

cases	doc_1		doc_2		decision	id
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	authors	<ul style="list-style-type: none"><li>M. Mattheakis</li><li>H. Joy</li><li>P. Protopapas</li></ul>	authors	<ul style="list-style-type: none"><li>Marios Mattheakis</li><li>Hayden Joy</li><li>Pavlos Protopapas</li></ul>		
	title	Unsupervised Reservoir Computing for Solving Ordinary Differential Equations	title	Unsupervised Reservoir Computing for Solving Ordinary Differential Equations		
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	urls	<ul style="list-style-type: none"><li>https://www.semanticscholar.org/paper/e179bccc99bacf35018e42c58013043f4df7b7e9</li></ul>	urls	<ul style="list-style-type: none"><li>http://arxiv.org/pdf/2108.11417v1</li><li>http://arxiv.org/abs/2108.11417v1</li><li>http://arxiv.org/pdf/2108.11417v1</li></ul>		
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	abstract	There is a wave of interest in using unsupervised neural networks for solving differential equations. The existing methods are based on feed-forward networks, while recurrent neural network differential equation solvers have not yet been reported. We introduce an unsupervised reservoir computing (RC), an echo-state recurrent neural network capable of discovering approximate solutions that satisfy ordinary differential equations (ODEs). We suggest an approach to calculate time derivatives of recurrent neural network outputs without using backpropagation. The internal weights of an RC are fixed, while only a linear output layer is trained, yielding efficient training. However, RC performance strongly depends on finding the optimal hyper-parameters, which is a computationally expensive process. We use Bayesian optimization to efficiently discover optimal sets in a high-dimensional hyper-parameter space and numerically show that one set is robust and can be used to solve an ODE for different initial conditions and time ranges. A closed-form formula for the optimal output weights is derived to solve first order linear equations in a backpropagation-free learning process. We extend the RC approach by solving nonlinear system of ODEs using a hybrid optimization method consisting of gradient descent and Bayesian optimization. Evaluation of linear and nonlinear systems of equations demonstrates the efficiency of the RC ODE solver.	abstract	There is a wave of interest in using unsupervised neural networks for solving differential equations. The existing methods are based on feed-forward networks, {while} recurrent neural network differential equation solvers have not yet been reported. We introduce an unsupervised reservoir computing (RC), an echo-state recurrent neural network capable of discovering approximate solutions that satisfy ordinary differential equations (ODEs). We suggest an approach to calculate time derivatives of recurrent neural network outputs without using backpropagation. The internal weights of an RC are fixed, while only a linear output layer is trained, yielding efficient training. However, RC performance strongly depends on finding the optimal hyper-parameters, which is a computationally expensive process. We use Bayesian optimization to efficiently discover optimal sets in a high-dimensional hyper-parameter space and numerically show that one set is robust and can be used to solve an ODE for different initial conditions and time ranges. A closed-form formula for the optimal output weights is derived to solve first order linear equations in a backpropagation-free learning process. We extend the RC approach by solving nonlinear system of ODEs using a hybrid optimization method consisting of gradient descent and Bayesian optimization. Evaluation of linear and nonlinear systems of equations demonstrates the efficiency of the RC ODE solver.		
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