| cases | doc_1 | doc_2 | decision | id |
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| | **authors**: Pengzhan Jin; Zhen Zhang; Ioannis G. Kevrekidis; George Em Karniadakis<br>**title**: Learning Poisson systems and trajectories of autonomous systems via Poisson neural networks<br>**publication_date**: 2020-12-05 22:18:29+00:00<br>**source**: SupportedSources.ARXIV<br>**journal**: None<br>**volume**: <br>**doi**: <br>**urls**: http://arxiv.org/pdf/2012.03133v1; http://arxiv.org/abs/2012.03133v1; http://arxiv.org/pdf/2012.03133v1<br>**id**: id-9115626794739639982<br>**abstract**: We propose the Poisson neural networks (PNNs) to learn Poisson systems and trajectories of autonomous systems from data. Based on the Darboux-Lie theorem, the phase flow of a Poisson system can be written as the composition of (1) a coordinate transformation, (2) an extended symplectic map and (3) the inverse of the transformation. In this work, we extend this result to the unknotted trajectories of autonomous systems. We employ structured neural networks with physical priors to approximate the three aforementioned maps. We demonstrate through several simulations that PNNs are capable of handling very accurately several challenging tasks, including the motion of a particle in the electromagnetic potential, the nonlinear Schr{\"o}dinger equation, and pixel observations of the two-body problem.<br>**versions**: | **authors**: Pengzhan Jin; Zhen Zhang; I. Kevrekidis; G. Karniadakis<br>**title**: Learning Poisson systems and trajectories of autonomous systems via Poisson neural networks<br>**publication_date**: 2020-12-05 00:00:00<br>**source**: SupportedSources.SEMANTIC_SCHOLAR<br>**journal**: IEEE transactions on neural networks and learning systems<br>**volume**: PP<br>**doi**: 10.1109/TNNLS.2022.3148734<br>**urls**: https://www.semanticscholar.org/paper/a521b4f034fc94a6ecbe6807c2183eed40320ca1<br>**id**: id-1579815318659059907<br>**abstract**: We propose the Poisson neural networks (PNNs) to learn Poisson systems and trajectories of autonomous systems from data. Based on the Darboux-Lie theorem, the phase flow of a Poisson system can be written as the composition of: 1) a coordinate transformation; 2) an extended symplectic map; and 3) the inverse of the transformation. In this work, we extend this result to the unknotted trajectories of autonomous systems. We employ structured neural networks with physical priors to approximate the three aforementioned maps. We demonstrate through several simulations that PNNs are capable of handling very accurately several challenging tasks, including the motion of a particle in the electromagnetic potential, the nonlinear SchrÃ¶dinger equation, and pixel observations of the two-body problem.<br>**versions**: | DUPLICATES | 294 |