Developmental approaches to sensorimotor and linguistic learning in robotics

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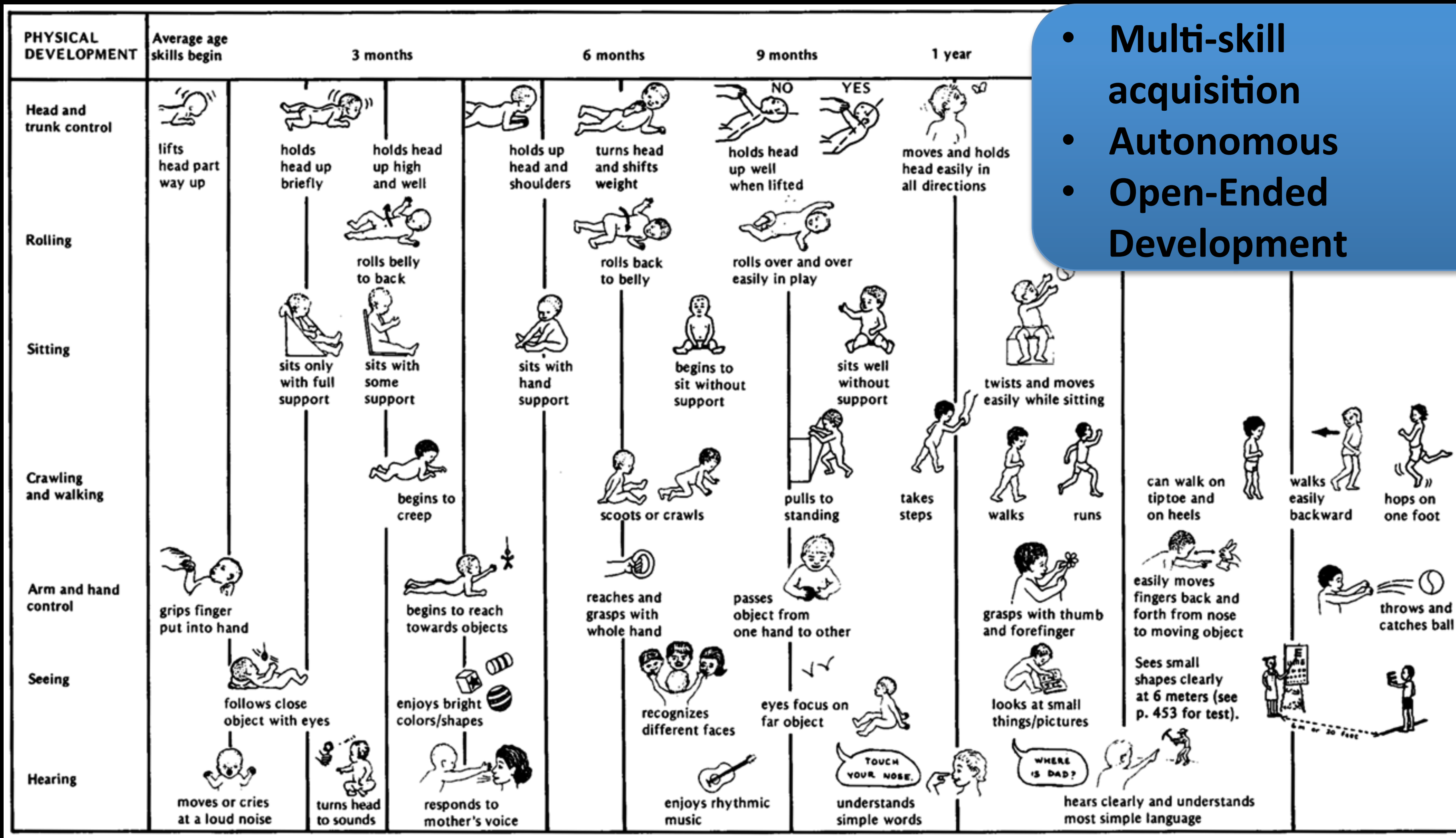
Behavioural and Cognitive Development in Human Infants



- **Multi-skill acquisition**
- **Autonomous**
- **Open-Ended Development**

An innate cerebral and morphological equipment …

Innate motivational system that fosters spontaneous BUT organized exploration (intrinsic motivation/curiosity-driven exploration)

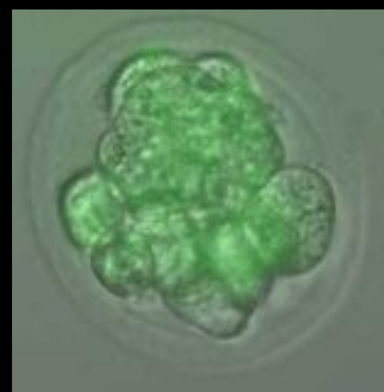
Motor primitives that constrain the space of motor commands and gestures: e.g. muscles are not controlled individually and independently, oscillators, …

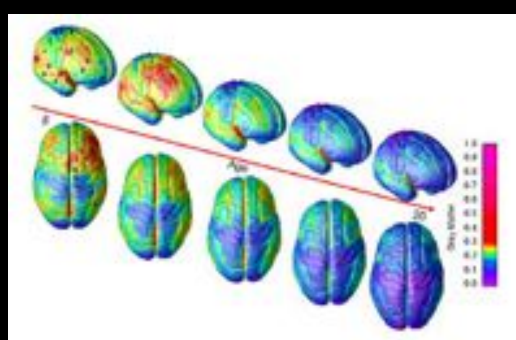
Sensori detectors and trackers that allow the baby to bootstrap its attentional and emotional systems: e.g. movement, high pitch, faces, …

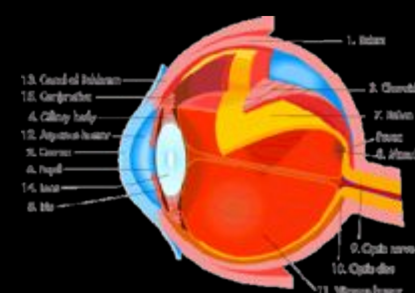
Sensorimotor reflexes: e.g. eye tracking of moving objects, closing hands when objects touched, …

Morphological properties that facilitate the control of the body, …

… built within a maturational program …







e.g. myelination/myelinogenesis progressively building brain regions, connecting them together and to muscles, increasing progressively resolution of senses and motor control, …

… in a structured physical and social environment

→ then continuously extended thanks to a generic learning and developmental system

Developmental Psychology
Biology

Functional Inspiration

→

Study how to build developmental machines

Developmental and Social Robotics

Developmental Psychology
Biology

Functional Modelling

←

Understand human development better

Developmental and Social Robotics

(Weng et al., 2001, *Science*)
(Lungarella et al., 2006, *Conn. Sc.*)
(Oudeyer, 2011, *Encycl. Lear. Sc.*)

Object of study: The Architecture of Sensorimotor and Social Development
→ Learning algorithms are only a component

Learning models for robot motor skill acquisition

Models of the self/body

Movements <-> Effects

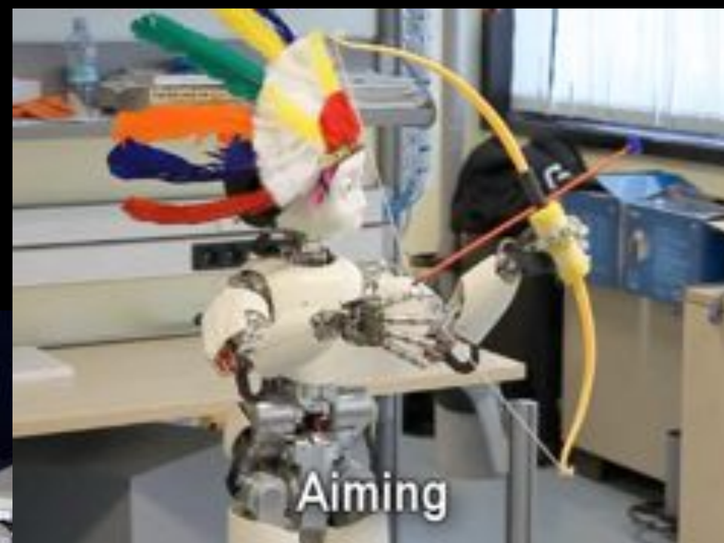
Learning models for robot motor skill acquisition

Models of physical interaction with objects

Movements <-> Effects

Learning models for robot motor skill acquisition

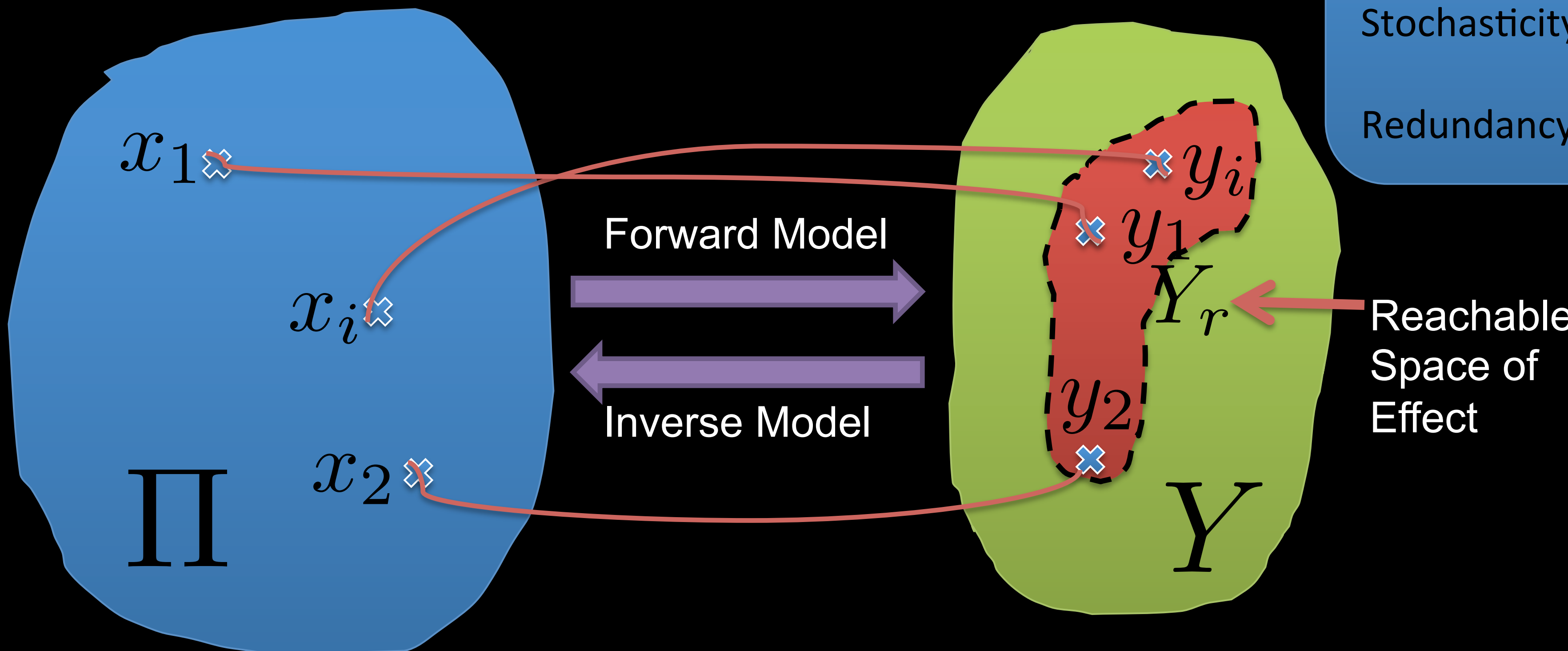
Models of tool use



Movements <-> Effects

Learning models for robot motor skill acquisition

- High-dimensions
- High-volume
- Stochasticity
- Redundancy



Space of Controllers

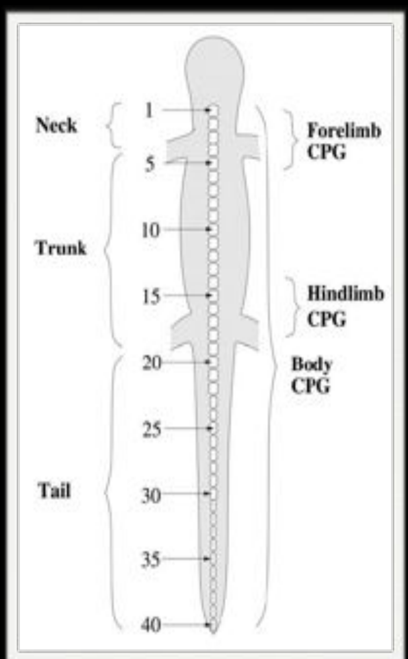
Task Space = Space of Effects

$$x_i = (C_i, \pi_i)$$
$$\pi_i : S \in \mathbb{R}^n \to A \in \mathbb{R}^l$$

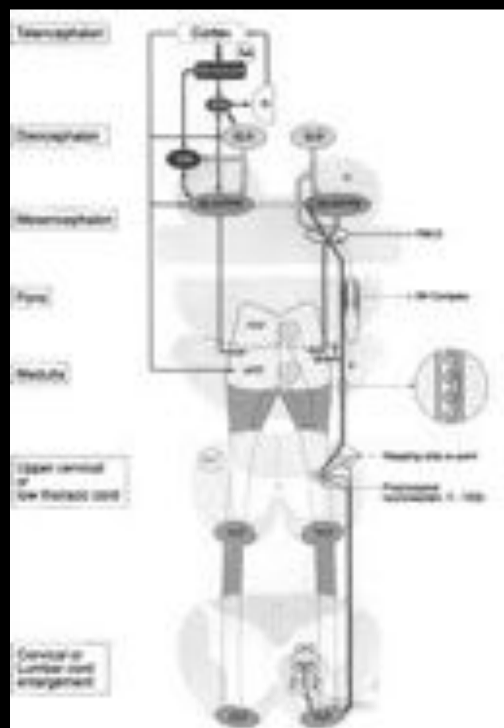
$$y_i(C_i, (s_1, a_1, \ldots, s_n, a_n)_{\pi_i}) \in \mathbb{R}^n$$

