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			authors	<ul style="list-style-type: none">Jiequn HanArnulf JentzenW. E	DUPLICATES	312
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	abstract	Developing algorithms for solving high-dimensional partial differential equations (PDEs) has been an exceedingly difficult task for a long time, due to the notoriously difficult problem known as the "curse of dimensionality". This paper introduces a deep learning-based approach that can handle general high-dimensional parabolic PDEs. To this end, the PDEs are reformulated using backward stochastic differential equations and the gradient of the unknown solution is approximated by neural networks, very much in the spirit of deep reinforcement learning with the gradient acting as the policy function. Numerical results on examples including the nonlinear Black-Scholes equation, the Hamilton-Jacobi-Bellman equation, and the Allen-Cahn equation suggest that the proposed algorithm is quite effective in high dimensions, in terms of both accuracy and cost. This opens up new possibilities in economics, finance, operational research, and physics, by considering all participating agents, assets, resources, or particles together at the same time, instead of making ad hoc assumptions on their inter-relationships.	abstract	Significance Partial differential equations (PDEs) are among the most ubiquitous tools used in modeling problems in nature. However, solving high-dimensional PDEs has been notoriously difficult due to the “curse of dimensionality.” This paper introduces a practical algorithm for solving nonlinear PDEs in very high (hundreds and potentially thousands of) dimensions. Numerical results suggest that the proposed algorithm is quite effective for a wide variety of problems, in terms of both accuracy and speed. We believe that this opens up a host of possibilities in economics, finance, operational research, and physics, by considering all participating agents, assets, resources, or particles together at the same time, instead of making ad hoc assumptions on their interrelationships. Developing algorithms for solving high-dimensional partial differential equations (PDEs) has been an exceedingly difficult task for a long time, due to the notoriously difficult problem known as the “curse of dimensionality.” This paper introduces a deep learning-based approach that can handle general high-dimensional parabolic PDEs. To this end, the PDEs are reformulated using backward stochastic differential equations and the gradient of the unknown solution is approximated by neural networks, very much in the spirit of deep reinforcement learning with the gradient acting as the policy function. Numerical results on examples including the nonlinear Black–Scholes equation, the Hamilton–Jacobi–Bellman equation, and the Allen–Cahn equation suggest that the proposed algorithm is quite effective in high dimensions, in terms of both accuracy and cost. This opens up possibilities in economics, finance, operational research, and physics, by considering all participating agents, assets, resources, or particles together at the same time, instead of making ad hoc assumptions on their interrelationships.		
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