Introduction To Statistical Learning Theory

with Applications in R
A Statistical View of Boosting
Neural Networks and Statistical Learning
Data Mining, Inference, and Prediction
Information Theory, Inference and Learning Algorithms
Information Theory and Statistical Learning
Statistical Learning and Data Science
An Elementary Introduction to Statistical Learning Theory
Data Mining, Inference, and Prediction
A Computational Approach to Statistical Learning
Principles of Statistics
Advanced Lectures on Machine Learning
A Bayesian and Optimization Perspective
Statistical Learning with Math and Python
The Nature of Statistical Learning Theory
Statistical Foundations of Data Science
a Concise Introduction
Who to Release?
Additive Logistic Regression
An Introduction to Statistical Learning
Reliable Reasoning
Statistical Learning Theory and Stochastic Optimization
Machine Learning
An Introduction to Computational Learning Theory
Introduction to Statistical and Machine Learning Methods for Data Science
with Applications in R
100 Exercises for Building Logic
The Elements of Statistical Learning
All of Statistics
Induction and Statistical Learning Theory
A Practical Approach on the Statistical Learning Theory
Machine Learning
An Introduction to Statistical Learning Methods with R
Applied Predictive Modeling
Machine Learning
Understanding Machine Learning
The Elements of Statistical Learning
Statistical Learning Theory

FINN ROACH

with Applications in R John Wiley & Sons
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.
A Statistical View of Boosting MIT Press
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.
Neural Networks and Statistical Learning Springer Science & Business Media
A Computational Approach to Statistical Learning gives a novel introduction to predictive modeling by focusing on the algorithmic and numeric motivations behind popular statistical methods. The text contains annotated code to over 80 original reference functions. These functions provide minimal working implementations of common statistical learning algorithms. Every chapter concludes with a fully worked out application that illustrates predictive modeling tasks using a real-world dataset. The text begins with a detailed analysis of linear models and ordinary least squares. Subsequent chapters explore extensions such as ridge regression, generalized linear models, and additive models. The second half focuses on the use of general-purpose algorithms for convex optimization and their application to tasks in statistical learning. Models covered include the elastic net, dense neural networks, convolutional neural networks (CNNs), and spectral clustering. A unifying theme throughout the text is the use of optimization theory in the description of predictive models, with a particular focus on the singular value decomposition (SVD). Through this theme, the computational approach motivates and clarifies the relationships between various predictive models. Taylor Arnold is an assistant professor of statistics at the University of Richmond. His work at the intersection of computer vision, natural language processing, and digital humanities has been supported by multiple grants from the National Endowment for the Humanities (NEH) and the American Council of Learned Societies (ACLS). His first book, Humanities Data in R, was published in 2015. Michael Kane is an assistant professor of biostatistics at Yale University. He is the recipient of grants from the National Institutes of Health (NIH), DARPA, and the Bill and Melinda Gates Foundation. His R package bigmemory won the Chamber's prize for statistical software in 2010. Bryan Lewis is an applied mathematician and author of many popular R packages, including irlba, doRedis, and threejs.
Data Mining, Inference, and Prediction MIT Press
Summary Machine Learning in Action is unique book that blends the foundational theories of machine learning with the practical realities of building tools for everyday data analysis. You'll use the flexible Python programming language to build programs that implement algorithms for data classification, forecasting, recommendations, and higher-level features like summarization and simplification. About the Book A machine is said to learn when its performance improves with experience. Learning requires algorithms and programs that capture data and ferret out the interestingor useful patterns. Once the specialized domain of analysts and mathematicians, machine learning is becoming a skill needed by many. Machine Learning in Action is a clearly written tutorial for developers. It avoids academic language and takes you straight to the techniques you'll use in your day-to-day work. Many (Python) examples present the core algorithms of statistical data processing, data analysis, and data visualization in code you can reuse. You'll understand the concepts and how they fit in with tactical tasks like classification, forecasting, recommendations, and higher-level features like summarization and simplification. Readers need no prior experience with machine learning or statistical processing. Familiarity with Python is helpful. Purchase of the print book comes with an offer of a free PDF, ePub, and Kindle eBook from Manning. Also available is all code from the book. What's Inside A no-nonsense introduction Examples showing common ML tasks Everyday data analysis Implementing classic algorithms like Apriori and Adaboos Table of Contents PART 1 CLASSIFICATION Machine learning basics Classifying with k-Nearest Neighbors Splitting datasets one feature at a time: decision trees Classifying with probability theory: naïve Bayes Logistic regression Support vector machines Improving classification with the AdaBoost meta algorithm PART 2 FORECASTING NUMERIC VALUES WITH REGRESSION Predicting numeric values: regression Tree-based regression PART 3 UNSUPERVISED LEARNING Grouping unlabeled items using k-means clustering Association analysis with the Apriori algorithm Efficiently finding frequent itemsets with FP-growth PART 4 ADDITIONAL TOOLS Using principal component analysis to simplify data Simplifying data with the singular value decomposition Big data and MapReduce
Information Theory, Inference and Learning Algorithms CRC Press
Table of contents
Information Theory and Statistical Learning Springer Nature
Applied Predictive Modeling covers the overall predictive modeling process, beginning with the crucial steps of data preprocessing, data splitting and foundations of model tuning. The text then provides intuitive explanations of numerous common and modern regression and classification techniques, always with an emphasis on illustrating and solving real data problems. The text illustrates all parts of the modeling process through many hands-on, real-life examples, and every chapter contains extensive R code for each step of the process. This multi-purpose text can be used as an introduction to predictive models and the overall modeling process, a practitioner's reference handbook, or as a text for advanced undergraduate or graduate level predictive modeling courses. To that end, each chapter contains problem sets to help solidify the covered concepts and uses data

