



1st ed. 2020, X, 502 p. 150 illus.

Printed book

Hardcover

Ca. 169,99 € | Ca. £149.99 | Ca. \$219.99

^[1]Ca. 181,89 € (D) | Ca. 186,99 € (A) | Ca. CHF 200,50

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R. Zoppoli, M. Sanguineti, G. Gnecco, T. Parisini

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Neural Approximations for Optimal Control and Decision

May 10, 2019

Springer

Berlin Heidelberg New York
Hong Kong London
Milan Paris Tokyo

To my beloved wife, Maria Giovanna, and our sons,
Federica and Gabriele
R. Z.

To my parents, Enrico and Maria, to my aunt, Gianna, and
in memory of my grandmother, Caterina
M. S.

To my mother, Rosanna, and in memory of my father, Giuseppe
G. G.

To my daughter, Francesca, to my beloved wife, Germana, and
in memory of Sandro
T. P.

Preface

Many scientific and technological areas of major interest require one to solve infinite-dimensional optimization problems, also called functional optimization problems. In such a context, one has to minimize (or maximize) a functional with respect to admissible solutions belonging to infinite-dimensional spaces of functions, often dependent on a large number of variables. This is the case, for example, with analysis and design of large-scale communication and traffic networks, stochastic optimal control of nonlinear dynamic systems with a large number of state variables, optimal management of complex team organizations, freeway traffic congestion control, optimal management of reservoir systems, reconstruction of unknown environments, Web exploration, etc. Typically, infinite dimension makes inapplicable many mathematical tools used in finite-dimensional optimization.

The subject of the book is the approximate solution of infinite-dimensional optimization problems arising in the fields of optimal control and decision. When optimal solutions to such problems cannot be found analytically and/or numerical solutions are not easily implementable, classical approaches to find approximate solutions often incur at least one form of the so-called “curse of dimensionality” (e.g., an extremely fast growth – with respect to the number of variables of the admissible solutions – of the computational load required to obtain suboptimal solutions within a desired accuracy).

The book aims at presenting into a unified framework theories and algorithms to solve approximately infinite-dimensional optimization problems whose admissible solutions may depend on a large number of variables. A multiplicity of tools, approaches, and results originating from different fields (e.g., functional optimization, optimal control and decision, neural computation, linear and nonlinear approximation theory, stochastic approximation, statistical and deterministic machine learning theories, Monte Carlo and quasi-Monte Carlo sampling) are brought together to construct a novel, general, and mathematically sound optimization methodology. The basic tool is the use of a family of nonlinear approximators, which include commonly-used neu-

ral networks, to reduce infinite-dimensional optimization problems to finite-dimensional nonlinear programming ones.

When admissible solutions depend on a large number of variables, as it typically happens in the kind of problems we are mostly interested in the book, various instances of the above-mentioned curse of dimensionality may arise with respect to a suitably-defined “dimension” of the task one is facing. Hence, we devote particular attention to develop a theoretical apparatus and algorithmic tools capable of coping with such a drawback. To this end, suitable computational models and sampling techniques are combined to cope with the curse of dimensionality in approximation of multivariable functions and in sampling high-dimensional domains, respectively.

A word has to be said on the role played in the book by data and learning from data. More specifically, in our approach we try to exploit the fruitful exchange between machine learning and optimization. Indeed, while machine learning exploits optimization models and algorithms, it simultaneously poses problems which often constitute optimization challenges. This cross-fertilization is particularly evident in the problems dealt with in the book.

The major special feature of the monograph is the fact that, to the best of the Authors’ knowledge, it is the first one explicitly devoted to the subject of neural networks and other nonlinear approximators for the solution of infinite-dimensional optimization problems arising in optimal control and decision.

The main benefit of reading the book is the possibility of understanding and becoming capable to apply the above-mentioned optimization methodology, whose ingredients come from scientific fields with high potentiality of interaction, but whose joint use seems to be still limited. Indeed, the book is conceived to combine into a unified framework the Authors’ different expertises. Their complementary backgrounds are exploited to develop solid mathematical foundations, a powerful solution methodology, and efficient algorithms. This represents the very strength of the book, which deals with problems whose complexity makes scientific and technological “contaminations” mandatory to be successful in finding accurate suboptimal solutions.

The examples provided, which often deal with real-world applications, are detailed numerically, so as to allow the reader not only to clearly understand the proposed methodology, but also to compare it in practice with traditional approaches.

The book offers:

- A thorough illustration of theoretical insights to solve approximately infinite-dimensional optimization problems whose admissible solutions depend on large numbers of variables.
- A derivation of the theoretical properties of a methodology of approximate infinite-dimensional optimization (named “Extended Ritz Method”, or shortly, ERIM), based on families of nonlinear approximators which include commonly used shallow and deep neural networks as special cases.

- An overview of classical numerical computational methods for optimal control and decision (e.g., discrete-time dynamic programming, batch and stochastic gradient techniques, the Ritz method).
- Bounds on the errors of the approximate solutions.
- Efficient algorithms for a wide range of problems, e.g.: optimal control and decision in a deterministic and in a stochastic environment, over a finite and an infinite time horizon, with and without guaranteed upper bounds on the approximation error, with a centralized and a decentralized structure.
- Several examples, often dealing with real-world applications of major interest (such as routing in communications networks, freeway traffic congestion control, and optimal management of reservoir systems, etc.), whose approximate solutions are detailed and compared numerically.

Thanks to its multidisciplinary nature, this monograph can be of interest to researchers, postgraduates, 4th-3rd year undergraduates, and practitioners in Automatic Control, Operations Research, Computer Science, and various branches of Engineering and Economics. In general, the prerequisites are basic concepts of multivariate calculus, probability theory, optimization, control engineering, and so on. For the reader's convenience, more advanced techniques are introduced when needed.

Finally, we are thankful to our institutions and to a number of scholars and colleagues for their contributions to the book. We wish to thank first and foremost Marco Baglietto and Angelo Alessandri for the discussions on most topics and, in particular, the former for suggestions about team optimal control theory. Then, we mention Cristiano Cervellera, who introduced us to important concepts of quasi-Monte Carlo methods and deterministic learning theory. Our work took advantage of discussions with Vera Kůrková and Paul Kainen on mathematical foundations of approximation and optimization via neural networks. Mauro Gaggero and Serena Ivaldi helped us in deriving numerical solutions for some examples. Aldo Grattarola clarified us some aspects of probability theory. We are most grateful to Alfredo Bellen, Stefano Maset, and Marino Zennaro at the University of Trieste for suggestions and advice on specific approximation theory concepts and to several other colleagues, among which Federico Girosi, Frank Lewis, and Marios M. Polycarpou, whose suggestions greatly improved the content of the book. Mrs. Daniela Solari supported the exchange of drafts among the authors and Mrs. Altea Ariano reviewed the English of the whole manuscript. The last author acknowledges the research support funding of the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No. 739551 (KIOS CoE), of ABB and of Danieli Group. The authors wish to thank their Publisher Dr. Oliver Jackson for his help, support, encouragement, and patience during this project and for the high-quality production of the book.

X Preface

Genoa, London, Lucca, Trieste. May 2019.

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