Motor synergies/primitives

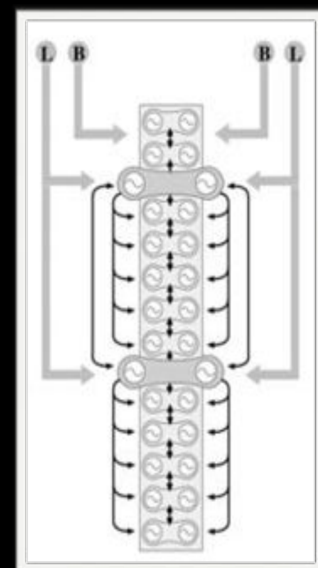
Humans: muscular synergies → **Robots:**



CPGs (Ijspeert et al., 2005)



(Rossignol, 1996)



$$
\begin{aligned}
\tau \dot{v}_i &= -\alpha \frac{(x_i - x_0)^2 + v_i^2 - E_i}{E_i} v_i \\
&\quad - (x_i - x_0) \sum_j \left(a_{ij}(x_j - x_0) + b_{ij} v_j \right) \\
\tau \dot{x}_i &= v_i
\end{aligned}
$$

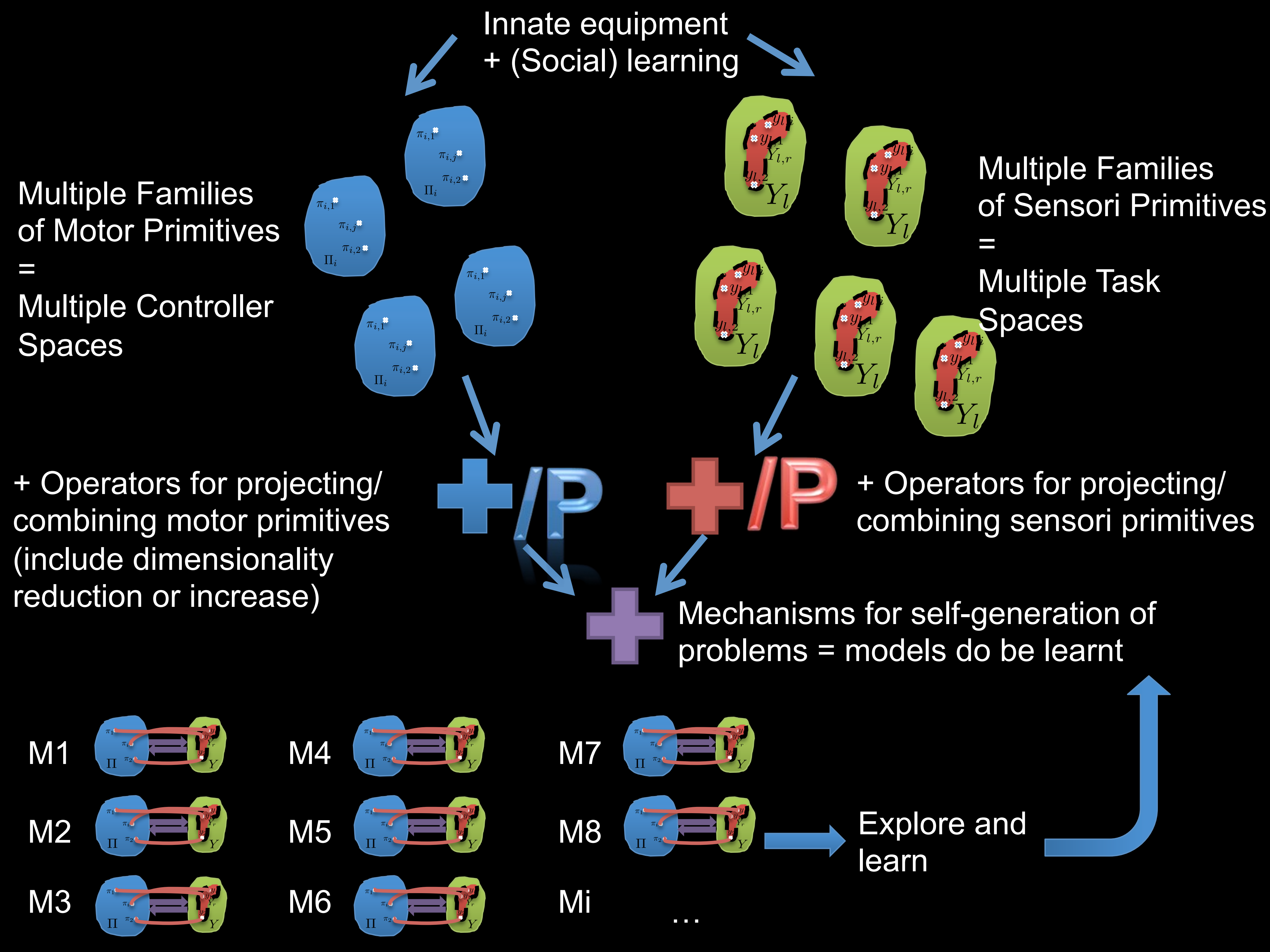
- DMP Formalism
- Recurrent Neural Nets
- GMR
- Splines + vector fields

Exploring and Learning multiple models and skills in a developmental robot

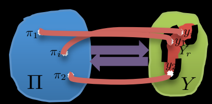
The Playground Experiment
IEEE Trans. Ev. Comp. (Oudeyer et al., 2007)

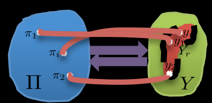
- Π_1 Bashing param. primitive
- Π_2 Biting param. primitive
- Π_3 Head turn param. primitive
- Π_4 Vocalizing param. primitive

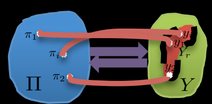
- Y_1 Mov. sensori. primitive
- Y_2 Visual patt. sensori. primitive
- Y_3 Mouth touch sensori. primitive
- Y_4 Leg touch sensori. primitive
- Y_5 Sound pitch sensori. primitive

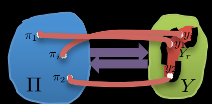

Innate equipment
+ (Social) learning
Multiple Families
of Motor Primitives
=
Multiple Controller
Spaces
Multiple Families
of Sensori Primitives
=
Multiple Task
Spaces
+ Operators for projecting/
combining motor primitives
(include dimensionality
reduction or increase)
+ Operators for projecting/
combining sensori primitives
Mechanisms for self-generation of
problems = models do be learnt
M1
M2
M3
M4
M5
M6
M7
M8
Mi
…
Explore and
learn

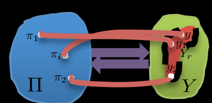
Active Exploration and Learning

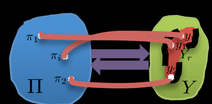
M1 

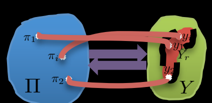
M2 

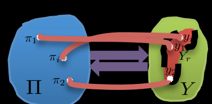
M3 

M4 

M5 

M6 

M7 

M8 

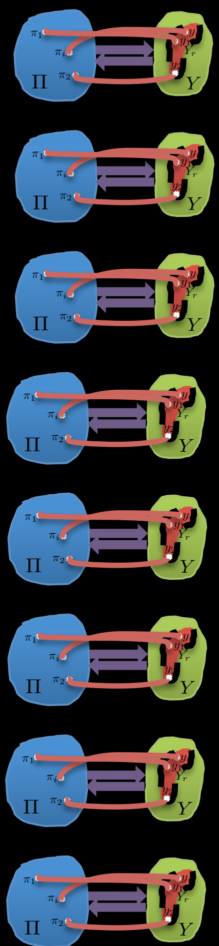
Mi …

What models to generate, explore and learn and in what order, given:

- High **<u>inhomogeneities</u>** in the mathematical properties of the mappings
- **<u>Diversity of complexity/dimensionality/volume</u>**, learnability, and level of noise
- Some are trivial, some other **<u>unlearnable</u>**
- Some may be **<u>non-stationary</u>**
- Life-time severely limited: **<u>the set of learnable models cannot be learnt entirely during lifetime</u>**

<u>➔ The goal is that learnt models can be reused to solve efficiently (predictive or control) problems unknown to the learner initially and taken for e.g. uniformly in a space of problems relevant in the environment in which the robot exists</u>

Technical challenges



M1
M2
M3
M4
M5
M6
M7
M8
Mi …

➔ Problem generation: Fixed or adaptive set of problems? Adaptive boundaries boundaries for a given problem? How to control of the growth of complexity (inside and across problems)?

➔ Problem selection: What problems to focus on ? How to build a useful learning curriculum?

➔ Which measure of interestingness?

Standard approaches to active learning will fail (most often do worse than random), i.e. approaches based on sampling where uncertainty is high, density approaches or approaches based on analytic hypothesis about the learning algorithm or the data (e.g. like when using GPs) (Whitehead, 1991; Linden and Weber, 1993; Thrun, 1995; Sutton, 1990; Cohn et al., 1996; Brafman and M. Tennenholtz, 2002; Strehl et Littman, 2006; Szita and Lorincz, 2008)

➔ In particular, very difficult to evaluate analytically the information gain, rather need to evaluate it empirically, but then how?

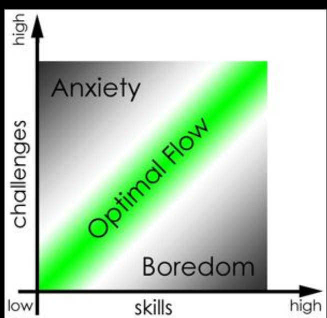
➔ If interaction between self-generated problems, then need for sequential decision optimization → Intrinsically Motivated Reinforcement Learning (IMRL, Barto et al. 04, Schmidhuber, 1991).

