Introduction To Computational Learning Theory Pdf

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CHOI KIERA

Learning Theory Springer Science & Business Media
This work explores probabilistic models of supervised learning problems and addresses the key statistical and computational questions. Chapters survey research on pattern classification with binary-output networks, including a discussion of the relevance of the Vapnik Chervonenkis dimension, and of estimates of the dimension for several neural network models. In addition, the authors develop a model of classification by real-output networks, and demonstrate the usefulness of classification...
Information Theory, Inference and Learning Algorithms Academic Press
Emphasizing issues of computational efficiency, Michael Kearns and Umesh Vazirani introduce a number of central topics in computational learning theory for researchers and students in artificial intelligence, neural networks, theoretical computer science, and statistics. Emphasizing issues of computational efficiency, Michael Kearns and Umesh Vazirani introduce a number of central topics in computational learning theory for researchers and students in artificial intelligence, neural networks, theoretical computer science, and statistics. Computational learning theory is a new and rapidly expanding area of research that examines formal models of induction with the goals of discovering the common methods underlying efficient learning algorithms and identifying the computational impediments to learning. Each topic in the book has been chosen to elucidate a general principle, which is explored in a precise formal setting. Intuition has been emphasized in the presentation to make the material accessible to the nontheoretician while still providing precise arguments for the specialist. This balance is the result of new proofs of established theorems, and new presentations of the standard proofs. The topics covered include the motivation, definitions, and fundamental results, both positive and negative, for the widely studied L. G. Valiant model of Probably Approximately Correct Learning; Occam's Razor, which formalizes a relationship between learning and data compression; the Vapnik-Chervonenkis dimension; the equivalence of weak and strong learning; efficient learning in the presence of noise by the method of statistical queries; relationships between learning and cryptography, and the resulting computational limitations on efficient learning; reducibility between learning problems; and algorithms for learning finite automata from active experimentation.
with Applications in R MIT Press
The aim of this book is to discuss the fundamental ideas which lie behind the statistical theory of learning and generalization. It considers learning as a general problem of function estimation based on empirical data. Omitting proofs and technical details, the author concentrates on discussing the main results of learning theory and their connections to fundamental problems in statistics. This second edition contains three new chapters devoted to further development of the learning theory and SVM techniques. Written in a readable and concise style, the book is intended for statisticians, mathematicians, physicists, and computer scientists.
Mathematics for Machine Learning Cambridge University Press
"Intended as an upper-level undergraduate or introductory graduate text in computer science theory," this book lucidly covers the key concepts and theorems of the theory of computation. The presentation is remarkably clear; for example, the "proof idea," which offers the reader an intuitive feel for how the proof was constructed, accompanies many of the theorems and a proof. Introduction to the Theory of Computation covers the usual topics for this type of text plus it features a solid section on complexity theory--including an entire chapter on space complexity. The final chapter introduces more advanced topics, such as the discussion of complexity classes associated with probabilistic algorithms.
Computational Learning Approaches to Data Analytics in Biomedical Applications MIT Press
An Introduction to Statistical Learning provides an accessible overview of the field of statistical learning, an essential toolset for making sense of the vast and complex data sets that have emerged in fields ranging from biology to finance to marketing to astrophysics in the past twenty years. This book presents some of the most important modeling and prediction techniques, along with relevant applications. Topics include linear regression, classification, resampling methods, shrinkage approaches, tree-based methods, support vector machines, clustering, and more. Color graphics and real-world examples are used to illustrate the methods presented. Since the goal of this textbook is to facilitate the use of these statistical learning techniques by practitioners in science, industry, and other fields, each chapter contains a tutorial on implementing the analyses and methods presented in R, an extremely popular open source statistical software platform. Two of the authors co-wrote The Elements of Statistical Learning (Hastie, Tibshirani and Friedman, 2nd edition 2009), a popular reference book for statistics and machine learning researchers. An Introduction to Statistical Learning covers many of the same topics, but at a level accessible to a much broader audience. This book is targeted at statisticians and non-statisticians alike who wish to use cutting-edge statistical learning techniques to analyze their data. The text assumes only a previous course in linear regression and no knowledge of matrix algebra.
Introduction to Machine Learning Cambridge University Press
Machine Learning, a vital and core area of artificial intelligence (AI), is propelling the AI field ever further and making it one of the most compelling areas of computer science research. This textbook offers a comprehensive and unbiased introduction to almost all aspects of machine learning, from the fundamentals to advanced topics. It consists of 16 chapters divided into three

parts: Part 1 (Chapters 1-3) introduces the fundamentals of machine learning, including terminology, basic principles, evaluation, and linear models; Part 2 (Chapters 4-10) presents classic and commonly used machine learning methods, such as decision trees, neural networks, support vector machines, Bayesian classifiers, ensemble methods, clustering, dimension reduction and metric learning; Part 3 (Chapters 11-16) introduces some advanced topics, covering feature selection and sparse learning, computational learning theory, semi-supervised learning, probabilistic graphical models, rule learning, and reinforcement learning. Each chapter includes exercises and further reading, so that readers can explore areas of interest. The book can be used as an undergraduate or postgraduate textbook for computer science, computer engineering, electrical engineering, data science, and related majors. It is also a useful reference resource for researchers and practitioners of machine learning.

