JOHNS HOPKINS
Center for Environmental
& Applied Fluid Mechanics

Friday, April 27, 2018
3:00 PM, 132 Gilman Hall

"Data-Driven Discovery and Control of Nonlinear Systems"

Presented by Prof. Steven Brunton

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Abstract: The ability to discover physical laws and governing equations from data is one of humankind's greatest intellectual achievements. A quantitative understanding of dynamic constraints and balances in nature has facilitated rapid development of knowledge and enabled advanced technology, including aircraft, combustion engines, satellites, and electrical power. There are many more critical data-driven problems, such as understanding cognition from neural recordings, inferring patterns in climate, determining stability of financial markets, predicting and suppressing the spread of disease, and controlling turbulence for greener transportation and energy. With abundant data and elusive laws, data-driven discovery of dynamics will continue to play an increasingly important role in these efforts.

This work develops a general framework to discover the governing equations underlying a dynamical system simply from data measurements, leveraging advances in sparsity-promoting techniques and machine learning. The resulting models are parsimonious, balancing model complexity with descriptive ability while avoiding overfitting. The only assumption about the structure of the model is that there are only a few important terms that govern the dynamics, so that the equations are sparse in the space of possible functions. This perspective, combining dynamical systems with machine learning and sparse sensing, is explored with the overarching goal of real-time closed-loop feedback control of complex systems. Connections to modern Koopman operator theory are also discussed.

Bio: Steven L. Brunton is an Assistant Professor of Mechanical Engineering and a Data Science Fellow at the eScience Institute at the University of Washington in Seattle. He received a B.S. in Mathematics with a minor in Control and Dynamical Systems from Caltech in 2006, and received a Ph.D. in Mechanical and Aerospace Engineering from Princeton in 2012. His research interests include data-driven modeling and control, dynamical systems, sparse sensing and machine learning applied to complex systems in fluid dynamics, optics, neuroscience, bio-locomotion, and renewable energy.