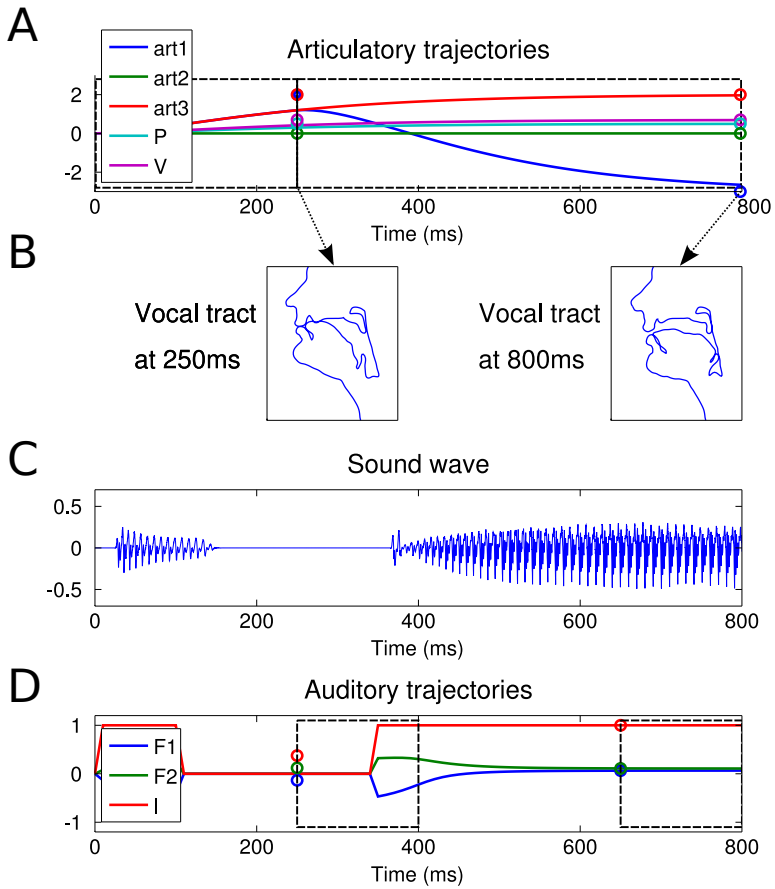


(after Waddington's epigenetic landscape)

Self-organization of vocal development



DIVA Vocal tract model (Guenther)



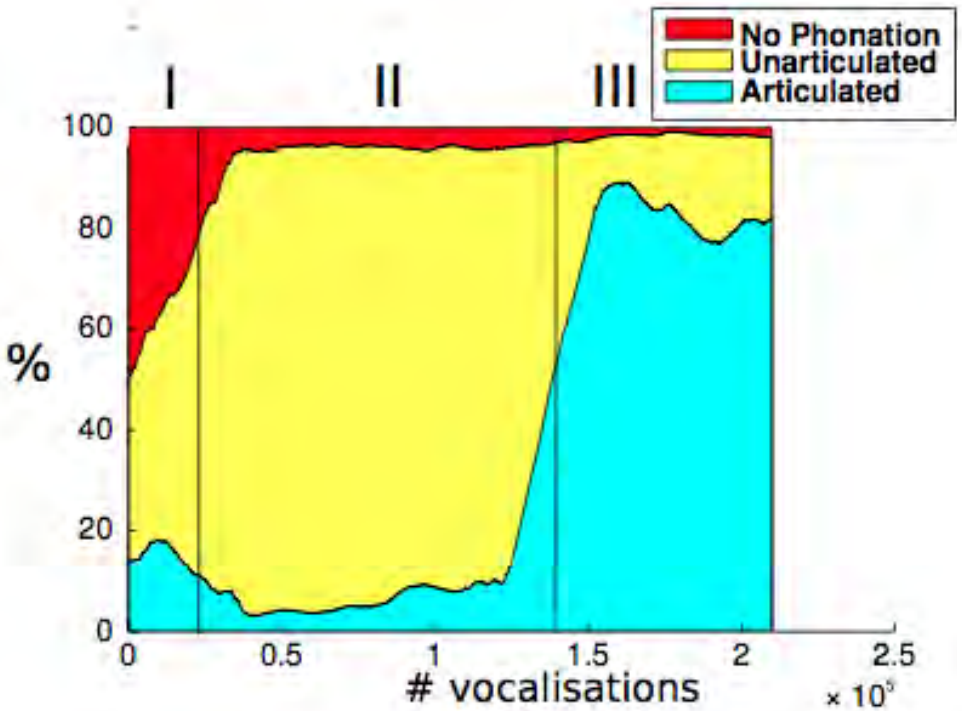
Two-layers active learning:

