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Activity Report 2017

Project-Team FLOWERS

Flowing Epigenetic Robots and Systems

RESEARCH CENTER
Bordeaux - Sud-Ouest

THEME
Robotics and Smart environments

Table of contents

Project-Team FLOWERS

Creation of the Team: 2008 April 01, updated into Project-Team: 2011 January 01

Keywords:

Computer Science and Digital Science:

A5.1.1. - Engineering of interactive systems
A5.1.2. - Evaluation of interactive systems
A5.1.4. - Brain-computer interfaces, physiological computing
A5.1.5. - Body-based interfaces
A5.1.6. - Tangible interfaces
A5.1.7. - Multimodal interfaces
A5.3.3. - Pattern recognition
A5.4.1. - Object recognition
A5.4.2. - Activity recognition
A5.7.3. - Speech
A5.8. - Natural language processing
A5.10.5. - Robot interaction (with the environment, humans, other robots)
A5.10.7. - Learning
A5.10.8. - Cognitive robotics and systems
A5.11.1. - Human activity analysis and recognition
A6.3.1. - Inverse problems
A9. - Artificial intelligence
A9.2. - Machine learning
A9.5. - Robotics
A9.7. - AI algorithmics

Other Research Topics and Application Domains:

B1.2.1. - Understanding and simulation of the brain and the nervous system
B1.2.2. - Cognitive science
B5.6. - Robotic systems
B5.7. - 3D printing
B5.8. - Learning and training
B9. - Society and Knowledge
B9.1. - Education
B9.1.1. - E-learning, MOOC
B9.2. - Art
B9.2.1. - Music, sound
B9.2.4. - Theater
B9.5. - Humanities
B9.5.1. - Psychology
B9.5.8. - Linguistics
B9.7. - Knowledge dissemination

1. Personnel

Research Scientists
Pierre-Yves Oudeyer [Team leader, Inria, Senior Researcher, HDR]
Olivier Sigaud [Inria, Senior Researcher, from Sep 2017, HDR]
Anna-Lisa Vollmer [Inria, Starting Research Position, until Feb 2017]

Faculty Member
David Filliat [École Nationale Supérieure de Techniques Avancées, Professor, HDR]

Post-Doctoral Fellow
Adrien Laversanne-Finot [Inria, from Nov 2017]

PhD Students
Baptiste Busch [Inria]
Benjamin Clement [Inria]
Cedric Colas [Inria, from Nov 2017]
Céline Craye [Thales, until Mar 2017]
Alexandra Delmas [ITWell]
Thibault Desprez [Inria]
Sébastien Forestier [Univ de Bordeaux]
Florian Golemo [Inria]
Antonin Raffin [Ensta]
Timothee Lesort [Ensta]
Adrien Matricon [Univ de Bordeaux, until Nov 2017]
Alvaro Ovalle Castaneda [Inria, until Aug 2017]
Gennaro Raiola [École Nationale Supérieure de Techniques Avancées, until Jan 2017]
William Schueller [Univ de Bordeaux]

Technical staff
Natalia Diaz Rodriguez [Armines]
Yoan Mollard [Inria, until Nov 2017, granted by FP7 /13-3RDHAND project]
Stephanie Noirpoudre [Inria]
Alexandre Pere [Inria, from Oct 2017]
Didier Roy [Inria, granted by Bibliothèques sans frontières]
Theo Segonds [Inria]
Damien Caselli [Inria]

Administrative Assistants
Nathalie Robin [Inria]
Catherine Cattaert Megrat [Inria]

2. Overall Objectives

2.1. Overall Objectives

Can a robot learn like a child? Can it learn new skills and new knowledge in an unknown and changing environment? How can it discover its body and its relationships with the physical and social environment? How can its cognitive capacities continuously develop without the intervention of an engineer? What can it learn through natural social interactions with humans?

These are the questions that are being investigated in the FLOWERS research team at Inria Bordeaux Sud-Ouest. Rather than trying to imitate the intelligence of adult humans like in the field of Artificial Intelligence, we believe that trying to reconstruct the processes of development of the child's mind will allow for more adaptive, more robust and more versatile machines. This approach is called developmental robotics, or epigenetic robotics, and imports concepts and theories from developmental psychology. As most of these theories are not formalized, this implies a crucial computational modeling activity, which in return provides means to assess the internal coherence of theories and sketch new hypothesis about the development of the human child's sensorimotor and cognitive abilities.

Our team focuses in particular on the study of developmental constraints that allow for efficient open-ended learning of novel sensorimotor and interaction skills in embodied systems. In particular, we study constraints that guide exploration in large sensorimotor spaces:

- Mechanisms of intrinsically motivated exploration and active learning, including artificial curiosity, allowing in particular to self-organize developmental trajectories and collect efficiently learning data;
- Mechanisms of adequately constrained optimization and statistical inference for sensorimotor skill acquisition (e.g. for optimizing motor policies in real robots);
- Mechanisms for social learning, e.g. learning by imitation or demonstration, which implies both issues related to machine learning and human-robot interaction;
- Constraints related to embodiment, in particular through the concept of morphological computation, as well as the structure of motor primitives/muscle synergies that can leverage the properties of morphology and physics for simplifying motor control and perception;
- Maturational constraints which, coupled with the other constraints, can allow the progressive release of novel sensorimotor degrees of freedom to be explored;

We also study how these constraints on exploration can allow a robot to bootstrap multimodal perceptual abstractions associated to motor skills, in particular in the context of modelling language acquisition as a developmental process grounded in action.

Among the developmental principles that characterize human infants and can be used in developmental robots, FLOWERS focuses on the following three principles:

- **Exploration is progressive.** The space of skills that can be learnt in real world sensorimotor spaces is so large and complicated that not everything can be learnt at the same time. Simple skills are learnt first, and only when they are mastered, new skills of progressively increasing difficulty become the behavioural focus;
- **Internal representations are (partially) not innate but learnt and adaptive.** For example, the body map, the distinction self/non-self and the concept of "object" are discovered through experience with initially uninterpreted sensors and actuators, guided by experience, the overall pre-determined connection structure of the brain, as well as a small set of simple innate values or preferences.
- **Exploration can be self-guided and/or socially guided.** On the one hand, internal and intrinsic motivation systems regulate and organize spontaneous exploration; on the other hand, exploration can be guided through social learning and interaction with caretakers.

2.1.1. Research axis

The work of FLOWERS is organized around the following axis:

- **Curiosity-driven exploration and sensorimotor learning:** intrinsic motivation are mechanisms that have been identified by developmental psychologists to explain important forms of spontaneous exploration and curiosity. In FLOWERS, we try to develop computational intrinsic motivation systems, and test them on robots, allowing to regulate the growth of complexity in exploratory behaviours. These mechanisms are studied as active learning mechanisms, allowing to learn efficiently in large inhomogeneous sensorimotor spaces;

- **Cumulative learning of sensorimotor skills:** FLOWERS develops machine learning algorithms that can allow embodied machines to acquire cumulatively sensorimotor skills. In particular, we develop optimization and reinforcement learning systems which allow robots to discover and learn dictionaries of motor primitives, and then combine them to form higher-level sensorimotor skills.
- **Natural and intuitive social learning:** FLOWERS develops interaction frameworks and learning mechanisms allowing non-engineer humans to teach a robot naturally. This involves two sub-themes: 1) techniques allowing for natural and intuitive human-robot interaction, including simple ergonomic interfaces for establishing joint attention; 2) learning mechanisms that allow the robot to use the guidance hints provided by the human to teach new skills;
- **Discovering and abstracting the structure of sets of uninterpreted sensors and motors:** FLOWERS studies mechanisms that allow a robot to infer structural information out of sets of sensorimotor channels whose semantics is unknown, for example the topology of the body and the sensorimotor contingencies (propriocetive, visual and acoustic). This process is meant to be open-ended, progressing in continuous operation from initially simple representations to abstract concepts and categories similar to those used by humans.
- **Body design and role of the body in sensorimotor and social development:** We study how the physical properties of the body (geometry, materials, distribution of mass, growth, ...) can impact the acquisition of sensorimotor and interaction skills. This requires to consider the body as an experimental variable, and for this we develop special methodologies for designing and evaluating rapidly new morphologies, especially using rapid prototyping techniques like 3D printing.
- **Intelligent Tutoring Systems:**FLOWERS develops methods for online personalization of teaching sequences for educational software and MOOCs. This work builds on top of online optimization methods and motivational research previously developed.

3. Research Program

3.1. Research Program

Research in artificial intelligence, machine learning and pattern recognition has produced a tremendous amount of results and concepts in the last decades. A blooming number of learning paradigms - supervised, unsupervised, reinforcement, active, associative, symbolic, connectionist, situated, hybrid, distributed learning... - nourished the elaboration of highly sophisticated algorithms for tasks such as visual object recognition, speech recognition, robot walking, grasping or navigation, the prediction of stock prices, the evaluation of risk for insurances, adaptive data routing on the internet, etc... Yet, we are still very far from being able to build machines capable of adapting to the physical and social environment with the flexibility, robustness, and versatility of a one-year-old human child.

Indeed, one striking characteristic of human children is the nearly open-ended diversity of the skills they learn. They not only can improve existing skills, but also continuously learn new ones. If evolution certainly provided them with specific pre-wiring for certain activities such as feeding or visual object tracking, evidence shows that there are also numerous skills that they learn smoothly but could not be “anticipated” by biological evolution, for example learning to drive a tricycle, using an electronic piano toy or using a video game joystick. On the contrary, existing learning machines, and robots in particular, are typically only able to learn a single pre-specified task or a single kind of skill. Once this task is learnt, for example walking with two legs, learning is over. If one wants the robot to learn a second task, for example grasping objects in its visual field, then an engineer needs to re-program manually its learning structures: traditional approaches to task-specific machine/robot learning typically include engineer choices of the relevant sensorimotor channels, specific design of the reward function, choices about when learning begins and ends, and what learning algorithms and associated parameters shall be optimized.

As can be seen, this requires a lot of important choices from the engineer, and one could hardly use the term “autonomous” learning. On the contrary, human children do not learn following anything looking like that process, at least during their very first years. Babies develop and explore the world by themselves, focusing their interest on various activities driven both by internal motives and social guidance from adults who only have a folk understanding of their brains. Adults provide learning opportunities and scaffolding, but eventually young babies always decide for themselves what activity to practice or not. Specific tasks are rarely imposed to them. Yet, they steadily discover and learn how to use their body as well as its relationships with the physical and social environment. Also, the spectrum of skills that they learn continuously expands in an organized manner: they undergo a developmental trajectory in which simple skills are learnt first, and skills of progressively increasing complexity are subsequently learnt.

A link can be made to educational systems where research in several domains have tried to study how to provide a good learning experience to learners. This includes the experiences that allow better learning, and in which sequence they must be experienced. This problem is complementary to that of the learner that tries to learn efficiently, and the teacher here has to use as efficiently the limited time and motivational resources of the learner. Several results from psychology [100] and neuroscience [22] have argued that the human brain feels intrinsic pleasure in practicing activities of optimal difficulty or challenge. A teacher must exploit such activities to create positive psychological states of flow [111].

A grand challenge is thus to be able to build robotic machines that possess this capability to discover, adapt and develop continuously new know-how and new knowledge in unknown and changing environments, like human children. In 1950, Turing wrote that the child’s brain would show us the way to intelligence: “Instead of trying to produce a program to simulate the adult mind, why not rather try to produce one which simulates the child’s” [173]. Maybe, in opposition to work in the field of Artificial Intelligence who has focused on mechanisms trying to match the capabilities of “intelligent” human adults such as chess playing or natural language dialogue [123], it is time to take the advice of Turing seriously. This is what a new field, called developmental (or epigenetic) robotics, is trying to achieve [141] [178]. The approach of developmental robotics consists in importing and implementing concepts and mechanisms from developmental psychology [145], cognitive linguistics [110], and developmental cognitive neuroscience [128] where there has been a considerable amount of research and theories to understand and explain how children learn and develop. A number of general principles are underlying this research agenda: embodiment [104] [153], grounding [121], situatedness [91], self-organization [169] [155], enaction [176], and incremental learning [107].

Among the many issues and challenges of developmental robotics, two of them are of paramount importance: exploration mechanisms and mechanisms for abstracting and making sense of initially unknown sensorimotor channels. Indeed, the typical space of sensorimotor skills that can be encountered and learnt by a developmental robot, as those encountered by human infants, is immensely vast and inhomogeneous. With a sufficiently rich environment and multimodal set of sensors and effectors, the space of possible sensorimotor activities is simply too large to be explored exhaustively in any robot’s life time: it is impossible to learn all possible skills and represent all conceivable sensory percepts. Moreover, some skills are very basic to learn, some other very complicated, and many of them require the mastery of others in order to be learnt. For example, learning to manipulate a piano toy requires first to know how to move one’s hand to reach the piano and how to touch specific parts of the toy with the fingers. And knowing how to move the hand might require to know how to track it visually.

Exploring such a space of skills randomly is bound to fail or result at best on very inefficient learning [150]. Thus, exploration needs to be organized and guided. The approach of epigenetic robotics is to take inspiration from the mechanisms that allow human infants to be progressively guided, i.e. to develop. There are two broad classes of guiding mechanisms which control exploration:

1. **internal guiding mechanisms,** and in particular intrinsic motivation, responsible of spontaneous exploration and curiosity in humans, which is one of the central mechanisms investigated in FLOWERS, and technically amounts to achieve online active self-regulation of the growth of complexity in learning situations;
2. **social learning and guidance,** a learning mechanisms that exploits the knowledge of other agents

in the environment and/or that is guided by those same agents. These mechanisms exist in many different forms like emotional reinforcement, stimulus enhancement, social motivation, guidance, feedback or imitation, some of which being also investigated in FLOWERS;

3.1.1. Internal guiding mechanisms

In infant development, one observes a progressive increase of the complexity of activities with an associated progressive increase of capabilities [145], children do not learn everything at one time: for example, they first learn to roll over, then to crawl and sit, and only when these skills are operational, they begin to learn how to stand. The perceptual system also gradually develops, increasing children perceptual capabilities other time while they engage in activities like throwing or manipulating objects. This make it possible to learn to identify objects in more and more complex situations and to learn more and more of their physical characteristics.

Development is therefore progressive and incremental, and this might be a crucial feature explaining the efficiency with which children explore and learn so fast. Taking inspiration from these observations, some roboticists and researchers in machine learning have argued that learning a given task could be made much easier for a robot if it followed a developmental sequence and "started simple" [95] [114]. However, in these experiments, the developmental sequence was crafted by hand: roboticists manually build simpler versions of a complex task and put the robot successively in versions of the task of increasing complexity. And when they wanted the robot to learn a new task, they had to design a novel reward function.

Thus, there is a need for mechanisms that allow the autonomous control and generation of the developmental trajectory. Psychologists have proposed that intrinsic motivations play a crucial role. Intrinsic motivations are mechanisms that push humans to explore activities or situations that have intermediate/optimal levels of novelty, cognitive dissonance, or challenge [100] [111] [113]. The role and structure of intrinsic motivation in humans have been made more precise thanks to recent discoveries in neuroscience showing the implication of dopaminergic circuits and in exploration behaviours and curiosity [112] [125] [164]. Based on this, a number of researchers have began in the past few years to build computational implementation of intrinsic motivation [150] [151] [162] [99] [126] [143] [163]. While initial models were developed for simple simulated worlds, a current challenge is to manage to build intrinsic motivation systems that can efficiently drive exploratory behaviour in high-dimensional unprepared real world robotic sensorimotor spaces [151], [150], [152], [161]. Specific and complex problems are posed by real sensorimotor spaces, in particular due to the fact that they are both high-dimensional as well as (usually) deeply inhomogeneous. As an example for the latter issue, some regions of real sensorimotor spaces are often unlearnable due to inherent stochasticity or difficulty, in which case heuristics based on the incentive to explore zones of maximal unpredictability or uncertainty, which are often used in the field of active learning [108] [122] typically lead to catastrophic results. The issue of high dimensionality does not only concern motor spaces, but also sensory spaces, leading to the problem of correctly identifying, among typically thousands of quantities, those latent variables that have links to behavioral choices. In FLOWERS, we aim at developing intrinsically motivated exploration mechanisms that scale in those spaces, by studying suitable abstraction processes in conjunction with exploration strategies.

3.1.2. Socially Guided and Interactive Learning

Social guidance is as important as intrinsic motivation in the cognitive development of human babies [145]. There is a vast literature on learning by demonstration in robots where the actions of humans in the environment are recognized and transferred to robots [94]. Most such approaches are completely passive: the human executes actions and the robot learns from the acquired data. Recently, the notion of interactive learning has been introduced in [170], [101], motivated by the various mechanisms that allow humans to socially guide a robot [158]. In an interactive context the steps of self-exploration and social guidances are not separated and a robot learns by self exploration and by receiving extra feedback from the social context [170], [134] [144].

Social guidance is also particularly important for learning to segment and categorize the perceptual space. Indeed, parents interact a lot with infants, for example teaching them to recognize and name objects or characteristics of these objects. Their role is particularly important in directing the infant attention towards objects of interest that will make it possible to simplify at first the perceptual space by pointing out a segment of the environment that can be isolated, named and acted upon. These interactions will then be complemented by the children own experiments on the objects chosen according to intrinsic motivation in order to improve the knowledge of the object, its physical properties and the actions that could be performed with it.

In FLOWERS, we are aiming at including intrinsic motivation system in the self-exploration part thus combining efficient self-learning with social guidance [147], [148]. We also work on developing perceptual capabilities by gradually segmenting the perceptual space and identifying objects and their characteristics through interaction with the user [34] and robots experiments [127]. Another challenge is to allow for more flexible interaction protocols with the user in terms of what type of feedback is provided and how it is provided [138].

Exploration mechanisms are combined with research in the following directions:

3.1.3. Cumulative learning, reinforcement learning and optimization of autonomous skill learning

FLOWERS develops machine learning algorithms that can allow embodied machines to acquire cumulatively sensorimotor skills. In particular, we develop optimization and reinforcement learning systems which allow robots to discover and learn dictionaries of motor primitives, and then combine them to form higher-level sensorimotor skills.

3.1.4. Autonomous perceptual and representation learning

In order to harness the complexity of perceptual and motor spaces, as well as to pave the way to higher-level cognitive skills, developmental learning requires abstraction mechanisms that can infer structural information out of sets of sensorimotor channels whose semantics is unknown, discovering for example the topology of the body or the sensorimotor contingencies (proprioceptive, visual and acoustic). This process is meant to be open- ended, progressing in continuous operation from initially simple representations towards abstract concepts and categories similar to those used by humans. Our work focuses on the study of various techniques for:

- autonomous multimodal dimensionality reduction and concept discovery;
- incremental discovery and learning of objects using vision and active exploration, as well as of auditory speech invariants;
- learning of dictionaries of motion primitives with combinatorial structures, in combination with linguistic description;
- active learning of visual descriptors useful for action (e.g. grasping);

3.1.5. Embodiment and maturational constraints

FLOWERS studies how adequate morphologies and materials (i.e. morphological computation), associated to relevant dynamical motor primitives, can importantly simplify the acquisition of apparently very complex skills such as full-body dynamic walking in biped. FLOWERS also studies maturational constraints, which are mechanisms that allow for the progressive and controlled release of new degrees of freedoms in the sensorimotor space of robots.

3.1.6. Discovering and abstracting the structure of sets of uninterpreted sensors and motors

FLOWERS studies mechanisms that allow a robot to infer structural information out of sets of sensorimotor channels whose semantics is unknown, for example the topology of the body and the sensorimotor contingencies (proprioceptive, visual and acoustic). This process is meant to be open-ended, progressing in continuous operation from initially simple representations to abstract concepts and categories similar to those used by humans.

4. Application Domains

4.1. Application Domains

Cognitive Sciences The computational modelling of life-long learning and development mechanisms achieved in the team centrally targets to contribute to our understanding of the processes of sensorimotor, cognitive and social development in humans. In particular, it provides a methodological basis to analyze the dynamics of the interaction across learning and inference processes, embodiment and the social environment, allowing to formalize precise hypotheses and later on test them in experimental paradigms with animals and humans. A paradigmatic example of this activity is the Neurocuriosity project achieved in collaboration with the cognitive neuroscience lab of Jacqueline Gottlieb, where theoretical models of the mechanisms of information seeking, active learning and spontaneous exploration have been developped in coordination with experimental evidence and investigation, see https://flowers.inria.fr/neurocuriosityproject/.

Personal and lifelong learning robotics Many indicators show that the arrival of personal robots in homes and everyday life will be a major fact of the 21st century. These robots will range from purely entertainment or educative applications to social companions that many argue will be of crucial help in our society. Yet, to realize this vision, important obstacles need to be overcome: these robots will have to evolve in unpredictable homes and learn new skills in a lifelong manner while interacting with non-engineer humans after they left factories, which is out of reach of current technology. In this context, the refoundation of intelligent systems that developmental robotics is exploring opens potentially novel horizons to solve these problems. In particular, this application domain requires advances in artificial intelligence that go beyond the current state-of-the-art in fields like deep learning. Currently these techniques require tremendous amounts of data in order to function properly, and they are severaly limited in terms of incremental and transfer learning. One of our goals is to drastically reduce the amount of data required in order for this very potent field to work. We try to achieve this by making neural networks aware of their knowledge, i.e. we introduce the concept of uncertainty, and use it as part of intrinsically motivated multitask learning architectures, and combined with techniques of learning by imitation.

Human-Robot Collaboration. Robots play a vital role for industry and ensure the efficient and competitive production of a wide range of goods. They replace humans in many tasks which otherwise would be too difficult, too dangerous, or too expensive to perform. However, the new needs and desires of the society call for manufacturing system centered around personalized products and small series productions. Human-robot collaboration could widen the use of robot in this new situations if robots become cheaper, easier to program and safe to interact with. The most relevant systems for such applications would follow an expert worker and works with (some) autonomy, but being always under supervision of the human and acts based on its task models.

Environment perception in intelligent vehicles. When working in simulated traffic environments, elements of FLOWERS research can be applied to the autonomous acquisition of increasingly abstract representations of both traffic objects and traffic scenes. In particular, the object classes of vehicles and pedestrians are if interest when considering detection tasks in safety systems, as well as scene categories ("scene context") that have a strong impact on the occurrence of these object classes. As already indicated by several investigations in the field, results from present-day simulation technology can be transferred to the real world with little impact on performance. Therefore, applications of FLOWERS research that is suitably verified by real-world benchmarks has direct applicability in safety-system products for intelligent vehicles.

Automated Tutoring Systems. Optimal teaching and efficient teaching/learning environments can be applied to aid teaching in schools aiming both at increase the achievement levels and the reduce time needed. From a practical perspective, improved models could be saving millions of hours of students' time (and effort) in learning. These models should also predict the achievement levels of students in order to influence teaching practices.