The search for intermediate complexity

<u>Child development: intrinsic motivation and mechanisms of spontaneous exploration</u>

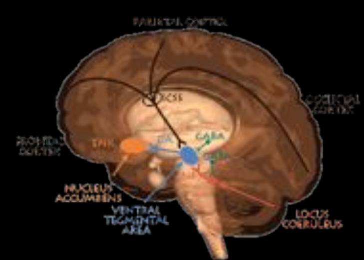
<u>In robots:</u>

Developmental psychology



White (1959), Berlyne (1960), Csikszentmihalyi (1996)

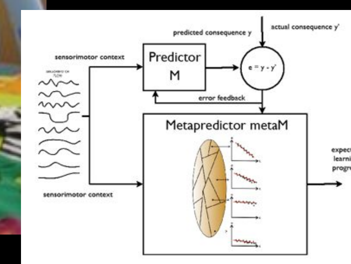
Neurosciences



Dayan and Belleine (2002), Kakade and Dayan (2002), Horvitz (2000)

➔Activities of intermediate complexity, as evaluated empirically, are intrinsically rewarding

➔ <u>Mechanisms for regulating the growth of complexity: the importance of starting small</u>



Models IAC, RIAC, SAGG-RIAC, McSAGG (Oudeyer et al., 2005; Oudeyer et al., 2007; Baranes and Kaplan, 2009; Baranes and Kaplan, 2010a,b)

Algorithmic aspects and qualitative modelling of sensorimotor development

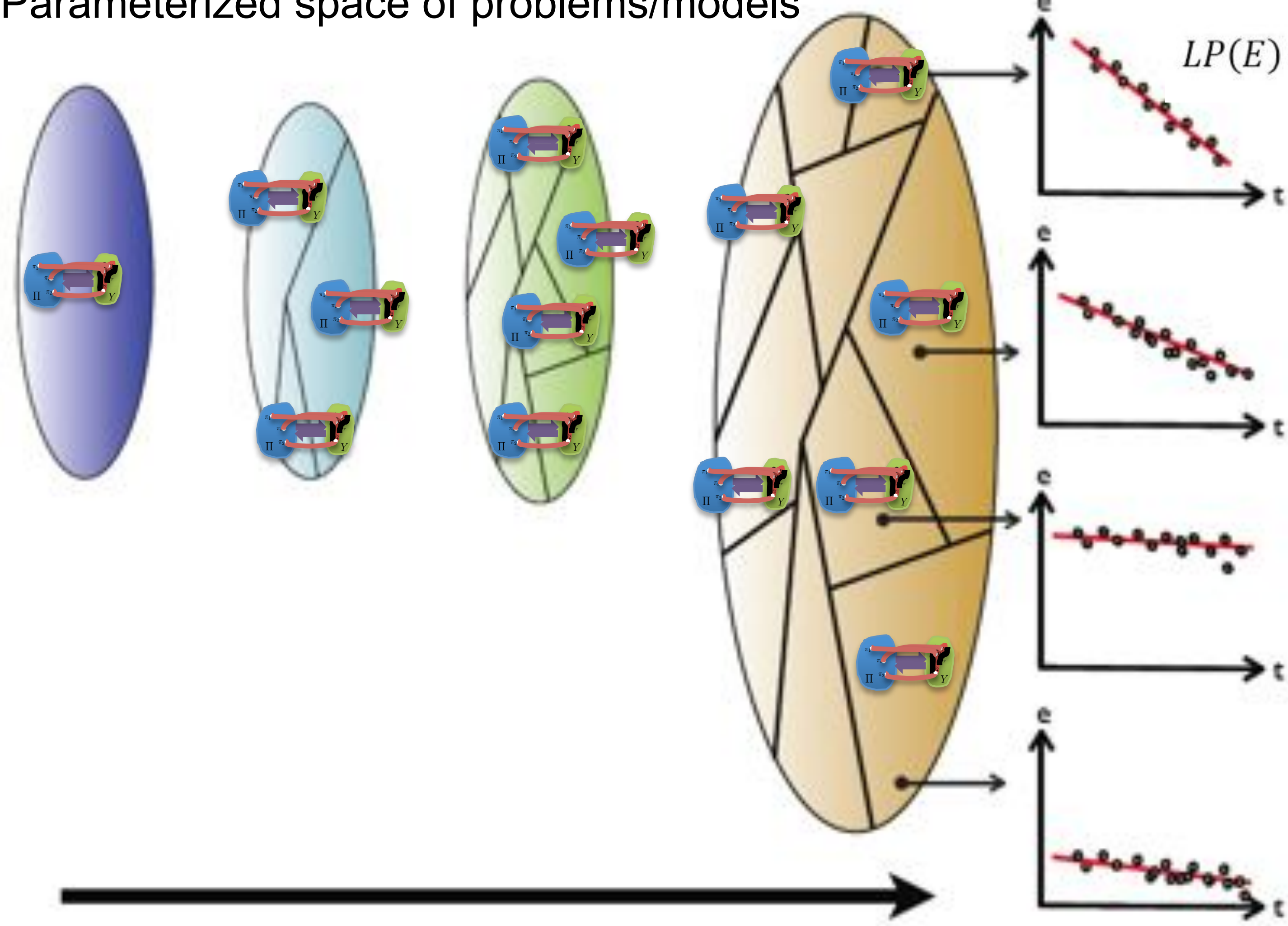
Intermediate complexity ⬄ Maximal learning progress as evaluated empirically

IAC (2007) R-IAC (2009) SAGG-RIAC (2010)

Interestingness
= Empirical measure of learning progress

$$LP(E) = \frac{\sum_{i=1}^{\frac{|E|}{2}} e(i) - \sum_{i=\frac{|E|}{2}}^{|E|} e(i)}{|E|}$$

Parameterized space of problems/models



Stochastic Choice of Problem according to a probability proportional to Learning Progress

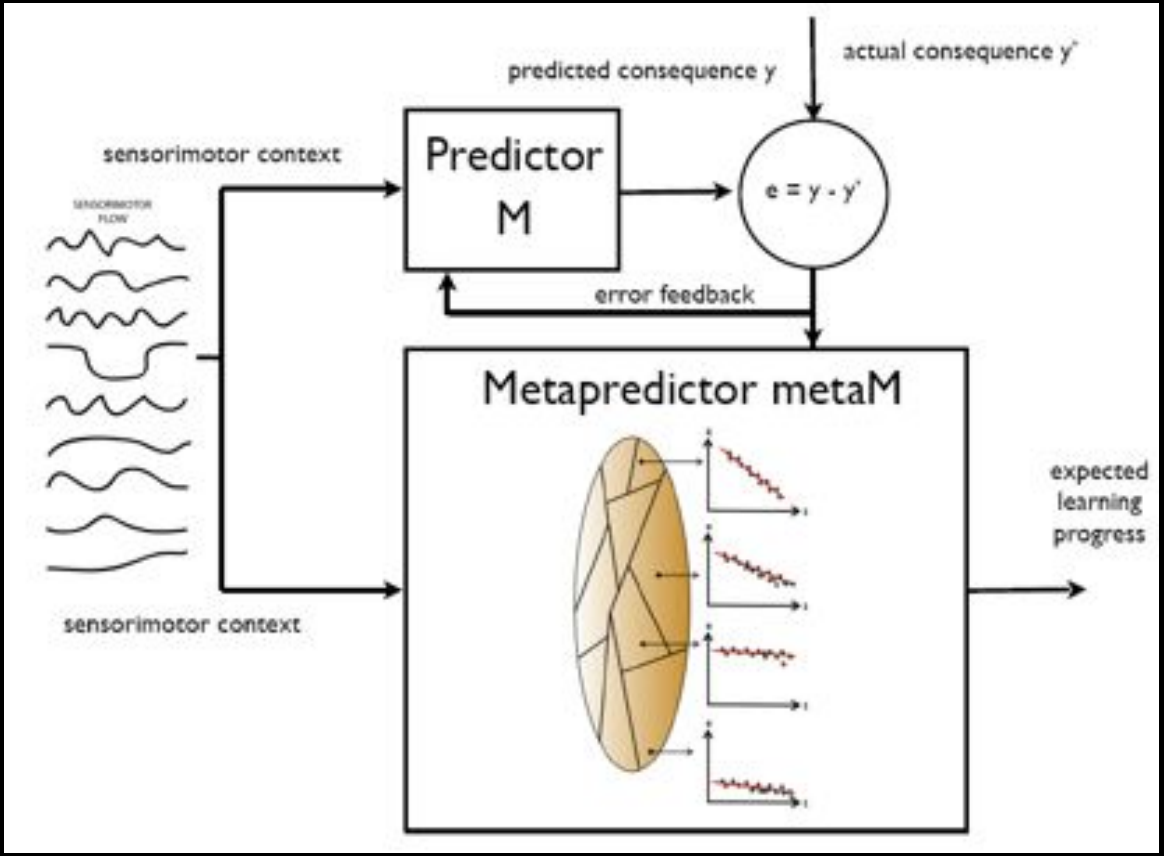
Recursive splitting or problem space optimizing difference in learning progress

Active regulation of the growth of complexity in exploration

Optimizing learning ***progress***, i.e. the decrease of prediction errors (derivative)

The IAC/R-IAC (Intelligent Adaptive Curiosity) architecture(s)

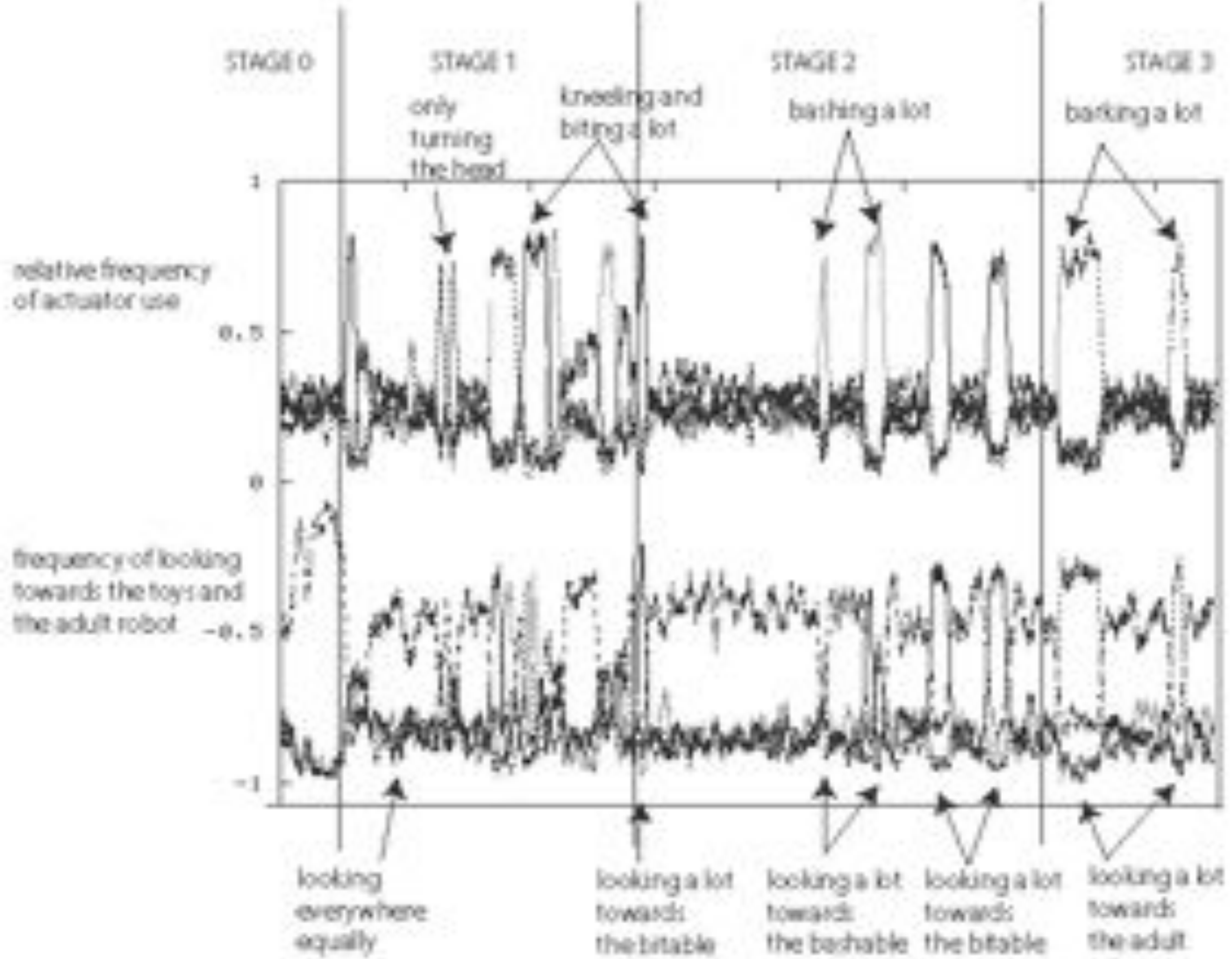
Makes no assumption on the regression algorithm used as "Predictor" (e.g. can be SVE, GP, or non-parametric)



