Improved Decentralized Methods for Smart Active Matter: from Nonequilibrium Statistical Physics to Decentralized Optimization

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Active particles designate individuals which are able to convert energy into force generation or motion. Active materials made of these units span all scales of the living (from molecular motors to large animal groups) and synthetic (from colloidal swimmers to robot swarms) worlds. Applications for these materials have mainly revolved around the extraction of useful work from their directed or collective motion [1]. More recently the concepts of "intelligent" or "smart" active matter have emerged to describe systems able to perform computations on their own [2] or learn features to optimise a given behaviour [3]. In this latter application, active units move through physical space and are able to exchange policies with neighbouring units in order to collectively maximise a given reward function. There is thus a coupling between, on the one hand, physical space and the motion of active units therein, and on the other hand, the motion in the space of policies to maximise the reward function. This coupling raises the question of the simultaneous optimisation of both collective motion, in order to maximise the most relevant encounters between active units, and policy exchange dynamics, in order to speed up convergence to optimal values of the reward function.

In the evolving networks define by smart active matter, simple optimization approaches like the one presented in [3] may not exploit the interactions to their full potential. Indeed, existing methods rely on simple decentralised zeroth order algorithms, which do not take full advantage of recent advances in decentralised zeroth order optimisation [4] and accelerated decentralised learning [5]. The collective motion perspective could also offer a natural way of defining interactions, where active units interact when their trajectories coincide. Studying this type of networks could also have broader implications for decentralised optimisation, by complementing existing analyses of time-varying communication networks [6, 7].

This research project aims at exploring models of active learning units which pursue simultaneously both optimisation goals (collective motion in physical space and enhanced convergence in reward function space), using analytical and numerical tools from both applied mathematics and theoretical physics. It will involve the recruitment of a postdoctoral research for a duration of 24 months at the CMAP (Centre de Mathématiques Appliquées de Polytechnique), under the supervision of Paul Mangold (CMAP); in close collaboration with Yann-Edwin Keta (PMMH).

We are looking for a motivated postdoctoral researcher, holding a PhD in machine learning, statistical physics, or related fields. We expect candidates to be comfortable with stochastic processes and their treatment from either the mathematical (*e.g.* Markov chains, stochastic differential equations) and physical (*e.g.* Langevin–Fokker-Planck duality, kinetic theory) points of view.

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