Learning and Generalisation CRC Press

Computational Learning Approaches to Data Analytics in Biomedical Applications provides a unified framework for biomedical data analysis using varied machine learning and statistical techniques. It presents insights on biomedical data processing, innovative clustering algorithms and techniques, and connections between statistical analysis and clustering. The book introduces and discusses the major problems relating to data analytics, provides a review of influential and state-of-the-art learning algorithms for biomedical applications, reviews cluster validity indices and how to select the appropriate index, and includes an overview of statistical methods that can be applied to increase confidence in the clustering framework and analysis of the results obtained. Includes an overview of data analytics in biomedical applications and current challenges Updates on the latest research in supervised learning algorithms and applications, clustering algorithms and cluster validation indices Provides complete coverage of computational and statistical analysis tools for biomedical data analysis Presents hands-on training on the use of Python libraries, MATLAB® tools, WEKA, SAP-HANA and R/Bioconductor

Discover How To Harness Uncertainty With Python Elsevier

The fundamental mathematical tools needed to understand machine learning include linear algebra, analytic geometry, matrix decompositions, vector calculus, optimization, probability and statistics. These topics are traditionally taught in disparate courses, making it hard for data science or computer science students, or professionals, to efficiently learn the mathematics. This self-contained textbook bridges the gap between mathematical and machine learning texts, introducing the mathematical concepts with a minimum of prerequisites. It uses these concepts to derive four central machine learning methods: linear regression, principal component analysis, Gaussian mixture models and support vector machines. For students and others with a mathematical background, these derivations provide a starting point to machine learning texts. For those learning the mathematics for the first time, the methods help build intuition and practical experience with applying mathematical concepts. Every chapter includes worked examples and exercises to test understanding. Programming tutorials are offered on the book's web site.

From Theory to Algorithms Cambridge University Press

A new edition of a graduate-level machine learning textbook that focuses on the analysis and theory of algorithms. This book is a general introduction to machine learning that can serve as a textbook for graduate students and a reference for researchers. It covers fundamental modern topics in machine learning while providing the theoretical basis and conceptual tools needed for the discussion and justification of algorithms. It also describes several key aspects of the application of these algorithms. The authors aim to present novel theoretical tools and concepts while giving concise proofs even for relatively advanced topics. Foundations of Machine Learning is unique in its focus on the analysis and theory of algorithms. The first four chapters lay the theoretical foundation for what follows; subsequent chapters are mostly self-contained. Topics covered include the Probably Approximately Correct (PAC) learning framework; generalization bounds based on Rademacher complexity and VC-dimension; Support Vector Machines (SVMs); kernel methods; boosting; on-line learning; multi-class classification; ranking; regression; algorithmic stability; dimensionality reduction; learning automata and languages; and reinforcement learning. Each chapter ends with a set of exercises. Appendixes provide additional material including concise probability review. This second edition offers three new chapters, on model selection, maximum entropy models, and conditional entropy models. New material in the appendixes includes a major section on Fenchel duality, expanded coverage of concentration inequalities, and an entirely new entry on information theory. More than half of the exercises are new to this edition.

Circuits of the Mind MIT Press

This an introduction to the theory of computational learning.

Introduction to Semi-supervised Learning Cengage Learning

Briefly, we review the basic elements of computability theory and prob ability theory that are required. Finally, in order to place the subject in the appropriate historical and conceptual context we trace the main roots of Kolmogorov complexity. This way the stage is set for Chapters 2 and 3, where we introduce the notion of optimal effective descriptions of objects. The length of such a description (or the number of bits of information in it) is its Kolmogorov complexity. We treat all aspects of the elementary mathematical theory of Kolmogorov complexity. This body of knowledge may be called algo rithmic complexity theory. The theory of Martin-Lof tests for random ness of finite objects and infinite sequences is inextricably intertwined with the theory of Kolmogorov complexity and is completely treated. We also investigate the statistical properties of finite strings with high Kolmogorov complexity. Both of these topics are eminently useful in the applications part of the book. We also investigate the recursion theoretic properties of Kolmogorov complexity (relations with Godel's incompleteness result), and the Kolmogorov complexity version of infor mation theory, which we may call "algorithmic information theory" or "absolute information theory. " The treatment of algorithmic probability theory in Chapter 4 presup poses Sections 1. 6, 1. 11. 2, and Chapter 3 (at least Sections 3. 1 through 3. 4).