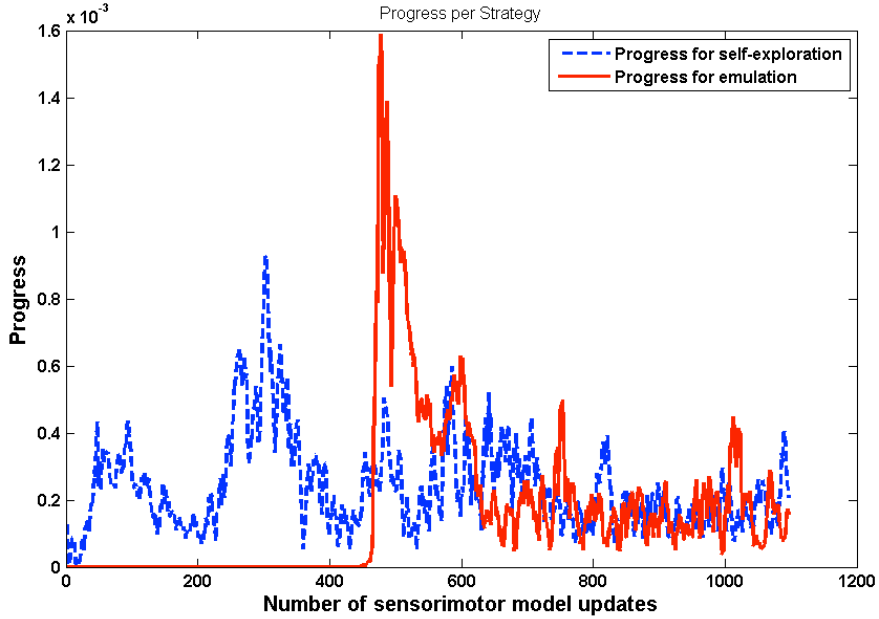
1) **Active choice self-exploration vs. Imitation**
2) **If self-exploration: active goal selection**

- Collaboration with D. K. Oller, Univ. Memphis, US

(Moulin-Frier, Nguyen and Oudeyer, Frontiers in Cognitive Science, 2013)

Emergent developmental stages





0-3 mo: squeals, growls, yeals ...

3-7 mo: quasi-vowels

7-10 mo: language-independent proto-syllables

10 mo: influence by ambient language

12 mo: first words

Approximate age

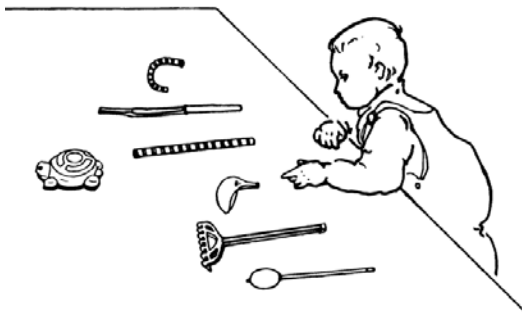
(Oller, 2000)

Learning tool use (nested affordances) + using intrinsic motivation to learn complex RL problem with rare rewards

https://www.youtube.com/watch?v=NOLAwD4ZTW0

Nested tool use, 2nd Best demo prize @NIPS, 2016
(in front of several GAFAs demos)

Reinterpreting infant tool use experiments?



