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Lie-Poisson Neural Networks

Physics-Informed Neural Networks (PINNs) have acquired a lot of attention in recent years due to their potential for high-performance computations for complex physical systems. The idea of PINNs is to approximate the equations, as well as boundary and initial conditions, through a loss function for a neural network. For applications to canonical Hamiltonian systems, structure-preserving Symplectic Neural Networks (SympNets) were developed, computing canonical transformations and further extended to non-canonical systems due to the application of Darboux's theorem by writing non-canonical systems locally in canonical coordinates. We extend this theory further by developing the Lie-Poisson neural networks (LPNets), which can approximate the motion of solutions on a Poisson manifold given the Poisson bracket. Our method is based on the approximation of the motion using analytically solved motion for test Hamiltonians and given Poisson bracket. The method preserves all Casimirs to machine precision and yields an efficient and promising computational method for the dynamics of several finite-dimensional Lie groups, such as SO(3) (rigid body or satellite), SE(3) (Kirchhoff's equations for underwater vehicle) and other finite-dimensional Lie groups. We also discuss the applications of these ideas to infinite-dimensional systems.

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