An Introduction to Kolmogorov Complexity and Its Applications MIT Press

This is the first comprehensive introduction to computational learning theory. The author's uniform presentation of fundamental results and their applications offers AI researchers a theoretical perspective on the problems they study. The book presents tools for the analysis of probabilistic models of learning, tools that crisply classify what is and is not efficiently learnable. After a general introduction to Valiant's PAC paradigm and the important notion of the Vapnik-Chervonenkis dimension, the author explores specific topics such as finite automata and neural networks. The presentation is intended for a broad audience--the author's ability to motivate and pace discussions for beginners has been praised by reviewers. Each chapter contains numerous examples and exercises, as well as a useful summary of important results. An excellent introduction to the area, suitable either for a first course, or as a component in general machine

learning and advanced AI courses. Also an important reference for AI researchers.
The Computational Complexity of Machine Learning Cambridge University Press
Computational intelligence is a well-established paradigm, where new theories with a sound biological understanding have been evolving. The current experimental systems have many of the characteristics of biological computers (brains in other words) and are beginning to be built to perform a variety of tasks that are difficult or impossible to do with conventional computers. As evident, the ultimate achievement in this field would be to mimic or exceed human cognitive capabilities including reasoning, recognition, creativity, emotions, understanding, learning and so on. This book comprising of 17 chapters offers a step-by-step introduction (in a chronological order) to the various modern computational intelligence tools used in practical problem solving. Staring with different search techniques including informed and uninformed search, heuristic search, minmax, alpha-beta pruning methods, evolutionary algorithms and swarm intelligent techniques; the authors illustrate the design of knowledge-based systems and advanced expert systems, which incorporate uncertainty and fuzziness. Machine learning algorithms including decision trees and artificial neural networks are presented and finally the fundamentals of hybrid intelligent systems are also depicted. Academics, scientists as well as engineers engaged in research, development and application of computational intelligence techniques, machine learning and data mining would find the comprehensive coverage of this book invaluable.
Probability for Machine Learning MIT Press
The significantly expanded and updated new edition of a widely used text on reinforcement learning, one of the most active research areas in artificial intelligence. Reinforcement learning, one of the most active research areas in artificial intelligence, is a computational approach to learning whereby an agent tries to maximize the total amount of reward it receives while interacting with a complex, uncertain environment. In Reinforcement Learning, Richard Sutton and Andrew Barto provide a clear and simple account of the field's key ideas and algorithms. This second edition has been significantly expanded and updated, presenting new topics and updating coverage of other topics. Like the first edition, this second edition focuses on core online learning algorithms, with the more mathematical material set off in shaded boxes. Part I covers as much of reinforcement learning as possible without going beyond the tabular case for which exact solutions can be found. Many algorithms presented in this part are new to the second edition, including UCB, Expected Sarsa, and Double Learning. Part II extends these ideas to function approximation, with new sections on such topics as artificial neural networks and the Fourier basis, and offers expanded treatment of off-policy learning and policy-gradient methods. Part III has new chapters on reinforcement learning's relationships to psychology and neuroscience, as well as an updated case-studies chapter including AlphaGo and AlphaGo Zero, Atari game playing, and IBM Watson's wagering strategy. The final chapter discusses the future societal impacts of reinforcement learning.
Cambridge University Press
Sure to be influential, Watanabe's book lays the foundations for the use of algebraic geometry in statistical learning theory. Many models/machines are singular: mixture models, neural networks, HMMs, Bayesian networks, stochastic context-free grammars are major examples. The theory achieved here underpins accurate estimation techniques in the presence of singularities.
Computational Learning Theory John Wiley & Sons
This book provides a broad yet detailed introduction to neural networks and machine learning in a statistical framework. A single, comprehensive resource for study and further research, it explores the major popular neural network models and statistical learning approaches with examples and exercises and allows readers to gain a practical working understanding of the content. This updated new edition presents recently published results and includes six new chapters that correspond to the recent advances in computational learning theory, sparse coding, deep learning, big data and cloud computing. Each chapter features state-of-the-art descriptions and significant research findings. The topics covered include: • multilayer perceptron; • the Hopfield network; • associative memory models;• clustering models and algorithms; • t he radial basis function network; • recurrent neural networks; • nonnegative matrix factorization; • independent component analysis; •probabilistic and Bayesian networks; and • fuzzy sets and logic. Focusing on the prominent accomplishments and their practical aspects, this book provides academic and technical staff, as well as graduate students and researchers with a solid foundation and comprehensive reference on the fields of neural networks, pattern recognition, signal processing, and machine learning.
A Modern Approach Springer Nature
Table of contents
An Introduction to Machine Learning Springer
We also give algorithms for learning powerful concept classes under the uniform distribution, and give equivalences between natural models of efficient learnability. This thesis also includes detailed definitions and motivation for the distribution-free model, a chapter discussing past research in this model and related models, and a short list of important open problems."
Understanding Machine Learning MIT Press
Presenting a theory of the theoryless, a computer scientist provides a model of how effective behavior can be learned even in a world as complex as our own, shedding new light on human nature.
Intelligent Systems Springer Science & Business Media
Machine Learning has become a key enabling technology for many engineering applications, investigating scientific questions and theoretical problems alike. To stimulate discussions and to disseminate new results, a summer school series was started in February 2002, the documentation of which is published as LNAI 2600. This book presents revised lectures of two subsequent summer schools held in 2003 in Canberra, Australia, and in Tübingen, Germany. The tutorial lectures included are devoted to statistical learning theory, unsupervised learning, Bayesian inference, and applications in pattern recognition; they provide in-depth overviews of exciting new developments and contain a large number of references. Graduate students, lecturers, researchers and professionals alike will find this book a useful resource in learning and teaching machine learning.