5. Highlights of the Year

5.1. Highlights of the Year

- P-Y. Oudeyer was invited to give the 29th Eleanor J. Gibson and James J. Gibson Lecture in Experimental Psychology, by Cornell University, US.
- P-Y. Oudeyer co-organized with colleagues at Univ. Waterloo (Canada) the interdisciplinary workshop "Designing for curiosity" at CHI 2016 in Denver, Colorado, US. This workshop aimed to build a community of academic researchers-such as computer scientists (in human-computer interaction, artificial intelligence, robotics), developmental psychologists, behavioral economists, education, marketing, neuroscience-as well as practitioners-such as painters, architects, game designers, screenwriters who have engaged with the term curiosity in their work. Web site: https://www.crowdcurio.com/research/workshops/chi2017/.
- P-Y. Oudeyer co-organized (with V. Santucci, G. Baldassarre, A. Barto) the 3rd International Workshop on Intrinsically Motivated Open-Ended Learning (IMOL 2017). It aimed to further explore the promise of intrinsically motivated open-ended lifelong learning in robots and artificial systems. Web: http://www.imol-conf.org/. We also organized a follow-up special issue in the journal Fronties in Robotics and AI:
http://goo.gl/YkMYNN.
- The Flowers team organized the 3rd "Colloque Robotique et Education" in Bordeaux (general chair: Didier Roy), gathering around 200 attendees on the topic of educational robotics. Web: http://dm1r.fr/roboeduc17/. The team also contributed to the organization of the Scratch international conference, web:http://www.scratch2017bdx.org/en/hello-world-2/.
- The Flowers team, the Potioc team and two research teams in robotics and HCI at the University of Waterloo (Canada) initiated a new interdisciplinary collaboration around the design of interactive environments that foster curiosity-driven learning, and obtained a funding from Idex/University of Bordeaux.

6. New Software and Platforms

6.1. 3rd hand infrastructure

KEYWORDS: Interaction - Robotics - Infrastructure software - Framework - Robot Operating System (ROS)
FUNCTIONAL DESCRIPTION: The infrastructure is predicate-based to handle relational actions and covers perception (scene description generation, human actions recognition), decision making (teleoperated, scripted or learning from demonstrations), interaction with end users (GUI, voice, gestures) and parallel executions of robotic actions (hold, pick, grasp, bring, ...).

- Contact: Yoan Mollard
- URL: https://github.com/3rdHand-project/thr_infrastructure

6.2. Aversive++

FUNCTIONAL DESCRIPTION: Aversive++ is a C++ library that eases micro-controller programming. Its aim is to provide an interface simple enough to be able to create complex applications, and optimized enough to enable small micro-controllers to execute these applications. The other aspect of this library is to be multiplatform. Indeed, it is designed to provide the same API for a simulator (named SASIAE) and for AVR-based and ARM-based micro-controllers.

- Contact: Loïc Dauphin
- URL: http://aversiveplusplus.com/

6.3. DMP-BBO

Black-Box Optimization for Dynamic Movement Primitives
FUNCTIONAL DESCRIPTION: The DMP-BBO Matlab library is a direct consequence of the insight that black-box optimization outperforms reinforcement learning when using policies represented as Dynamic Movement Primitives. It implements several variants of the PIBB algorithm for direct policy search. The dmp-bbo C++ library has been extended to include the “unified model for regression”. The implementation of several of the function approximators have been made real-time compatible.

- Participant: Freek Stulp
- Partner: ENSTA
- Contact: Freek Stulp
- URL: https://github.com/stulp/dmpbbo

6.4. Explauto

an autonomous exploration library
SCIENTIFIC DESCRIPTION: An important challenge in developmental robotics is how robots can be intrinsically motivated to learn efficiently parametrized policies to solve parametrized multi-task reinforcement learning problems, i.e. learn the mappings between the actions and the problem they solve, or sensory effects they produce. This can be a robot learning how arm movements make physical objects move, or how movements of a virtual vocal tract modulates vocalization sounds. The way the robot will collects its own sensorimotor experience have a strong impact on learning efficiency because for most robotic systems the involved spaces are high dimensional, the mapping between them is non-linear and redundant, and there is limited time allowed for learning. If robots explore the world in an unorganized manner, e.g. randomly, learning algorithms will be often ineffective because very sparse data points will be collected. Data are precious due to the high dimensionality and the limited time, whereas data are not equally useful due to non-linearity and redundancy. This is why learning has to be guided using efficient exploration strategies, allowing the robot to actively drive its own interaction with the environment in order to gather maximally informative data to optimize the parametrized policies. In the recent year, work in developmental learning has explored various families of algorithmic principles which allow the efficient guiding of learning and exploration.

Explauto is a framework developed to study, model and simulate curiosity-driven learning and exploration in real and simulated robotic agents. Explauto's scientific roots trace back from Intelligent Adaptive Curiosity algorithmic architecture [51], which has been extended to a more general family of autonomous exploration architectures by [3] and recently expressed as a compact and unified formalism [40]. The library is detailed in [41]. In Explauto, interest models are implementing the strategies of active selection of particular problems / goals in a parametrized multi-task reinforcement learning setup to efficiently learn parametrized policies. The agent can have different available strategies, parametrized problems, models, sources of information, or learning mechanisms (for instance imitate by mimicking vs by emulation, or asking help to one teacher or to another), and chooses between them in order to optimize learning (a processus called strategic learning [47]). Given a set of parametrized problems, a particular exploration strategy is to randomly draw goals/ RL problems to solve in the motor or problem space. More efficient strategies are based on the active choice of learning experiments that maximize learning progress using bandit algorithms, e.g. maximizing improvement of predictions or of competences to solve RL problems [51]. This automatically drives the system to explore and learn first easy skills, and then explore skills of progressively increasing complexity. Both random and learning progress strategies can act either on the motor or on the problem space, resulting in motor babbling or goal babbling strategies.

- Motor babbling consists in sampling commands in the motor space according to a given strategy (random or learning progress), predicting the expected effect, executing the command through the environment and observing the actual effect. Both the parametrized policies and interest models are finally updated according to this experience.

- Goal babbling consists in sampling goals in the problem space and to use the current policies to infer a motor action supposed to solve the problem (inverse prediction). The robot/agent then executes the command through the environment and observes the actual effect. Both the parametrized policies and interest models are finally updated according to this experience.It has been shown that this second strategy allows a progressive solving of problems much more uniformly in the problem space than with a motor babbling strategy, where the agent samples directly in the motor space [3].

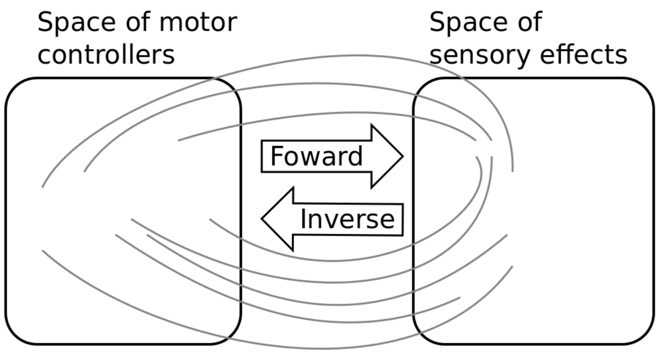

Figure 1. Complex parametrized policies involve high dimensional action and effect spaces. For the sake of visualization, the motor M and sensory S spaces are only 2D each in this example. The relationship between M and S is non-linear, dividing the sensorimotor space into regions of unequal stability: small regions of S can be reached very precisely by large regions of M, or large regions in S can be very sensitive to variations in M.: s as well as a non-linear and redundant relationship. This non-linearity can imply redundancy, where the same sensory effect can be attained using distinct regions in M.

FUNCTIONAL DESCRIPTION: This library provides high-level API for an easy definition of:

- Real and simulated robotic setups (Environment level),
- Incremental learning of parametrized policies (Sensorimotor level),
- Active selection of parametrized RL problems (Interest level).

The library comes with several built-in environments. Two of them corresponds to simulated environments: a multi-DoF arm acting on a 2D plan, and an under-actuated torque-controlled pendulum. The third one allows to control real robots based on Dynamixel actuators using the Pypot library. Learning parametrized policies involves machine learning algorithms, which are typically regression algorithms to learn forward models, from motor controllers to sensory effects, and optimization algorithms to learn inverse models, from sensory effects, or problems, to the motor programs allowing to reach them. We call these sensorimotor learning algorithms sensorimotor models. The library comes with several built-in sensorimotor models: simple nearest-neighbor look-up, non-parametric models combining classical regressions and optimization algorithms, online mixtures of Gaussians, and discrete Lidstone distributions. Explauto sensorimotor models are online learning algorithms, i.e. they are trained iteratively during the interaction of the robot in theenvironment in which it evolves. Explauto provides also a unified interface to define exploration strategies using the InterestModel class. The library comes with two built-in interest models: random sampling as well as sampling maximizing the learning progress in forward or inverse predictions.

Explauto environments now handle actions depending on a current context, as for instance in an environment where a robotic arm is trying to catch a ball: the arm trajectories will depend on the current position of the ball (context). Also, if the dynamic of the environment is changing over time, a new sensorimotor model

(Non-Stationary Nearest Neighbor) is able to cope with those changes by taking more into account recent experiences. Those new features are explained in Jupyter notebooks.

This library has been used in many experiments including:

- the control of a 2D simulated arm,
- the exploration of the inverse kinematics of a poppy humanoid (both on the real robot and on the simulated version),
- acoustic model of a vocal tract.

Explauto is crossed-platform and has been tested on Linux, Windows and Mac OS. It has been released under the GPLv3 license.

- Contact: Sébastien Forestier
- URL: https://github.com/flowersteam/explauto

6.5. HiPi Board

FUNCTIONAL DESCRIPTION: Hipi is a board to control robots on Raspberry Pi. It is an extension of the Pixl board with the following features:

- A DC/DC power converter from 12V (motor) to 5V (Raspberry Pi) at 3A.
- A stereo audio amplifier 3W.
- A MPU9250 central motion unit .
- A RS232 and a RS485 bus connected to the Raspberry Pi by SPI for driving MX and RX Dynamixel motor series.

This board will be integrated soon in the new head of the Poppy Humanoid and Poppy Torso.

Using the Raspberry Pi for every Poppy robots will simplify the hardware complexity (we maintain 4 types of embedded boards, with different Linux kernel and configurations) and improve the usage and installation of new robots.

- Contact: Theo Segonds
- URL: https://forum.poppy-project.org/t/poppy-1-1-hipi/2137

6.6. IKPy

Inverse Kinematics Python Library

FUNCTIONAL DESCRIPTION: IKPy is a Python Inverse Kinematics library, designed to be simple to use and extend. It provides Forward and Inverse kinematics functionality, bundled with helper tools such as 3D plotting of the kinematics chains. Being written entirely in Python, IKPy is lightweight and is based on numpy and scipy for fast optimization. IKPy is compatible with many robots, by automatically parsing URDF files. It also supports other (such as DH-parameters) and custom representations. Moreover, it provides a framework to easily implement new Inverse Kinematics strategies. Originally developed for the Poppy project, it can also be used as a standalone library.

- Contact: Pierre Manceron
- URL: https://github.com/Phylliade/ikpy

6.7. KERAS-QR

KERAS with Quick Reset

KEYWORDS: Library - Deep learning

- Participant: Florian Golemo
- Contact: Florian Golemo
- URL: https://github.com/fgolemo/keras

6.8. KidBreath

FUNCTIONAL DESCRIPTION: KidBreath is a web responsive application composed by several interactive contents linked to asthma and displayed to different forms: learning activities with quiz, short games and videos. There are profil creation and personalization, and a part which describes historic and scoring of learning activities, to see evolution of Kidreath use. To test Kidlearn algorithm, it is iadapted and integrated on this platform. Development in PHP, HTML-5, CSS, MySQL, JQuery, Javascript. Hosting in APACHE, LINUX, PHP 5.5, MySQL, OVH.

- Partner: ItWell SAS
- Contact: Alexandra Delmas
- URL: http://www.kidbreath.fr

6.9. Kidlearn: money game application

FUNCTIONAL DESCRIPTION: The games is instantiated in a browser environment where students are proposed exercises in the form of money/token games (see Figure 2). For an exercise type, one object is presented with a given tagged price and the learner has to choose which combination of bank notes, coins or abstract tokens need to be taken from the wallet to buy the object, with various constraints depending on exercises parameters. The games have been developed using web technologies, HTML5, javascript and Django.

Figure 2. Four principal regions are defined in the graphical interface. The first is the wallet location where users can pick and drag the money items and drop them on the repository location to compose the correct price. The object and the price are present in the object location. Four different types of exercises exist: M : customer/one object, R : merchant/one object, MM : customer/two objects, RM : merchant/two objects.

- Contact: Benjamin Clement
- URL: https://flowers.inria.fr/research/kidlearn/

6.10. Kidlearn: script for Kidbreath use

FUNCTIONAL DESCRIPTION: A new way to test Kidlearn algorithms is to use them on Kidbreath Plateform. The Kidbreath Plateform use apache/PHP server, so to facilitate the integration of our algorithm, a python script have been made to allow PHP code to use easily the python library already made which include our algorithms.

Github link to explanation about it : https://github.com/flowersteam/kidlearn/.

- Contact: Benjamin Clement

6.11. KidLearn

KEYWORD: Automatic Learning

FUNCTIONAL DESCRIPTION: KidLearn is a software which adaptively personalize sequences of learning activities to the particularities of each individual student. It aims at proposing to the student the right activity at the right time, maximizing concurrently his learning progress and its motivation.

- Participants: Benjamin Clement, Didier Roy, Manuel Lopes and Pierre Yves Oudeyer
- Contact: Manuel Lopes
- URL: https://flowers.inria.fr/research/kidlearn/

6.12. Kinect 2 Server

Kinect 2 server

KEYWORDS: Depth Perception - Speech recognition - Gesture recognition - Kinect

FUNCTIONAL DESCRIPTION: The server written in C# uses the Kinect SDK v2 to get the RGBD raw image, skeleton tracking information, recognized speech. It also uses the text-to-speech from Microsoft. Then it streams JSON data over the network using the Publisher/Subscriber pattern from the ZeroMQ network library. A Linux client has been written in Python but it can be written in any other language that is compatible with ZeroMQ. Features are controllable through a Graphical User Interface on Windows, or through the code from any Linux/Windows client. The clients can for instance enable features (speech recognition on, skeleton tracking off, . . .) and parameters (set new speech to recognize, change language, . . .) from remote.

- Contact: Yoan Mollard
- URL: https://github.com/baxter-flowers/kinect_2_server/

6.13. Multimodal

FUNCTIONAL DESCRIPTION: The python code provides a minimum set of tools and associated libraries to reproduce the experiments in [98] , together with the choreography datasets. The code is primarily intended for reproduction of the mulimodal learning experiment mentioned above. It has already been reused in several experimentations by other member of the team and is expected to play an important role in further collaborations. It is also expected that the public availability of the code encourages further experimentation by other scientists with data coming from other domains, thus increasing both the impact of the aforementioned publication and the knowledge on the algorithm behaviors.

- Participant: Olivier Mangin
- Contact: Olivier Mangin
- URL: https://github.com/omangin/multimodal

6.14. OptiTrack

FUNCTIONAL DESCRIPTION: This python library allows you to connect to an OptiTrack from NaturalPoint. This camera permits the tracking of 3D markers efficiently and robustly. With this library, you can connect to the Motive software used by the OptiTrack and retrieve the 3D position and orientation of all your tracked markers directly from python.

- Participant: Pierre Rouanet
- Contact: Pierre Rouanet
- URL: http://www.optitrack.com/

6.15. Pixl Board

FUNCTIONAL DESCRIPTION: Pixl is a tiny board used to create low cost robots based on Raspberry Pi board and Dynamixel XL-320 motors. This board has 2 main features:

- The power part, allowing the user to plug a 7.5V AC/DC converter or a battery directly into the Pixl. This power is distributed to all XL320 motors and is converted to 5V for the Raspberry Pi board.
- The communication part, which converts full duplex to half duplex and vice-versa. The half duplex part switch between RX and TX automatically. Another connector allows the user to connect his XL320 network.

The board is used in the Poppy Ergo Jr robot.

- Contact: Theo Segonds
- URL: https://github.com/poppy-project/pixl

6.16. Poppy

FUNCTIONAL DESCRIPTION: The Poppy Project team develops open-source 3D printed robots platforms based on robust, flexible, easy-to-use and reproduce hardware and software. In particular, the use of 3D printing and rapid prototyping technologies is a central aspect of this project, and makes it easy and fast not only to reproduce the platform, but also to explore morphological variants. Poppy targets three domains of use: science, education and art.

In the Poppy project we are working on the Poppy System which is a new modular and open-source robotic architecture. It is designed to help people create and build custom robots. It permits, in a similar approach as Lego, building robots or smart objects using standardized elements.

Poppy System is a unified system in which essential robotic components (actuators, sensors...) are independent modules connected with other modules through standardized interfaces:

- Unified mechanical interfaces, simplifying the assembly process and the design of 3D printable parts.
- Unified communication between elements using the same connector and bus for each module.
- Unified software, making it easy to program each module independently.

Our ambition is to create an ecosystem around this system so communities can develop custom modules, following the Poppy System standards, which can be compatible with all other Poppy robots.

- Participants: Jonathan Grizou, Matthieu Lapeyre, Pierre Rouanet and Pierre-Yves Oudeyer
- Contact: Pierre-Yves Oudeyer
- URL: https://www.poppy-project.org/

6.17. Poppy Ergo Jr

FUNCTIONAL DESCRIPTION: Poppy Ergo Jr is an open hardware robot developed by the Poppy Project to explore the use of robots in classrooms for learning robotic and computer science.

It is available as a 6 or 4 degrees of freedom arm designed to be both expressive and low-cost. This is achieved by the use of FDM 3D printing and low cost Robotis XL-320 actuators. A Raspberry Pi camera is attached to the robot so it can detect object, faces or QR codes.

The Ergo Jr is controlled by the Pypot library and runs on a Raspberry pi 2 or 3 board. Communication between the Raspberry Pi and the actuators is made possible by the Pixl board we have designed.

The Poppy Ergo Jr robot has several 3D printed tools extending its capabilities. There are currently the lampshade, the gripper and a pen holder.

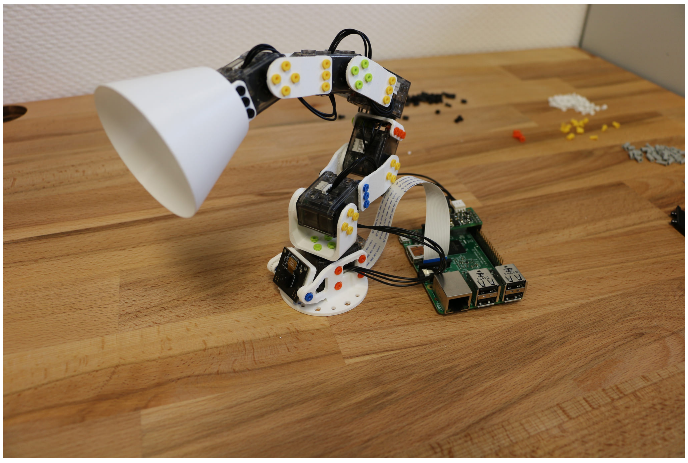

Figure 3. Poppy Ergo Jr, 6-DoFs arm robot for education

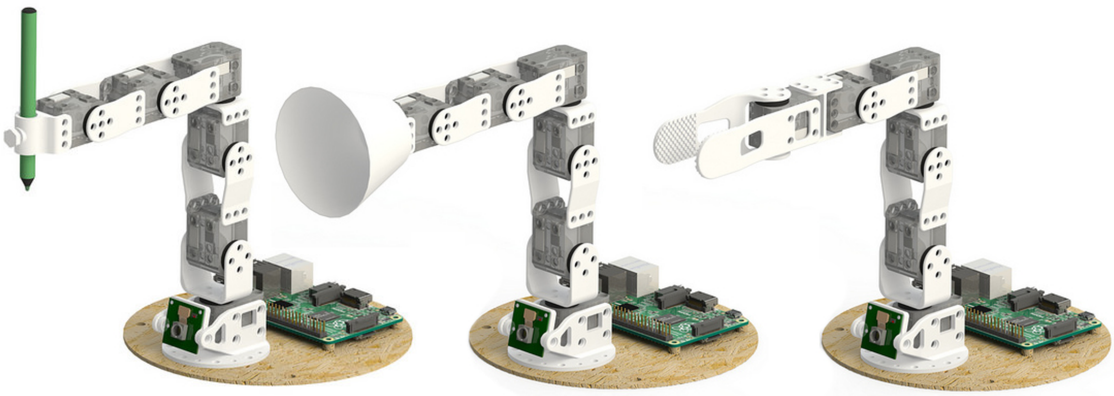

Figure 4. The available Ergo Jr tools: a pen holder, a lampshade and a gripper

With the release of a new Raspberry Pi board early 2016, the Poppy Ergo Jr disk image was updated to support Raspberry Pi 2 and 3 boards. The disk image can be used seamlessly with a board or the other.

- Contact: Theo Segonds
- URL: https://github.com/poppy-project/poppy-ergo-jr

6.18. Poppy Ergo Jr Installer

FUNCTIONAL DESCRIPTION: An alternative way to install the Ergo Jr robot software is made available using containers.

Users can own their own operating system installation, then add the Ergo Jr required software in a sandboxed environment. This results in a non-intrusive installation on the host system.

Docker containers implementation were used, and image is hosted at Docker Hub.

- Contact: Damien Caselli
- URL: https://hub.docker.com/r/poppycommunity/ergo-jr/

6.19. Poppy Ergo Jr Simulator

FUNCTIONAL DESCRIPTION: Poppy Project, through Poppy Education, wants users to get used to robotics, even without owning a physical robot.

For that purpose, Poppy Project team created a dummy robot in Pypot that is meant to be used in conjunction with a consumer application. We choose to develop a web hosted application using a 3D engine (Threejs) to render the robot.

Our ambition is to have a completely standalone simulated robot with physics. Some prototypes were created to benchmark possible solutions.

- Contact: Damien Caselli
- URL: https://github.com/poppy-project/poppy-simu

6.20. ProMP

Probabilistic Movement Primitives
KEYWORDS: Interaction - Robotics - Probability - Motion model - Robot Operating System (ROS)
FUNCTIONAL DESCRIPTION: Joint-space primitives with a task-space constraint: The primitives are stored in joint-space but demonstrations are provided both in joint space and task space, context. Thanks to this context, task-space goals can be requested to these joint-space primitives. The benefit is that requesting a new task-space goal does not require to call an IK method which would return demonstrations-agnostic joint configurations.

Vocal interactive learning and clustering: This work includes an interactive learning aspect which allows to automatically cluster motor primitives based on the standard deviation of their demonstrations. A new primitive is created automatically if the provided demonstration is out of 2 standard deviation of the existing primitives, otherwise the demonstration is distributed to an existing one.