IAC: Oudeyer P-Y, Kaplan , F. and Hafner, V. (2007), R-IAC: Baranes and Oudeyer (2009)
Related Work: Schmidhuber (1991, 2006)

http://playground.csl.sony.fr

(Oudeyer, Kaplan, Hafner, 2007, IEEE Trans. Evol. Comp.)
Here a classic non-parametric regressor is used (Schaal and Atkeson, 1994)

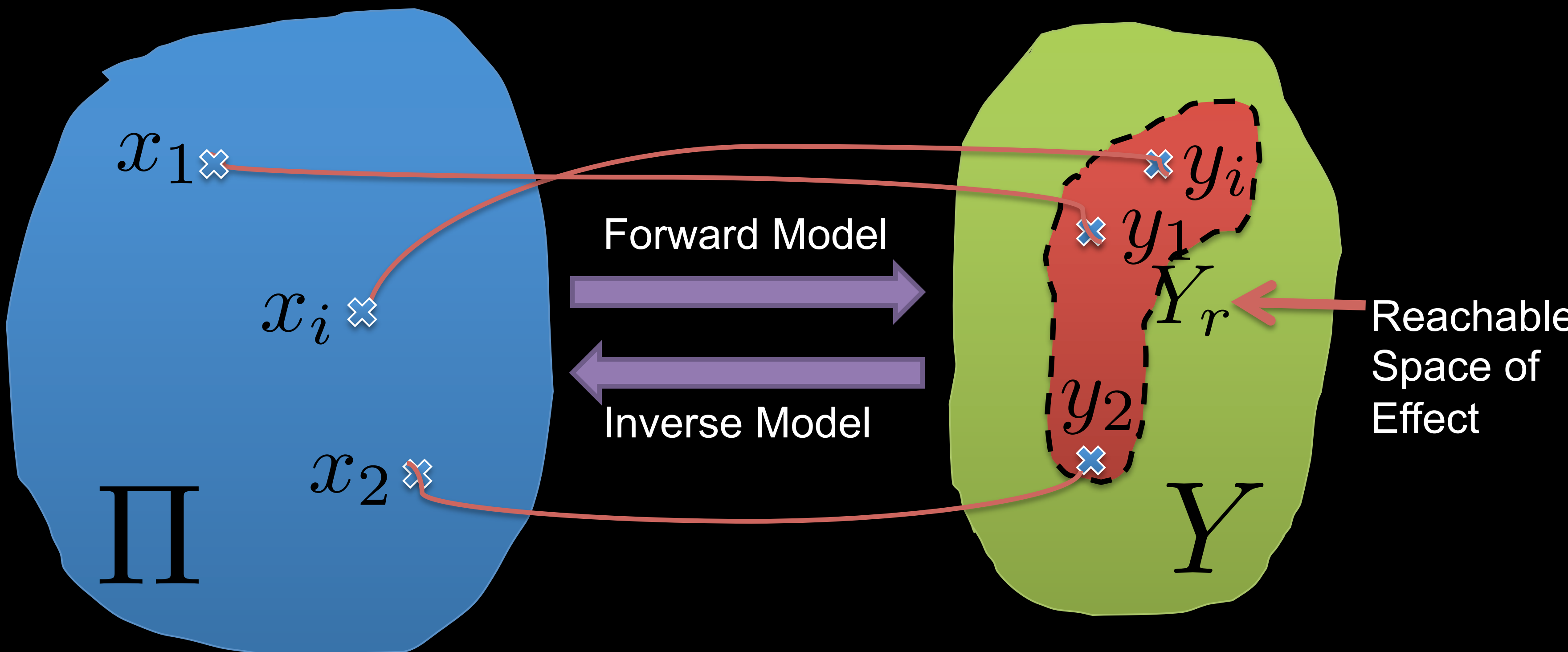


Self-organization of developmental patterns with universals and diversity *and* discovery of communication

Infant and Child Dev. 2008
Frontiers in Neuroscience, 2007
Connection Science, 2006

Measure 1 (number of peaks?)	9.67
Measure 2 (complete scenario?)	Yes: 34 %, **No: 66 %**
Measure 3 (near complete scenario?)	**Yes: 53 %**, No: 47%
Measure 4 (non-affordant bite before affordant bite?)	**Yes: 93 %**, No: 7 %
Measure 5 (non-affordant bash before affordant bash?)	**Yes: 57 %**, No: 43 %
Measure 6 (period of systematic successful bite?)	**Yes: 100 %**, No: 0 %
Measure 7 (period of systematic successful bash?)	**Yes: 78 %**, No: 11 %
Measure 8 (bite before bash?)	**Yes: 92 %**, No: 8 %
Measure 9 (successful bite before successful bash?)	**Yes: 77 %**, No: 23 %

Active learning of single high-dimensional models



Space of Controllers

Task Space = Space of Effects

$$x_i = (C_i, \pi_i)$$

$$\pi_i : S \in \mathbb{R}^n \to A \in \mathbb{R}^l$$

$$y_i(C_i, (s_1, a_1, \ldots, s_n, a_n)_{\pi_i}) \in \mathbb{R}^n$$

Teleogical exploration in human infants

SAGG-RIAC
(Self-Adaptive Goal Generation RIAC)

SAGG

Algorithm 2 Global Pseudo-Code of SAGG

Input: Current Position: x_0, θ_0
loop
  Goal Self-Generation:
  Selection of a Region R_i according to Interest Values
  Generation of a Random Goal x_g in R_i
  Generation of Sub-Goal x_i
  Goal Directed Learning:
  for each sub-goal, and goal x_j **do**
    while Constraints unrespected and $x_0 \neq x_j$ **do**
      Exploration Phase
      Reaching Phase
    end while
    Interest Update:
    Effectiveness Computation
    Interest Computation
    Region Update
  end for
end loop

Active goal self-generation

(SSA, Schaal et Atkeson, 1994)

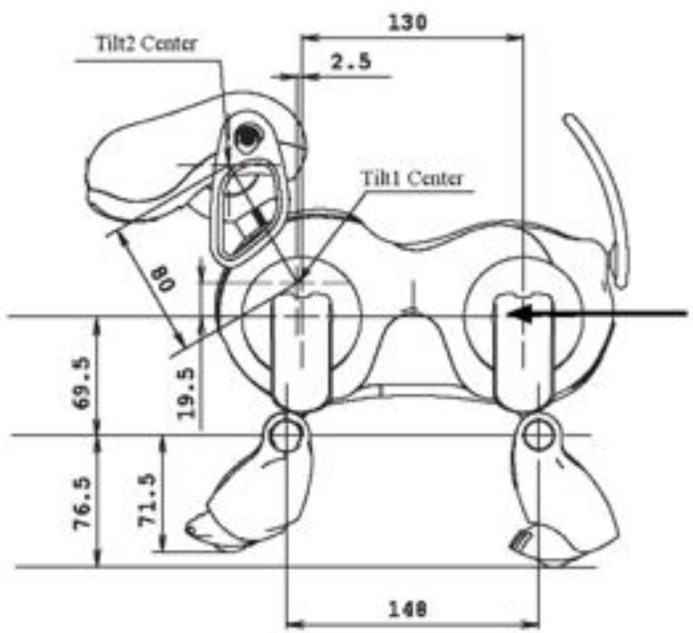
Algorithm 1 Goal Directed Learning

Input: x_g, x_0, θ_0, $m = 0$, m_{max}, v, γ, ε_{max}
Output: m
while $x_0 \neq x_g$ and $m < m_{max}$ **do**
  $\Delta x_{next} = v \cdot \frac{x_0 - x_{goal}}{\|x_0 - x_{goal}\|}$
  $\tilde{J}$ =**get current Jacobian**(θ_0)
  $\widetilde{\Delta x}_{next}$ =**move**$(\Delta\theta_{next} = \tilde{J}^{+} \cdot \Delta x_{next})$
  $\varepsilon = \|\widetilde{\Delta x}_{next} - \Delta x_{next}\|$
  if $\varepsilon > \varepsilon_{max}$ **then**
    move$(-\Delta\theta_{next})$
    for $i = 1 : \gamma$ **do**
      $\Delta\theta_{next}$ = **random**
      move$(\Delta\theta_{next})$, **move**$(-\Delta\theta_{next})$
    end for
  end if
end while

Active goal directed learning

(Baranes and Oudeyer, IROS 2010; IEEE ICDL/Epirob 2011)
Competence-based models Oudeyer and Kaplan, Frontiers in Neurorobotics, 2008)

Example: Developmental learning of locomotion

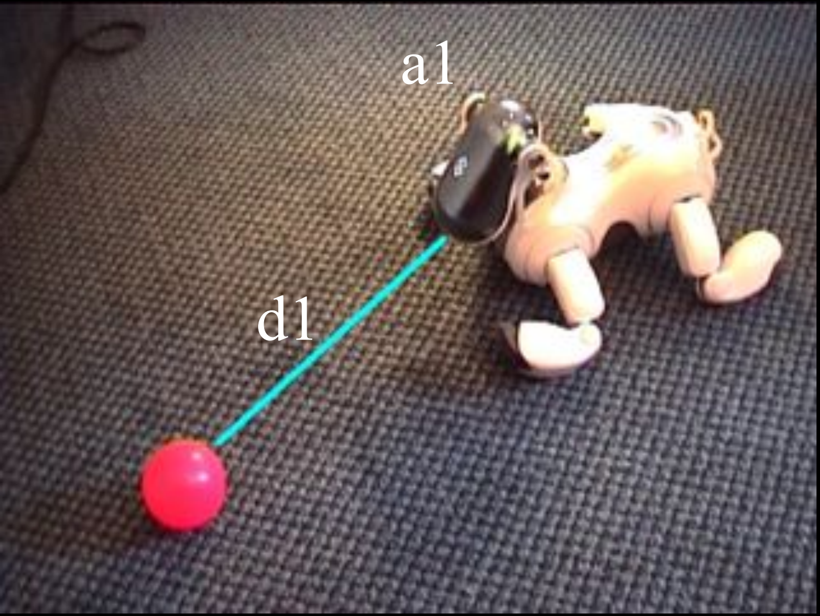


$j(t) = m + a.\sin(\omega.t + \phi)$

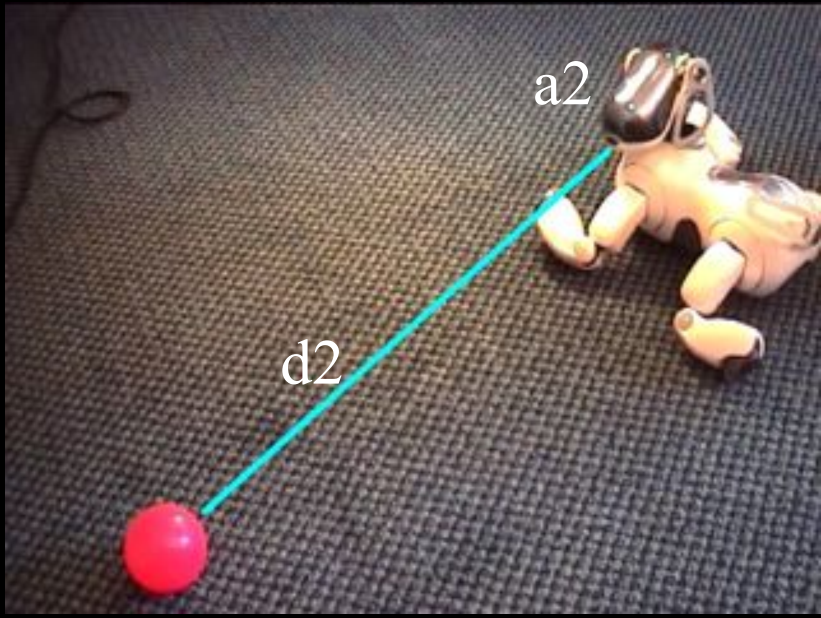
8 joints * 3 parameters
=
Motor primitive M
with 24 dimensions

