

second chapter, but at the same time basic notions of convex optimization are introduced as well. Descent algorithms are discussed and analyzed in detail in the third chapter. In the corresponding convergence theorems and proofs, the modern view of the whole book becomes clear compared to [1]. In the foreground are complexity bounds of optimization algorithms, concerning the amount of computational effort required to obtain solutions of a given accuracy. These then allow one in particular to compare the frequently occurring sublinear convergence properties of algorithms with other algorithms in a concrete context.

The momentum methods and stochastic gradient methods frequently used in the context of data science are analyzed in detail in the following two chapters, although the Adam optimizer (adaptive momentum [2]), which is used as a quasi-standard in neural networks, is surprisingly not explicitly mentioned. But also in these chapters—as in the entire book—the theorems are didactically well prepared and the proofs are presented in detail with all necessary transformations. After the chapters on coordinate descent and first-order methods for constrained optimization, two central chapters on nonsmooth functions and nonsmooth optimization follow, discussing in particular the current approaches to proximal gradient and similar methods. Duality aspects and especially the ADMM (alternating direction method of multipliers), which is so important in applications, are presented in Chapter 10, which I would call the final chapter of the main text. Chapter 11, on algorithmic differentiation and adjoints, has rather the character of a preferred appendix.

This book by Stephen Wright and Benjamin Recht provides a very good basis for a course on optimization algorithms in data science. It is also suitable for self-study. For almost every chapter, exercises are provided to deepen the content. In addition, there is an extensive index that makes it much easier to search for individual keywords in the book. I highly recommend this book to anyone with an interest in data science and its foundations in algorithmic optimization.

REFERENCES

- [1] J. NOCEDAL AND S. J. WRIGHT, *Numerical Optimization*, 2nd ed., Springer, New York, 2006.
- [2] D. P. KINGMA AND J. BA, *Adam: A Method for Stochastic Optimization*, <https://arxiv.org/abs/1412.6980>, 2014–2017.

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Foundations of Computational Imaging: A Model-Based Approach. By Charles A. Bouman. SIAM, Philadelphia, 2022. \$84.00. xii+337, softcover. ISBN 978-1-611977-12-7. <https://doi.org/10.1137/1.9781611977134>.

Let me begin this review with the conclusion: This is an excellent text for a graduate-level course in computational imaging. The book was written by Dr. Charles A. Bouman, Showalter Professor of Electrical and Computer Engineering and Biomedical Engineering at Purdue University. Dr. Bouman noted in the preface that when he first started writing this book 20 years ago for the course that he was teaching, “Computational Imaging did not yet exist as a field.” I imagine for many readers that is difficult to imagine now, given the broad range of applications of computational imaging, which include computational microscopy, tomographic imaging, MRI, ultrasound imaging, computational photography, Synthetic Aperture Radar (SAR), seismic imaging, and so many others.

What is the one thing that I like most about *Foundations of Computational Imaging: A Model-Based Approach*? I would say it is how the book has achieved the author’s stated goal of providing “a foundation for a collection of theoretical material that can serve as a common language for both researchers and practitioners of Computational Imaging.” Indeed, this book is the first (and so far only) one that I have encountered that almost seamlessly compiles a range of traditional and cutting-edge methods into a single resource. As such, it establishes a shared groundwork for the mathematical and statistical tech-

niques employed in computational imaging, a concept previously dispersed across multiple sources. That shared groundwork renders the book both accessible and useful to researchers from diverse fields, such as applied mathematics, physics, chemistry, optics, and signal processing.

Image reconstruction is a major part of computational imaging. Dr. Bouman presents the image reconstruction challenge as a classical inverse problem, via the lens of the Bayesian framework. Here is the question we ask: How do we reconstruct the original image X from some physical sensing system that yields measurements Y , which are contingent on this unknown image X ? These measurements Y are typically characterized by substantial redundancy and noise. The data representing the crucial components of an authentic image are akin to a sparse set within another large set. The modeling approach that the author takes considers the physical system and the image X as random quantities. A forward model of the system is given by $p(y|x)$, the conditional distribution of the data Y given the original (unknown) image X . This distribution describes how the measurements are related to the original image and captures both the deterministic characteristics of the imaging system and probabilistic elements (e.g., noise and perturbations). Within this framework, problems can be categorized based on several distinctive aspects, including single versus dual physical dimensions, causal versus non-causal analysis, continuous versus discrete time, and Gaussian versus non-Gaussian frameworks.

The book is structured to unveil the intricacies that emerge within the aforementioned defining dimensions. It comprises a total of 17 short chapters and four appendices. The opening chapter offers a concise introduction to computational imaging. Following this, Chapters 2 to 4 provide an overview of fundamental probabilistic tools, as well as 1D and 2D causal and noncausal Gaussian (Markov random field) models. The subsequent trio of chapters (5 through 7) delves into essential tools and algorithms for maximum a posteriori (MAP) estimation. Chapters 8 to 10 encompass the results derived from constrained optimization

algorithms that are necessary for advancing through the rest of the book.

Chapter 11 offers an in-depth discussion of model parameter estimation. The subsequent four chapters (12 to 15) deliver a comprehensive introduction to vital concepts related to the EM algorithm, Markov chains, hidden Markov chains (HMM), and stochastic simulation, which includes a variety of sampling techniques. The final two chapters (16 and 17) expound on Bayesian segmentation and Poisson data models. To complement the core content, four appendices provide additional insights.

Each chapter includes a set of exercise problems (always good in a textbook) at varying difficulty levels. At the end of the book there is a list of nearly 100 pertinent references to the literature that span several decades. It is noteworthy that the very first citation concerns the development of computed tomography (CT) by Cormack and Hounsfield, who won the Nobel Prize in Physiology or Medicine in 1979—that brings home the importance of computational imaging.

To reiterate, this is an excellent text for a graduate-level course where students have a decent background in probability and statistics. It is also a helpful text for researchers or practitioners in medical and other types of imaging. While computing-related fields often evolve rapidly, I can see this book staying relevant for years to come.

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Climate, Chaos and COVID: How Mathematical Models Describe the Universe. By *Chris Budd*. World Scientific, London, 2023. \$78.00. xii+301 pp., hardcover. ISBN 978-1-80061-304-1.

Mathematical modeling played a high profile and, at times, controversial role in the world's response to the COVID-19 pandemic. The modeling of Neil Ferguson and his team at Imperial College is credited with derailing the UK government's laissez-faire approach to the pandemic in early March 2020. Here in New Zealand, where I live, mathematical models underpinned our elimination of the virus and, together