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	abstract	Well known to the machine learning community, the random feature model, originally introduced by Rahimi and Recht in 2008, is a parametric approximation to kernel interpolation or regression methods. It is typically used to approximate functions mapping a finite-dimensional input space to the real line. In this paper, we instead propose a methodology for use of the random feature model as a data-driven surrogate for operators that map an input Banach space to an output Banach space. Although the methodology is quite general, we consider operators defined by partial differential equations (PDEs); here, the inputs and outputs are themselves functions, with the input parameters being functions required to specify the problem, such as initial data or coefficients, and the outputs being solutions of the problem. Upon discretization, the model inherits several desirable attributes from this infinite-dimensional, function space viewpoint, including mesh-invariant approximation error with respect to the true PDE solution map and the capability to be trained at one mesh resolution and then deployed at different mesh resolutions. We view the random feature model as a non-intrusive data-driven emulator, provide a mathematical framework for its interpretation, and demonstrate its ability to efficiently and accurately approximate the nonlinear parameter-to-solution maps of two prototypical PDEs arising in physical science and engineering applications: viscous Burgers' equation and a variable coefficient elliptic equation	Well known to the machine learning community, the random feature model, originally introduced by Rahimi and Recht in 2008, is a parametric approximation to kernel interpolation or regression methods. It is typically used to approximate functions mapping a finite-dimensional input space to the real line. In this paper, we instead propose a methodology for use of the random feature model as a data-driven surrogate for operators that map an input Banach space to an output Banach space. Although the methodology is quite general, we consider operators defined by partial differential equations (PDEs); here, the inputs and outputs are themselves functions, with the input parameters being functions required to specify the problem, such as initial data or coefficients, and the outputs being solutions of the problem. Upon discretization, the model inherits several desirable attributes from this infinite-dimensional, function space viewpoint, including mesh-invariant approximation error with respect to the true PDE solution map and the capability to be trained at one mesh resolution and then deployed at different mesh resolutions. We view the random feature model as a non-intrusive data-driven emulator, provide a mathematical framework for its interpretation, and demonstrate its ability to efficiently and accurately approximate the nonlinear parameter-to-solution maps of two prototypical PDEs arising in physical science and engineering applications: viscous Burgers' equation and a variable coefficient elliptic equation		
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