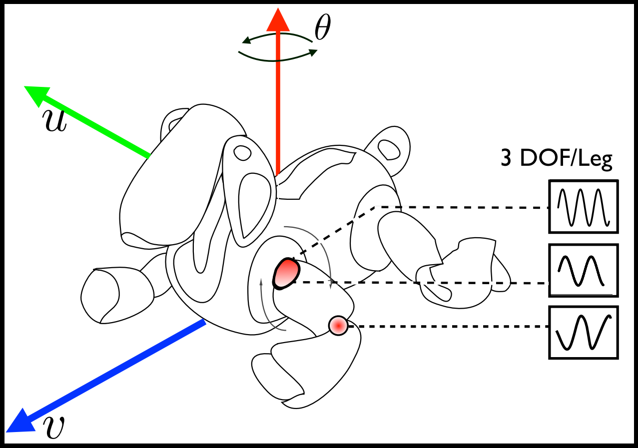
The motor primitive: a CPG

Explore the consequence of one's movements



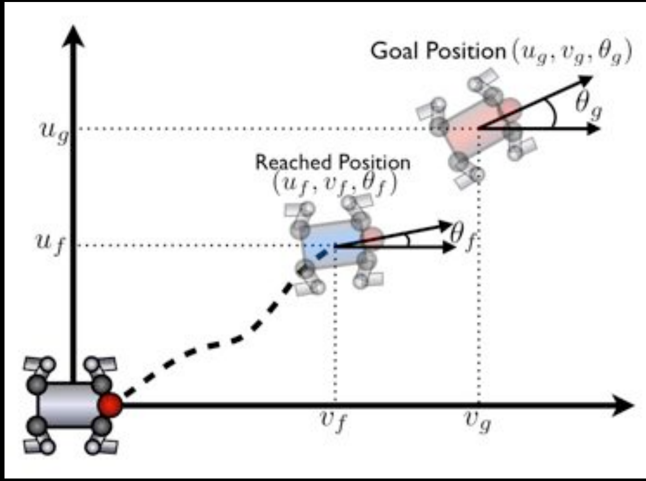
M





The sensori-primitive:

Translation +
Rotation
of COM

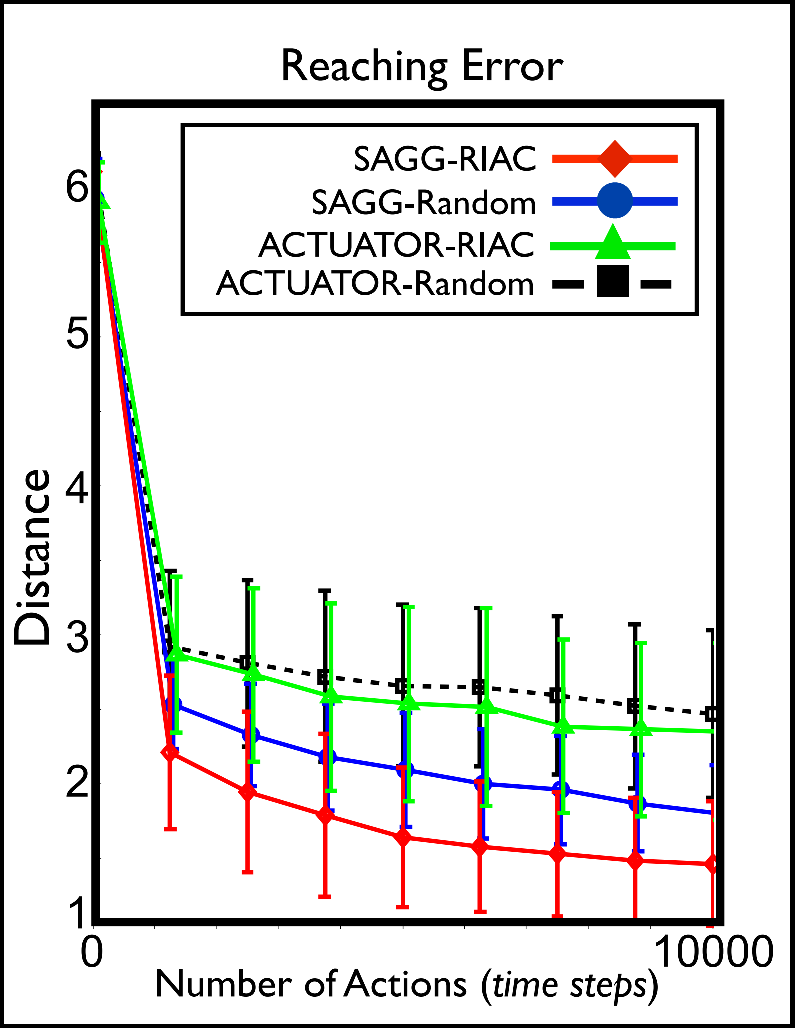


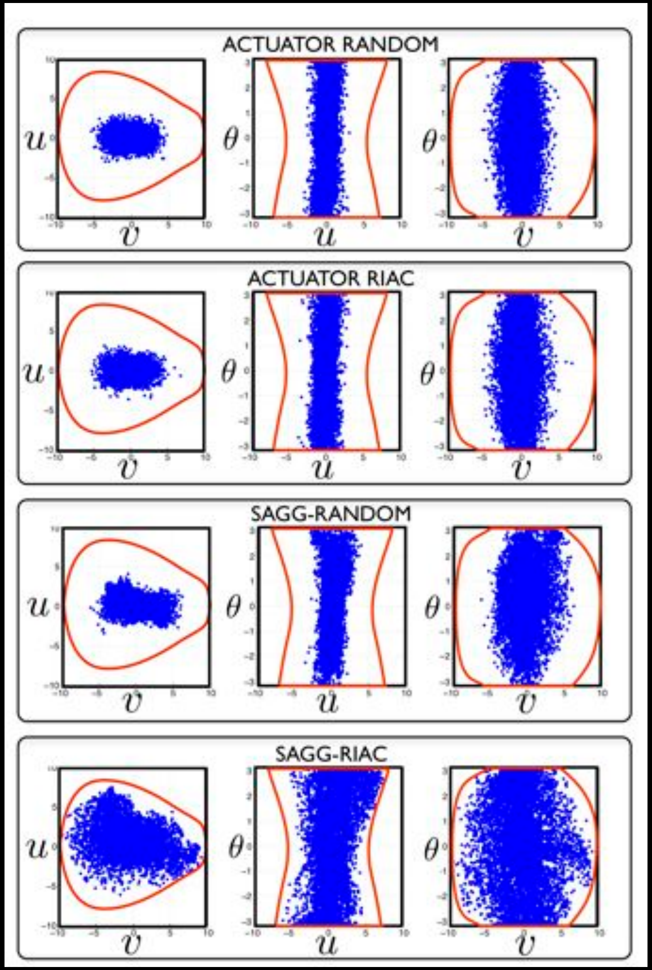
Learnt skills

The robot can re-use its curiosity-driven learnt forward and inverse models to reach any particular location in its field of view

Note: Here the forward and inverse model are learnt actively using a local learning algorithm (Local Gaussian Mixture Regression, ILO-GMR, Cederborg et al., 2010)

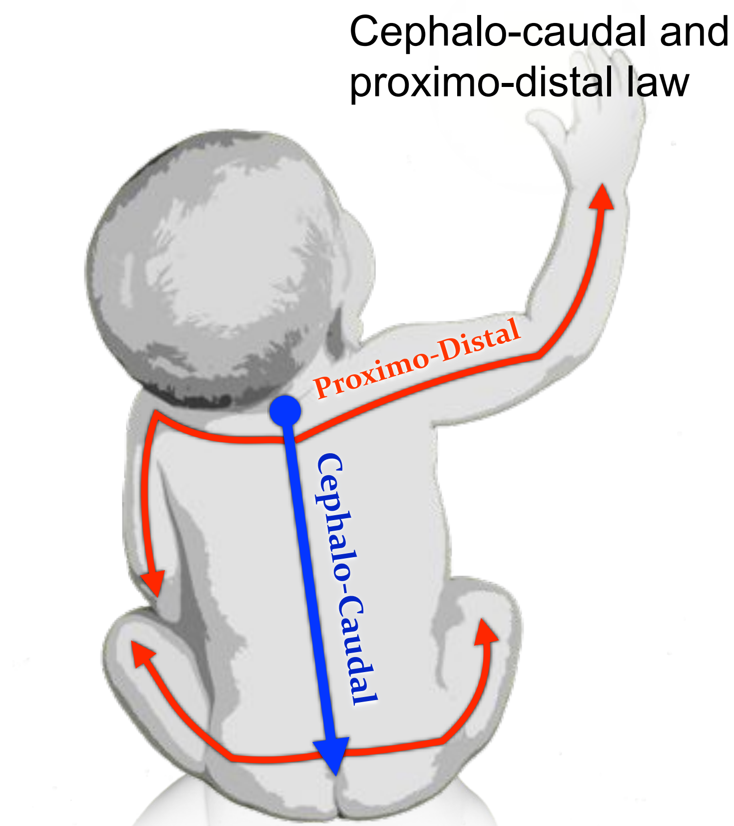
Faster learning and better performances in generalization





Maturational constraints

Humans: maturation of the sensorimotor system → **Robots:**



(Eyre, 2003; Berthier et al., 1999)

$$\psi(t+1) = \begin{cases} \psi(t) + \lambda.interest(S') & \text{if } interest(S') > 0 \\ \psi(t) & \text{otherwise} \end{cases}$$

$$f(t) = \left(-\frac{(p_{max} - p_{min})}{\psi_{max}}.\psi(t) + p_{max} \right)^{-1}$$

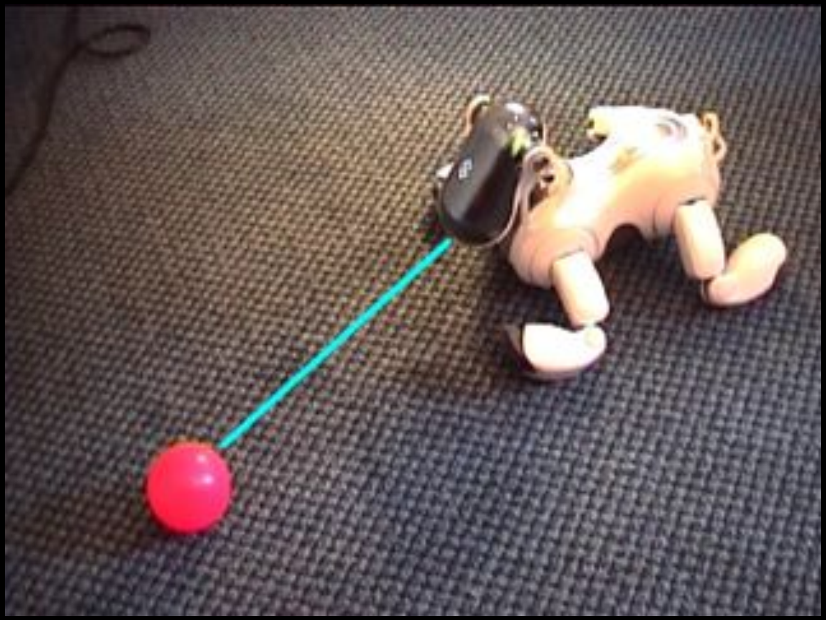
$$\varepsilon_D(t) = -\frac{(\varepsilon_{D_{max}} - \varepsilon_{D_{min}})}{\psi_{max}}.\psi(t) + \varepsilon_{D_{max}}$$

