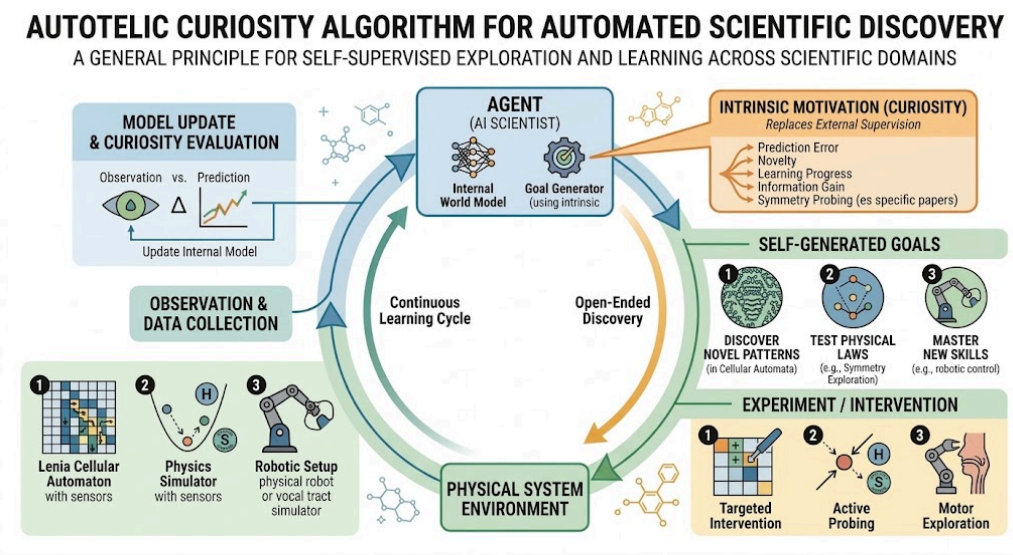
Internship project, master level, 2026

[AI for Science] Developing novel algorithms for the curiosity-driven exploration of fiber trajectories in structured microfluidic environments



Supervision: Blaise Delmotte, Jonathan Grizou, and Pierre-Yves Oudeyer

Research group: Flowers team, Inria, Bordeaux, France, in collaboration with LadHyX (CNRS / École Polytechnique), ABEL (CNRS / Imperial College London), and the University of Glasgow.

Location: Flowers team, Inria centre at the University of Bordeaux.
Potential visits to LadHyX and/or ABEL which will be discussed with the selected candidate.

Duration: 6 months, around February 2027 (with flexibility)
Level: Master 2 research internship

Keywords: AI for science, automated scientific discovery, curiosity-driven learning, autotelic agents, intrinsic motivation, microfluidics, fluid-structure interaction.

How to apply: contact blaise.delmotte@cnrs.fr , jonathan.grizou@glasgow.ac.uk , pierre-yves.oudeyer@inria.fr , using the tag [application] in the object of the email, with a CV and a letter of motivation, ideally by December 2026 (but applicants who apply earlier will be given priority). We strongly recommend sending information on previous projects you have been working on (even if they are not directly related to the topic), as well as your grades and links to code repositories.

Requirements: We are looking for highly motivated MSc students (Master II) with:
- Strong scientific knowledge and expertise in training generative AI systems (SFT, RLHF, RLVR, etc)
- Strong experience with modern deep learning frameworks (PyTorch, TensorFlow, Hugging Face ecosystem)
- Interest in AI4Science, curiosity-driven/intrinsically motivated exploration, and recursive self-improvement

No prior background in fluid dynamics is required: the simulation code will be provided as a black box.

Context

A major contribution of the Flowers team in recent years has been the development of curiosity-driven learning algorithms in order to efficiently explore the diversity of behaviors of complex systems [4]. Such algorithms were originally developed as a model of how children or artificial agents proactively explore their environment [3] (hence the term “curiosity-driven”). Indeed, contrary to gradient-descent algorithms, curiosity-driven algorithms do not optimise for a predefined target, but set themselves goals and try to discover as large a variety of “interesting observations” within a limited experimental budget.

This process can be compared to a scientist trying to understand a system that is of interest to them. The scientist will make experiments on the system, sometimes more or less at random, sometimes following an intuition or an hypothesis. In so doing, the scientist accumulates observations and can build a model mapping the input parameters of the system (e.g. a sequence of amino acids) to its corresponding observed behavior (e.g. the resulting 3D shape of a protein), which often leads to a formalised model or simulation that is able to predict the behavior of the system studied.

This exploration loop is an important stage in many scientific fields. And as systems of study become more complex, consisting of multiple entities interacting with each other, they give rise to emergent phenomena that are difficult to predict. This is challenging both because the parameter space is often in high dimensions and the mapping from parameters to behaviors is highly non-linear and unpredictable.

