

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none"><li>Muhammad Firmansyah Kasim</li><li>Yi Heng Lim</li></ul>	authors	<ul style="list-style-type: none"><li>Kasim, Muhammad Firmansyah</li><li>Lim, Yi Heng</li></ul>	DUPLICATES	196
	title	Constants of motion network	title	Constants of motion network		
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	urls	<ul style="list-style-type: none"><li>https://web.archive.org/web/20221007121637/https://arxiv.org/pdf/2208.10387v3.pdf</li></ul>	urls	<ul style="list-style-type: none"><li>http://arxiv.org/abs/2208.10387</li></ul>		
	id	id-6624862456826072147	id	id-6663553174597844191		
	abstract	The beauty of physics is that there is usually a conserved quantity in an always-changing system, known as the constant of motion. Finding the constant of motion is important in understanding the dynamics of the system, but typically requires mathematical proficiency and manual analytical work. In this paper, we present a neural network that can simultaneously learn the dynamics of the system and the constants of motion from data. By exploiting the discovered constants of motion, it can produce better predictions on dynamics and can work on a wider range of systems than Hamiltonian-based neural networks. In addition, the training progresses of our method can be used as an indication of the number of constants of motion in a system which could be useful in studying a novel physical system.	abstract	The beauty of physics is that there is usually a conserved quantity in an always-changing system, known as the constant of motion. Finding the constant of motion is important in understanding the dynamics of the system, but typically requires mathematical proficiency and manual analytical work. In this paper, we present a neural network that can simultaneously learn the dynamics of the system and the constants of motion from data. By exploiting the discovered constants of motion, it can produce better predictions on dynamics and can work on a wider range of systems than Hamiltonian-based neural networks. In addition, the training progresses of our method can be used as an indication of the number of constants of motion in a system which could be useful in studying a novel physical system.Comment: Accepted to NeurIPS 202		
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