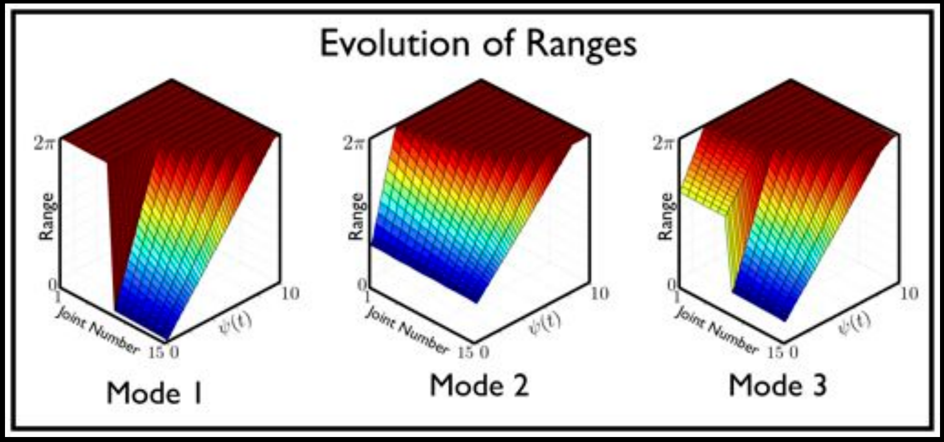
$$r_i(t) = \psi(t).k_i \quad (7)$$

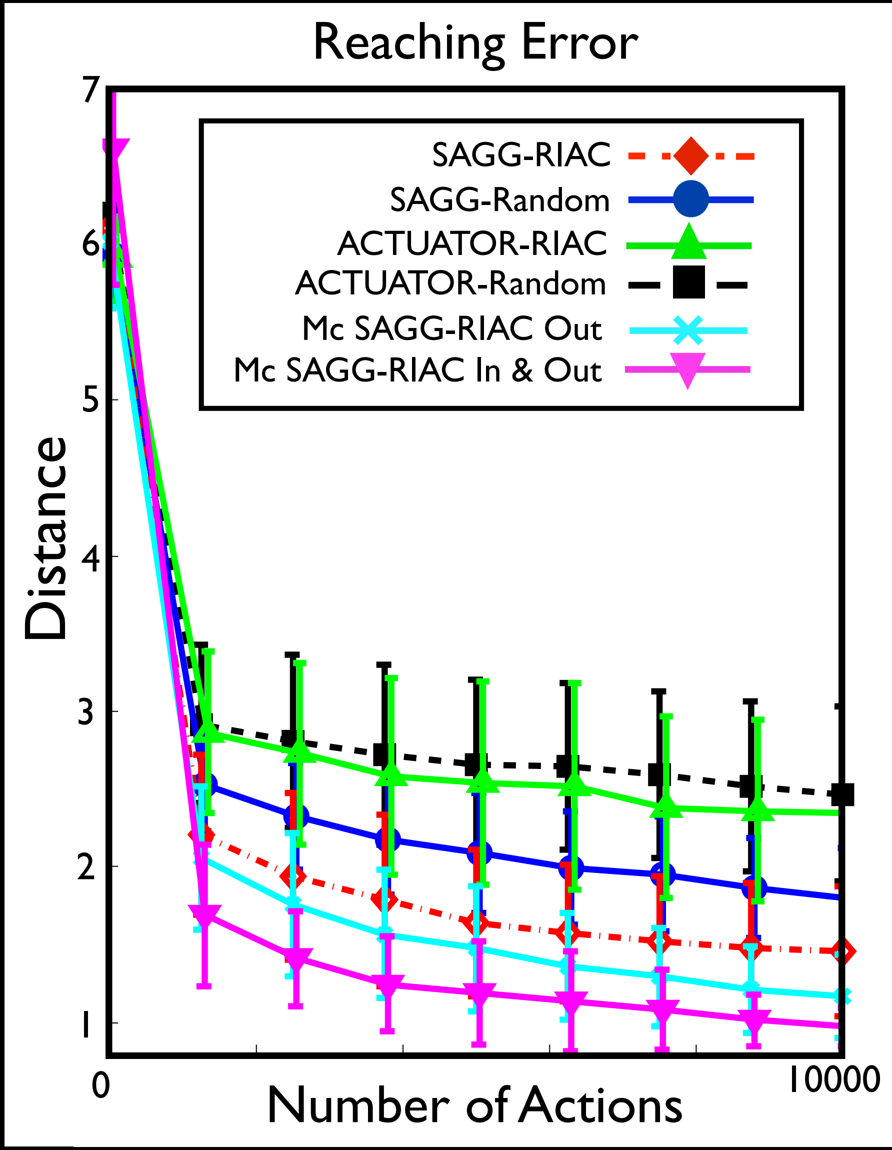
Where k_i represents an intrinsic value determining the difference of evolution velocities between each joint. Here we fix: $k_1 \geq k_2 \geq ... \geq k_n$, where k_1 is the first proximal joint.

Baranes, A., Oudeyer, P-Y., 2011, *IEEE ICDL 2011*

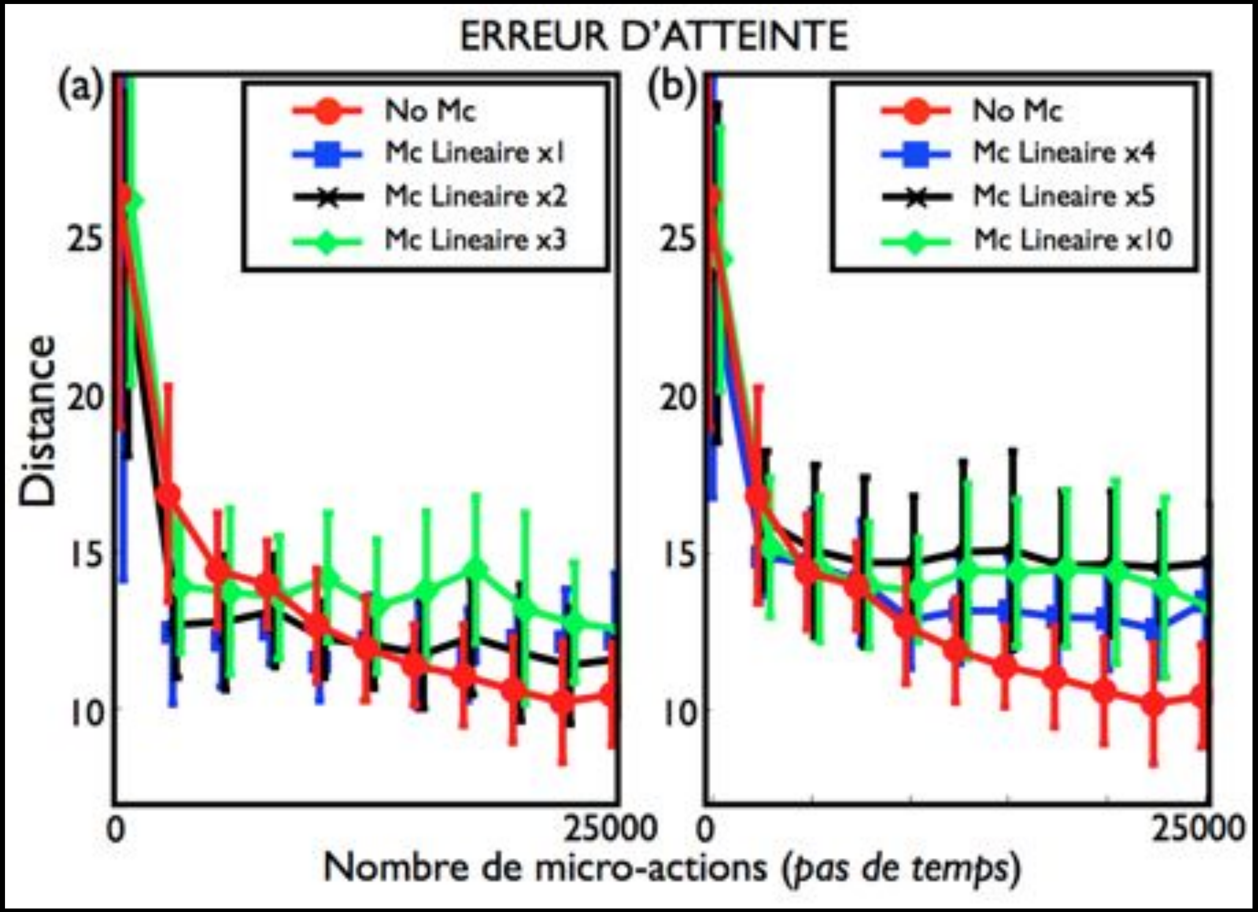
McSAGG-RIAC: Experimental Results





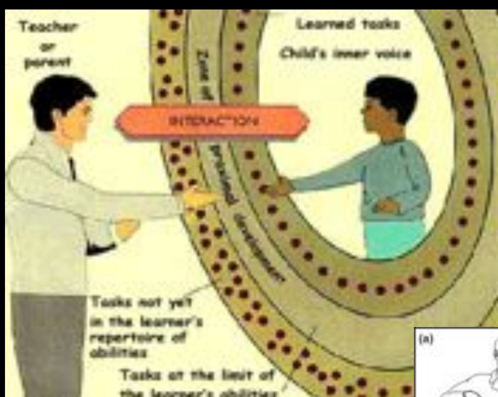


Importance of the bi-directional coupling between maturation and active learning

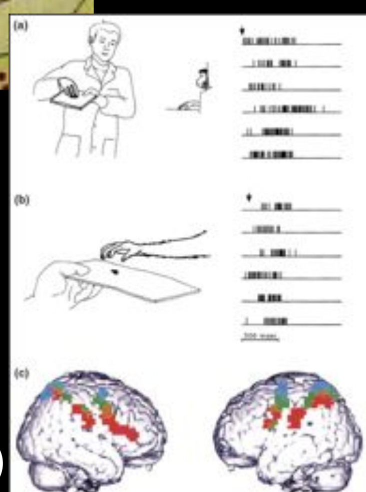


Social guidance

Humans: Social guidance in the Zone of Proximal Development



Vygotski, ZPD



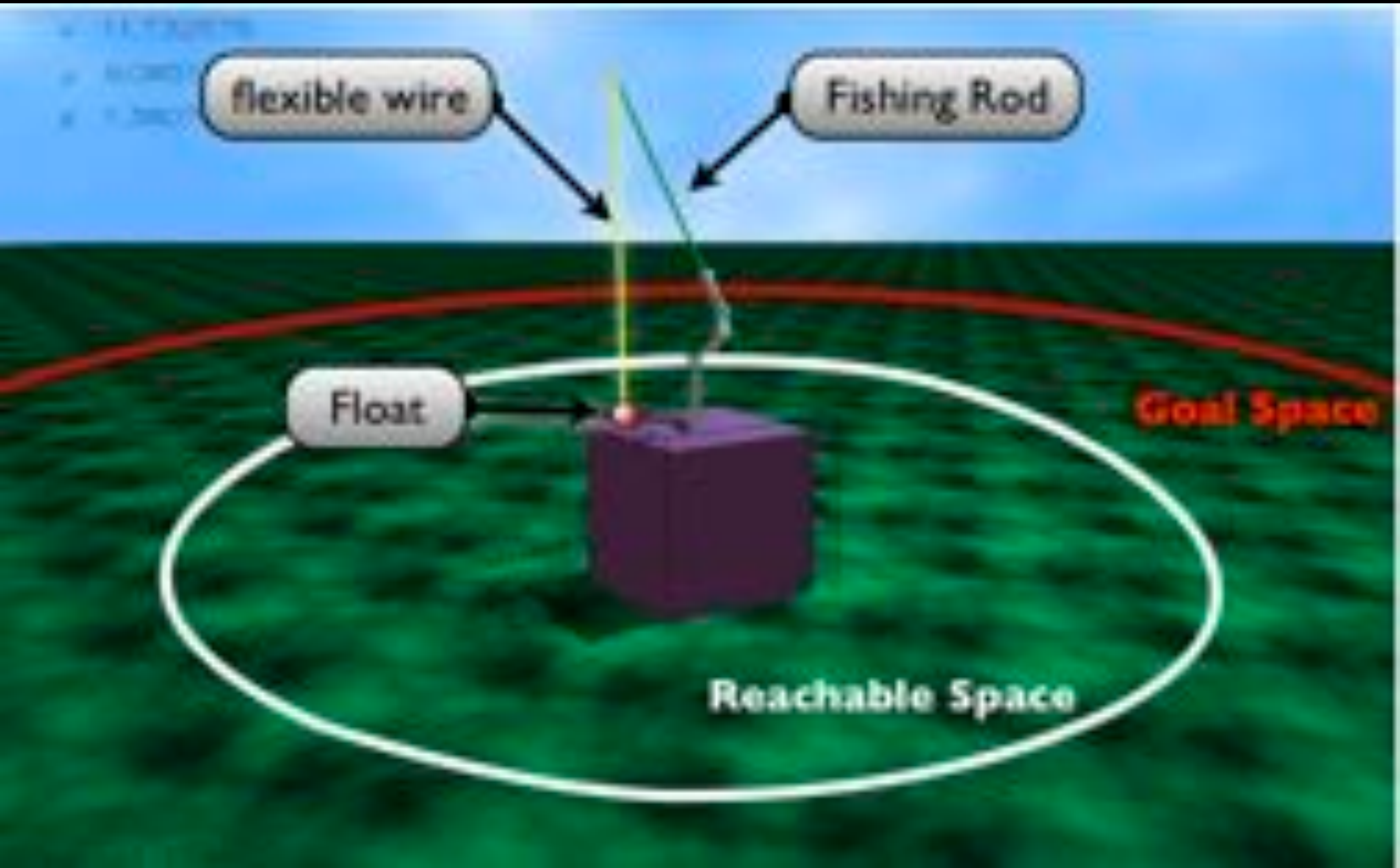
Mirror neurons
(Gallese et al., 1996)