- Contact: Yoan Mollard
- URL: https://github.com/baxter-flowers/promplib

6.21. PyPot

SCIENTIFIC DESCRIPTION: Pypot is a framework developed to make it easy and fast to control custom robots based on Dynamixel motors. This framework provides different levels of abstraction corresponding to different types of use. Pypot can be used to:

- control Robotis motors through a USB2serial device,
- define the structure of a custom robot and control it through high-level commands,
- define primitives and easily combine them to create complex behavior.

Pypot is part of the Poppy project. It is the core library used by the Poppy robots. This abstraction layer allows to seamlessly switch from a given Poppy robot to another. It also provides a common set of tools, such as forward and inverse kinematics, simple computer vision, recording and replaying moves, or easy access to the autonomous exploration library Explauto.

To extend pypot application domains and connection to outside world, it also provides an HTTP API. On top of providing an easy way to connect to smart sensors or connected devices, it is notably used to connect to Snap!, a variant of the well-known Scratch visual programming language.

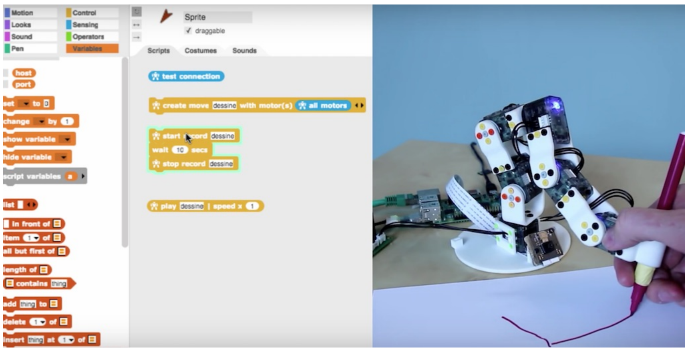

Figure 5. Example of using pypot to program a robot to reproduce a drawn shape

FUNCTIONAL DESCRIPTION: Pypot is entirely written in Python to allow for fast development, easy deployment and quick scripting by non-expert developers. It can also benefit from the scientific and machine learning libraries existing in Python. The serial communication is handled through the standard library and offers high performance (10ms sensorimotor loop) for common Poppy uses. It is cross-platform and has been tested on Linux, Windows and Mac OS.

Pypot is also compatible with the V-REP simulator. This allows the transparent switch from a real robot to its simulated equivalent with a single code base.

Finally, it has been developed to be easily and quickly extended for other types of motors and sensors.

It works with Python 2.7 or Python 3.3 or later, and has also been adapted to the Raspberry Pi board.

Pypot has been connected to Snap!, a variant of the famous Scratch visual language, developed to teach computer science to children. It is based on a drag-and-drop blocks interface to write scripts by assembling those blocks.

Thanks to the Snap! HTTP block, a connection can be made to pypot allowing users to directly control robots through their visual interfaces. A set of dedicated Snap! blocks have been designed, such as *set motor position* or *get motor temperature*. Thanks to the Snap! HTTP block, users can control robots through this visual interfaces connecting to Pypot. A set of dedicated Snap! blocks has been designed, such as *set motor position* or *get motor temperature*.

Snap! is also used as a tool to program the robot by demonstration. Using the *record* and *play* blocks, users can easily trigger kinesthetic recording of the whole robot or only a specific subpart, such as an arm. These records can then be played or "mixed" - either played in sequence or simultaneously - with other recordings to compose complex choreographies. The moves are encoded as a model of mixture of gaussians (GMM) which allows the definition of clean mathematical operators for combining them.

This recording tool has been developed and used in collaboration with artists who show interest in the concept of robotic moves.

Figure 6. Using Snap! to program a robot by demonstration and create complex choreographies

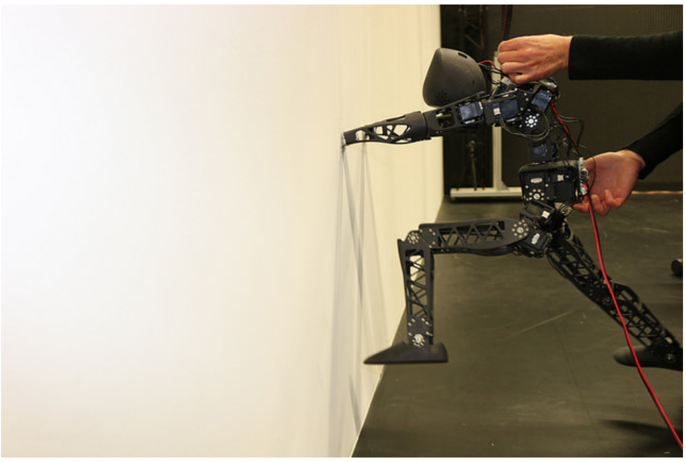

Figure 7. Artistic project exploring the concept of robotic move.

- Participants: Damien Caselli, Matthieu Lapeyre, Pierre Rouanet, Steve Nguyen and Theo Segonds
- Contact: Theo Segonds
- URL: https://github.com/poppy-project/pypot

6.22. PyQMC

Python library for Quasi-Metric Control
FUNCTIONAL DESCRIPTION: PyQMC is a python library implementing the control method described in http://dx.doi.org/10.1371/journal.pone.0083411 It allows to solve discrete markovian decision processes by computing a Quasi-Metric on the state space. This model based method has the advantage to be goal independant and thus can produce a policy for any goal with relatively few recomputation. New addition to this method is the possibility of online learning of the transition model and the Quasi-Metric.

- Participant: Steve Nguyen
- Contact: Steve Nguyen
- URL: https://github.com/SteveNguyen/pyqmc

6.23. ROS Optitrack Publisher

KEYWORDS: Target tracking - Robot Operating System (ROS)
FUNCTIONAL DESCRIPTION: This package allows to publish optitrack markers declared as rigid bodies as TF transforms. Data is gathered through the embedded VRPN server of Motive/Arena. Only rigid bodies are requested to the server, thus single points in 2D/3D are ignored. VRPN server can be enable in View > Data streaming in Motive.

- Contact: Yoan Mollard
- URL: https://github.com/baxter-flowers/optitrack_publisher

6.24. ThifloNet

KEYWORDS: Deep learning - Policy Learning
SCIENTIFIC DESCRIPTION: We created a software architecture that combines a state-of-the-art computer vision system with a policy learning framework. This system is able to perceive a visual scene, given by a still image, extract facts (“predicates”), and propose an optimal action to achieve a given goal. Both systems are chained into a pipeline that is trained by presenting images and demonstrating an optimal action. By providing this information, both the predicate recognition model and the policy learning model are updated.

Our architecture is based on the recent works of Lerer, A., Gross, S., & Fergus, R., 2016 ("Learning Physical Intuition of Block Towers by Example"). They created a large network able to identify physical properties of stacked blocks. Analogously our vision system utilizes the same network layout (without the image prediction auxiliary output), with an added output layer for predicates, based on the expected number and arity of predicates. The vision subsystem is not trained with a common cross-entropy or MSE loss function, but instead receives its loss form the policy learning subsystem. The policy learning module calculates the loss as optimal combination of predicates for the given expert action.

By using this combination of systems, the architecture as a whole requires significantly fewer data samples than other systems (which exclusively utilize neural networks). This makes the approach more feasible to real-life applciation with actual live demonstration.
FUNCTIONAL DESCRIPTION: The neural network consists of ResNet-50 (the currently best-performing computer vision system), with 50 layers, 2 layers for converting the output of ResNet to predicates and a varying amount of output neurons, corresponding to the estimated number of n-arity predicates. The network was pretrained on the ImageNet dataset. The policy learning module incorporates the ACE tree learning tool and a wrapper in Prolog.

Our example domain consists of 2-4 cubes colored in red, blue, green, and yellow and randomly stacked on top of each other in a virtual 3D environment. The dataset used for training and testing contains a total of 30000 elements, each with an image of the scene, the correct predicates, a list of blocks that are present and the corresponding expert action, that would lead to stacking the blocks to a tower.

- Participants: Florian Golemo, Manuel Lopes and Thibaut Munzer
- Contact: Florian Golemo

7. New Results

7.1. Computational Models Of Human Development and Cognition

7.1.1. Computational Models Of Information-Seeking and Curiosity-Driven Learning in Humans and Animals

Participants: Pierre-Yves Oudeyer [correspondant], William Schueller, Sebastien Forestier, Alvaro Ovalle.

This project involves a collaboration between the Flowers team, the Cognitive Neuroscience Lab of J. Gottlieb at Columbia Univ. (NY, US), and the developmental psychology lab of Celeste Kidd at Univ. Rochester, US, on the understanding and modeling of mechanisms of curiosity, attention and active intrinsically motivated exploration that until now have been little explored in neuroscience, machine learning and cognitive robotics.

It is organized around the study of the hypothesis that information gain (or control gain) could generate intrinsic reward in the brain (living or artificial), driving attention and exploration independently from material rewards, and allowing for autonomous lifelong acquisition of open repertoires of skills. The project combines expertise about attention and exploration in the brain and a strong methodological framework for conducting experimentations with monkeys, human adults (Gottlieb's lab) and children (Kidd's lab) together with computational modeling of curiosity/intrinsic motivation and learning in the Flowers team.

Such a collaboration paves the way towards a central objective, which is now a central strategic objective of the Flowers team: designing and conducting experiments in animals and humans informed by computational/mathematical theories of information seeking, and allowing to test the predictions of these computational theories.

7.1.1.1. Context

Curiosity can be understood as a family of mechanisms that evolved to allow agents to maximize their knowledge (or their control) of the useful properties of the world - i.e., the regularities that exist in the world - using active, targeted investigations. In other words, we view curiosity as a decision process that maximizes learning/competence progress (rather than minimizing uncertainty) and assigns value ("interest") to competing tasks based on their epistemic qualities - i.e., their estimated potential allow discovery and learning about the structure of the world.

Because a curiosity-based system acts in conditions of extreme uncertainty (when the distributions of events may be entirely unknown) there is in general no optimal solution to the question of which exploratory action to take [31], [152], [160]. Therefore we hypothesize that, rather than using a single optimization process as it has been the case in most previous theoretical work [120], curiosity is comprised of a family of mechanisms that include simple heuristics related to novelty/surprise and measures of learning progress over longer time scales [150] [98], [146]. These different components are related to the subject's epistemic state (knowledge and beliefs) and may be integrated with fluctuating weights that vary according to the task context. We will quantitatively characterize this dynamic, multi-dimensional system in the framework of Bayesian Reinforcement Learning, as described below.

Because of its reliance on epistemic currencies, curiosity is also very likely to be sensitive to individual differences in personality and cognitive functions. Humans show well-documented individual differences in curiosity and exploratory drives [137], [159], and rats show individual variation in learning styles and novelty seeking behaviors [115], but the basis of these differences is not understood. We postulate that an important component of this variation is related to differences in working memory capacity and executive control which, by affecting the encoding and retention of information, will impact the individual's assessment of learning, novelty and surprise and ultimately, the value they place on these factors [156], [168], [93], [174]. To start understanding these relationships, about which nothing is known, we will search for correlations between curiosity and measures of working memory and executive control in the population of children we test in our tasks, analyzed from the point of view of a computational model based on Bayesian reinforcement learning.

A final premise guiding our research is that essential elements of curiosity are shared by humans and non-human primates. Human beings have a superior capacity for abstract reasoning and building causal models, which is a prerequisite for sophisticated forms of curiosity such as scientific research. However, if the task is adequately simplified, essential elements of curiosity are also found in monkeys [137], [132] and, with adequate characterization, this species can become a useful model system for understanding the neurophysiological mechanisms.

7.1.1.2. Objectives

Our studies have several highly innovative aspects, both with respect to curiosity and to the traditional research field of each member team.

- Linking curiosity with quantitative theories of learning and decision making: While existing investigations examined curiosity in qualitative, descriptive terms, here we propose a novel approach that integrates quantitative behavioral and neuronal measures with computationally defined theories of Bayesian Reinforcement Learning and decision making.
- Linking curiosity in children and monkeys: While existing investigations examined curiosity in humans, here we propose a novel line of research that coordinates its study in humans and non-human primates. This will address key open questions about differences in curiosity between species, and allow access to its cellular mechanisms.
- Neurophysiology of intrinsic motivation: Whereas virtually all the animal studies of learning and decision making focus on operant tasks (where behavior is shaped by experimenter-determined primary rewards) our studies are among the very first to examine behaviors that are intrinsically motivated by the animals' own learning, beliefs or expectations.
- Neurophysiology of learning and attention: While multiple experiments have explored the single-neuron basis of visual attention in monkeys, all of these studies focused on vision and eye movement control. Our studies are the first to examine the links between attention and learning, which are recognized in psychophysical studies but have been neglected in physiological investigations.
- Computer science: biological basis for artificial exploration: While computer science has proposed and tested many algorithms that can guide intrinsically motivated exploration, our studies are the first to test the biological plausibility of these algorithms.
- Developmental psychology: linking curiosity with development: While it has long been appreciated that children learn selectively from some sources but not others, there has been no systematic investigation of the factors that engender curiosity, or how they depend on cognitive traits.

7.1.1.3. Current results

In particular, new works and results in 2017 include:

7.1.1.4. Experiments in Active Categorization

In 2017, we have been occupied by the implementation, running and analysis of the human adult experiment piloted the year before. A distinguishing feature of curiosity is that, rather than seeking to obtain information in a known task context (e.g., reading the menu in a restaurant) curiosity has to discover regularities whose existence is a priori unknown. This raises the question of how active learners become interested in specific items: how do agents decide which task to be interested in – i.e., allocate “study time" - given that the underlying rewards or patterns are sparse and unknown? A theoretical solution to this problem is suggested by the optimal learning literature, and proposes that allocation of resources may be based on the relative difficulty of competing tasks , or the learning progress (LP) expected from engaging a task. While these strategies can make equivalent predictions in certain simple situations (e.g., when learning curves are known and concave), LP-based mechanisms are superior in open-ended environments that contain unlearnable tasks. In such situations, LP-based strategies assign lower value to tasks where little progress is made and allow the learner to disengage from such tasks, while performance-based mechanisms, by assigning higher value to the lower-competence task, can push the learner to labor in vain. In the present experiment we asked whether humans possess, and use, metacognitive abilities to guide performance-based or LP-based exploration in two contexts in which they could freely choose to learn about 4 competing tasks. Participants (n = 505, recruited via Amazon Mechanical Turk) were tested on a paradigm in which they could freely choose to engage with one of four different classification tasks. We are currently analyzing the results and working on a computational models of the underlying cognitive and motivational mechanisms.

7.1.2. Computational Models Of Tool Use and Speech Development: the Roles of Active Learning, Curiosity and Self-Organization

Participants: Pierre-Yves Oudeyer [correspondant], Sébastien Forestier.

7.1.2.1. Modeling Speech and Tool Use Development in Infants

A scientific challenge in developmental and social robotics is to model how autonomous organisms can develop and learn open repertoires of skills in high-dimensional sensorimotor spaces, given limited resources of time and energy. This challenge is important both from the fundamental and application perspectives. First, recent work in robotic modeling of development has shown that it could make decisive contributions to improve our understanding of development in human children, within cognitive sciences [120]. Second, these models are key for enabling future robots to learn new skills through lifelong natural interaction with human users, for example in assistive robotics [154].

In recent years, two strands of work have shown significant advances in the scientific community. On the one hand, algorithmic models of active learning and imitation learning combined with adequately designed properties of robotic bodies have allowed robots to learn how to control an initially unknown high-dimensional body (for example locomotion with a soft material body [3]). On the other hand, other algorithmic models have shown how several social learning mechanisms could allow robots to acquire elements of speech and language [105], allowing them to interact with humans. Yet, these two strands of models have so far mostly remained disconnected, where models of sensorimotor learning were too “low-level” to reach capabilities for language, and models of language acquisition assumed strong language specific machinery limiting their flexibility. Preliminary work has been showing that strong connections are underlying mechanisms of hierarchical sensorimotor learning, artificial curiosity, and language acquisition [54].

Recent robotic modeling work in this direction has shown how mechanisms of active curiosity-driven learning could progressively self-organize developmental stages of increasing complexity in vocal skills sharing many properties with the vocal development of infants [39]. Interestingly, these mechanisms were shown to be exactly the same as those that can allow a robot to discover other parts of its body, and how to interact with external physical objects [149].

In such current models, the vocal agents do not associate sounds to meaning, and do not link vocal production to other forms of action. In other models of language acquisition, one assumes that vocal production is mastered, and hand code the meta-knowledge that sounds should be associated to referents or actions [105]. But understanding what kind of algorithmic mechanisms can explain the smooth transition between the learning of vocal sound production and their use as tools to affect the world is still largely an open question.

The goal of this work is to elaborate and study computational models of curiosity-driven learning that allow flexible learning of skill hierarchies, in particular for learning how to use tools and how to engage in social interaction, following those presented in [51], [3], [45], [39]. The aim is to make steps towards addressing the fundamental question of how speech communication is acquired through embodied interaction, and how it is linked to tool discovery and learning.

We take two approaches to study those questions. One approach is to develop robotic models of infant development by looking at the developmental psychology literature about tool use and speech and trying to implement and test the psychologists' hypotheses about the learning mechanisms underlying infant development. Our second approach is to directly collaborate with developmental psychologists to analyze together the data of their experiments and develop other experimental setup that are well suited to answering modeling questions about the underlying exploration and learning mechanisms. We thus started to collaborate with Lauriane Rat-Fischer, a developmental psychologist working in Toulouse on the emergence of tool use in the first years of human life. We are currently analyzing together the behaviour of 22 month old infants in a tool use task where the infants have to retrieve a toy put in the middle of a tube by inserting sticks into the tube and pushing the toy out. We are looking at the different actions of the infant with tools and toys but also its looking behaviour, towards the tool, toys or the experimenter, and we are trying to infer the goals and exploration strategies of the infant.

In our recent robotic modeling work, we showed that the Model Babbling learning architecture allows the development of tool use in a robotic setup, through several fundamental ideas. First, goal babbling is a powerful form of exploration to produce a diversity of effects by self-generating goals in a task space. Second, the possible movements of each object define a task space in which to choose goals, and the different task spaces form an object-based representation that facilitates prediction and generalization. Also, cross-learning between tasks updates all skills while exploring one in particular. A novel insight was that early development of tool use could happen without a combinatorial action planning mechanism: modular goal babbling in itself allowed the emergence of nested tool use behaviors.

This year we extended this architecture so that the agent can imitate caregiver's sounds in addition to exploring autonomously [78]. We hypothesized that these same algorithmic ingredients could allow a joint unified development of speech and tool use. Our learning agent is situated in a simulated environment where a vocal tract and a robotic arm are to be explored with the help of a caregiver. The environment is composed of three toys, one stick that can be used as a tool to move toys, and a caregiver moving around. The caregiver helps in two ways. If the agent touches a toy, the caregiver produces this toy's name, but otherwise produces a distractor word as if it was talking to another adult. If the agent produces a sound close to a toy's name, the caregiver moves this toy within agent reach 8.

We show that our learning architecture based on Model Babbling allows agents to learn how to 1) use the robotic arm to grab a toy or a stick, 2) use the stick as a tool to get a toy, 3) learn to produce toy names with the vocal tract, 4) use these vocal skills to get the caregiver to bring a specific toy within reach, and 5) choose the most relevant of those strategies to retrieve a toy that can be out-of-reach. Also, the grounded exploration of toys accelerates the learning of the production of accurate sounds for toy names once the caregiver is able to recognize them and react by bringing them within reach, with respect to distractor sounds without any meaning in the environment. Our model is the first to allow the study of the early development of tool use and speech in a unified framework.

This model focuses on the role of one important form of body babbling where exploration is directed towards self-generated goals in free play, combined with imitation learning of a contingent caregiver. This model does not assume capabilities for complex sequencing and combinatorial planning which are often considered necessary for tool use. Yet, we show that the mechanisms in this model allow a learner to progressively discover how to grab objects with the hand, how to use objects as tools to reach further objects, how to produce vocal sounds, and how to leverage these vocal sounds to use a caregiver as a social tool to retrieve objects. Also, the discovery that certain sounds can be used as a social tool further guides vocal learning. This model predicts that infants learn to vocalize the name of toys in a natural play scenario faster than learning other words because they often choose goals related to those toys and engage caregiver's help by trying to vocalize those toys' names. We presented those results at the 39th Annual Conference of the Cognitive Science Society (CogSci 2017).

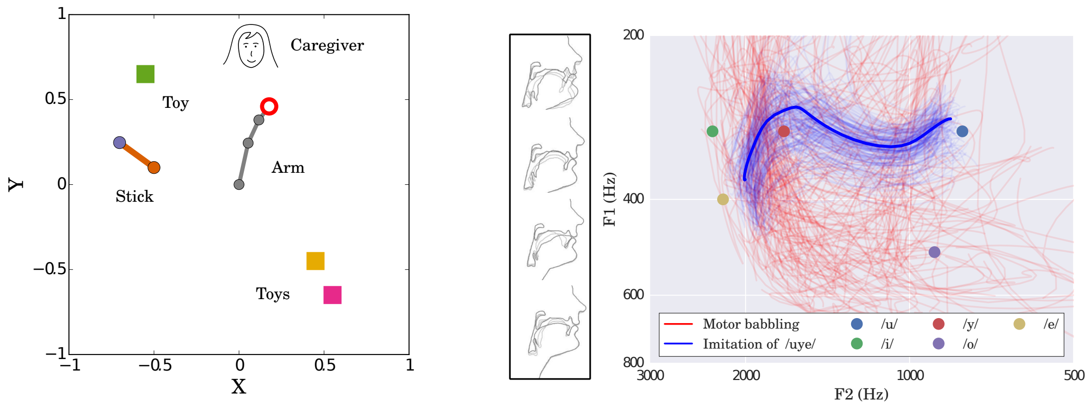

Figure 8. Agent's robotic and vocal environment. Left: Agent's 3 DOF arm, controlled with 21 parameters, grabs toys with its hand, or uses the stick to reach toys. Caregiver brings a toy within reach if the agent says its name. Right: Agent's vocal environment representing sounds as trajectories in the two first formants space. Agent's simulated vocal tract produces sounds given 28 parameters. When agent touches a toy, caregiver says toy's name. Some sounds corresponding to random parameters are plotted in red, and some sounds produced when imitating caregiver's /uye/ word in blue (best imitation in bold, error 0.3*).*

7.1.3. Computational Models Of Developmental Exploration Mechanisms in Vocal Babbling and Arm Reaching in Infants

Participants: Pierre-Yves Oudeyer [correspondant], Clement Moulin-Frier, Freek Stulp, Jules Brochard.

