

Preface

This book is an introduction to machine learning control (MLC), a surprisingly simple model-free methodology to tame complex nonlinear systems. These systems are assumed to be manipulated by a finite number of actuators (inputs) and monitored by a finite number of sensors (outputs). The control logic is chosen to minimize a well-defined cost functional.

MLC brings together three well-established disciplines: the theory of closed-loop feedback control, machine learning and regression, and the nonlinear dynamical systems that are characteristic of turbulent fluid flows. Over the past decades, control theory has developed into a mature discipline with a beautiful theoretical foundation and powerful associated numerical algorithms. Important advances have been made to enable robust control of systems with sensor noise, external disturbances, and model uncertainty. Modern methods from control theory now pervade the engineering sciences and have transformed the industrial landscape. However, challenges remain for the control of systems with strongly nonlinear dynamics leading to broadband frequency spectra, a high-dimensional state space, and large time delays. MLC begins to address these challenges using advanced methods from machine learning to *discover* effective control laws.

Many turbulence control problems are not adequately described by linear models, have exceedingly large state spaces, and suffer from time delays from actuators to sensors via nonlinear convective fluid dynamic effects. Take for instance the aerodynamic drag minimization of a car with actuators at the back side, pressure sensors distributed over the car, and a smart feedback control logic. Numerical simulation of the underlying dynamics given by the Navier–Stokes equations requires days or weeks, while the control system requires actuation decisions on the order of milliseconds. Reduced-order models that incorporate nonlinearities, multiscale phenomena, and actuation effects have eluded many serious efforts and will likely remain elusive for years to come. In short, there may not even be a viable model for robust control design. Nevertheless, the literature contains many studies on turbulence control, with the majority either employing open-loop forcing such as periodic blowing, slowly adapting a working open-loop

strategy, or stabilizing an underlying laminar solution such as a laminar boundary layer on an aircraft wing. Feedback control responding to dominant flow structures in real time may be found in numerical studies but is rarely found in real-world experiments with turbulent flows. Indeed, turbulence control is a grand challenge problem in engineering, with far-reaching potential scientific, industrial, and societal impact.

Yet, just looking at the flight maneuvers of a bird, bat, or insect, it is clear that nature has found impressive feedback flow control solutions without employing advanced mathematical models. An eagle, for instance, can land gently on a rocky surface under gusty wind conditions and in rain by moving its wings and feathers to expertly manipulate fluid forces. More than 50 years ago, Ingo Rechenberg and Hans-Peter Schwefel have emulated nature's evolutionary way to optimize flow properties at the former Hermann-Föttinger-Institut of the Berlin Institute of Technology, Germany. Their pioneering evolutionary strategies started evolutionary computations. Subsequent innovations include evolutionary programming (Fogel Owens and Walsh 1966), genetic algorithms (Holland 1975) and genetic programming (Koza 1992). These evolutionary computations constitute an important pillar of machine learning. In a visionary publication in 1959, the artificial intelligence pioneer Arthur Samuel defined machine learning as a 'field of study that gives computers the ability to learn without being explicitly programmed.' Machine learning is a rapidly evolving discipline of computer science that is benefiting from the current explosion of big data. It has successfully improved an immense range of technologies—from the smart phone to the autopilot in Tesla's Sedan and to large-scale factory processes. In academia, nearly all scientific disciplines are profiting from machine learning.

Not surprisingly, machine learning methods may augment or replace control design in myriad applications. Robots learn to walk with dynamic programming. Genetic algorithms are used to optimize the coefficients in proportional–integral–derivative (PID) controllers. The groups of N. Benard and E. Moreau employ genetic algorithms to optimize linear sensor feedback in a flow control experiment. Reinforcement learning has been successfully applied to stabilize chaotic dynamics, and has recently also reduced cavity noise in an experiment operated by F. Lusseyran, L. Pastur and L. Mathelin. The authors of this book have pushed the first applications of genetic programming in feedback control of nonlinear dynamics, direct Navier–Stokes simulations and experimental turbulent shear flows. This book focuses on arguably one of the simplest, most versatile and yet very powerful version of machine learning control: Optimal nonlinear control laws are identified with genetic programming. Corresponding success stories are described throughout this book.

The authors have taught material from this book in several university courses. These courses focus on basic principles using simple examples, and the content requires anywhere from 15 to 30 h to cover. Our students have had backgrounds in computer science, control theory, nonlinear dynamics, or fluid mechanics. The prospective reader is not expected to have hands-on expertise in any of these fields but should come with the ambition to control a complex system. The book is

organized as follows. In Chap. 1, the reader is introduced to feedback control and its challenges for complex real-world problems. Chapter 2 constitutes the core of the book. This chapter formulates feedback control as a regression problem and employs genetic programming as a powerful regression technique to identify the best feedback law. Chapter 3 reviews classical methods of control theory against which MLC is benchmarked in Chap. 4 for linear and weakly nonlinear dynamics. These chapters provide context for feedback control, but they are not required to implement the MLC methods in Chap. 2. The hurried reader may jump to Chap. 5 if she/he is interested in strongly nonlinear dynamics applications or to Chap. 6 if she/he is interested in experimental implementations of feedback flow control. Chapter 7 distills good practices for real-world experiments that need to be taken into account in any MLC implementation. In Chap. 8 we provide an outlook on future methodological advances, which are expected to drastically amplify the applicability and performance of MLC. In addition, we list a number of future MLC applications with epic proportions.

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Thomas Duriez
Steven L. Brunton
Bernd R. Noack

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Duriez, Th.; Brunton, S.; Noack, B.R.

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