Robots:

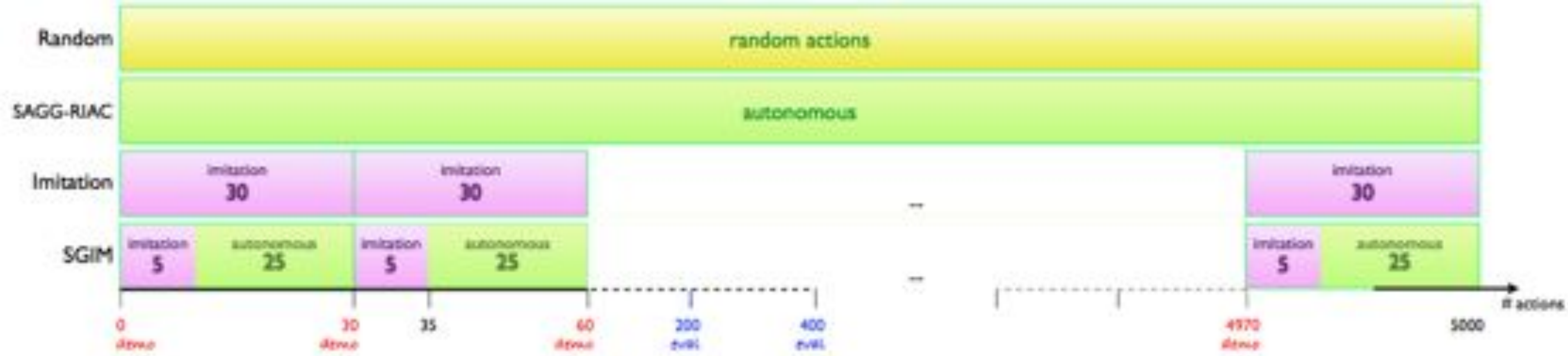
Learning by demonstration and imitation
(Schaal et al., Billard et al., Asfour and Dillman, Lopes et al., Demiris et al., …)

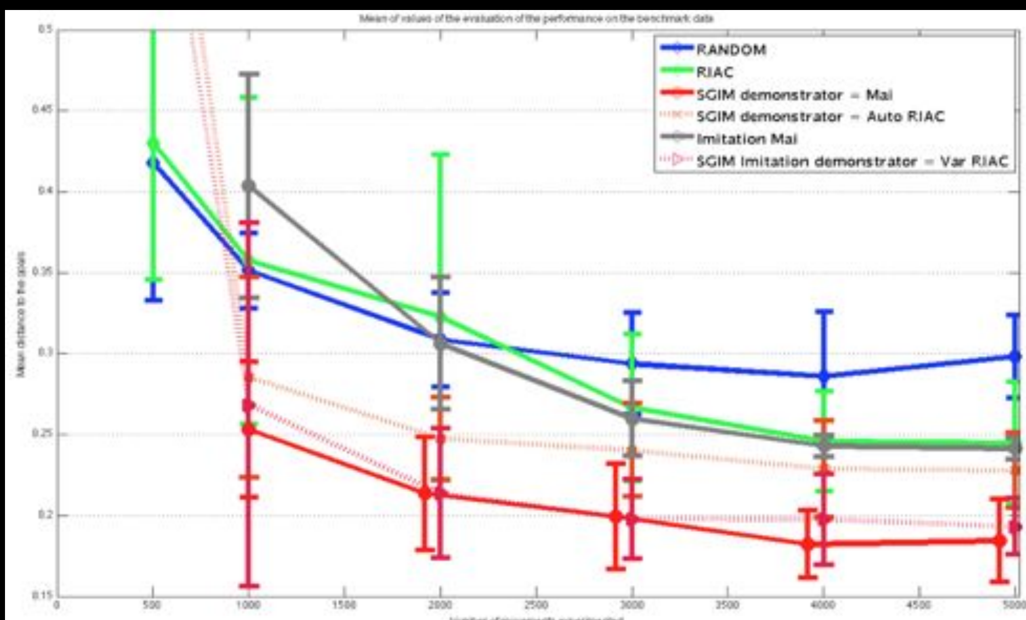
➔ **Coupling of social guidance and intrinsically motivated learning**

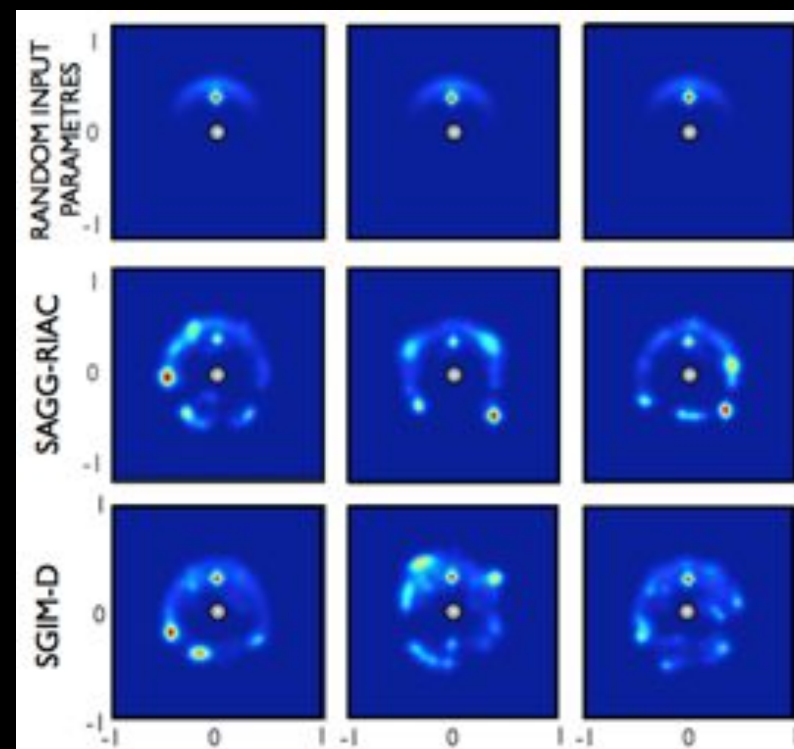
SGIM: Experimental Results



SGIM: Experimental Results







(Nguyen et al., IEEE ICDL/Epirob 2011)

How can a robot learn novel visually grounded words from a human?

Problem: How to teach a robot to recognize new visual objects associated to new words ?

Just a matter of making efficient statistics over multimodal observations?

No ! Also a matter of collecting data that is good enough through adequate human-robot interaction

The crucial role of joint attention

Humans use heavily social cues to coordinate social interaction, realize « joint attention », and thus allow the child learner to collect good training data

Shall we mimick human-human natural mechanisms for ensuring human-robot joint attention (e.g. use of pointing, gaze direction, « waving », …) ?

Maybe not … as hinted by the Wizard of Oz

Even with human intelligence, the sensorimotor apparatus of a robot is so different from the one of humans that it is very difficult to use social cues such as pointing or waving (for example, big different in the field of view that makes it very difficult for a non-engineer human teacher to understand what the robot is seeing).

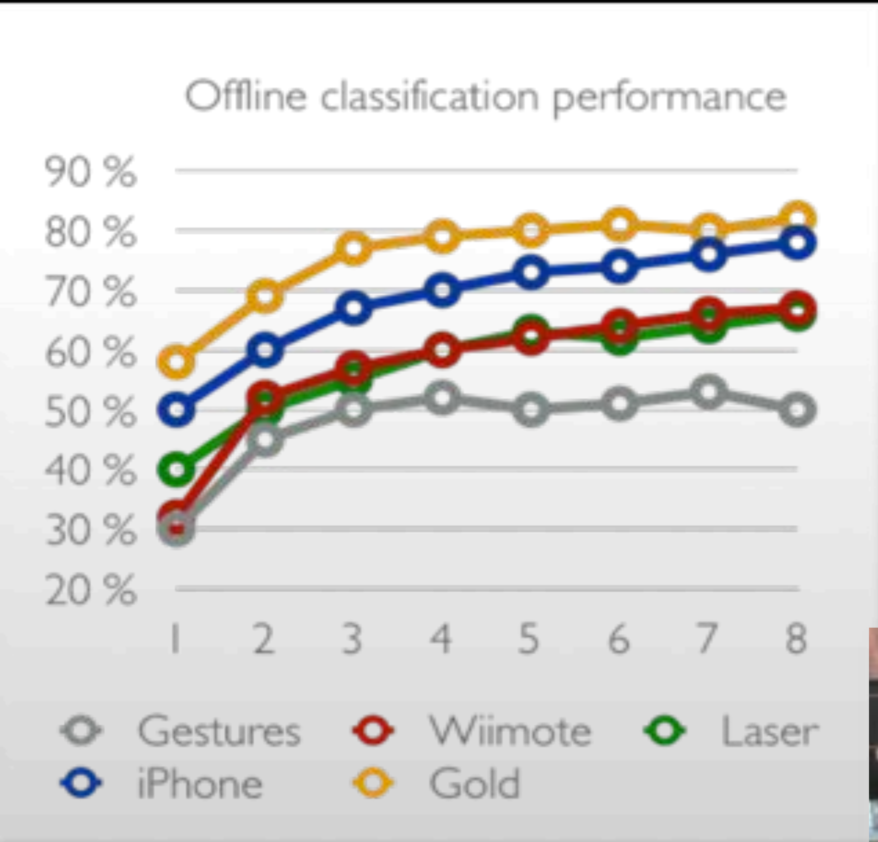
Introducing mediator interfaces

Allowing organisms that do not share the same tools for perception and action to still manage to communicate

Developing novel human-robot interfaces based on mediator objects

Mediator interfaces

(Rouanet et al., SIGGRAPH 2010)
(Rouanet, Danieau and Oudeyer,2011, HRI 2011)
(Rouanet et al., 2009, Humanoids 2009)



- Cap Sciences, Bordeaux
- 107 participants : 77 hommes, 30 femmes
- Age: 10 à 76 (M = 26.3)

➔ Using well-designed interfaces/ interaction schemes allows the robot to collect much better training data and to improve its learning dramatically (the increase is much higher than the different between a naive and a sophisticated statistical learning approach for a given dataset)

Families of developmental constraints allowing for versatile sensorimotor development

Humans		*Robots*
Intrinsically motivated exploration	→	Active learning alg.
Muscular synergies	→	Function basis for constraining movement
Eco-adapted morphology	→	Bio-inspired morphology
Myelination	→	Models of maturational constraints
Cognitive bias for inference and abstraction	→	Alg. for inference and abstraction building
Socially guided exploration	→	Techniques for learning through social interaction

Thank you!

http://flowers.inria.fr
http://www.pyoudeyer.com

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Inria ENSTA ParisTech

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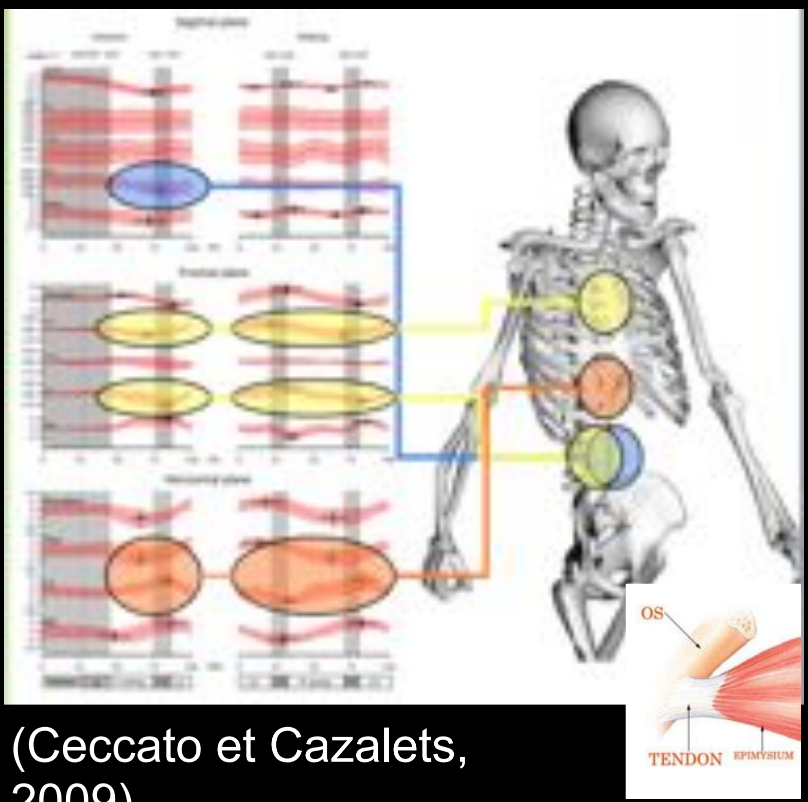
Contraintes morphologiques

