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Titolo	Deep Learning in Multi-step Prediction of Chaotic Dynamics : From Deterministic Models to Real-World Systems / / by Matteo Sangiorgio, Fabio Dercole, Giorgio Guariso
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ISBN	3-030-94482-4
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Disciplina	003.857015118
Soggetti	Neural networks (Computer science) Computational intelligence Artificial intelligence System theory Mathematical Models of Cognitive Processes and Neural Networks Computational Intelligence Artificial Intelligence Complex Systems
Lingua di pubblicazione	Inglese
Formato	Materiale a stampa
Livello bibliografico	Monografia
Nota di contenuto	Introduction to chaotic dynamics' forecasting,. Basic concepts of chaos theory and nonlinear time-series analysis -- Artificial and real-world chaotic oscillators -- Neural approaches for time series forecasting -- Neural predictors' accuracy -- Neural predictors' sensitivity and robustness -- Concluding remarks on chaotic dynamics' forecasting.
Sommario/riassunto	The book represents the first attempt to systematically deal with the use of deep neural networks to forecast chaotic time series. Differently from most of the current literature, it implements a multi-step approach, i.e., the forecast of an entire interval of future values. This is relevant for many applications, such as model predictive control, that requires predicting the values for the whole receding horizon. Going progressively from deterministic models with different degrees of complexity and chaoticity to noisy systems and then to real-world cases, the book compares the performances of various neural network

architectures (feed-forward and recurrent). It also introduces an innovative and powerful approach for training recurrent structures specific for sequence-to-sequence tasks. The book also presents one of the first attempts in the context of environmental time series forecasting of applying transfer-learning techniques such as domain adaptation.