➔ e.g. Chen and Siegler on strategy selection
(see Forestier and Oudeyer, CogSci 2016; ICDL-Epirob 2016)

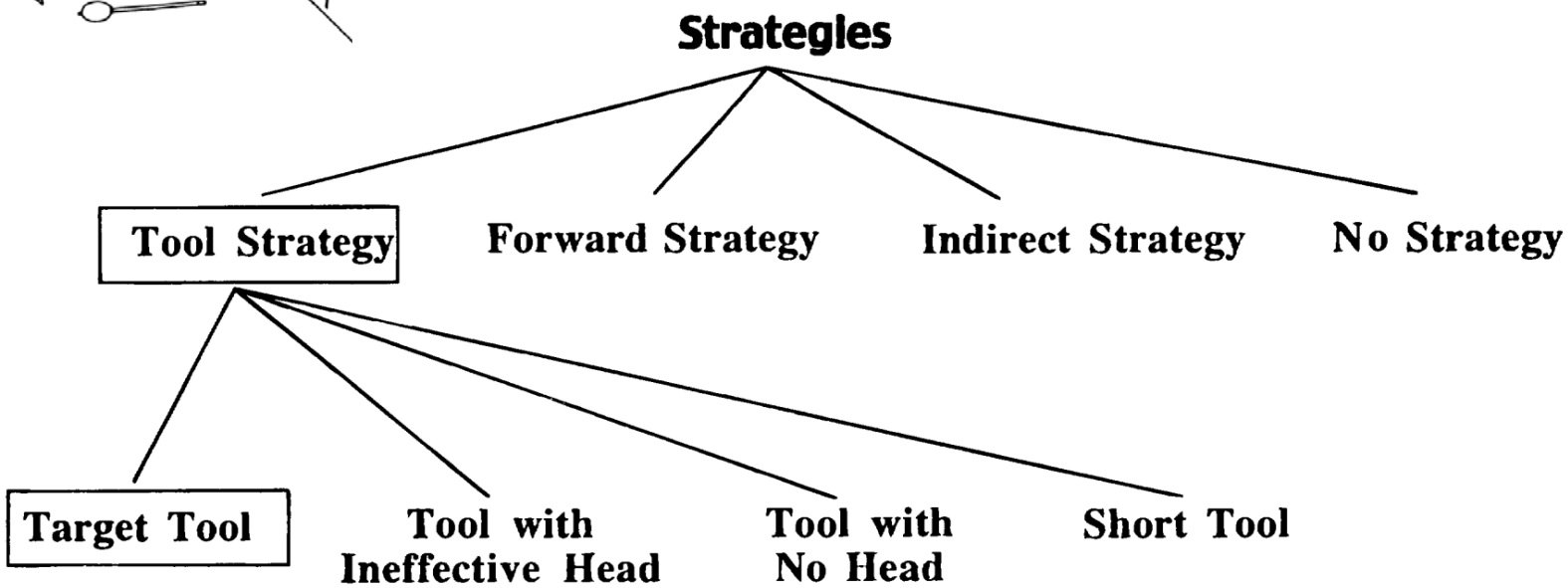


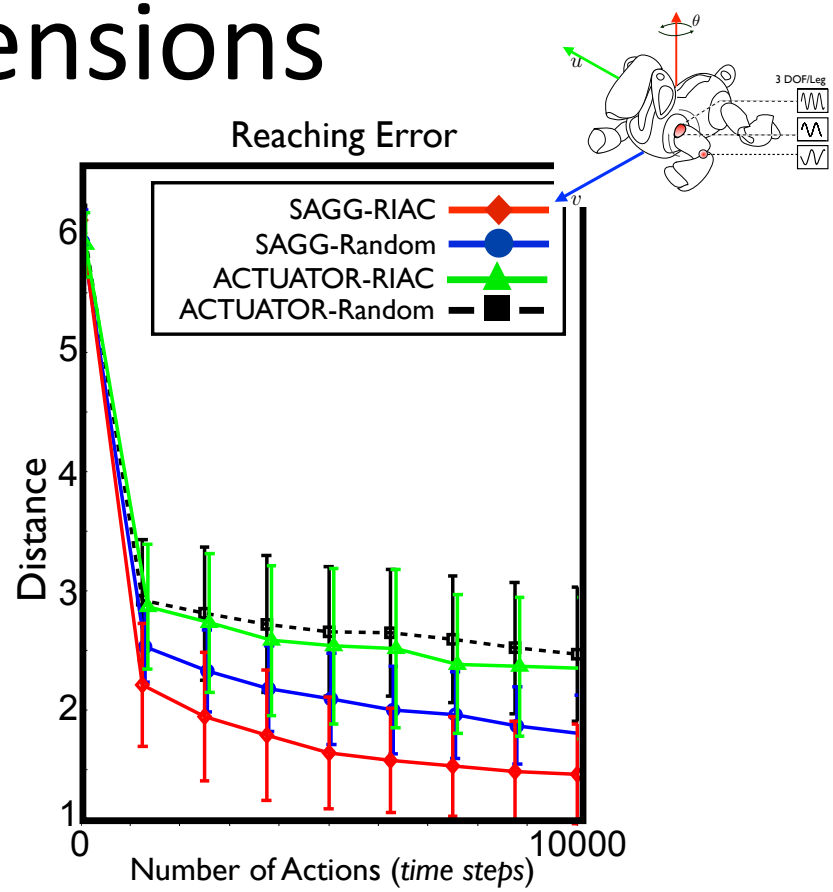
FIGURE 3.—The hierarchy of strategies among which children needed to choose.

Chen & Siegler 2000

Efficiency of LP-based curiosity-driven learning of skills

Efficiency of active learning in high-dimensions

Active learning of omnidirectional locomotion



Control Space: $[-1;1]^{24}$ Task Space: $[-1;1]^{3}$ https://www.youtube.com/watch?v=_HusNBLV7yM

➔ Performance higher than more classical active learning algorithms in real sensorimotor spaces (non-stationary, non homogeneous)
(Baranes and Oudeyer, IEEE TAMD 2009; Robotics and Autonomous Systems; 2013)

Learning omnidirectional control of soft/deformable objects
(Autonomous Robots, 2014)