7.1.3.1. Proximodistal Exploration in Motor Learning as an Emergent Property of Optimization

To harness the complexity of their high-dimensional bodies during sensorimotor development, infants are guided by patterns of freezing and freeing of degrees of freedom. For instance, when learning to reach, infants free the degrees of freedom in their arm proximodis-tally, i.e. from joints that are closer to the body to those that are more distant. We formulated and studied computationally the hypothesis that such patterns can emerge spontaneously as the result of a family of stochastic optimization processes (evolution strategies with covariance-matrix adaptation), without an innate encoding of a maturational schedule. In particular, we made simulated experiments with an arm where a computational learner progressively acquires reaching skills through adaptive exploration, and we showed that a proximodistal organization appears spontaneously, which we denoted PDFF (ProximoDistal Freezing and Freeing of degrees of freedom). We also compared this emergent organization between different arm morphologies – from human-like to quite unnatural ones – to study the effect of different kinematic structures on the emergence of PDFF. This work was published in the journal *Developmental Science*[74].

7.1.3.2. Emergent Jaw Predominance in Vocal Development through Stochastic Optimization

Infant vocal babbling is strongly relying on jaw oscillations, especially at the stage of canonical babbling, which underlies the syllabic structure of world languages. We have proposed, modelled and analyzed an hypothesis to explain this predominance of the jaw in early babbling. This hypothesis states that general stochastic optimization principles, when applied to learning sensorimotor control, automatically generate ordered babbling stages with a predominant exploration of jaw movements in early stages, just like they generate proximo-distal organization of exploration in arm reaching as described in the paragraph above. In particular, such stochastic optimization principles predominantly explore jaw movement at the beginning of vocal learning, and when close to the rest position of the vocal tract, as it impacts the auditory effects more than other articulators. This work was published in the journal *IEEE Transactions on Cognitive and Developmental Systems*[73].

7.1.4. Models of Self-organization of lexical conventions: the role of Active Learning and Active Teaching in Naming Games

Participants: William Schueller [correspondant], Pierre-Yves Oudeyer.

How does language emerge, evolve and gets transmitted between individuals? What mechanisms underly the formation and evolution of linguistic conventions, and what are their dynamics? Computational linguistic studies have shown that local interactions within groups of individuals (e.g. humans or robots) can lead to self-organization of lexica associating semantic categories to words [165]. However, it still doesn't scale well to complex meaning spaces and a large number of possible word-meaning associations (or lexical conventions), suggesting high competition among those conventions.

In statistical machine learning and in developmental sciences, it has been argued that an active control of the complexity of learning situations can have a significant impact on the global dynamics of the learning process [120] [130] [139]. This approach has been mostly studied for single robotic agents learning sensorimotor affordances [150][40]. However active learning might represent an evolutionary advantage for language formation at the population level as well [54] [167].

Naming Games are a computational framework, elaborated to simulate the self-organization of lexical conventions in the form of a multi-agent model [166]. Through repeated local interactions between random couples of agents (designated *speaker* and *hearer*), shared conventions emerge. Interactions consist of uttering a word – or an abstract signal – referring to a topic, and evaluating the success or failure of communication.

However, in existing works processes involved in these interactions are typically random choices, especially the choice of a communication topic.

The introduction of active learning algorithms in these models produces significant improvement of the convergence process towards a shared vocabulary, with the speaker [49], [60] [109] or the hearer [61] actively controlling vocabulary growth.

7.1.4.1. Definition of a local measure of convergence for the Naming Game: Local Approximated Probability of Success (LAPS), using limited memory of past interactions

In the Naming Game, one measure is usually used to represent the state of convergence of the population: the success rate, or probability of success at a given time step. It increases over time, from 0 to 1. This measure is however global, and not accessible to individual agents; in which case it would have been a perfect candidate for a functional whose maximization would drive local behavior. Several other measures have been suggested, as one based on local information gain, or entropy reduction [60]. Those measures however are either defined in a very constrained case (without synonymy and homonymy, and fixed and known numbers of words and meanings), and their minimization can actually block the process of convergence – as their evolution is not easily predictable.

Instead, we defined a local approximation of the success rate. For this, we need a representation of the state of the population. This is done by constructing an *average vocabulary* representing the population, using a partial memory of the past interactions. This vocabulary is then used together with the agent's own vocabulary to compute a probability of success. A key element of this measure is the time scale associated to the memory: in fact, it allows not only to define a degree of certainty of a given association, but also a degree of uncertainty at a higher level (word or meaning). This measure is local (available to an agent through only its own knowledge) but its convergence to 100% is bound to global dynamics. In other words, we can use it as a functional to maximize at the local level to reinforce agreement at the population level.

7.1.4.2. Active Topic Choice: LAPS and Multi-Armed Bandits

Usually, the topic used in an interaction of the Naming Game is picked randomly. A first way of introducing active control of complexity growth is through the mechanism of topic choice: choosing it according to past memory. It allows each agent to balance reinforcement of known associations and invention of new ones,

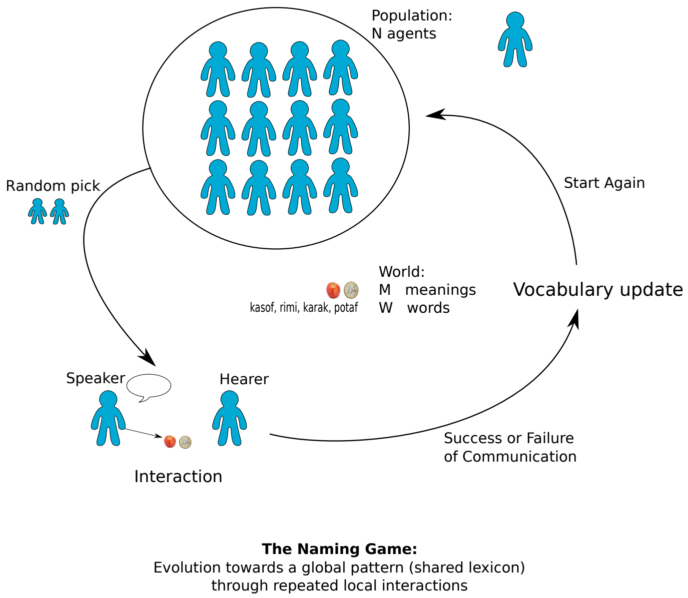

Figure 9.

which can be seen as an exploitation vs. exploration problem. This can speed up convergence processes, and even lower significantly local and global complexity: for example in [60], [61], where heuristics based on the number of past successful interactions were used.

However, we can now define new strategies directly maximizing the LAPS measure. At each step, the agent picking a topic will choose one that yields maximum expected increase of the LAPS measure. However, this expected value being computationally really costly, we use a Multi-Armed Bandit algorithm. At the beginning, only one *machine* is available, the exploration machine. When used by the agent, its parameters are updated through Thompson Sampling algorithm, and a new machine is created with the exact same parameters, corresponding to the newly explored meaning. At any time, the number of machines available to the agent is then equal to the number of already known meanings, plus one (the exploration machine).

This strategy can speed up convergence the convergence process, but also diminishes significantly the global complexity – i.e. the maximum number of distinct word-meaning association present in the population. See figure 10.

7.1.4.3. Acceptance policy: Updating or not vocabulary based on memory of past interactions

Another way to control complexity in the Naming Game is to choose whether to trust or not other agents during a given interaction, by taking into account or not their own word-meaning associations. In previous work, a purely stochastic acceptance of new information has been studied [97]. However, accepting or not new information should depend on the memory provided by past interactions to be efficient. To do so, we use a local approximation of the global agreement as a functional to optimize at each interaction, based on recent information: the LAPS measure 7.1.4.1. We can show that for an appropriate time scale of this recent information, local complexity (amount of word-meaning association to be remembered) remains low, without impacting the duration of the global agreement process. The exact dependance on parameters (time scale, population size, meaning and word spaces size) is still to be explored.

7.1.4.4. Structured meaning spaces exploration

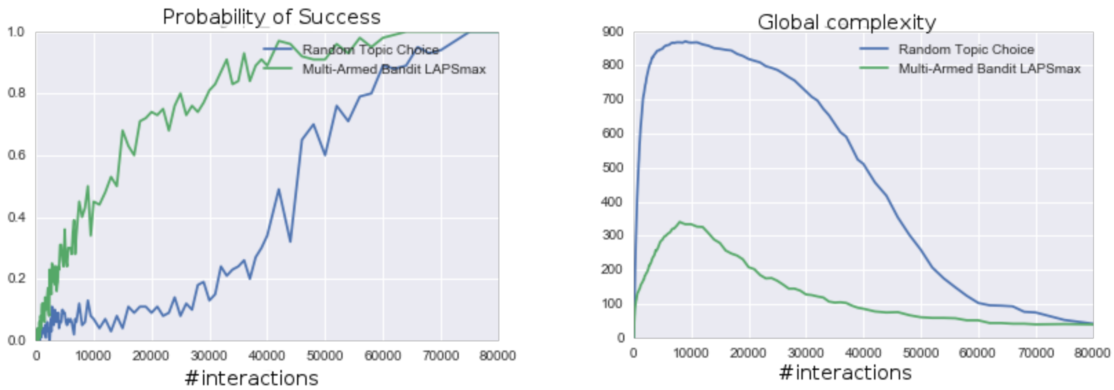

Figure 10. Measures of convergence (global probability of success) and global complexity (number of distinct word-meaning association present in the population) for simulations using Random Topic Choice and MAB LAPS maximization Topic Choice. The active topic choice strategy yields faster convergence, with less complexity. Parameters used: 60 agents, 40 meanings, 40 words, time scale for LAPS 10 interactions.

In the models we have considered so far, meanings were always in a finite number, and without any structure or relative importance. Also, the whole meaning space is accessible from the start. We studied a scenario where meanings are not all available from the beginning, but taken from a growing space: known meanings plus the *Adjacent Possible* [131] [172]. In practice, we consider a graph of meanings, and a starting meaning m_0. The adjacent possible is the set of nodes connected to m_0. Whenever a meaning from this set is explored, it is withdrawn from the adjacent possible, but all its neighbors not already known are added to it. In this case, Active Topic Choice helps to keep a quasi-linear pace of exploration, while agreeing on explored meanings. Random Topic Choice explores all available meanings before starting the agreement process: hence, on a big meaning space, possibly infinite, this is really inefficient in terms of communication success. See figure 11.

7.1.4.5. Interactive application for collaborative creation of a language: Experimenting how humans actively negotiate new linguistic conventions

How do humans agree and negotiate linguistic conventions? This question is at the root of the domain of experimental semiotics [118], which is the context of our experiment/application. Typically, the experiments of this field consist in making human subjects play a game where they have to learn how to interact/collaborate through a new unknown communication medium (such as abstract symbols). In recent years, such experiments allowed to see how new conventions could be formed and evolve in population of individuals, shading light on the origins and evolution of languages [133] [116].

We consider a version of the Naming Game [177] [140], focusing on the influence of active learning/teaching mechanisms on the global dynamics. In particular, agreement is reached sooner when agents actively choose the topic of each interaction [49], [60], [61].

Through this experiment, we confront existing topic choice algorithms to actual human behavior. Participants interact through the mediation of a controlled communication system – a web application – by choosing words to refer to objects. Similar experiments have been conducted in previous work to study the agreement dynamics on a name for a single picture [106]. Here, we make several pictures or interaction topics available, and quantify the extent to which participants actively choose topics in their interactions.

- **Individual short experiment (implemented):** each user interacts for about 3-4 min (<30 interactions) with a brand new population of 7 simulated agents. They take the role of one designated agent, and play the Naming Game as this agent. Each time they interact as speakers, they can select the topics of conversation from a set of 5 objects, and are offered 6 possible words to refer to

Figure 11. Comparison of Random and Active Topic Choice on a structured meaning space. The space used is a balanced tree, with initially accessible meaning being the root of the tree. On the left, evolution of global complexity (number of distinct word-meaning association present in the population): Active Topic Choice helps keeping a low complexity, with quasi linear growth, whereas Random Topic Choice first goes to a maximum way higher than the final expected value. Parameters used: 10 agents, 100 meanings, 100 words. On the right, illustration of the status of a population in both cases, after half of the interactions needed to converge to global agreement. Nodes represent meanings, their size the number of agents having at least a word for them, and their color the level of agreement between all agents of the population for the given meaning. We can see that Active Topic Choice population has not talked about all meanings, but agrees on all the one that were used; whereas in the other case all meanings were used but almost no agreement is reached.

them. Their choices influence the global emergence of a common lexical convention, reached when communications are successful. The goal is to maximize a score based on the number of successful interactions (among the 50 in total for each run). They can see a list of the past interactions, with chosen topic, chosen word, and whether the interaction was succesful or not. This experiment allows us to directly measure if there is a bias in the choice of topics, compared to random choice, based on memory of past interactions. Performance can then be compared to existing topic choice algorithms [49], [60], [61].

- **Collective creation of a language and conceptual exploration (under development):** Users interact with agents picked from a population which is kept for the whole duration of the experiment, common to all users. Meanings that can be used as topics are drawn from a bigger space than for the first experiment. Word space is a combination of a few basic available syllables (to avoid direct usage of known words). Users interact with a slowly increasing subset of this population, so that newcomers have the same level of influence within their own part of the experiment as people who interacted at the beginning of the day. Successfully communicating about certain meanings/objects unlocks new available meanings, and therefore we can observe the whole process of collective conceptual exploration. Linguistic conventions are set and learned/shared by users, through the interaction with simulated agents. Users never interact directly with each other, therefore no synchronization is needed. In other words, if one user decides not to finish the current interaction, it will not affect other users. We can measure in this scenario statistical properties of the language like frequency distribution, rate of exploration as well as degree of convergence.

Figure 12. Example of a game with the interface already existing. Play it here: http://naming-game.bordeaux.inria.fr

The experiment – available at http://naming-game.bordeaux.inria.fr – was presented at the Kreyon Conference in Rome, in september 2017, during a talk and as part of interactive installation consisting in numerous scientific experiments. Insufficient data was collected to get significant results. To recruit more players and collect a large amount of data, we plan to use crowdsourcing platforms.

7.2. Autonomous Machine Learning and Applications to Developmental Robotics

7.2.1. Intrinsically Motivated Goal Exploration and Multi-Task Reinforcement Learning

Participants: Sébastien Forestier, Pierre-Yves Oudeyer [correspondant], Alexandre Péré, Olivier Sigaud, Pierre Manceron, Yoan Mollard.

7.2.1.1. Intrinsically Motivated Exploration of Spaces of Parameterized Skills/Tasks and Application to Robot Tool Learning

A major challenge in robotics is to learn parametrized policies to solve multi-task reinforcement learning problems in high-dimensional continuous action and effect spaces. Of particular interest is the acquisition of inverse models which map a space of sensorimotor problems to a space of motor programs that solve them. For example, this could be a robot learning which movements of the arm and hand can push or throw an object in each of several target locations, or which arm movements allow to produce which displacements of several objects potentially interacting with each other, e.g. in the case of tool use. Specifically, acquiring such repertoires of skills through incremental exploration of the environment has been argued to be a key target for life-long developmental learning [96].

This year we developed a formal framework called "Unsupervised Multi-Goal Reinforcement Learning", as well as a formalization of intrinsically motivated goal exploration processes (IMGEPs), that is both more compact and more general than our previous models [89]. We experimented several implementations of these processes in a complex robotic setup with multiple objects 13, associated to multiple spaces of parameterized reinforcement learning problems, and where the robot can learn how to use certain objects as tools to manipulate other objects. We analyzed how curriculum learning is automated in this unsupervised multi-goal exploration process, and compared the trajectory of exploration and learning of these spaces of problems with the one generated by other mechanisms such as hand-designed learning curriculum, or exploration targeting a single space of problems, and random motor exploration. We showed that learning several spaces of diverse problems can be more efficient for learning complex skills than only trying to directly learn these complex skills. We illustrated the computational efficiency of IMGEPs as these robotic experiments use a simple memory-based low-level policy representations and search algorithm, enabling the whole system to learn online and incrementally on a Raspberry Pi 3.

Figure 13. Robotic setup. Left: a Poppy Torso robot (the learning agent) is mounted in front of two joysticks. Right: full setup: a Poppy Ergo robot (seen as a robotic toy) is controlled by the right joystick and can hit a tennis ball in the arena which changes some lights and sounds.

In order to run more scientific experiments in a shorter time, we scaled up this experimental setup to a platform of 6 identical Poppy Torso robots, each of them having the same environment to interact with. Every robot can run a different task with a specific algorithm and parameters each 14. In this setup Poppy Torso robots are requesting jobs to a dedicated computer acting as a job manager which monitors execution and distributes jobs to available robots. Moreover, each Poppy Torso can also perceives the motion of a second Poppy Ergo robot, than can be used, this time, as a distractor performing random motions to complicate the learning problem. 12 top cameras and 6 head cameras can dump video streams during experiments, in order to record video datasets. Data and videos are stored on-the-fly on 6 hard disks.

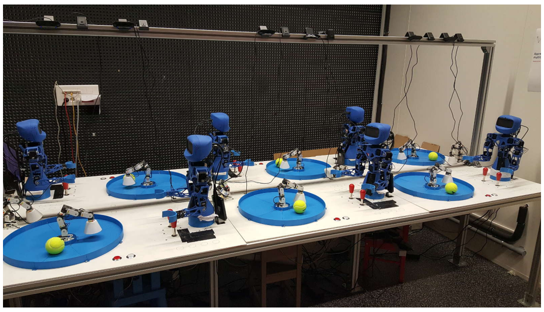

Figure 14. Platform of 6 robots with identical environment: joysticks, Poppy Ergo, ball in an arena, and a distractor. The central bar supports the 12 top cameras.

7.2.1.2. Unsupervised Deep Learning of Goal Spaces for Goal Intrinsically Motivated Goal Exploration

Intrinsically motivated goal exploration algorithms enable machines to discover repertoires of policies that produce a diversity of effects in complex environ- ments. These exploration algorithms have been shown to allow real world robots to acquire skills such as tool use in high-dimensional continuous state and action spaces. However, they have so far assumed that self-generated goals are sampled in a specifically engineered feature space, limiting their autonomy. We have proposed an approach using deep representation learning algorithms to learn an adequate goal space. This is a developmental 2-stage approach: first, in a perceptual learning stage, deep learning algorithms use passive raw sensor observations of world changes to learn a corresponding latent space; then goal exploration happens in a second stage by sampling goals in this latent space. We made experiments with a simulated robot arm interacting with an object, and we show that exploration algorithms using such learned representations can closely match, and even sometimes improve, the performance obtained using engineered representations.

7.2.1.3. Combining deep reinforcement learning and curiosity-driven exploration

A major challenge of autonomous robot learning is to design efficient algorithms to learn sensorimotor skills in complex and high-dimensional continuous spaces. Deep reinforcement learning (RL) algorithms are natural candidates in this context, because they can be adapted to the problem of learning continuous control policies with low sample complexity. However, these algorithms, such as DDPG (Lillicrap et al., 2016) suffer from exploration issues in the context of sparse or deceptive reward signals.

In this project, we investigate how to integrate deep reinforcement learning algorithms with curiosity-driven exploration methods. A key idea consists in decorrelating the exploration stage from the policy learning stage by using a memory structure used in deep RL called a replay buffer. Curiosity-driven exploration algorithms, also called Goal Exploration Processes (GEPs) are used in a first stage to efficiently explore the state and action space of the problem, and the corresponding data is stored into a replay buffer. Then a DDPG learns a control policy from the content of this replay buffer.

The internship of Pierre Manceron has been dedicated to trying this methodology in practice. Pierre has combined GEPs obtained from the Explauto open-source library (Moulin-Frier et al., 2014) and his own implementation of DDPG, and benchmarked the combination using the openAI Gym toolkit (Duan et al., 2016).

Preliminary results have revealed some stability issues in DDPG, whereas encouraging results where obtained about the combination with GEPs. Beyond getting more robust results and publishing them, our next goal is to envision other ways to integrate deep RL with curiosity-driven exploration processes by using the tools of the former to more efficiently implement the latter.

7.2.2. Social Learning of Interactive Skills

Participants: Manuel Lopes [correspondant], Baptiste Busch, Yoan Mollard, Thibaut Munzer.

This work was made in collaboration with Marc Toussaint and Guilherme Maeda.

7.2.2.1. Preference learning on the execution of collaborative human-robot tasks

One important aspect of the human-robot collaboration is to be able to learn the user's preferences on the sequence of actions. By querying the user on the next action, when the uncertainty is high, the robot learns the user preferences (Q-function) to solve the task. From a planning point of view, this Q-function can then be integrated into the solver to select the user preferred route to solve a task when multiple choices are available. Therefore, this work aims at reducing the human cognitive load by:

- querying demonstrations only when the uncertainty is above a certain threshold,
- always choose the user preferred actions.

This work has been accepted for publication in the *International Conference on Robotics and Automation* (ICRA) 2017 and presented during the conference [80].

Interestingly, this also raises questions on the robot autonomy and its perception by the human coworker. By interacting with a user, the robot starts to learn the preferred actions and will takes initiative to perform them on the next assembly. The question is, how does the user perceives this initiative taking? To answer this question, we have conducted a user study to analyze the impact of robot initiative on the collaboration. Two conditions were considered:

- a semi-autonomous robot that learns and decides when to execute a supporting action,
- a support robot that has to be instructed of each action on a collaborative task.

We found that users prefer the semi-autonomous robot and that the behavior was closer to their expectations despite them being more afraid of it. We also found that even if users noticed the robot was learning in one case, they wanted more autonomy in both conditions. This research was published in the companion of the *Conference on Human-Robot Interaction* (HRI) 2017 and presented during the poster sessions of the conference [82].

7.2.2.2. Learning legible motions from interaction

In a human-robot collaboration context, understanding and anticipating the robot intentions ease the completion of a joint-task. Whereas previous work has sought to explicitly optimize the legibility of behavior, we investigate legibility as a property that arises automatically from general requirements on the efficiency and robustness of joint human-robot task completion.

Following our previous work on legibility of robot motions [64], we have conducted several user experiments to analyze the effects of the policy representation on the universality of the legibility.

This work lead to a submission of a journal article to the International Journal of Social Robotics (IJSR) [69]

7.2.2.3. Postural optimization for an ergonomic human-robot interaction

When we, humans, accomplish a task our body posture is (partially) constrained. For example, acting on an object constrains the pose of the hand relatively to the object, and the head faces the object we are acting upon. But due to the large number of degrees of freedom (DOF) of the human body, other body parts are unconstrained and several body postures are viable with respect to the task. However, not all of them are viable in terms of ergonomics. Using a personalized human model, observational postural assessment techniques can be automatized. Optimizing the model body posture is then the logical next step to find an ergonomically correct posture for the worker to accomplish a specific task.

To optimize the subject's model to achieve a specific task, we define an objective function that minimizes the efforts of the whole body posture, based on the Rapid Entire Body Assessment (REBA) technique [124]. The objective function also account for visibility of the target object and worker's laterality. We have also implemented an automatic assessment of the worker's body posture based on the REBA method.