Humains: rôle de la colonne vertébrale et de la flexibilité du corps

Robots



(Ceccato et Cazalets, 2009)
Institut de Neurosciences Cognitives et Intégratives d'Aquitaine

- Modélisation et exp. du tronc;
- Extension aux jambes;

(Ly et Oudeyer, SIGGRAPH 2010, emerging technologies)

Contraintes morphologiques sur l'apprentissage de la marche: le rôle de la souplesse et de la colonne vertébrale

- **Acroban (Olivier Ly), 32 DOFs**
- **Structure souple qui peut absorber et stocker de l'énergie (tendons élastiques ressorts, moteurs)**
- **Torse semi-passif avec colonne vertébrale multi-articulée**
- **Primitive motrice d'équilibrage générique**
- **La marche comme une auto-perturbation**
- **Une interface homme-robot « auto-organisée », permettant de guider intuitivement le robot en le prenant par la main**

Ly, O., Oudeyer, P-Y. (2010) Acroban the humanoid: Playful and compliant physical child robot interaction, SIGGRAPH'2010 *Emergent Technologies. Videos on* *http://flowers.inria.fr/acroban.php*

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Manuel Lopes (INRIA CR2)
David Filliat (MdC, ENSTA)
Frekk Stulp (MdC, ENSTA)
Alexander Gepperth (MdC ENSTA)

Administrative assistant
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Engineers
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Olivier Mangin (Bourse AMX – Polytechnique)
Fabien Benureau (Bourse ENS Lyon)
Islem Jebari (ENSTA PhD)
Natalia Lyubova (ENSTA PhD)
Alexandre Chapoulie (ENSTA PhD)

Collaborations interdisciplinaires

psychologie développementale

IMClever European project on Intrinsically motivated cumulative learning (motivations intrinsèques)

Philippe Rochat, Emory State University, US (découverte des cartes corporelles)

Linda Smith, Indiana University, US (Acquisition of symbolic communication

Neurosciences cognitives et intégratives

Jacqueline Gottlieb, Columbia University, NY, US, (motivations intrinsèques, attention visuelle)

J-R. Cazalets, Inst. Neur. Int. De Bordeaux (Acroban, physiologie de la colonne vertébrale)

Robotique

O. Sigaud, V. Padois ISIR, Univ. Paris VI (Operational space control)

F. Chaumette (LAGADIC) (ROMEO 2/ PAL, robot grasper in an assistive context)

P. Rives (AROBAS) (Slam)

M. Cakmak, Georgia Tech Univ. US (Human-Robot interaction and learning)

Stefan Schaal, UCSD, US (dynamic motor primitives,

Entreprises GOSTAI, Aldebaran Robotics, Robot Studio

Mécanique

Alexandre Lasserre, lab. De mécanique, Bordeaux (conception mécanique, Acroban)

FLOWERS

Linguistique

Louis ten Bosch, Radboud University, The Netherlands (prof. invité) (modèles de la découverte d'invariants moteurs, approche NMF)

Benjamin Bergen, USC, US (linguistique cognitive, modèles de représentation du sens et d'affordances)

Ergonomie et facteurs humains

INRIA Iparla (interfaces)

Institut de Cognitique, Bordeaux (évaluation des interfaces)

Inférence statistique et apprentissage automatique

Marc Toussaint, FU Berlin, Germany, (Inférence probabiliste pour la décision et la planification);

Rich Sutton, Univ. Alberta, Canada (Intrinsic motivation and RL)

INRIA Alea, Pierre Del Moral, François Caron (méthodes de Monte-Carlo, informal collaboration);

Andrew Barto, Univ. Mass., US (RL et théorie des options)

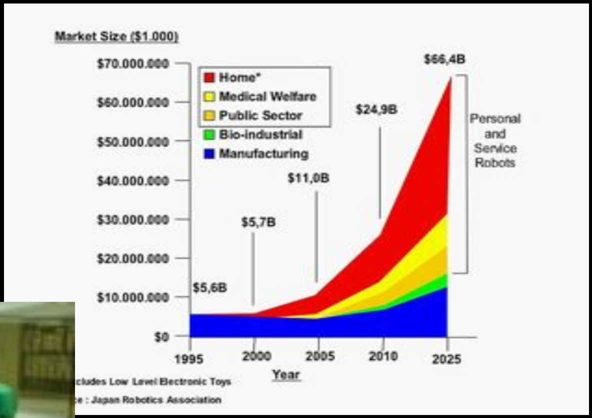
Coll. déjà commencées

Coll. Déjà planifiées (ERC, ANR, …)

Dimension sociétale et économique

« As I look at the trends that are now starting to converge, I can envision a future in which robotic devices will become a nearly ubiquitous part of our day-to-day lives »

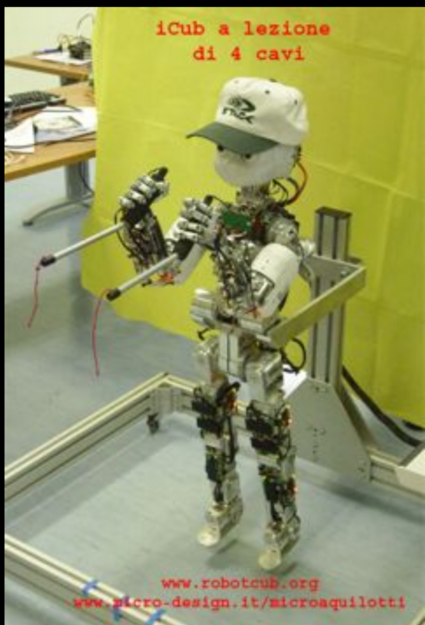
Bill Gates, Scientific American, january 2007



- Assistance à la personne
- Société vieillissante
- Education, confort et jeu

Défi: ***Interaction et interfaces*** (utilisabilité et acceptation sociale) et ***adaptation*** (apprentissage)

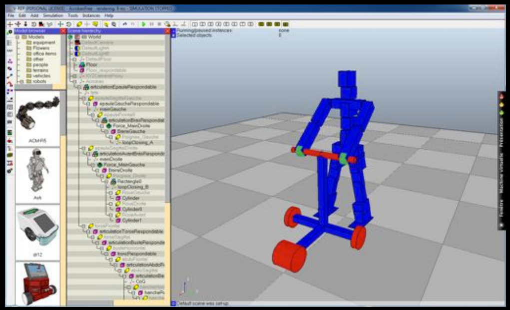
Plateformes expérimentales



Icub (avec l'ISIR, Open Call Robocub en 2007)

Nao

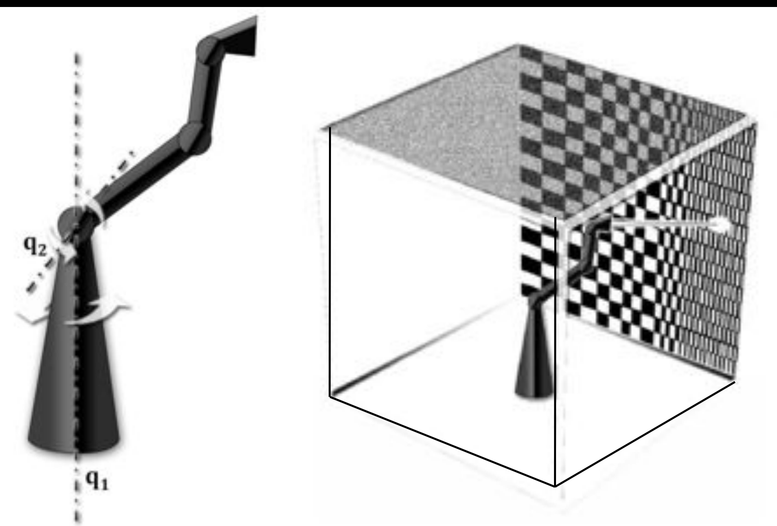
Acroban



Simulateurs: Webots et VREP

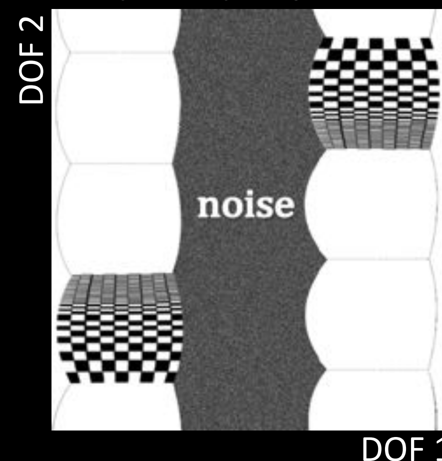
→ TOUS programmés dans le framework middleware URBI

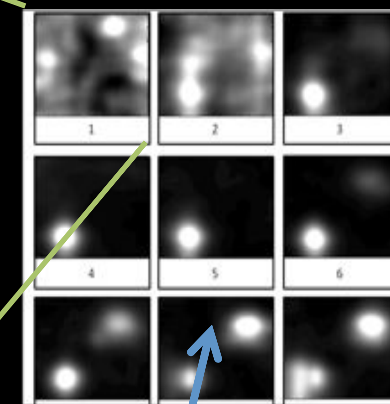
Un exemple simple du fonctionnement de R-IAC

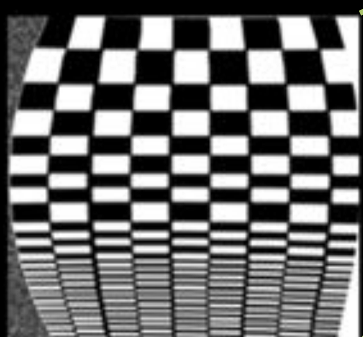


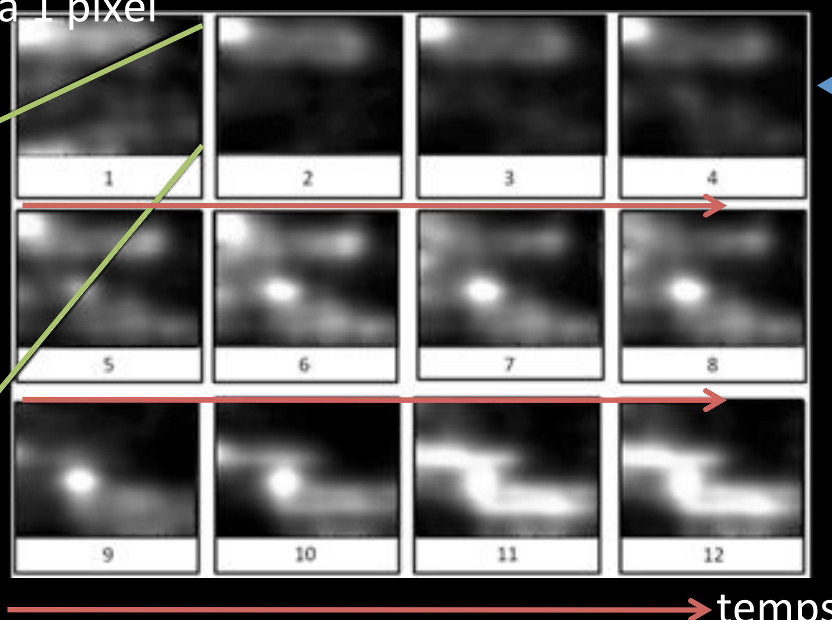
Bras redondant, caméra à 1 pixel

Espace perçu









Evolution du focus d'exploration avec le temps: le bruit est évité, et les régions "simples" sont explorées avant les régions compliquéesregions