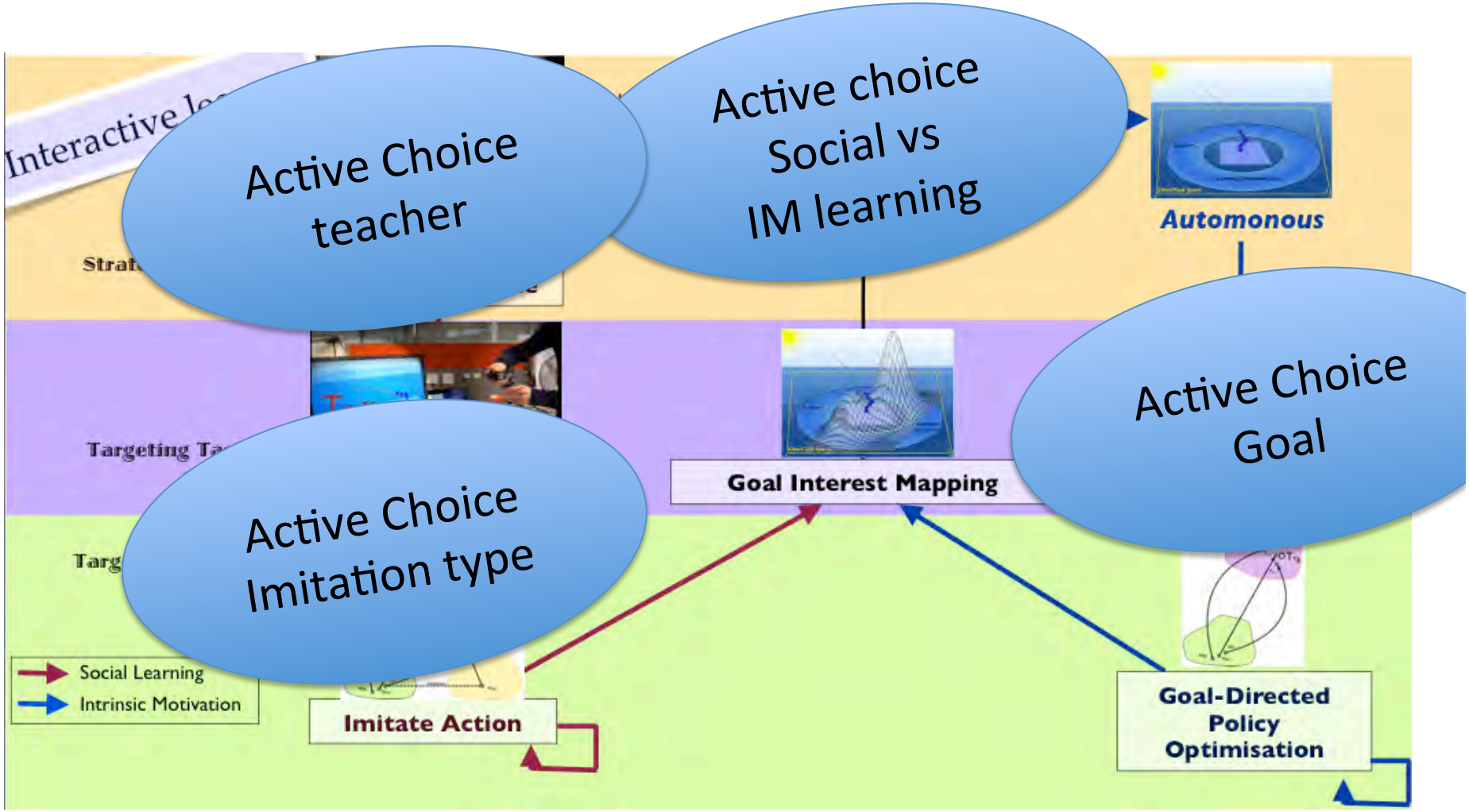
Active scheduling of both tasks and learning strategies by active selection of when to ask help to human teachers, which teacher to ask, and what to ask them
(Paladyn journal of Behavioural Robotics, 2013)

https://www.youtube.com/watch?v=OWjLaGv33i0

https://www.youtube.com/watch?v=m-desi46Uwk

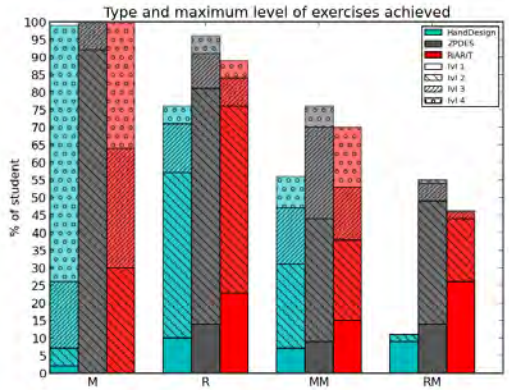
Perceptual/visual representations
(IEEE TAMD, 2014; ICRA 2016; IROS 2016)

Curiosity-driven **active choice of teachers and modes of imitation**



(Nguyen and Oudeyer, Palad. Behav. Rob., 2013; Autonomous Rob. 2013)

Education tech application: automated generation of personalized learning curriculum for human brains