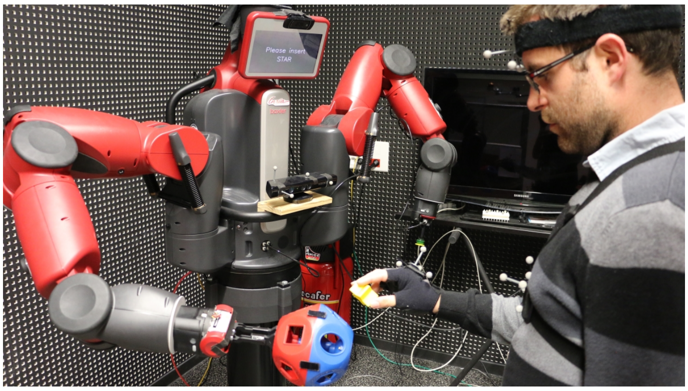

Figure 15. Representation of the setup considered in the user study. The robot presents to the user a spherical ball in which multiple shapes can be inserted. Final pose of the object is calculated from the user posture at his current location. Body motions during the insertion are recorded using a suit made from OptiTrack markers.

Using a spherical object, carried by a Baxter humanoid robot as illustrated in Fig. 15, we mimic an industrial scenario where the robot helps the worker by positioning and orienting an object in which the worker has to insert specific shapes. In a user-study with forty participants, we compare three different robot's behaviors, one of them being the result of the postural optimization of the subject's personalized model. By the mean of a survey session, and the online assessment of the subject's posture during the interaction, we prove that our method leads to a safer posture, and is perceived as more comfortable.

This work has been published to the International Conference on Intelligent Robots and Systems (IROS) [75] and was presented during the conference.

7.2.2.4. Planning ergonomic sequences of actions in human-robot interaction

Following our work on physical ergonomics [75], we have extended our method to include it in the Logic-Geometric Program (LGP) [171]. This method allows us to solve Task and Motion Planning (TAMP) problems simultaneously while optimizing for maximum ergonomics on the human side.

In a simulated experimented we prove that the solver is able to choose the logic actions (e.g. "the robot places the screwdriver on the table") that provides maximum ergonomics throughout the interaction. By the mean of an experiment on our Baxter robot, we also prove that optimizing ergonomics over the full sequences of actions, as opposed to the step-wise approach we were considering in [75] where ergonomics was optimized for single atomic actions, lead to a more ergonomic interaction.

As both human and robot agents are capable of performing the same task, this creates a need to communicate the planned sequence of actions efficiently to the human. Two problems are raised by this dynamic task allocation. First, the human need to understand the current action performed by the robot to anticipate and react if necessary. Second, the human must know beforehand or during the executions the actions that he or she has to perform and when to perform them.

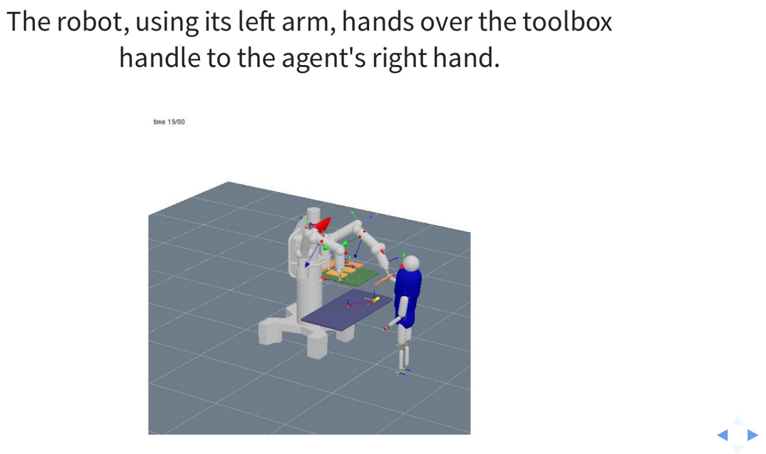

Figure 16. A representation of an action generated by the solver and displayed on a webpage to simplify the visualization. The agent can click on the image to start a video of the action. Arrows on the right corner are also clickable to navigate between the previous and the next actions.

To this purpose, we also introduce a graphical interface that displays the current action and the geometric of the scene as illustrated in figure 16. This graphical interface can be used offline to train the human on the steps required for the whole task. It can also be displayed online to show the current action to reduce the human cognitive load of understanding the action performed by the robot and understanding the action that he or her is expected to perform.

This work was submitted to the International Conference on Robotics and Automation (ICRA) and is currently under review.

7.2.2.5. Active incremental learning of robot movement primitives

A robot coworker acting as a third hand brings the challenge that its skills must be augmented and tailored as needed, over time. To this end, imitation learning can rely on the presence of the human coworker as a teacher. However, imitation learning has primarily addressed *how* to endow and refine robots with motor skills but not *when* the learning should take place. Reasoning when improvement is actually needed is, nevertheless, an essential and difficult problem to be solved. We propose an active learning algorithm that allows a robot to reason about the confidence of its movement primitives. It allows the robot to decide when a demonstration is required, making active requests to the human coworker depending on its confidence.

This capability also sheds light onto the problem of deciding how many demonstrations are needed to construct a probabilistic model when learning from demonstrations. Under active learning, the number of demonstrations is indicated by the robot, on-demand. The method can be used on a single demonstration, in a *one-shot learning* fashion. If the extrapolation is, however, beyond the scope of the existing demonstration—indicated by the uncertainty—an active request will be made. The proposed method also offers a principled way to train Dynamical Movement Primitives (DMPs) with contextualized demonstrations encoded by Gaussian Processes (GPs)— details can be found in [79].

Algorithm 1 GP-DMP($\{\mathbf{x}^d, t^d\}_{1:D}, \mathbf{x}_*, u_{\text{trig}}$)

1: $GP.train(\{\mathbf{x}^d, t^d\}_{1:D})$
2: $(\mu_{1:N}, \sigma^2_{1:N}) \leftarrow GP.predict(\mathbf{x}_*)$
3: **if** TRAJ_UNC($\sigma^2_{1:N}$) $< u_{\text{trig}}$ **then**
4: $\quad DMP.train(\mu_{1:N})$
5: $\quad y \leftarrow DMP.reach\_goal(\mathbf{x}_*)$
6: $\quad$ ROBOT_EXECUTION(y)
7: **else**
8: $\quad \{\mathbf{x}^{D+1}, t^{D+1}\} \leftarrow$ ACTIVE_REQUEST
9: $\quad$ go to line 1

Figure 17. Pseudocode of the algorithm to add a demonstration only if required

The method is based on a combination of GPs and DMPs, where the former provides the confidence bounds in which the demonstrations are being extrapolated, and the latter accounts for prediction errors due to the nonlinearities of the function being approximated. Algorithm 17 shows a pseudocode of the proposed method.

Figure 18 shows the decrease of the uncertainty on the prediction of 10 trajectories as the number of demonstrations increase (the ellipses represent the projections of one standard deviation along the trajectory). Figure 18(a)(b) and (c) show the predictions after one, two and five demonstrations, respectively. The blue color in (c) indicates that the robot has confidence it can execute the 10 predicted trajectories.

7.3. Representation Learning

7.3.1. Cross-situational noun and adjective learning in an interactive scenario

Participants: David Filliat [correspondant], Yuxin Chen.

Future intelligent robots are expected to be able to adapt continuously to their environment. For this purpose, recognizing new objects and learning new words through interactive learning with humans is fundamental. Such setup results in ambiguous teaching data which humans have been shown to address using cross-situational learning, i.e. by analyzing common factors between multiple learning situations. Moreover, they have been shown to be more efficient when actively choosing the learning samples, e.g. which object they want to learn. Implementing such abilities on robots can be performed by latent-topic learning models such as Non-Negative Matrix Factorization or Latent Dirichlet Allocation. These cross-situational learning methods tackle referential and linguistic ambiguities, and can be associated with active learning strategies. We propose two such methods: the Maximum Reconstruction Error based Selection (MRES) and Confidence Base Exploration (CBE). We present extensive experiments using these two learning algorithms through a systematic analysis on the effects of these active learning strategies in contrast with random choice. In addition, we study the factors underlying the active learning by focusing on the use of sample repetition, one of the learning behaviors that have been shown to be important for humans. These results have been published in a journal paper [70]

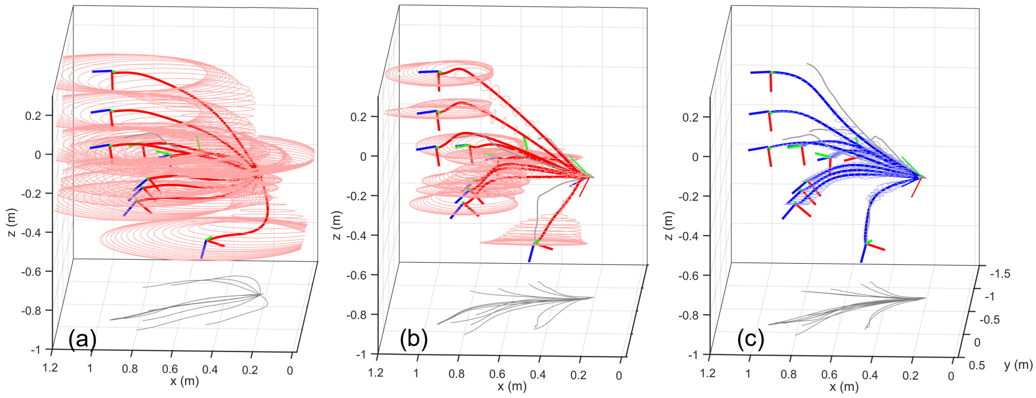

Figure 18. Decrease of the trajectory uncertainties as demonstrations for objects are being requested. The ellipses show a single standard deviation. Uncertainties above the threshold are shown in red. The blue trajectories indicate that the robot is confident in executing the primitives. (a) The uncertainties for all contexts after one demonstration. (b) Predictions after two demonstrations. (c) Predictions after five demonstrations.

7.3.2. State Representation Learning in the Context of Robotics

Participants: David Filliat [correspondant], Natalia Diaz Rodriguez, Timothee Lesort, Mathieu Seurin.

Our understanding of the world depends highly on our capacity to produce intuitive and simplified representations which can be manipulated and combined easily to solve problems. We worked on reproducing this simplification process using a neural network to build a low dimensional state representation of the world from images acquired by a robot. As in the approach from Jonschkowski [129], we learn in an unsupervised way using prior knowledge about the world as loss functions called robotic priors.

The robotic priors loss function impose constraint in a low dimension space. We call this space the representation space and it contains the underlying parameters of the robot environment. This constraint are physic related as the time coherence of the representation, the repeatability, the proportionality and causality of the actions inside the representation space.

Imposing those constraint to sequences of images makes it possible to learn a mapping from image to our representation state space. We extend the previous approach to high dimension richer images to learn a 3D representation of the hand position of a robot from RGB images.

We propose a quantitative evaluation of the learned representation using nearest neighbors in the state space that allows to assess its quality and show both the potential and limitations of robotic priors in realistic environments. We augment image size, add distractors and domain randomization, all crucial components to achieve transfer learning to real robots.

Finally, we also contribute a new prior to improve the robustness of the representation. This prior takes profit of the initial state of the robot to bring together representation of different sequences. The applications of such low dimensional state representation range from easing reinforcement learning (RL) and knowledge transfer across tasks, to facilitating learning from raw data with more efficient and compact high level representations.

Our experiments [90] (see figure 19 for an illustration) compare results in different setup with state representation in 2 and 3D, with different amount of distractors. The results show that the robotic prior approach is able to extract high level representation such as the 3D position of an arm and organize it into a compact and coherent space of states in a challenging dataset.

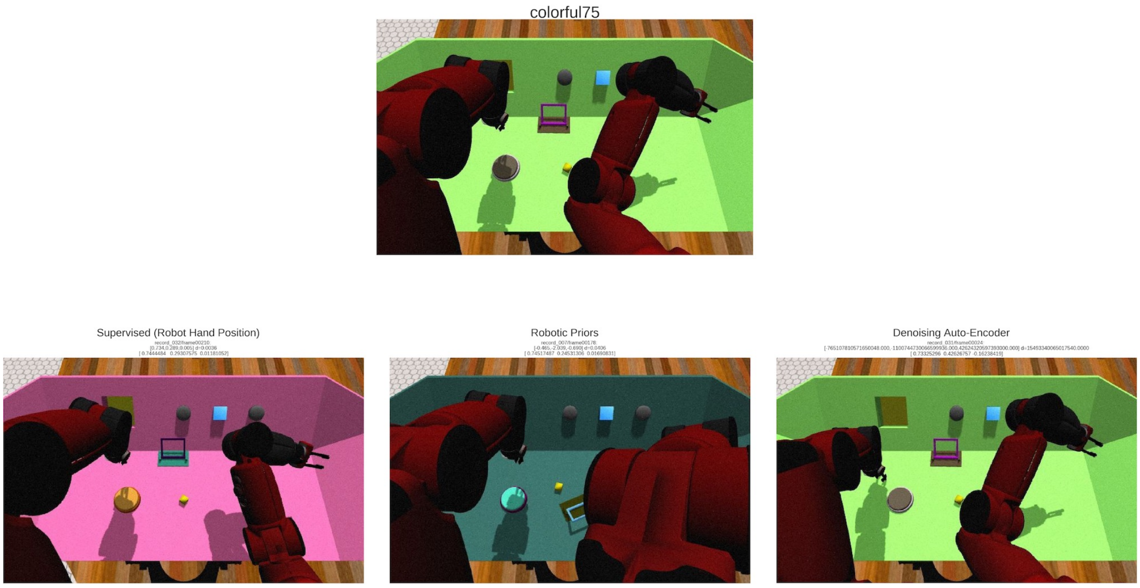

Figure 19. Nearest neighbors retrieved in the learned state space. The neighbors should represent the same button-hand relative position. Performance is shown in a left-right decreasing performance for the supervised (hand position) learning, 5 robotic priors and the autoencoder (better seen in video material)

7.3.3. Transfer Learning from Simulated to Real World Robotic Setups

Participants: Florian Golemo [correspondant], Pierre-Yves Oudeyer.

This work was made in collaboration with Adrien Ali Taiga and Aaron Courville. Reinforcement learning with function approximation has demonstrated remarkable performance in recent years. Prominent examples include playing Atari games from raw pixels, learning complex policies for continuous control, or surpassing human performance on the game of Go. However most of these successes were achieved in non-physical environments (simulations, video games, etc.). Learning complex policies on physical systems remains an open challenge. Typical reinforcement learning methods require a lot of data which makes it unsuitable to learn a policy on a physical system like a robot, especially for dynamic tasks like throwing or catching a ball. One approach to this problem is to use simulation to learn control policies before applying them in the real world. This raises new problems as the discrepancies between simulation and real world environments ("reality gap") prevent policies trained in simulation from performing well when transfered to the real world. This is an instance of *domain adaption* where the input distribution of a model changes between training (in simulation) and testing (in real environment). The focus of this work is in settings where resetting the environment frequently in order to learn a policy directly in the real environment is highly impractical. In these settings the policy has to be learned entirely in simulation but is evaluated in the real environment, as *zero-shot transfer*.

In simulation there are differences in physical properties (like torques, link weights, noise, or friction) and in control of the agent, specifically joint control in robots. We propose to compensate for both of these source of issues with a generative model to bridge the gap between the source and target domain. By using data collected in the target domain through task-independent exploration we train our model to map state transitions from the source domain to state transition in the target domain. This allows us to improve the quality of our simulated robot by grounding its trajectories in realistic ones. With this learned transformation of simulated trajectories we are able to run an arbitrary RL algorithm on this augmented simulator and transfer the learned policy directly to the target task. We evaluate our approach in several OpenAI gym environments that were modified to allow for drastic torque and link length differences.

7.3.4. *Measuring Uncertainty in Deep Learning Networks*

Participants: Florian Golemo [correspondant], Manuel Lopes.

As precursor to the main objective of the IGLU project, we investigated methods that would enable deep neural networks to judge their knowledge about a domain.

Neural networks, especially deep ones, have been shown to be able to model arbitrarily complex problems, and thus offer powerful tools for machine learning. Yet they come with a significant flaw of not being inherently able to represent certainty of their predictions. By adding a measure of uncertainty to neural networks, this technology could be applied to autonomous exploration and open-ended learning tasks.

Thus the goal of this project was to find a method to measure how much knowledge a neural network has about about an unlabeled data item (measure of uncertainty), and to apply this new measure in an active learning context. The objective of the latter was to demonstrate the efficiency in handpicking interesting data, to optimally extend the system's own capabilities.

We were successful in finding a measure of uncertainty that would reliably distinguish data that the network has seen before, from data that was generally unfamiliar to the network. This measure was created by measuring the entropy of the network's last layer across a batch of stochastic samples generated by adding Poisson noise to the inputs.

The measure failed however to outperform random sampling in several active learning scenarios. Yarin Gal published related work as part of his dissertation [117] after this project was concluded. He elaborated that deep neural networks are very effective in canceling out input noise. The author suggested to use existing "Dropout" layers instead for stochastic sampling, but he reaches the same conclusion of using the last layer entropy as measure of uncertainty.

7.4. Applications in Robotic myoelectric prostheses

Participants: Pierre-Yves Oudeyer [correspondant], Manuel Lopes, Mathilde Couraud, Sebastien Mick, Aymar de Rugy, Daniel Cattaert, Florent Paclet.

Together with the Hybrid team at INCIA, CNRS, the Flowers team continued to work on establishing the foundations of a long-term project related to the design and study of myoelectric robotic prosthesis. The ultimate goal of this project is to enable an amputee to produce natural movements with a robotic prosthetic arm (open-source, cheap, easily reconfigurable, and that can learn the particularities/preferences of each user). This will be achieved by 1) using the natural mapping between neural (muscle) activity and limb movements in healthy users, 2) developing a low-cost, modular robotic prosthetic arm and 3) enabling the user and the prosthesis to co-adapt to each other, using machine learning and error signals from the brain, with incremental learning algorithms inspired from the field of developmental and human-robot interaction.

7.4.1. *Model and experiments to optimize co-adaptation in a simplified myoelectric control system*

To compensate for a limb lost in an amputation, myoelectric prostheses use surface electromyography (EMG) from the remaining muscles to control the prosthesis. Despite considerable progress, myoelectric controls remain markedly different from the way we normally control movements, and require intense user adaptation. To overcome this, our goal is to explore concurrent machine co-adaptation techniques that are developed in the field of brain-machine interface, and that are beginning to be used in myoelectric controls. We combined a simplified myoelectric control with a perturbation for which human adaptation is well characterized and modeled, in order to explore co-adaptation settings in a principled manner. First, we reproduced results obtained in a classical visuomotor rotation paradigm in our simplified myoelectric context, where we rotate the muscle pulling vectors used to reconstruct wrist force from EMG. Then, a model of human adaptation in response to directional error was used to simulate various co-adaptation settings, where perturbations and machine co-adaptation are both applied on muscle pulling vectors. These simulations established that a relatively low gain of machine co-adaptation that minimizes final errors generates slow and incomplete adaptation, while higher gains increase adaptation rate but also errors by amplifying noise. After experimental verification on real subjects, we tested a variable gain that cumulates the advantages of both, and implemented it with directionally tuned neurons similar to those used to model human adaptation. This enables machine co-adaptation to locally improve myoelectric control, and to absorb more challenging perturbations. Significance. The simplified context used here enabled to explore co-adaptation settings in both simulations and experiments, and to raise important considerations such as the need for a variable gain encoded locally. This work was published in the *Journal Of Neural Engineering* in [71]

7.4.2. Performance and Usability of Various Robotic Arm Control Modes from Human Force Signals

Elaborating an efficient and usable mapping between input commands and output movements is still a key challenge for the design of robotic arm prostheses. In order to address this issue, we developped and compared three different control modes, by assessing them in terms of performance as well as general usability. Using an isometric force transducer as the command device, these modes convert the force input signal into either a position or a velocity vector, whose magnitude is linearly or quadratically related to force input magnitude. With the robotic arm from the open source 3D-printed Poppy Humanoid platform simulating a mobile prosthesis, an experiment was carried out with eighteen able-bodied subjects performing a 3-D target-reaching task using each of the three modes. The subjects were given questionnaires to evaluate the quality of their experience with each mode, providing an assessment of their global usability in the context of the task. According to performance metrics and questionnaire results, velocity control modes were found to perform better than position control mode in terms of accuracy and quality of control as well as user satisfaction and comfort. Subjects also seemed to favor quadratic velocity control over linear (proportional) velocity control, even if these two modes did not clearly distinguish from one another when it comes to performance and usability assessment. These results highlight the need to take into account user experience as one of the key criteria for the design of control modes intended to operate limb prostheses. This work was published in the journal *Frontiers in Neurorobotics* [72].

7.5. Applications in Educational Technologies

7.5.1. Machine Learning for Adaptive Personalization in Intelligent Tutoring Systems

Participants: Manuel Lopes [correspondant], Pierre-Yves Oudeyer, Didier Roy, Alexandra Delmas, Benjamin Clement.

7.5.1.1. The Kidlearn project

Kidlearn is a research project studying how machine learning can be applied to intelligent tutoring systems. It aims at developing methodologies and software which adaptively personalize sequences of learning activities to the particularities of each individual student. Our systems aim at proposing to the student the right activity at the right time, maximizing concurrently his learning progress and its motivation. In addition to contributing to the efficiency of learning and motivation, the approach is also made to reduce the time needed to design ITS systems.

We present an approach to Intelligent Tutoring Systems which adaptively personalizes sequences of learning activities to maximize skills acquired by students, taking into account the limited time and motivational resources. At a given point in time, the system proposes to the students the activity which makes them progress faster. We introduce two algorithms that rely on the empirical estimation of the learning progress, **RiARiT** that uses information about the difficulty of each exercise and **ZPDES** that uses much less knowledge about the problem.

The system is based on the combination of three approaches. First, it leverages recent models of intrinsically motivated learning by transposing them to active teaching, relying on empirical estimation of learning progress provided by specific activities to particular students. Second, it uses state-of-the-art Multi-Arm Bandit (MAB) techniques to efficiently manage the exploration/exploitation challenge of this optimization process. Third, it leverages expert knowledge to constrain and bootstrap initial exploration of the MAB, while requiring only coarse guidance information of the expert and allowing the system to deal with didactic gaps in its knowledge. The system is evaluated in a scenario where 7-8 year old schoolchildren learn how to decompose numbers while manipulating money. Systematic experiments are presented with simulated students, followed by results of a user study across a population of 400 school children. [14]

7.5.1.2. Linear UCB for intelligent tutoring system

What we wanted to do was to use the feature space considering features of students, features of explanations and maybe feature about the exercises. We wanted use this feature space to guide the bandit algorithm to recommend explanations. The algorithms that we already developed cannot be used in this kind of problem, because the order and the value of the bandit values depends on the time and on the learning progress the actions give in time. And in this new experiment, we wanted to recommend feedback, base on the population results depending on student's and explanation's features. In this problem, there is no consideration about temporality and the long-term progression of the student is too hard to correlate with a particular explanation. So different algorithms have been studied in the literature to use contextual bandit to make recommendation over a population. The algorithm that we wanted to use and adapt to our purpose is the LinUCB algorithm from [136].

