Learning the Dynamics of the Galaxy

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OVERVIEW: This PhD project aims to explore and develop Deep Learning methods to interpret the dynamics of our Galaxy and its environment, as constrained by the state-of-the-art surveys that are coming on-line over the next decade. The PhD project will develop non-supervised methods to solve the underlying differential equations, to allow the data to tell us more directly the physical properties of interest (such as the Galactic mass distribution, or the distribution of stars in phase-space).

CONTEXT: Astrophysics stands at the dawn of a new era, with many large billion-euro class instruments and experiments coming on-line (in particular Gaia, Euclid and LSST, but also WEAVE, 4MOST and perhaps MSE). The revolutionary aspect of these endeavours is the large-scale mapping of the parameter space of observables. Given these huge infrastructure investments, our team has been active developing Deep Learning algorithms to allow us to thrive in this "Big Data" era. Our main effort last year in this direction was the development of an algorithm that we call the "ActionFinder" (Ibata et al. 2020, arXiv:2012.05250), which is able to find, in an unsupervised manner, the transformation from sky coordinates to canonical action and angle phase-space coordinates, either using observed stellar streams or using particles at different timesteps in a numerical simulation. The novelty of this technique is that it does not require the Hamiltonian of the system to be known in advance, and the potential can be quite general. This recent work has made us realize the huge scope for Deep Learning approaches in dynamics, which is enabled by the key technologies of massive parallelism and automatic differentiation in modern machine learning frameworks.

The approach we wish to take is to begin drifting away from the "traditional" Bayesian comparison of models to data, towards an approach where the data themselves take center-stage. This was the case with our "ActionFinder" algorithm mentioned above, which we will use over the coming months to derive a neural network to represent the acceleration field of the Galaxy, based solely on the assumption that the action derivatives are minimized along streams (orbits). We hope that the function represented by the neural network should provide a more faithful model of reality than a traditional analytical or parametric model.

Of course, the vast majority of stars are not in streams, and so in the thesis we intend to focus on developing new Deep Learning methods that can be used to analyse **normal field stars**. Recently, Green & Ting (2020, arXiv:2011.04673) have shown that it is possible to solve the collisionless Boltzmann equation (CBE) using an unsupervised scheme in which a normalising flow converts the discrete x,v of stars to predict the phase-space distribution function of the system. The distribution function, in turn, must obey the CBE and be consistent with a mass distribution that is positive everywhere. Green & Ting (2020) only show a proof of concept with a Plummer sphere (the simplest stellar model).

AIM: The present PhD project will explore the possibilities of using Deep Learning, and especially unsupervised methods to derive the properties of the Galaxy. At this stage we deliberately have very open goals, as the field is new but the technology is progressing rapidly. We will begin by generalising the work of Green & Ting (2020) to allow for more realistic configurations for the solution of the CBE. Ultimately, the aim here is to devise a method that can use the ultra-precise astrometric measurements from the Gaia space mission and all relevant complementary surveys to derive the phase space structure of the Galaxy and its mass distribution. We expect this to be challenging, especially due to the variations in depth, completeness and sky coverage of each survey.