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authors	• M. Raissi • P. Perdikaris • G. Karniadakis	• M. Raissi • P. Perdikaris • G. Karniadakis	NOT DUPLICATES	374
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abstract	We introduce physics informed neural networks -- neural networks that are trained to solve supervised learning tasks while respecting any given law of physics described by general nonlinear partial differential equations. In this second part of our two-part treatise, we focus on the problem of data-driven discovery of partial differential equations. Depending on whether the available data is scattered in space-time or arranged in fixed temporal snapshots, we introduce two main classes of algorithms, namely continuous time and discrete time models. The effectiveness of our approach is demonstrated using a wide range of benchmark problems in mathematical physics, including conservation laws, incompressible fluid flow, and the propagation of nonlinear shallow-water waves.	We introduce physics informed neural networks â€“ neural networks that are trained to solve supervised learning tasks while respecting any given law of physics described by general nonlinear partial differential equations. In this two part treatise, we present our developments in the context of solving two main classes of problems: data-driven solution and data-driven discovery of partial differential equations. Depending on the nature and arrangement of the available data, we devise two distinct classes of algorithms, namely continuous time and discrete time models. The resulting neural networks form a new class of data-efficient universal function approximators that naturally encode any underlying physical laws as prior information. In this first part, we demonstrate how these networks can be used to infer solutions to partial differential equations, and obtain physics-informed surrogate models that are fully differentiable with respect to all input coordinates and free parameters.		
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