KidLearn project:

Personalization of teaching sequences (curriculum) in Intelligent Tutoring Systems

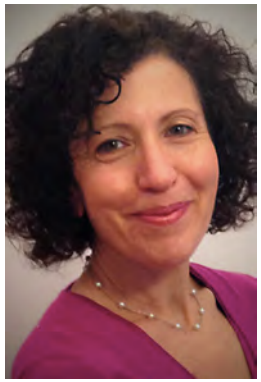
(Journal of Educational Data Mining, 2015)

- 500 children in more than 10 schools
- More students reached and succeed more difficult type of exercises.

+ contract with ITWell company and transfer in Skillogs company

Interdisciplinary collaborations

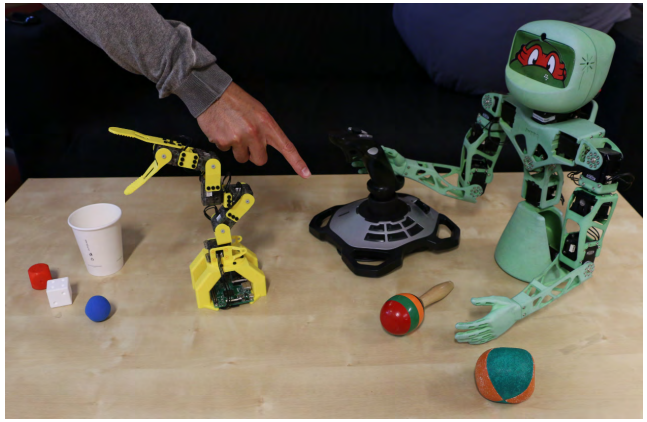
(ERC Grant + HFSP + associate team Neurocuriosity)



Jacqueline Gottlieb,
Cognitive Neuroscience Lab
NY, US

Monkeys

Flowers Lab
Inria and Ensta ParisTech



Robots

Human children

Celeste Kidd
Dev. Psychology lab
Univ. Rochester

Linda Smith
Dev. Psych.
Indiana Univ., US

Second Interdisciplinary Symposium on Information Seeking, Curiosity and Attention (Neurocuriosity 2016)

Curiosity in humans and animals

oudeyer

23 May 18

First interdisciplinary symposium on Information-seeking, curiosity and attention 37

The Centre for Brain and Cognitive Development (Birkbeck) hosted the second interdisciplinary symposium on information-seeking, curiosity and attention.

Date and Location

6-8 Oct. 2016, British Medical Association 19 , London

Programme

Click below to download a full programme with titles.
Neurocuriosity Programme.pdf 8 (416.6 KB)

Thursday 6th October: 9.00am-5.45pm

Topics

The past few years have seen a surge of interest in the mechanisms of active learning, curiosity and information seeking, and this body work has highlighted a number of highly significant questions regarding higher cognition and its development (for a recent review, see Tics13 23). One question is how subjects explore to build explanatory models of their environment, and how these models further constrain the sampling of additional information. A related question is how the brain generates the intrinsic motivation to seek information when physical rewards are absent or unknown, and how this impacts cognitive development in the long term.

The goal of the meeting is to foster a vigorous exchange of ideas among pre-eminent researchers who investigate these questions in neuroscience, psychology, developmental psychology, and computational modeling. The meeting will be single-track and include sessions on (1) behavior, (2) cognitive neuroscience, (3) computational modeling and (4) single neuron physiology.