Different kind of simulation have been made to test this framework. These experiments were made by generating various population of student defined by binary features with a number of dimension between 5 and 20. Also a set of activity have been defined and depending of the features of the students, their result for each activity was right or wrong. The algorithm was trained by making the student work on random activities, this way, the algorithm would learn the correlation between the student feature space and the success/failure to activities. After that the tests was made by letting the algorithms to choose the activity to propose to the student depending of their features. A lot of different configurations have been tested. The algorithm showed good results for low dimension feature space (3 to 9 features) with 90% accuracy, but for high dimension feature space, the results dropped to 20-30% accuracy.

7.5.1.3. Experiment in class in 2018

An experiment will be held in mars 2018 about testing the kidlearn framework in classroom in Bordeaux Metropole. The goal is to test a new feature by giving the student the opportunity to have different kinds of choice. This choice would be managed by a multi-armed bandit algorithm. We want to make an experiment with 600 student from bordeaux Metropole and we are currently discussing with the Local Education Authority to also test the application in other school in other departments.

7.5.1.4. The KidBreath project

To create learning contents linked to asthma to personalize it like mathematics activities in Kidlearn project [14] we used recommandation criterias in Therapeutic Education Program for asthma kids made by Health High Autority. Following an approach of participatory design [102], contents were validated by medical experts like health educators, pulmonoligists and pediatrics. Then, we conducted a workshop with forty kids aged 8 in order to iterate over the application interfaces and evaluate enjoy about it with observations. Finally, we realized a focus group with 5 asthma kids to validate the global comprehension of a part of the content. It revealed that children wanted more contents about the crisis treatment and how the asthma works in the human system (verbatims).

In a preliminary study, we experimented the participatory design process (PD) in the context of asthma e-learning using KidBreath tool. We evaluated in two Year 4 classes its efficacy in a motivation way [175], usability [142], [157], disease knowledge [92] and interests of children by their system [119]. After two weeks a use, results showed, in acceptance with behaviors, high level of intrinsic motivation when using KidBreath, usability and enjoyment of edutainment activities. This pilot study tends to confirm to continue with this approach with asthma kids at home (study in progress). These results was presented in the 29st Conference in Computer-Human Interaction in Poitiers, France.

We presented Thesis project in some events this year, with one publication surbmitted and validated:

- 21ème Congrès de Pneumologie de la Langue Française, January 2017, Marseille, France (Poster)
- Journée IHM et IA, March 2017, Paris, France (oral presentation)
- Ma Thèse en 180 secondes, March 2017, Bordeaux, France (oral presentation),
- 29ème conférence francophone sur l'Interaction Homme-Machine, August 2017, Poitiers, France (article and oral presentation) [76],
- La nuit européenne des chercheurs, September 2017, Bordeaux, France (oral presentation).

7.5.2. Poppy Education: Designing and Evaluating Educational Robotics Kits

Participants: Pierre-Yves Oudeyer [correspondant], Didier Roy, Théo Segonds, Stéphanie Noirpoudre, Thibault Desprez, Damien Caselli, Aurélie Lopes, Kelian Schindowsky.

Poppy Education project aims to create, evaluate and disseminate all-inclusive pedagogical kits, open-source and low cost, for teaching computer science and robotics.

It is designed to help young people to take ownership with concepts and technologies of the digital world, and provide the tools they need to allow them to become actors of this world, with a considerable socio-economic potential. It is carried out in collaboration with teachers and several official french structures (French National Education, High schools, engineer schools, ...). For secondary education and higher education, scientific literacy centers, Fablabs.

Poppy Education is based on the robotic platform poppy (open-source platform for the creation, use and sharing of interactive 3D printed robots), including:

- Poppy Humanoid, a robust and complete robotics platform designed for genuine experiments in the real world and can be adapted to specific user needs.
- Poppy Torso, a variant of Poppy Humanoid that can be easily installed on any flat support.
- Ergo Jr, a robotic arm. Durable and inexpensive, it is perfect to be used in class. Python. Directly from a web browser, using Ipython notebooks (an interactive terminal, in a web interface for the Python Programming Language).
- Snap. The visual programming system Snap, which is a variant of Scratch. Its features allow a thorough introduction of information technology.
- C++, Java, Matlab, Ruby, Javascript, etc. thanks to a REST API that allows you to send commands and receive information from the robot with simple HTTP requests.
- Virtual robots (Poppy Humanoid, Torso and Ergo) can be simulated with the free simulator V-REP. It is possible in the classroom to work on the simulated model and then allow students to run their program on the physical robot.

7.5.2.1. Pedagogical experimentations : Design and experiment robots and the pedagogical activities in classroom.

This project is user centered design. The pedagogical tools of the project (robots and ressources) are being created directly with the users and evaluated in real life by experiments. So teachers and researchers co-creatie activities, test with students in class-room, exchange their uses and develop the platform as needed [81].
The activities were designed mainly with Snap! and Python. Most activities use Poppy Ergo Jr, but some use Poppy Torso (mostly in higher school because of its cost).

Figure 20. Experiment robots and pedagogical activities in classroom

The pedagogical experiments in classroom carried out during the first year of the project notably allowed to create and experiment many robotic activities and to create pedagogical resources to taking in hand the robot. The main objective of the second year was to make all the activities and resources reusable (with description, documentation and illustration) easily and accessible while continuing the experiments and the diffusion of the robotic kits.

- Pedagogical working group : in the second year, the teacher partners continued to use the robots in the classroom and to create and test new classroom activities. Four new schools (including 10 new teachers) from different backgrounds (middle-school and high school teachers) have been added to the group to add diversity. We organized some training to help them to discover and learn how to use the robotics platform. As well an engineer of the Poppy Education team went to visit the teachers in their school to see and to evaluate the pedagogical tools (robots and activities) in real contexts of use.
  Five meetings have been organized during the year will all teachers partners and Poppy Education team to exchange about their projects with robots, to understand their need and to get some feedbacks from them. This experimentations are still helping us to understand better the educational needs, to create and improve the pedagogical tools.
  You can see the videos of pedagogical robotics activities here:
  https://www.youtube.com/playlist?list=PLdX8RO6QsgB7hM_7SQNLvyp2QjDAkkzLn

7.5.2.2. Pedagogical documents and resources

- We continued to improve the documentation of the robotic platform Poppy (https://docs.poppy-project.org/en/) and the documentation has been translated into French (https://docs.poppy-project.org/fr/.
  We configured a professional platform to manage the translation of the documentation (https://crowdin.com/project/poppy-docs. This allow whoever wants to participate in the translation of the language of their choice.
- To complete the pedagogical booklet [48] that provides guided activities and small challenges to become familiar with Poppy Ergo Jr robot and the Programming language Snap! (https://drive.google.com/file/d/0B2jV8VX-lQHwTUxXZjF3OGxHVGM/view) we provided a list of Education projects. Educational projects have been written for each activity carried out and tested in class. So each projects have its own web page including resources allowing any other teacher to carry out the

activity (description, pedagogical sheet, photos / videos, pupil's sheet, teacher's sheet with correction etc.).
You can see the activities here :
https://www.poppy-education.org/activites/activites-lycee The pedagogical activities are also available on the Poppy project forum where everyone is invited to comment and create new ones:
https://forum.poppy-project.org/t/liste-dactivites-pedagogiques-avec-les-robots-poppy/2305

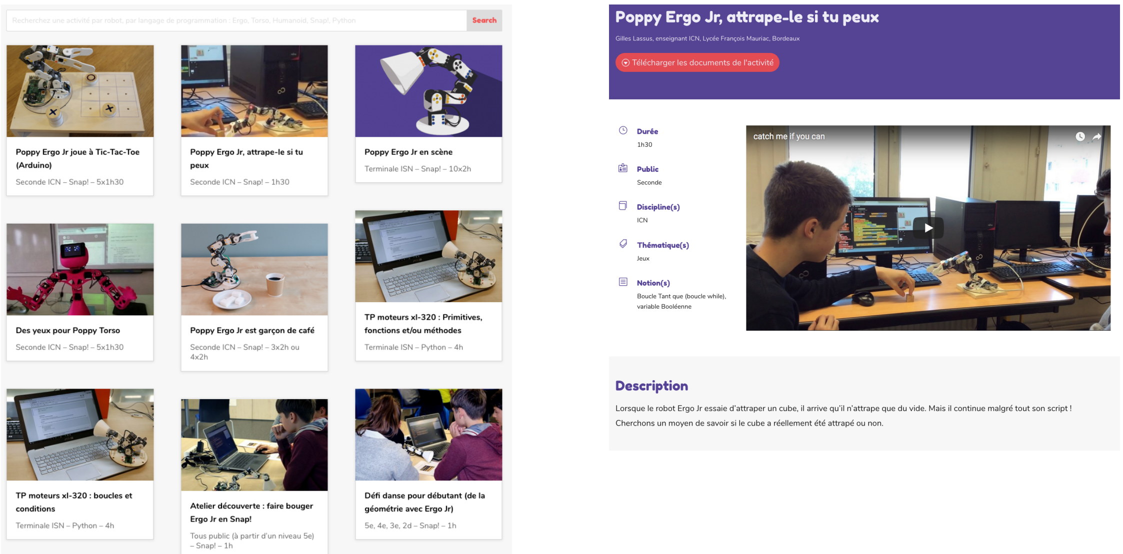

Figure 21. Open-source educational activities with Poppy robots are available on Poppy-Education.org

- A FAQ have been written with the most frequents questions to help the users: https://www.poppy-education.org/aide/

7.5.2.3. Diffusion

- A website have been created to present the project and to share all resources and activities. https://www.poppy-education.org/
- A press release was issued to announce the poppy education website release. https://www.inria.fr/actualite/mediacenter/poppy-education-la-robotique-pedagogique-s-enrichit-d-un-nouveau-site?mediego_ruuid=09f6a0c0-2ab3-11e7-a75f-fd895fe51065
- To promote educational uses of the platform, we participated in events (conference, seminar etc.). We participated as well at some workshops to introduce students to robotics and programming. See the chapter "popularization" to know the whole list.
- We sent 6 newsletters https://us13.campaign-archive.com/home/?u=17b68155l4db7361fc260e0ce&id=95e9e13ae2.
- We wrote blog articles to describe workshops / activities and give feedback from experiences. https://www.poppy-education.org/#

7.5.2.4. Symposium robotics

We organized a symposium robotics for the third year (http://dm1r.fr/colloque-robotique-education/) that present research results and feedback on the use of Poppy and Thymio robots in education (other robots have been discussed as well). Poppy Education team and the working group teachers helped with the organisation of the event and during the event (talk and workshops).

7.5.2.5. Evaluate the pedagogical kits

After experimenting and create tools with educational activities in class and for the class, it is now to evaluate qualitatively and quantitatively the impact of these tools. We must therefore assess, at first, if these tools offer good usability (i.e. effectiveness, efficiency, satisfaction). Then, in a second step, select items that can be influenced by the use of these tools. For example, students' representations of robotics, their motivation to perform this type of activity, or the evolution of their skills in these areas. In 2017 we conducted experiments to evaluate the usability of kits. We also collected data on students' perceptions of robotics.

- Population

  Our sample is made up of 28 teachers and 146 students from the "New Aquitaine" region who completed survey (online) during the month of June 2017. Here, we study several groups of individuals: teachers and students. Among the students we are interested in those who practiced classroom activities with the Ergo Jr kit during the school year 2016 - 2017 (N = 68) (age = 16, S = 2, 44), 37 are from section "Computer Science and Digital Sciences" (BAC S option ISN), 12 of section "Computer and Digital Creation" (BAC S option ICN) and 18 of the middle School. His 68 students are then divided into different modalities according to the characteristics of the activities they have followed: they may have declared using the educational booklet provided in the kit (N = 13) or not (N = 55) ; have used other robotic kits (N = 16) have practiced less than 6 hours of activity with the robot (N = 30), between 6 and 25 hours (N = 22) or more than 25 hours (N = 16); having built the robot (N = 12); have used the visual programming language Snap! (N = 46), the language of Python textual programming (N = 21), both (N = 8) or none (N = 9), it should be noted that these two languages are directly accessible via the main interface of the robot.

- Evaluation of the tool

  We have selected two standardized survey dealing with this issue: SUS (The Systeme Usability Scales) [103] and The AttrakDiff [135]. These two survey are complementary and allow to identify the design problems and to account for the perception of the user during the activities. The results of these are available in the article (in French) [77] publish in the conference Didapro (Lausanne Feb, 2018). Figures 22 and 23 show the averages of the 96 respondents (68 students + 28 teachers) for each of the 10 statements from the SUS and 28 pairs of antonyms to be scored on a scale of 1 to 5 and a 7-point scale, respectively.

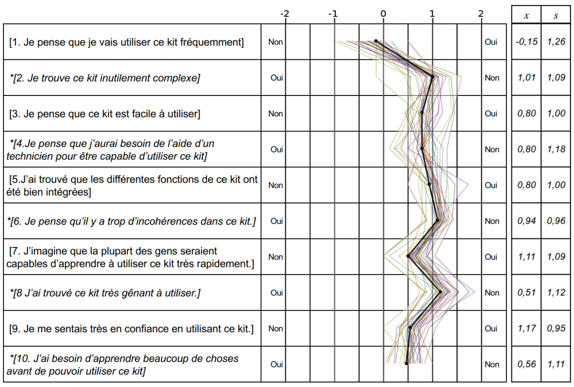

Figure 22. Result of SUS survey

- Evaluation of impact on learner

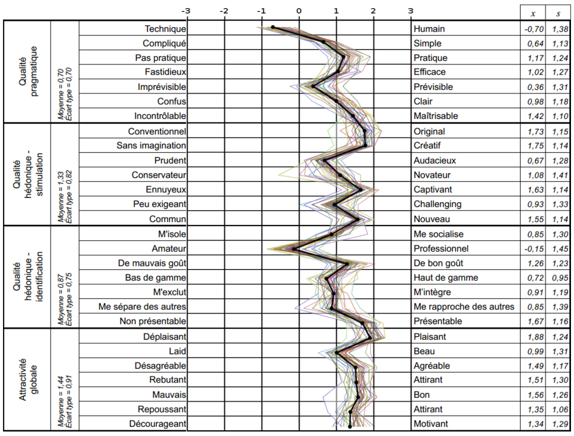

Figure 23. Result of AttrakDiff survey

One of the objectives of the integration of digital sciences in school is to allow students to have a better understanding of the technological tools that surround them daily (i.e. web, data, algorithm, connected object, etc.). So, we wanted to measure how the practice of activities with ErgoJr robot had changed this apprehension; especially towards robots. For that, we used a standardized survey: "attitude towards robot" *EuroBarometer 382* originally distributed in 2012 to more than 1000 people in each country of the European Union. On the one hand, we sought to establish whether there had been a change in response between 2012 and 2017, and secondly whether there was an impact on the responses of 2017 according to the participation, or not, in educational activities with ErgoJr robot. The analysis of the results is in progress and will be published in 2018.

7.5.2.6. Partnership on education projects

- Ensam

  The Arts and Métiers campus at Bordeaux-Talence in partnership with Inria wishes to contribute to its educational and scientific expertise to the development of new teaching methods and tools. The objective is to develop teaching sequences based on a project approach, relying on an attractive multidisciplinary technological system: the humanoid Inria Poppy robot.

  The humanoid Inria Poppy robot offers an open platform capable of providing an unifying thread for the different subjects covered during the 3-years of the Bachelor training: mechanics, manufacturing (3D printing), electrical, mecha-tronics, computer sciences, design.

  Last year students of "bachelor degree" (ENSAM-Talence) have designed, manufactured, assembled and programmed 4 different solutions to replace the fixed hand of Poppy by a gripper device: https://www.youtube.com/watch?v=DZjGaJk2fQk. For the second year, students of "bachelor degree" have designed Wheels for Poppy Torso.
  https://www.poppy-education.org/2017/06/19/des-roues-pour-poppy-torso-2eme-edition-du-projet-etudiant-de-lensam

- Poppy entre dans la danse (Poppy enters the dance)

  The project "Poppy enters the dance" (Canope 33) took place for the second year. It uses the humanoid robot Poppy. This robot is able to move and experience the dance. The purpose of this project is to allow children to understand the interactions between science and choreography, to play with the random and programmable, to experience movement in dialogue with the machine. At the beginning of the project they attended two days of training on the humanoid robot (Inria -

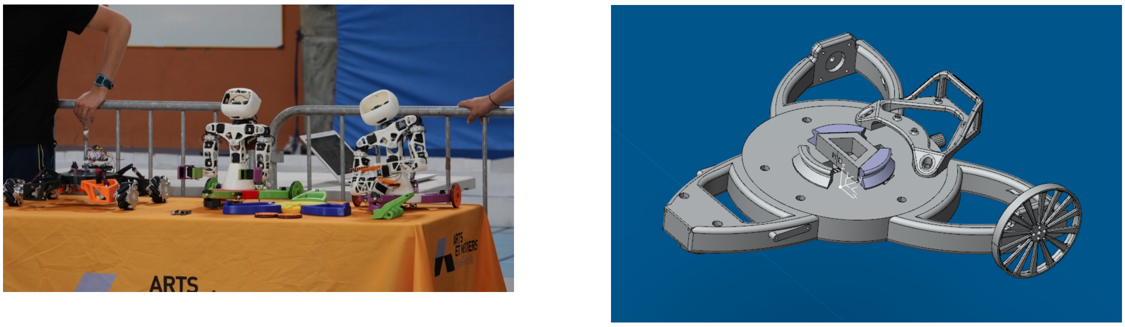

Figure 24.

Poppy Education). During the project, they met the choreographer Eric Minh Cuong Castaing and the engineer Segonds Theo (Inria - Poppy Education).

You can see a description and an overview of the project here:
https://www.youtube.com/watch?v=XfxXaq899kY

7.5.3. IniRobot: Educational Robotics in Primary Schools

Participants: Didier Roy [correspondant], Pierre-Yves Oudeyer.

IniRobot (a project done in collaboration with EPFL/Mobsya) aims to create, evaluate and disseminate a pedagogical kit which uses Thymio robot, open-source and low cost, for teaching computer science and robotics.

IniRobot Project consists to produce and diffuse a pedagogical kit for teachers and animators, to help to train them directly or by the way of external structures. The aim of the kit is to initiate children to computer science and robotics. The kit provides a micro-world for learning, and takes an enquiry-based educational approach, where kids are led to construct their understanding through practicing an active investigation methodology within teams. It is based on the use of the Thymio II robotic platform. More details about this projects were published in RIE 2015 [50] , which presents the detailed pedagogical objectives and a first measure of results showing that children acquired several robotics-related concepts. See also http://www.inirobot.fr.

Deployment: After 30 months of activity, IniRobot is used by about 1800 adults and 20 000 children in 72 cities of France. Example of action in university: MEEF teacher training for the hope of Aquitaine. Example of action in school: training of all Gironde Pedagogical ICT Advisors, covering nearly 1000 schools. Example of action in the extracurricular time: training 82 facilitators TAP cities of Talence, Pessac, Lille, ..., CDC Gates of inter-seas. Example of national action: Training of the digital mediators of the 8 Inria centers.

7.5.3.1. Partnership

The project is carried out in main collaboration with the LSRO Laboratory from EPFL (Lausanne) and others collaborations with French National Education/Rectorat d'Aquitaine, with Canopé Educational Network, with ESPE (teacher's school) Aquitaine, ESPE Martinique, ESPE Poitiers, National Directorate of Digital Education

7.5.3.2. Created pedagogical documents and resources

- Inirobot pedagogical kit [24]: This pedagogical booklet provides activities scenarized as missions to do. An update of Inirobot pedagogical kit : https://dm1r.inria.fr/uploads/default/original/1X/70037bdd5c290e48c7ec4cb4f26f0e426a4b4cf6.pdf Another pedagogical booklet has been also created by three pedagogical advisers for primary school, with pedagogical instructions and aims, under ou supervision. new pedagogical kit is available, "Inirobot Scolaire, Langages et robotique", which extends Inirobot in a full primary school approach. http://tice33.ac-bordeaux.fr/Ecolien/ASTEP/tabid/5953/language/fr-FR/Default.aspx

- Inirobot website and forum https://dm1r.inria.fr/inirobot or http://www.inirobot.fr With this website, teachers, animators and general public can download documents, exchange about their use of inirobot's kit.
- Publication about Inirobot and Poppy Education La robotique éducative au service du développement de la pensée informatique Didier Roy (2017) dans "L'informatique et le numérique dans la classe (Presses universitaires de Namur)" http://pun.be/fr/livre/?GCOI=99993100805880 Inirobot et Poppy education, deux dispositifs robotiques open source pour l'enseignement des Sciences du Numérique Didier Roy (2017) Revue Sésamath 55 http://revue.sesamath.net/spip.php?article922 Poppy Education : un dispositif robotique open source pour l'enseignement de l'informatique et de la robotique Stéphanie Noirpoudre, Didier Roy, Thibault Desprez, Théo Segonds, Damien Caselli, Pierre-Yves Oudeyer (2017) EIAH 2017, Strasbourg, France [81] Thymio nella didattica in Francia e in Svizzera, Morgane Chevalier, Gordana Gerber, Didier Roy (2017) Pedagogika, Anno XXI, n1 Gennaio/Febbraio/Marzo http://www.pedagogia.it/ Une brève histoire de la robotique, d'Electric Dog à Poppy, Revue du Palais de la Découverte (2017) : http://www.palais-decouverte.fr/fr/ressources/revue-decouverte/n-412-septembre-octobre-2017/articles/

7.5.3.3. Scientific mediation

Inirobot is very popular and often presented in events (conferences, workshops, ...) by us and by others.

7.5.3.4. Symposium robotics

With Poppy Education, Inirobot is a main line in our colloquium "Robotics and Education" (http://dm1r.fr/)

7.5.3.5. Spread of Inirobot activities

Inirobot activities are inside several projects : Dossier 123 codez from Main à la Pâte Fundation, Classcode project, ...

7.5.3.6. Future MOOC Thymio

A new project is coming, MOOC Thymio, in collaboration with Inria Learning Lab and EPFL (Lausanne, Switzerland), on FUN platform and edX EPFL Platform.) To teach how to use Thymio robot in education.

8. Bilateral Contracts and Grants with Industry

8.1. Bilateral Contracts with Industry

8.1.1. Autonomous Driving Commuter Car

Participants: David Filliat [correspondant], Emmanuel Battesti.

We further developed a planning algorithm for a autonomous electric car for Renault SAS in the continuation of the previous PAMU project. We improved our planning algorithm in order to go toward navigation on open roads, in particular with the ability to reach higher speed than previously possible, deal with more road intersection case (roundabouts), and with multiple lane roads (overtake, insertion...).

