The Flowers team studies computational mechanisms allowing robots and humans to acquire open-ended repertoires of skills through life-long learning. This includes the processes for progressively discovering their bodies and interaction with objects, tools and others. In particular, we study mechanisms of intrinsically motivated learning (also called curiosity-driven active learning), autonomous unsupervised exploration, imitation and social learning, multimodal statistical inference, embodiment and maturation and self-organization.

The team considers cognitive development as a complex dynamical system which needs to be understood through systemic thinking, leveraging tools and concepts from computational sciences (artificial intelligence, machine learning and robotics), neuroscience and psychology. In this perspective, algorithms and robotics models are powerful scientific languages to express theories of cognitive development in the living.

Of particular interest to the Flowers team is the formation of repertoires of sensorimotor and interaction skills as well as their relation with the acquisition and evolution of languages.

The team is also working on applications of this research in three fields: adaptive human-computer interfaces, educational technologies and open-source robotics for art and education.

Contexte et atouts du poste

Scientific priorities at Inria and strategic role for the Flowers team:

Link with Inria strategic plan. Because this topic deals with mechanisms of intrinsically motivated machine learning and is based on statistical inference, it is directly relevant to the strategic plan axis “Priority research within our sciences: The challenge of unsupervised learning...” The main idea is to enable a software system to adapt to its context based on past experiences. Machine learning techniques, particularly statistical techniques used to address the uncertainties often encountered in digital systems, are one of the illustrations of this principle, which needs to be improved and expanded. Artificial intelligence and autonomous learning are also being integrated as central parts of the new Inria strategic plan being written in 2017-18.

Strategic importance for the Flowers team. Combining recent advances in Deep learning and intrinsically motivated learning has become a very hot topic in artificial intelligence and machine learning in the last 3-6 months, as shown by the attempts of Google Deepmind and Open AI companies to reuse our ideas of intrinsically motivated learning which allowed them to solve deep RL problems that could not be solved by state-of-the-art algorithms only 6 months ago (Bellemare et al., 2016; Tang et al., 2016). Our ideas are right now being reused and having an indirect impact on this field. At the same time, a central scientific challenge is to follow this movement and leverage ideas that we developed to make state-of-the-art visible contributions and become a visible player in this domain of deep learning-based artificial intelligence. The unique opportunity that the Flowers team has is to introduce intrinsically motivated deep learning algorithms that enable to solve difficult learning problems such as those encountered in robotics or physical sciences, where this could be a major breakthrough for the field. The second best demo prize we got at NIPS 2016 (6000 thousands participants, most selective conference in AI and machine learning) shows a light structure like an Inria team can compete with large scale research organizations in AI (Google, Facebook, Microsoft and others were also in the competition).

Furthermore, in addition to the reuse of algorithm of intrinsically motivated exploration by the Deep Reinforcement Learning community, these algorithms have begun to be used in the field of automated/assisted discovery of chemical structures (oil droplet dynamics) in the Cronin Lab in University of Glasgow (http://www.chem.gla.ac.uk/cronin/lab/), which is world renown in this domain. This has been made possible through the hiring of my previous PhD student Jonathan Grizou in the Cronin Lab, who is now head of a research team working on using exploration algorithms in this chemical context. This has generated already enabled discoveries of new chemical structures, leading to several major publications in high-impact journals, and they organized a workshop a few months ago to demonstrate these applications of algorithms coming from Developmental Robotics (https://croningp.github.io/tutorialbcdelpirob_2017/). This is very exciting as this opens a new very important area of application for our algorithms.
The postdoc topic proposed here would enable to help us 1) keep in the international race of machine learning algorithms driven by intrinsically motivated exploration; 2) develop our expertise in the new application domain of automated exploration and discovery of physical/chemical dynamical systems. This postdoc would potentially also be an opportunity to start an operational collaboration with the Cronin Lab.

**Scientific context:**

Intrinsically motivated goal exploration algorithms enable machines to discover repertoires of action policies that produce a diversity of effects in complex environments. In robotics, 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 (e.g. Baranes and Oudeyer, 2013; Forestier et al., 2017). An example is the Poppy/Explauto experiment with a humanoid robot learning to use tools in a few hours, which obtained the 2nd position in the demonstration competition at NIPS 2016 (See https://www.youtube.com/watch?v=NOLAwD4ZTW0, Forestier et al., 2016). In other domains such as chemistry and physics, they open the possibility to automate the discovery of novel chemical or physical structures produced by complex dynamical systems (e.g. Grizou, Points et al., 2017).

However, they have so far assumed that self-generated goals are sampled in a specifically engineered feature space, limiting their autonomy. Recent work has shown how unsupervised deep learning approaches could be used to learn goal space representations (e.g. Pére et al., 2018), but they have focused on goals represented as static target configurations of the environment in robotics sensorimotor spaces.

In this project, we will study how these new families of machine learning algorithms can be extended and used for automated discovery of behaviours of dynamical systems in physics/chemistry, through exploration of their parameter space, and when these behaviours are perceived through raw sensors (e.g. pixels of images).

**Web site of Flowers Lab:** https://flowers.inria.fr

**Mission confiée**

The work will begin by a familiarization with algorithms for intrinsically motivated exploration with unsupervised learning of goal spaces developed in the team. Then, a few interesting numerical/simulation models of physical/chemical phenomena, associated to rich behavioral patterns (such as Turing-like reaction-diffusion models or oil droplet models), will be selected as a basis for developing and experimenting updates of existing exploration and learning algorithms.

These algorithmic updates will focus in particular on the use of recurrent neural networks to learn goal spaces that can encode dynamical phenomena. Several algorithmic implementations will be compared, e.g. using several techniques for encoding times series as goal spaces, and compared using various information theoretic measures of the diversity of discovered behaviours in the target dynamical systems. It will be also possible to test these algorithmic updates in more traditional (simulated) sensorimotor learning problems, using standard benchmarks of the literature (e.g. Open Gym environments or Minecraft/Malmo).

Experiments will extend the DeepExplauto open-source library developed in the team, as well as Keras and other Deep Learning libraries for the algorithms.

**Principales activités**

**Keywords:** deep learning, intrinsically motivated exploration, unsupervised learning, automated discovery, complex systems, dynamical systems

**References:**


**Compétences**

**Required knowledge and background:**

Candidates should have a strong expertise in at least one of these areas:

- Experience with Deep Learning algorithms (theory and practical implementations)
- Stochastic optimization, black-box optimization
- Intrinsically motivated exploration algorithms

Knowledge and competence in physics/chemical modelling would be welcome.

Other requirements:
- Strong skills in mathematics, statistical inference, machine learning
- Advanced programming skills in script languages like python/Matlab
- Motivation to work in an interdisciplinary project

Avantages sociaux
- Subsidised catering service
- Partially-reimbursed public transport

Rémunération
2653€ / month (before taxes)