Video Presentations

Organized by Inria Flowers (PY Oudeyer, M Lopes), Columbia Univ (J. Gottlieb) and Birbeck College (T. Gliga)

Neuroscience, Computational modelling, Developmental psychology, Ethology/animal research

Speakers: J. Nelson, D. Markant, S. Kouider, M. Gruber, K. Murayama, J. O'Reilly, K. Friston, G. Baldassarre, P. Dayan, K. Doya, W. Shultz, A. Bell, L. Hunt, D. Bell, K. Begus, L. Goupil, L. Feigenson, D. Bavellier, A. Gopnik.

https://openlab-flowers.inria.fr/t/second-interdisciplinary-symposium-on-information-seeking-curiosity-and-attention-neurocuriosity-2016/187

Selected publications

- Baranes, A., Oudeyer, P.-Y., 2013. Active learning of inverse models with intrinsically motivated goal exploration in robots. Robot. Auton. Syst. 61 (1), 49–73.
- Baranes, A.F., Oudeyer, P.Y., Gottlieb, J., 2014. The effects of task difficulty, novelty and the size of the search space on intrinsically motivated exploration. Front. Neurosci. 8, 1–9.
- Baranes, A., Oudeyer, P.Y., Gottlieb, J., 2015. Eye movements reveal epistemic curiosity in human observers. Vis. Res. 117, 81–90.
- Benureau, F.C.Y., Oudeyer, P.-Y., 2016. Behavioral diversity generation in autonomous ex- ploration through reuse of past experience. Front. Robot. AI 3, 8. http://dx.doi.org/ 10.3389/frobt.2016.00008.
- Clement, B., Roy, D., Oudeyer, P.-Y., Lopes, M., 2015. Multi-armed bandits for intelligent tutoring systems. J. Educ. Data Mining 7 (2), 20–48.
- Forestier S, Oudeyer P-Y. 2016 Modular Active Curiosity-Driven Discovery of Tool Use. 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).
- Gottlieb, J., Oudeyer, P.-Y., Lopes, M., Baranes, A., 2013. Information seeking, curiosity and attention: computational and neural mechanisms. Trends Cogn. Sci. 17 (11), 585–596.
- Kaplan, F., Oudeyer, P.-Y., 2003. Motivational principles for visual know-how development. In: Prince, C.G., Berthouze, L., Kozima, H., Bullock, D., Stojanov, G., Balkenius, C. (Eds.), Proceedings of the 3rd International Workshop on Epigenetic Robotics: Modeling Cognitive Development in Robotic Systems, vol. 101. Lund University Cognitive Studies, Lund, pp. 73–80.
- Kaplan, F., Oudeyer, P.-Y., 2007b. In search of the neural circuits of intrinsic motivation. Front. Neurosci. 1 (1), 225–236.

- Lopes, M., Oudeyer, P.Y., 2012. The strategic student approach for life-long exploration and learning. In: IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL). IEEE, pp. 1–8.
- Lopes, M., Lang, T., Toussaint, M., Oudeyer, P.-Y., 2012. Exploration in Model-Based Reinforcement Learning by Empirically Estimating Learning Progress. In: Proceedings of Neural Information Processing Systems (NIPS 2012). NIPS, Tahoe, USA.
- Moulin-Frier, C., Nguyen, M., Oudeyer, P.-Y., 2014. Self-organization of early vocal development in infants and machines: the role of intrinsic motivation. Front. Cogn. Sci. 4, 1–20. http://dx.doi.org/10.3389/fpsyg.2013.01006.
- Oudeyer, P.-Y., Kaplan, F., 2007. What is intrinsic motivation? A typology of computational approaches. Front. Neurorobot. 1, 6. http://dx.doi.org/10.3389/neuro.12.006.2007.
- Oudeyer, P.-Y., Smith, L., 2016. How evolution can work through curiosity-driven developmental process. Top. Cogn. Sci. 8 (2), 492–502.
- Oudeyer, P.-Y., Kaplan, F., Hafner, V., 2007. Intrinsic motivation systems for autonomous mental development. IEEE Trans. Evol. Comput. 11 (2), 265–286.
- Oudeyer, P. Y., Gottlieb, J., & Lopes, M. (2016). Intrinsic motivation, curiosity, and learning: Theory and applications in educational technologies. *Progress in brain research*, *229*, 257-284.