8.2. Bilateral Grants with Industry

8.2.1. Adaptive device for disease awareness and treatment adherence of asthma in children

Participants: Manuel Lopes [correspondant], Alexandra Delmas, Pierre-Yves Oudeyer.

Financing of the CIFRE PhD grant of Alexandra Delmas by Itwell with the goal of developing a tool for self-learning for patients to improve their compliance to treatment.

9. Partnerships and Cooperations

9.1. Regional Initiatives

9.1.1. Poppy Education

Poppy Education
Program: Feder - Région Aquitaine
Duration: January 2014 - December 2017
Coordinator: PY Oudeyer, Inria Flowers
Partners: Inria Flowers
Funding: 1 million euros (co-funded by Feder/EU Commission, Region Aquitaine and Inria)

Poppy Education aims to create, evaluate and disseminate pedagogical kits “turnkey solutions” complete, open-source and low cost, for teaching computer science and robotics. It is designed to help young people to take ownership with concepts and technologies of the digital world, and provide the tools they need to allow them to become actors of this world, with a considerable socio-economic potential. It is carried out in collaboration with teachers and several official french structures (French National Education/Rectorat, Highschools, engineering schools, ...). It targets secondary education and higher education, scientific literacy centers, Fablabs.

Poppy robotic platform used in the project is free hardware and software, printed in 3D, and is intended primarily for:

- learning of computer science and robotics,
- introduction to digital manufacturing (3D printing ...)
- initiation to the integration of IT in physical objects in humanoid robotics, mechatronics.
- artistic activities.

Educational sectors covered by the project are mainly: Enseignement d’exploration ICN en seconde, enseignement ISN en terminale S et bientôt en 1ère , filière STI2D, MPS seconde. Web: http://www.poppy-project.org/education .

9.1.1.1. Perseverons Project

The Perseverons project (Perseverance with / by digital objects), carried by the university via the ESPE (Higher School of Teaching and Education) of Aquitaine, and by the Rectorate of Bordeaux via the DANE (Academic Delegation digital education), aims to measure the real effectiveness of digital techniques in education to improve school motivation and perseverance, and, in the long term, reduce dropout. The project proposes to analyze the real effects of the use of two types of objects, robots, tablets, by comparing the school and non-school contexts of the *fablabs*. He is one of the 22 winners http://www.gouvernement.fr/efran-les-22-laureats of the "E-Fran" call for projects (training, research and digital animation spaces), following the Monteil mission on digital education, as part of the Investissement d’Avenir 2 program http://ecolenumerique.education.gouv.fr/2016/09/23/1244/. Formed of 12 sub-projects, "perseverons" has many partnerships, especially with the Poppy Education project http://perseverons.espe-aquitaine.fr/sp6-robotique-inria/.

9.1.1.2. Partner schools

In 2017, we have 36 partner schools (show Fig 25). 15 directly from the Poppy Education project. 19 new establishments were equipped in September 2017 by the Perseverons project. 21 of these establishments are located in Gironde. We have 27 high schools, 5 middle school.

9.1.2. ENSAM

The orientation of a (high school) student, choosing a career, is often based on an imagined representation of a discipline, sector of activity or training. Moreover, higher education is sometimes for a college student or a student a self centered universe, with inaccessible teaching methodologies and level of competence.

Attachement	Type	Name	Adresse	Tel	Web
Poppy Éducation	High School	Alfred Kastler	14 Avenue de l'Université,33402 Talence, France	+33 5 57 35 40 70	http://www.lyceekastler.fr/
Poppy Éducation	Middle School	Anatole France	28 Rue des Micocouliers,33410 Cadillac, France	+33 5 56 62 98 42	http://www.afcadillac.net/
PERSEVERONS	High School	André Malraux	3 Rue du 8 Mai 1945,64200 Biarritz, France	+33 5 59 01 20 40	http://lycee-malraux-biarritz.fr/
Poppy Éducation	High School	Camille Jullian	29 Rue de la Croix Blanche,33000 Bordeaux, France	+33 5 56 01 47 47	http://www.camillejullian.com/
Poppy Éducation	Middle School	de France	Rue du Cimetière Saint-Benoist,75005 Paris, France	+33 1 44 27 12 11	http://www.college-de-france.fr/
Poppy Éducation	High School	des Graves	238 Cours du Général de Gaulle,33170 Gradignan, France	+33 5 56 75 77 56	http://www.grandlebrun.com/
PERSEVERONS	High School	Élie Faure	63 Avenue de la Libération,33310 Lormont, France	+33 5 56 38 23 23	http://www.lyc-eliefaure.fr/
PERSEVERONS	High School	Elisée Reclus	7 Avenue de Verdun,33220 Pineuilh, France	+33 5 57 41 92 50	http://lycee-foyen.fr/
Poppy Éducation	High School	François Mauriac	1 Rue Henri Dunant,33000 Bordeaux, France	+33 5 56 38 52 82	http://lyceemauriac.fr/
PERSEVERONS	High School	Gaston Febus	20 Avenue Georges Moutet,64300 Orthez, France	+33 5 59 67 07 26	http://webetab.ac-bordeaux.fr/cite-gaston-febus-orthez/
PERSEVERONS	Middle School	Giraud de Borneil	10 Boulevard André Dupuy,24160 Excideuil, France	+33 5 53 62 21 16	http://www.gdeborneil.fr/
PERSEVERONS	High School	Grand Air	Avenue du Docteur Lorentz Monod,33120 Arcachon, France	+33 5 56 22 38 00	http://webetab.ac-bordeaux.fr/lycee-grand-air/
PERSEVERONS	High School	Gustave Eiffel	143 Rue Ferbos,33000 Bordeaux, France	+33 5 56 33 83 00	http://www.eiffel-bordeaux.org/
PERSEVERONS	High School	Jacques Monod	10 Rue du Parvis,64230 Lescar, France	+33 5 59 77 92 00	http://lyceejacquesmonod.fr/
Poppy Éducation	High School	Jean Moulin	Avenue de la République,33210 Langon, France	+33 5 56 63 62 30	http://webetab.ac-bordeaux.fr/lycee-jean-moulin-langon/
Poppy Éducation	Middle School	Jean Zay	41 Rue Henri Cochet,33380 Biganos, France	+33 5 57 17 01 70	http://collegebiganos.fr/
Poppy Éducation	High School	La Morlette	62 Rue du Docteur Roux,33150 Cenon, France	+33 5 57 80 37 00	http://lycee-lamorlette.fr/
PERSEVERONS	High School	Les Iris	13 Rue Sourbès,33310 Lormont, France	+33 5 57 80 10 60	http://www.lyceelesiris.fr/
PERSEVERONS	High School	Louis Barthou	2 Boulevard Barbanègre,64000 Pau, France	+33 5 59 98 98 00	http://www.cyberlycee.fr/
PERSEVERONS	High School	Louis de Foix	4 Avenue Jean Rostand,64100 Bayonne/Bayona/Baiona, France	+33 5 59 63 31 10	http://www.louisdefoix.com/
PERSEVERONS	High School	Maine de Biran	108 Rue Valette,24100 Bergerac, France	+33 5 53 74 50 00	http://webetab.ac-bordeaux.fr/lycee-maine-de-biran/
Poppy Éducation	Middle School	Mios	Route du Pujeau,33380 Mios, France	+33 5 56 03 00 77	http://www.villemios.fr/enfance-jeunesse/college/
PERSEVERONS	High School	Nord Bassin	128 Avenue de Bordeaux,33510 Andernos-les-Bains, France	+33 5 56 82 20 77	http://www.lyceenordbassin.com/
Forum Poppy	Primary School	Notre-Dame du Mur	19 Rue de Kermadiou,29600 Morlaix, France	+33 2 98 88 18 69	http://lycee.ecmorlaix.fr/
PERSEVERONS	High School	Pape Clément	1 Rue Léo Lagrange,33600 Pessac, France	+33 5 57 26 63 00	http://lyceepapeclement.fr/
PERSEVERONS	High School	Pays de Soule	Avenue Jean Monnet,64130 Chéraute, France	+33 5 59 28 22 28	http://www.lyceedupaysdesoule.fr/index.php
PERSEVERONS	High School	Pré De Cordy	5 Avenue Joséphine Baker,24200 Sarlat-la-Canéda, France	+33 5 53 31 70 70	http://lycee-predecordy-sarlat.com/
Poppy Éducation	High School	Raoul Follereau	9 Boulevard Saint-Exupéry,58000 Nevers, France	+33 3 86 60 36 00	http://lyc58-renardfollereau.ac-dijon.fr/
PERSEVERONS	High School	René Cassin	2 Rue de Lasseguette,64100 Bayonne/Bayona/Baiona, France	+33 5 59 58 42 00	http://webetab.ac-bordeaux.fr/lycee-rene-cassin/
PERSEVERONS	High School	Saint-Cricq	4 Piste Cyclable,64000 Pau, France	+33 5 59 30 50 55	http://www.lycee-saint-cricq.org/
Poppy Éducation	High School	Saint-Genès	160 Rue de Saint-Genès,33000 Bordeaux, France	+33 5 56 33 84 84	http://www.saint-genes.com/
PERSEVERONS	High School	Saint-John Perse	2 Chemin de Barincou,64000 Pau, France	+33 5 59 62 73 11	http://www.lycee-saint-john-perse.fr/
Poppy Éducation	High School	Sainte-Marie Grand Lebrun	164 Rue François Mauriac,33200 Bordeaux, France	+33 5 56 08 32 13	http://www.grandlebrun.com/
inria	High School	Sainte-Saintonge	12 Rue de Saintonge,33000 Bordeaux, France	+33 5 56 99 39 29	http://www.lyceesaintefamille.com/
Poppy Éducation	High School	Sud-Médoc	Piste du Médoc Bleu,33320 Le Taillan-Médoc, France	+33 5 56 70 10 10	http://www.lyceesudmedoc.fr/
Poppy Éducation	High School	Victor Louis	2 Rue de Mégret,33400 Talence, France	+33 5 56 80 76 40	http://lyceevictorlouis.fr/

Figure 25. List of partner schools of the Poppy Education project

The Arts and Métiers campus at Bordeaux-Talence in partnership with Inria contributes with its educational and scientific expertise to the development of new teaching methods and tools. The objective is to develop teaching sequences based on a project approach relying on an attractive multidisciplinary technological system: the humanoid Inria Poppy robot. These teaching sequences will be built and tailored to different levels of training, from high schools to Engineer schools.

The new formation "Bachelor of Technology", started in September 2014 at Ensam Bordeaux, is resolutely turned towards a project based pedagogy, outlining concepts from concrete situations. The humanoid Inria Poppy robot offers an open platform capable of providing an unifying thread for the different subjects covered during the 3-years of the Bachelor formation: mechanics, manufacturing (3D printing), electrical, mechatronics, computer sciences, design...

For the 1st and 2nd year of the ENSAM Engineer cursus, the Poppy robot is now used to support the teaching and to conduct further investigation.

9.1.3. KidLearn and Region Aquitaine

A Conseil Régional d'Aquitaine Project (KidLearn, 2015-) began, coordinated by Manuel Lopes entitled KidLearn. Will fund 50% of a 3 years PhD student.

We propose here a research project that aims at elaborating algorithms and software systems to help humans learn efficiently, at school, at home or at work, by adapting and personalizing sequences of learning activities to the particularities of each individual student. This project leverages recent innovative algorithmic models of human learning (curiosity in particular, developed as a result of ERC European project of the Flowers team), and combines it with state-of-the-art optimization algorithms and an original integration with existing expert knowledge (human teachers). Given a knowledge domain and a set of possible learning activities, it will be able to propose the right activity at the right time to maximize learning progress. It can be applied to many learning situations and potential users: children learning basic knowledge in schools and with the support of their teachers, older kids using educational software at home, of adults needing to acquire new skills through professional training ("formation professionnelle"). Because it combines innovations in computational sciences (machine learning and optimization) with theories of human cognition (theories of human learning and of education), this project is also implementing a strong cross-fertilization between technology and human sciences (SHS).

9.1.4. Comacina Capsule Creative Art/Science project and Idex/Univ. Bordeaux

The artist community is a rich source of inspiration and can provide new perspectives to scientific and technological questions. This complementarity is a great opportunity that we want to enforce in the Poppy project by making the robot accessible to non-robotic-expert users. The Comacina project, in collaboration with the Flowers team and supported by funding from Idex/Univ. Bordeaux, explored the role of movements and light in expressing emotions: http://comacina.org . This project was implemented through several residencies during the year, and several performances at various cultural places in Aquitaine, including at Pole Evasion in Ambares-et-Lagrave. a report is available at https://flowers.inria.fr/RencontreAutourDuGeste.pdf . It benefitted from funding from the Art/Science Idex call for project.

9.2. National Initiatives

PY Oudeyer collaborated with Aymar de Rugy, Daniel Cattaert, Mathilde Couraud, Sébastien Mick and Florent Paclet (INCIA, CNRS/Univ. Bordeaux) about the design of myoelectric robotic prostheses based on the Poppy platform, and on the design of algorithms for co-adaptation learning between the human user and the prosthesis. This was funded by a PEPS CNRS grant.

D. Roy is the Inria leader of project "Voyageurs du Code - Code Décode" https://www.bibliosansfrontieres.org/tag/les-voyageurs-du-codecode-decode/, https://www.code-decode.net/ which provides teachers and animators formations and learning games to initiate young people to computer science and robotics.

Around Robotics for education, many collaborations were put in place. With the LSRO Laboratory from EPFL (Lausanne) and others collaborations with French National Education/Rectorat d'Aquitaine, with Canopé Educational Network, with ESPE (teacher's school) Aquitaine, ESPE Martinique, ESPE Poitiers, LINE Laboratory (ESPE Nice University), National Directorate of Digital Education, Fondation "La Main à la Pâte", Maison for Science in Bordeaux University, Orange Fondation.

9.3. European Initiatives

9.3.1. FP7 & H2020 Projects

9.3.1.1. 3rd HAND

Title: Semi-Autonomous 3rd Hand

Programm: FP7

Duration: October 2013 - September 2017

Coordinator: Inria

Partners:

- Technische Universität Darmstadt (Germany)
- Universität Innsbruck (Austria)
- Universität Stuttgart (Germany)

Inria contact: Manuel Lopes

Robots have been essential for keeping industrial manufacturing in Europe. Most factories have large numbers of robots in a fixed setup and few programs that produce the exact same product hundreds of thousands times. The only common interaction between the robot and the human worker has become the so-called 'emergency stop button'. As a result, re-programming robots for new or personalized products has become a key bottleneck for keeping manufacturing jobs in Europe. The core requirement to date has been the production in large numbers or at a high price.Robot-based small series production requires a major breakthrough in robotics: the development of a new class of semi-autonomous robots that can decrease this cost substantially. Such robots need to be aware of the human worker, alleviating him from the monotonous repetitive tasks while keeping him in the loop where his intelligence makes a substantial difference.In this project, we pursue this breakthrough by developing a semi-autonomous robot assistant that acts as a third hand of a human worker. It will be straightforward to instruct even by an untrained layman worker, allow for efficient knowledge transfer between tasks and enable a effective collaboration between a human worker with a robot third hand. The main contributions of this project will be the scientific principles of semi-autonomous human-robot collaboration, a new semi-autonomous robotic system that is able to: i) learn cooperative tasks from demonstration; ii) learn from instruction; and iii) transfer knowledge between tasks and environments. We will demonstrate its efficiency in the collaborative assembly of an IKEA-like shelf where the robot acts as a semiautonomous 3rd-Hand .

9.3.1.2. DREAM

Title: Deferred Restructuring of Experience in Autonomous Machines

Programm: H2020

Duration: January 2015 - December 2018

Coordinator: UPMC

Partners:

- Armines (ENSTA ParisTech)
- Queen Mary University London (England)
- University of A Coruna (Spain)
- Vrije University Amsterdam (Holland)

Contact: David Filliat

Abstract: A holy grail in robotics and artificial intelligence is to design a machine that can accumulate adaptations on developmental time scales of months and years. From infancy through adult- hood, such a system must continually consolidate and bootstrap its knowledge, to ensure that the learned knowledge and skills are compositional, and organized into meaningful hierarchies. Consolidation of previous experience and knowledge appears to be one of the main purposes of sleep and dreams for humans, that serve to tidy the brain by removing excess information, to recombine concepts to improve information processing, and to consolidate memory. Our approach – Deferred Restructuring of Experience in Autonomous Machines (DREAM) – incorporates sleep and dream-like processes within a cognitive architecture. This enables an individual robot or groups of robots to consolidate their experience into more useful and generic formats, thus improving their future ability to learn and adapt. DREAM relies on Evo- lutionary Neurodynamic ensemble methods (Fernando et al, 2012 Frontiers in Comp Neuro; Bellas et al., IEEE-TAMD, 2010) as a unifying principle for discovery, optimization, re- structuring and consolidation of knowledge. This new paradigm will make the robot more autonomous in its acquisition, organization and use of knowledge and skills just as long as they comply with the satisfaction of pre-established basic motivations. DREAM will enable robots to cope with the complexity of being an information-processing entity in domains that are open-ended both in terms of space and time. It paves the way for a new generation of robots whose existence and purpose goes far beyond the mere execution of dull tasks. http://www.robotsthatdream.eu

9.3.2. Collaborations in European Programs, except FP7 & H2020

9.3.2.1. IGLU

Title: Interactive Grounded Language Understanding (IGLU)

Programm: CHIST-ERA

Duration: October 2015 - September 2018

Coordinator: University of Sherbrooke, Canada

Partners:

University of Sherbrooke, Canada

Inria Bordeaux, France

University of Mons, Belgium

KTH Royal Institute of Technology, Sweden

University of Zaragoza, Spain

University of Lille 1 , France

University of Montreal, Canada

Inria contact: Pierre-Yves Oudeyer

Language is an ability that develops in young children through joint interaction with their caretakers and their physical environment. At this level, human language understanding could be referred as interpreting and expressing semantic concepts (e.g. objects, actions and relations) through what can be perceived (or inferred) from current context in the environment. Previous work in the field of artificial intelligence has failed to address the acquisition of such perceptually-grounded knowledge in virtual agents (avatars), mainly because of the lack of physical embodiment (ability to interact physically) and dialogue, communication skills (ability to interact verbally). We believe that robotic agents are more appropriate for this task, and that interaction is a so important aspect of human language learning and understanding that pragmatic knowledge (identifying or conveying intention) must be present to complement semantic knowledge. Through a developmental approach where knowledge grows in complexity while driven by multimodal experience and language interaction with a human, we propose an agent that will incorporate models of dialogues, human emotions and intentions as part of its decision-making process. This will lead anticipation and reaction not only based on its internal state (own goal and intention, perception of the environment), but also on the perceived state and intention of the human interactant. This will be possible through the development of advanced machine learning methods (combining developmental, deep and reinforcement learning) to handle large-scale multimodal inputs, besides leveraging state-of-the-art technological components involved in a language-based dialog system available within the consortium. Evaluations of learned skills and knowledge will be performed using an integrated architecture in a culinary use-case, and novel databases enabling research in grounded human language understanding will be released. IGLU will gather an interdisciplinary consortium composed of committed and experienced researchers in machine learning, neurosciences and cognitive sciences, developmental robotics, speech and language technologies, and multimodal/multimedia signal processing. We expect to have key impacts in the development of more interactive and adaptable systems sharing our environment in everyday life. http://iglu-chistera.github.io/

9.4. International Initiatives

9.4.1. Inria Associate Teams Not Involved in an Inria International Labs

9.4.1.1. NEUROCURIOSITY

Title: NeuroCuriosity

International Partner (Institution - Laboratory - Researcher):

Columbia Neuroscience (United States) - Cognitive Neuroscience - JACQUELINE GOTTLIEB

Start year: 2016

See also: https://flowers.inria.fr/neurocuriosity

Curiosity can be understood as a family of mechanisms that evolved to allow agents to maximize their knowledge of the useful properties of the world. In this project we will study how different internal drives of an animal, e.g. for novelty, for action, for liking, are combined to generate the rich variety of behaviors found in nature. We will approach such challenge by studying monkeys, children and by developing new computational tools.

9.4.1.2. Informal International Partners

Pierre-Yves Oudeyer and Didier Roy have create a collaboration with LSRO EPFL and Pr Francesco Mondada, about Robotics and education. The two teams co-organize the annual conference "Robotics and Education"in Bordeaux. Didier Roy teaches "Robotics and Education" in EPFL several times a year.

Pierre-Yves Oudeyer collaborated with Edith Law's HCI research group at University of Waterloo on the topic of "Curiosity in HCI system". They co-organized the "Designing for curiosity" workshop at CHI 2017, Denver, Colorado, and obtained a grant from Univ. Bordeaux to set up a project with Inria Potioc team and with Dana Kulic, Robotics lab, Univ. Waterloo.

Didier Roy has created a collaboration with HEP VAud (Teachers High School) and Bernard Baumberger and Morgane Chevalier, about Robotics and education. Scientific discussions and shared professional training.

Florian Golemo is in an active collaboration with Aaron Courville from MILA Montreal to work on the IGLU project together.

William Schueller visited Vittorio Loreto's team in Rome from January till August 2017, funded by the Idex program of the University of Bordeaux. Vittorio Loreto is an Associate Professor in Physics at University Sapienza of Rome, and head of the research team Social Dynamics Lab. William Schueller also participated to a conference organized by V. Loreto in Rome, the Kreyon Conference, by giving a talk and presenting a user experiment: an interactive Naming Game.

9.4.2. Participation in Other International Programs

David Filliat participates in the ITEA3 DANGUN project with Renault S.A.S. in france and partners in Korea. The purpose of the DANGUN project is to develop a Traffic Jam Pilot function with autonomous capabilities using low-cost automotive components operating in France and Korea. By incorporating low-cost advanced sensors and simplifying the vehicle designs as well as testing in different scenarios (France & Korea), a solution that is the result of technical cooperation between both countries should lead to more affordable propositions to respond to client needs in the fast moving market of intelligent mobility.

9.5. International Research Visitors

9.5.1. Visits of International Scientists

- Georges Kachergis, University of Radboud, The Netherlands
- Cynthia Liem, University of Delft, The Netherlands
- Mike Schaekermann, Univ. Waterloo, Canada
- Roboy team, Univiersity of Munich, Germany
- Lauriane Rat-Fiseher, Univ. Toulouse, France
- Lisa Jacquey, LPP, Paris (May 12th, 2017)
- Mai Nguyen, ENST Bretagne, France

9.5.1.1. Internships

- Kelian Schindowski, project Poppy Education
- Octave Delorme, project Poppy Education
- Alexandre Péré, Deep learning and intrinsic motivation
- Pierre Manceron, Deep Reinforcement Learning
- Timothée Anne, Intrinsically Motivated Goal Exploration

10. Dissemination

10.1. Promoting Scientific Activities

10.1.1. Scientific Events Organisation

10.1.1.1. General Chair, Scientific Chair

- PY. Oudeyer has been general co-chair of the "Designing for curiosity" workshop at CHI 2017, Denver, Colorado, US;
- PY. Oudeyer has co-organized the 3rd International Symposium on Intrinsically Motivated Open-Ended Learning, Rome, Italy;
- PY. Oudeyer has co-organized the IEEE IJCNN 2017 Special Session on COGNITION AND DEVELOPMENT;
- D. Roy was general chair for the conference "Robotique et Education", Bordeaux, France.