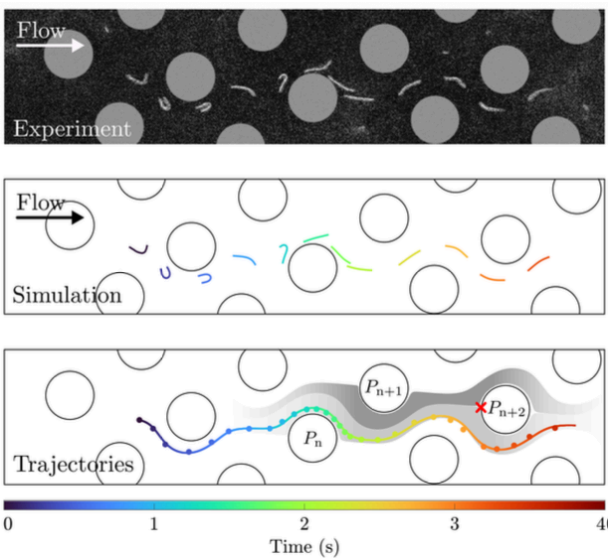
To help with this problem, the Flowers team has proposed to specialise curiosity-driven algorithms to help scientists in their work, which is part of the AI for Science movement. We have recently developed a framework for using them to explore any type of complex systems [4] (chapters 1,2,3, 2023). For example, the Flowers team has uncovered self-organised “creatures” in cellular automata [5, 8, 9] and hidden competencies in gene regulatory networks [6]. In the physical sciences, similar principles have been used to discover a new protocell droplet behavior [7] and to reveal new non-equilibrium behaviors in Kuramoto models [10].

In this internship, in close collaboration with researchers in the field of fluid dynamics, you will specialise curiosity-driven algorithms to find “interesting fiber behaviors” in a microfluidic fiber system.

System of study: Flexible fibers in microfluidic pillar arrays

It was recently discovered that when pushing flexible fibers through an array of micropillars tilted with respect to the flow, they act as a band-pass filter. Fibers whose length is close to the spacing of the array wrap around the pillars, build up internal tension and drift sideways, while shorter and longer ones are carried straight through [1].

To quote directly from their paper: “This migration arises from the interplay of fluid–structure interactions between



fibers and the complex flow and steric interactions with the pillars. Depending on their length, fibers exhibit distinct transport regimes: short fibers zigzag in between pillars following the flow, intermediate length fibers exhibit wrapping and jumping from one pillar to another, leading to lateral displacement, and long fibers deform extensively, following mixed zigzag-jump trajectories with small lateral migration.” [1]

That effect was found by sweeping two parameters of the system, the tilt angle and the fiber length under a steady flow. If we change the pillar pattern, or make the flow pulse in time, none of us can predict what the fibers will do without simulating it. Unfortunately, the parameter space is too large and simulations are too computationally expensive to swipe every possible combination of parameters.

Simulated environment

Blaise Delmotte's group developed a simulation which reproduces microfluidic fibre experiments very accurately [1, 2]. Their code splits the problem into two independent stages with different computational costs.

	Stage 1: Flow field	**Stage 2: Fiber trajectory**
What does it do?	The flow inside a square unit cell, with the lattice Boltzmann method	The trajectory and deformation of an elastic fiber carried by that flow, with a bead-spring model.
What are the parameters?	The geometry: pillar pattern, pillar radius, tilt angle of the array	Fiber length L, bending rigidity B, the time dependence of the flow (truncated Fourier decomposition), initial conditions.
What is the output?	≈ 3 minutes	≈ 30 minutes
How costly is it to run?	One flow field serves arbitrarily many fiber runs	One run yields one trajectory
Can we reuse it?	The velocity field in the unit cell	The position and the shape of the fiber at every time step

The output of Stage 2 is a whole spatio-temporal trajectory, i.e. a video of a fiber navigating through the pillars. This video can be used to define what an "interesting fiber behavior” is, and the migration angle measured in [1] was only one possible metric of interest. Modern curiosity-driven algorithms can learn from observations to define their own metrics as they interact with the system.

The chained two-stage structure of the simulator makes the exploration problem interesting and potentially differ from standard curiosity-driven algorithms formulations. Specifically, if computing the flow field is 10x faster than running a fiber trajectory, an agent might maintain predictive models over each stage, as well as over the overall pipeline, and use these predictions in innovative ways to decide on the next experiment considering its computational budget.

Internship project

The first two months will be spent building a working implementation and establishing baseline performance. This means getting familiar with the literature, running the simulator, and interfacing it with an autotelic exploration loop. Most of this initial work will be to connect existing code from the Flowers team to the microfluidic fiber simulator from Blaise's group and run a comparison of a few established curiosity-driven algorithms. During this phase, the pillars' geometry will stay fixed and only the second stage of the simulation will be explored (i.e. changing fiber length, rigidity and potentially the time dependence of the flow).

The project can then go in several directions, depending on what the first experiments reveal and on the interests of the candidate. Three questions interest us particularly, and we do not expect a single internship to address them all.

- **How to spend the computational budget across the two stages?** Could we predict, from a flow field alone, how much diversity of behavior it might support? Multi-stage simulators with such asymmetric costs are common in physics, but have received less attention in automated discovery.

- **How to represent the "fiber behavior" in ways that are useful to physicists?** Can a useful representation be learned directly from the raw trajectories alone (similar to [4, 8])? Could we constrain the exploration space to "plausibly real" outcomes based on the fundamental physics of the system?

- **How could a physicist interactively help refine what interesting means?** The algorithm might spend a lot of its computational budget on apparently novel behaviors that experts do not care about or that are within a "behavior category" experts already understand. How can a physicist look at a selection of trajectories and redirect the search towards their interest (see [4, 6, 10])?

By the end, a successful internship will lead to an open-source implementation of the full exploration loop, a comparison of exploration strategies (potentially including new variants based on the research questions above), and a catalogue of the transport regimes found (ideally shared on an accompanying website).

Depending on results and the candidate preferences, we will aim to publish the results in either high-impact interdisciplinary journals or more specialised AI/ML conferences (ICML, NeurIPS, ICLR).

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