[Review published in *SIAM Review*, Vol. 60, Issue 2, pp. 483.]

Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems. *By J. Nathan Kutz, Steven L. Brunton, Bingni W. Brunton, and Joshua L. Proctor*. SIAM, Philadelphia, 2016. $69.00. xvi+228 pp., softcover. ISBN 978-1-61197-449-2. https://doi.org/10.1137/1.9781611974508.

This book is a timely introduction to and exposition of dynamic mode decomposition (DMD), a data-driven method for the discovery of (low-dimensional) dynamical systems from high-dimensional data. The book not only introduces theory, connections, and innovations, but also contains a variety of realistic examples with accompanying MATLAB code. I like that the book brings many ideas and algorithms together, such as Koopman analysis, DMD, and compressed sensing. The chapters in the book are a balanced mixture of fundamental theory and application. For instance, Chapter 1 introduces DMD and in Chapter 2 the reader learns how to dynamically decompose data obtained from the fluid flow around a circular cylinder (provided on the book's website). This structure makes the book ideal not only for self-learners, but also as a (supplemental) text for a course which involves data analysis and/or dynamical systems.

Chapter 1 introduces DMD and sets the stage for the rest of the book. The definition of DMD is relatively straightforward. However, it turns out that DMD is connected to the Koopman operator (Chapters 3, 10), which is an infinite-dimensional linear operator that describes how measurements of a dynamical system evolve through the nonlinear dynamics. Moreover, it also is related to particular system identification methods (Chapter 6, 7), which identify input-output relationships from data. The addition of an explicitly controlled input to DMD is called DMD with control (DMDc). Employing tools from other fields, e.g., machine learning, compressed sensing, and data science, DMD becomes "innovated DMD." Chapter 5 is inspired by the idea of wavelets and describes multiresolution DMD (mrDMD), which targets resolution of multiscale features. In Chapter 8, noise rejection algorithms specifically designed for DMD of noisy data sets are reviewed. In Chapter 9, compressed and compressed-sensing DMD are described, which exploit the low-dimensional features in the data that can be extracted by DMD. The remaining chapters discuss a variety of (mainly diagnostic) applications: modal decomposition of fluid data (Chapter 2), video background separation (Chapter 4), modal decomposition of epidemiological data (Chapter 11), modal decomposition of neuroscience data (Chapter 12), and DMD-based prediction for financial trading (Chapter 13).

Altogether, the book is well structured and well written. If the reader is only interested in a definition of DMD, there is no need to buy this book. However, if one is interested in how DMD fits in the broader framework of applied mathematics, or how the method can be tailored for specific uses, or if one likes to contribute to the exciting and ongoing research of system identification for complex nonlinear systems, this book is a must-have. The authors have made every effort to present the material in a succinct and clear manner. I believe this book will provide many researchers with a head start in the field of data-based modeling. Are you DMD-ing yet?

DIRK M. LUCHTENBURG
The Cooper Union for the Advancement of Science and Art