10.1.1.2. Member of the Organizing Committees

- PY. Oudeyer has been "Robotics Liaison" of IJCNN 2017, Anchorage, Alaska.

10.1.2. Scientific Events Selection

10.1.2.1. Member of the Conference Program Committees

- PY. Oudeyer has been in the conference program committee of IEEE ICDL-Epirob conference.

10.1.2.2. Reviewer

- David Filliat was reviewer for the IROS, ECMR, ICDL, HRI, ICRA conferences.
- Sébastien Forestier was reviewer for IEEE ICDL-Epirob, ICRA
- Natalia Díaz Rodríguez was reviewer for JAIR 2017 (Journal of AI Research) and Area Chair (meta-reviewer) for WIML 2017 (Women in Machine Learning Workshops at NIPS 2017).

10.1.3. Journal

10.1.3.1. Member of the Editorial Boards

- PY. Oudeyer was associate editor of IEEE Transactions on CDS and Frontiers in Neurorobotics.

10.1.3.2. Reviewer - Reviewing Activities

- David Filliat was reviewer for IEEE Transaction on Robotics, IEEE Transactions on Cognitive and Developmental Systems, Robotics and Automation Letters.
- O. Sigaud has been a reviewer for the Autonomous Robots journal and for the ICLR and the NIPS conferences
- PY. Oudeyer has been a reviewer for the journals IEEE Transactions on CDS and Child and Development Perspectives.

10.1.4. Invited Talks

- David Filliat gave an invited presentation “Autonomous Learning and AI for interactive Robotics” during the 50 years of Inria event on november 8th.
- O. Sigaud gave an invited presentation “Deep Learning for Robotics: Promises and Issues” at the Journées Nationales de la Recherche en Robotique on november 16th.
- O. Sigaud gave an invited presentation “Towards developmental discovery of objects in dynamical scenes" at the workshop on Intrinsically Motivated Open-Ended Learning, Rome, Italy, 9th october
- PY. Oudeyer gave an invited presentation "Intrinsically Motivated Goal Exploration Processes" at the worchop on Intrinsically Motivated Open-Ended Learning, Rome, Italy, 9th october;
- PY. Oudeyer gave an invited presentation "Computational Models of Human Cognitive Development" at the 29th Eleanor Gibson lecture, Cornell Univ., US, April,
- PY. Oudeyer gave an invited presentation "Models of curiosity-driven learning" at Univ. Rochester, US, April.
- PY. Oudeyer gave an invited presentation "Curiosity-driven learning and language acquisition" at the workshop on language acquisition at IEEE ICDL-Epirob, Lisbon, Portugal, Sept.;
- PY. Oudeyer gave an invited presentation "Robotique Pédagogique" at the Journées Nationales de la Recherche en Robotique on november 16th.
- PY. Oudeyer gave an invited presentation "Intrinsically motivated learning and curiosity in humans and robots" at the "Designing for curiosity" workshop at CHI 2017, Denver, US;

10.1.5. Leadership within the Scientific Community

- Natalia Díaz Rodríguez attended and organized a workshop within the Heidelberg Laureate Forum Sept. 2017 on Machine learning and Human-Computer Interaction.
- PY. Oudeyer co-organized the "Designing for curiosity" workshop at CHI 2017 (Denver, US), the IMOL 2017 workshop (Rome, Italy), and was co-editor of the special issue on "Modeling play in early infant development" in Frontiers in Psychology.
- PY. Oudeyer has been editor of the IEEE CIS Newsletter on Cognitive and Developmental systems, organizing two interdisciplinary dialogs, see https://openlab-flowers.inria.fr/t/ieee-cis-newsletter-on-cognitive-and-developmental-systems/129.

10.1.6. Scientific Expertise

- PY. Oudeyer has been a reviewer for the European Commission (FET program).

10.2. Teaching - Supervision - Juries

10.2.1. Teaching

License: Introduction to Matlab, 21 heures. L3, ENSTA - ParisTech (David Filliat).

Master: Robotique Mobile, 21 heures. M2, ENSTA - ParisTech (David Filliat).

Master: Perception pour la Robotique, 6 heures. M2, ENSTA - ParisTech (David Filliat).

Master: Perception pour la robotique, 12 heures. M2 Systemes Avances et Robotique, University Pierre et Marie Curie (David Filliat)

Master: Perception pour la Robotique Développementale, 3 hours, CogMaster (David Filliat)

Licence Informatique, 64h Bordeaux University (Sébastien Forestier)

Master: Perception pour les systemes autonomes (ROB313), 7.50 h. Natalia Díaz Rodríguez

Master: Projet Informatique (IN104), 18.25h. Natalia Díaz Rodríguez.

Master: Cours de robotique développementale, option robot, ENSEIRB (2h), PY. Oudeyer

10.2.2. Supervision

PhD in progress: Cédric Colas, Algorithms for intrinsically motivated goal exploration (superv. P-Y. Oudeyer)

PhD in progress: Sébastien Forestier, Models of curiosity-driven learning of tool use and speech development, started in sept. 2015 (superv. P-Y. Oudeyer)

PhD in progress: William Schueller, Study of the impact of active learning and teaching in naming games dynamics, started in sept. 2015 (superv. P-Y. Oudeyer)

PhD in progress: Thibault Desprez, Design and study of the impact of educational robotic kits in computer science education, started in dec. 2016 (superv. P-Y. Oudeyer)

PY. Oudeyer supervised a team of computer and pedagogical engineers and researchers for the project Poppy Education (Didier Roy, Stéphanie Noirpoudre, Théo Segonds, Damien Caselli)

PhD in progress: Benjamin Clement, Intelligent Tutoring Systems, started oct 2015 (superv. Manuel Lopes and Pierre-Yves Oudeyer).

PhD: Thibaut Munzer, Learning from Instruction, defended (superv. Manuel Lopes).

PhD in progress: Baptiste Busch, Interactive Learning, started oct 2014 (superv. Manuel Lopes).

PhD in progress: Alexandra Delmas, Auto-Apprentissage Auto-Adaptable pour la compliance au traitement, started oct 2014 (superv. Manuel Lopes).

PhD: Yuxin Chen, Interactive learning of objects and names on a humanoid robot, defended 02/2017 (superv. David Filliat).

PhD: Celine Craye, Curiosity and visual attention for the guidance of an exploration robot, defended 04/2017 (superv. David Filliat).

PhD: Joris Guery, Robust visual recognition by artificial neural networks in robotic exploration scenarios, defended 11/2017 (superv. David Filliat and Bertrand Le Saulx (ONERA))

PhD in progress: Adrien Matricon : Task dependent visual feature selection for optimising and generalizing robotics skills (superv. David Filliat, Pierre-Yves Oudeyer).

PhD in progress: José Magno Mendes Filho, Planning and control of an autonomous AGV in environment shared with humans, started Oct. 2015 (superv. David Filliat and Eric Lucet (CEA))

PhD in progress: Timothée Lesort, Incremental Deep Learning for Detection and Classification in a Robotic Context. started june 2017 (superv. David Filliat and Jean-Francois Goudou (THALES)).

PhD in progress: Vyshakh Palli Thazha, Data fusion for autonomous vehicles. started sept 2017 (superv. David Filliat and Hervé Illy (Renault)).

10.2.3. Juries

David Filliat was in the jury of Houssem Nouira (20/04/2017, Examinateur) : Affinement de relevés laser mobiles issus de Lidars multi-couches

David Filliat was in the jury of Quan Nguyen (06/10/2017, Rapporteur) : Mapping of a sound environment by a mobile robot

David Filliat was in the jury of Vijaya kumar Ghorpade (20/12/2017, Examinateur) : 3D Semantic mapping for indoor navigation

PY. Oudeyer was in the PhD juries of Céline Craye (ENSTA), Gabriel Sulem (ENS), Arthur Prat-Carrabin (ENS), Miquel Cornudella (ENS)

PY. Oudeyer was in the HdR jury of Alexandre Pitti (Univ. Cergy Pontoise)

10.3. Popularization

10.3.1. Duties

D. Roy is member of the Class'code team (Inria is member of the consortium of this project) https://pixees.fr/classcode/accueil/. Class'code is a blended formation for teachers and animators who aim to initate young people to computer science and robotics. D. Roy has in charge the robotics module of the project.

D. Roy is adviser of the organization of computer science exhibition in "Palais de la découverte" which will begin on 2018 March. He helps for robotics part.

D. Roy is member of the team "Education en Scène" which organize educational activities with robotics in Bordeaux Digital City.

D. Roy is member of the scientific committee of "Didapro Didastic" Conference which will be held in Lausanne (Switzer on 2018 February.

D. Roy is member of the Robocup Junior French committee, an international robotics challenge http://rcj.robocup.org/.

D. Roy is member of the scientific committee of "Ludovia CH" Conference which will be held in Yverdon (Switzerland) on 2018 March.

D. Roy is project leader of Thymio Simulator for Classcode project. Specifications and coordination of work.

D. Roy is project leader of Thymio Scratch and Thymio Snap! development, with D. Sherman. Inria, EPFL and Mobsya collaboration.

PY. Oudeyer continued to be the PI of the Poppy Education project.

10.3.2. Online content

Stephanie Noirpoudre. Atelier Poppy Ergo Jr au CERN. Description and feedback of a workshop on the construction and programming of the robotic arm Poppy Ergo Jr as part of the Coding Pi Science Event. [83]

Stephanie Noirpoudre. Robotic workshop at CERN. Description and feedback of a workshop on the construction and programming of the robotic arm Poppy Ergo Jr as part of the Coding Pi Science Event. [84]

Stephanie Noirpoudre, Kelian Schindowsky. Poppy Education présent à la journée EIDOS 64 : Le forum des pratiques numériques pour l'éducation. Description and feedback of the 9th edition of the EIDOS64 day (the digital practice forum for education). [85]

Sylvain Soulard, Kelian Schindowsky. Description of activity "Modeling of the Port of Rotterdam" using the robot arm Poppy Ergo Jr and created by Sylvain Soulard, middle school teacher in technology. He started the problem: how to optimize and secure the transport of containers in a commercial port? [88]

Kelian Schindowsky. Un projet étudiant : des mains pour Poppy Torso ! Utilisation de la plateforme Poppy pour un projet étudiant. A use of the Poppy platform for a student project: 4 Poppy Torso robots modified by the students of the Bordeaux-Talence campus clashed in the large amphitheater. A competition of a new kind including free figures and imposed figures. [87]

Kelian Schindowsky. Des roues pour le robot Poppy Torso : New Bachelor of Technology students from ENSAM (Talence) worked on the Poppy Torso robot, the goal this time was to equip it with a mobile platform. [86]

10.3.3. Teaching and Education

10.3.3.1. Poppy Education

January 2017, meeting with partner teachers

March 2017, meeting with partner teachers

March 2017, training day with new teachers partners - Building and programming the robot Poppy Ergo Jr

May 2017, meeting with partner teachers

September 2017, meeting with partner teachers

June 2017, training day with workers from Cap'Metier and Cultures éléctroniques (for scientific mediation purpose) to initiate to robotic - Building and programming the robot Poppy Ergo Jr

10.3.3.2. Inirobot

May 2017, Plan national de formation organised by La main à la pâte (Paris): D. ROY - Train future trainers to initobot curriculum

April 2017, Training days organized by Main à la pâte for National Education (CEA Saclay): T. Desprez, S. Noiropudre, D. Roy, Théo Segonds - Train a group of teachers to inirobot

10.3.4. Talks and Hands-on

10.3.4.1. KidBreath

Ma Thèse en 180 secondes, March 2017, Bordeaux, France, A. Delmas (oral presentation),

La nuit européenne des chercheurs, September 2017, Bordeaux, France, A. Delmas (oral presentation).

10.3.4.2. Poppy Education

January 2017, Eidos64 event - Le forum des pratiques numériques pour l'éducation (Lons): S. Noirpoudre, K. Schindowsky - Talk to present Poppy Education

Janvier 2017, Visit organized by Le Conseil Départemental des Jeunes (Inria Bordeaux Sud-Ouest): S. Noirpoudre - Programming workshops (for middle school students) to initiate in programmation with Poppy Ergo Jr robot

January 2017, Robotics training day organised by Maison pour la Science (Inria Bordeaux Sud-Ouest): S. Noirpoudre, T. Desprez - Programming workshop (for futur trainers) to initiatie in programmation with Poppy Ergo Jr robot

January 2017, R2T2 AmeriCarabean (island of Martinique) : D. Roy - Co-organization with EPFL and ESPE of Martinique - International event (Mexico, Quebec, Guyane, Sainte Lucie) about robotics for education http://www.reseau-espe.fr/actualites/espe-de-martinique-le-defi-r2t2-americaraibe-ete-releve

March 2017, Education exhibition Eduspot (Paris): S. Noirpoudre - Exhibition stand to present the robotic platform Poppy and the use in Education

March 2017, Le printemps de la mixité event (Inria Bordeaux Sud-Ouest): S. Noirpoudre - Robotics workshops (for high school students) to initiate in programmation with Poppy Ergo Jr robot

April 2017, Training days organized by Main à la pâte for National Education (CEA Saclay): T. Desprez, S. Noiropudre, D. Roy, Théo Segonds - Train a group of teachers to robotics and programmation with Poppy Ergo Jr robot

May 2017, Plan national de formation organised by La main à la pâte (Paris): S. Noirpoudre - Talk to present Poppy Education project and Poppy Ergo Jr

May 2017, Innorobo (Paris): S. Noirpoudre, K. Schindowsky, T. Segonds, D. Roy: Exhibition stand to present the robotics platform Poppy and the use in Education

May 2017, Innorobo Robotics and Education Forum (Paris): S. Noirpoudre - Talk to present Poppy Education and the robot Poppy Ergo Jr

May 2017, Robot makers'day (Talence): K. Schindowsky - Exhibition stand to present Poppy Education and Poppy robots

May 2017, RII Santiago (Santiago de Chile, Chile): T. Segonds - Exhibition stand to present Poppy Education and Poppy robots - Event organized by Inria Chile

May 2017, Bordeaux Geek Festival (Bordeaux): K. Schindowsky - Workshops to initiate in programming

May 2017, PY. Oudeyer gave an invited presentation on "Robotics and cognitive sciences" at Festival Filosofia, St. Emilion, France

June 2017, Internships: observation Sequence for Grade 3 Students (Inria Bordeaux Sud-Ouest - Welcomed two students from middle-school during a week to discover the working environment and to introduce them to robotics

June 2017, Robotics workshop for a primary class (Inria Bordeaux Sud-Ouest): S. Noirpoudre, T. Desprez - Poppy Education and inirobot workshops

June 2017, EIAH : Environnements informatiques pour l'apprentissage humain (Strasbourg): S. Noirpoudre, T. Desprez - Talk to present the article “Poppy Education : un dispositif robotique open source pour l'enseignement de l'informatique et de la robotique”

June 2017, EIAH : Environnements informatiques pour l'apprentissage humain (Strasbourg): T. Desprez, S. Noirpoudre - Exhibition stand to present the robotics platform Poppy and the use in Education

June 2017, Rencontre avenir numérique alsace (strasbourg): S. Noirpoudre - Talk in videoconference to present Poppy Education and the robot Poppy Ergo Jr

June 2017, Playback of "Poppy entre dans la danse" project (Le Cuvier, Artigues-près-Bordeaux): T. Deprez, T. Segonds - Technical assistance of a secondary school performance melting danse and robotics

July 2017, Symposium Education and Robotics (Bordeaux): D. Roy (coordinator) and Flowers Team Members - Organization of the colloquium

July 2017, Symposium Education and Robotics (Bordeaux): S. Noirpoudre - Talk to present Poppy Education project

July 2017, Symposium Education and Robotics (Bordeaux): PY. Oudeyer - Talk to present Flowers educational robotics projects

July 2017, Symposium Education and Robotics (Bordeaux): S. Noirpoudre - Exhibition stand to present the robotics platform Poppy and the use in Education

July 2017, 10th International Scratch conference (Bordeaux): D. Roy - Member of the Scratch organizing commitee, member of the scientific committee - the conference organization begun on december 2017

July 2017, 10th International Scratch conference (Bordeaux): T. Segonds - Talk to present Poppy Education project

July 2017, 10th International Scratch conference (Bordeaux): S. Noirpoudre - Exhibition stand to present the robotics platform Poppy and the use in Education

August 2017, Fab13 Fabricating Society Conference (Santiago de Chile, Chile): T. Segonds - Talk on Poppy Education - Two days workshop on using and modifing Poppy robots

August 2017, Ludovia Conference (Ax-Les-Thermes): D. Roy - PArtnership with Region Nouvelle Aquitaine and Académie of Bordeaux for an exhibition stand with Poppy Education - Exhibitions, demos, talks

October 2017, Coding Pi Science Days (CERN and Hepia engineering school at Geneva): T. Segonds, T. Desprez - Talk to present the robotics platform Poppy and the use in Education - Three days robotics workshops on building and programming a Poppy Ergo Jr robot

October 2017, Fête de la science (Inria Bordeaux Sud-Ouest): D. Roy - special event with a robotics workshop and several demos at Inria Center, with members of staff of Bordeaux Metropole and polotical actors

October 2017, Fête de la science (Inria Bordeaux Sud-Ouest): T. Segonds, T. Desprez - 8 programming workshop in 2 days (with middle school students) using Snap! and the robot Poppy Ergo Jr

November 2017, JNRR (National Days of Robotics Reseach, Biarritz): D. Roy (moderator), P.-Y. Oudeyer (speaker) - Talk on Educational Robotics -

December 2017, Digital Tech Rennes (Rennes): T. Segonds, B. Busch - Talk on Poppy Education - Poppy Ergo Jr programming workshop

December 2017, Aperobot Bordeaux (Bordeaux): T. Segonds - Poppy Ergo Jr programming workshop

December 2017, Internships: observation Sequence for Grade 3 Students (Inria Bordeaux Sud-Ouest) - Welcomed three students from middle-school during a week to discover the working environment and to introduce them to robotics

10.3.4.3. Other

Members of the Flowers team participated to many interviews and documentaries for the press, the radio and television.

10.3.5. Popularizing inside Inria

- March 2017, training day with Inria workers from scientific mediation - Building and programming the robot Poppy Ergo Jr
- October 2017, DevDays (Inria Bordeaux Sud-Ouest): D. Caselli - Presentation of the hotspot tool used in Poppy Ergo Jr robot
- December 2017, Séminaire de la médiation Inria (CNAM, Paris): T. Segonds, S. Noirpoudre, D. Roy - Poppy Ergo Jr programming workshop for people involving in scientific outreach of Inria

10.3.6. Creation of Material for Popularization

As part of the Poppy Education project, thanks the robotic platform Poppy we created pedagogical kits open-source and low cost for teaching computer science and robotics. It is designed to help young people to take ownership with concepts and technologies of the digital world.

The Pedagogical kits includes robots and pedagogical resources. They have been co-created directly with users (mainly high schools teachers) and evaluated in real life by experiments in classrooms [81].
The activities were designed with the visual programming language Snap! (Scratch like) and Python, but some are in Java / Processing (thanks the robot API you can use the language of your choice).

Most activities are using the robot Poppy Ergo Jr, but some use Poppy Torso (mostly in higher school because of its cost) and Poppy Humanoid (in kinder-garden for dance projects) :

- The Poppy Ergo Jr robot is a small and low cost 6-degree-of-freedom robot arm. It consists of simple shapes which can be easily 3D printed. It has several 3D printed tools extending its capabilities (there are currently the lampshade, the gripper and a pen holder but you can design new ones). They are assembled via rivets which can be removed and added very quickly with the OLLO tool. Each motor has LEDs on (8 different color can be activated). The electronic card (raspberry Pi) is visible next to the robot, that allow to manipulate, and plug extra sensors.
- The Poppy Torso robot is an open-source humanoid robot torso which can be installed easily on tabletops. More affordable than the robot Poppy Humanoid, it is an ideal medium to learn science, technology, engineering and mathematics.

We continued to improve the robots functionalities and you can see below the resources we created :

- A website have been created to present the project and to share all resources and activities. https://www.poppy-education.org/
- To complete the pedagogical booklet [48] that provides guided activities and small challenges to become familiar with Poppy Ergo Jr robot and the Programming language Snap! (https://drive.google.com/file/d/0B2jV8VX-lQHwTUxXZjF3OGxHVGM/view) we provided a list of Education projects. Educational projects have been written for each activity carried out and tested in class. So each projects have its own web page including resources allowing any other teacher to carry out the activity (description, pedagogical sheet, photos / videos, pupil's sheet, teacher's sheet with correction etc.). Their is now 32 activities documented available on Poppy Education website.

  You can see the activities on this links (in french):

  – Introduction to Ergo Jr and Snap! :
    https://www.poppy-education.org/activites/initiation-ergo-jr-et-snap
  – Ergo Jr and Python tutorials :
    https://www.poppy-education.org/activites/tuto-python-robot-ergojr
  – High-school levels :
    www.poppy-education.org/activites/activites-lycee
  – Middle-school level :
    www.poppy-education.org/activites/activites-college
  – Primary Schools level :
    https://www.poppy-education.org/activites/activites-primaire/
  – Demonstrations (just videos to show the possibilities) :
    https://www.poppy-education.org/activites/demos/
- We continued to improve the documentation of the robotic platform Poppy (https://docs.poppy-project.org/en/) and the documentation has been translated into French (https://docs.poppy-project.org/fr/.
- A FAQ have been written with the most frequents questions to help users: https://www.poppy-education.org/aide/

10.3.7. Innovation and transfer

- Since 1 september 2017 until february 2019, PerPoppy and Poppy Station Projects : D. Roy, P.-Y. Oudeyer. These projects aim to perpetuate the Poppy robot ecosystem by creating an external structure from outside Inria, with various partners. After the Poppy Robot Project, the Poppy Education Project is ending and Inria doesn't

  Many exchanges have already taken place with potential partners such as the EPFL, the ENSAM network, the «Ligue de l'Enseignement», Génération Robots, the French Institute of Education, several academies, the direction of digital education of the Ministry of Education, ... PerPoppy is the project which is building the new structure, and Poppy Station is the name of the new structure. Poppy Station, which will include Poppy robot ecosystem (hardware, software, community) from the beginning, will be a place of excellence to build future educational robots and to design pedagogical activities to teach computer science, robotics and Artificial Intelligence.

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