available in the book’s R package. This text is intended for a broad audience as both an introduction to predictive models as well as a guide to applying them. Non-mathematical readers will appreciate the intuitive explanations of the techniques while an emphasis on problem-solving with real data across a wide variety of applications will aid practitioners who wish to extend their expertise. Readers should have knowledge of basic statistical ideas, such as correlation and linear regression analysis. While the text is biased against complex equations, a mathematical background is needed for advanced topics.

Statistical Learning and Data Science Routledge

This interdisciplinary text offers theoretical and practical results of information theoretic methods used in statistical learning. It presents a comprehensive overview of the many different methods that have been developed in numerous contexts.

An Elementary Introduction to Statistical Learning Theory Springer

Statistical learning theory is aimed at analyzing complex data with necessarily approximate models. This book is intended for an audience with a graduate background in probability theory and statistics. It will be useful to any reader wondering why it may be a good idea, to use as is often done in practice a notoriously "wrong'' (i.e. over-simplified) model to predict, estimate or classify. This point of view takes its roots in three fields: information theory, statistical mechanics, and PAC-Bayesian theorems. Results on the large deviations of trajectories of Markov chains with rare transitions are also included. They are meant to provide a better understanding of stochastic optimization algorithms of common use in computing estimators. The author focuses on non-asymptotic bounds of the statistical risk, allowing one to choose adaptively between rich and structured families of models and corresponding estimators. Two mathematical objects pervade the book: entropy and Gibbs measures. The goal is to show how to turn them into versatile and efficient technical tools, that will stimulate further studies and results.

Data Mining, Inference, and Prediction Morgan Kaufmann

Taken literally, the title "All of Statistics" is an exaggeration. But in spirit, the title is apt, as the book does cover a much broader range of topics than a typical introductory book on mathematical statistics. This book is for people who want to learn probability and statistics quickly. It is suitable for graduate or advanced undergraduate students in computer science, mathematics, statistics, and related disciplines. The book includes modern topics like non-parametric curve estimation, bootstrapping, and classification, topics that are usually relegated to follow-up courses. The reader is presumed to know calculus and a little linear algebra. No previous knowledge of probability and statistics is required. Statistics, data mining, and machine learning are all concerned with collecting and analysing data.

A Computational Approach to Statistical Learning Springer Nature

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.

Principles of Statistics Springer Science & Business Media

A practitioner’s tools have a direct impact on the success of his or her work. This book will provide the data scientist with the tools and techniques required to excel with statistical learning methods in the areas of data access, data munging, exploratory data analysis, supervised machine learning, unsupervised machine learning and model evaluation. Machine learning and data science are large disciplines, requiring years of study in order to gain proficiency. This book can be viewed as a set of essential tools we need for a long-term career in the data science field – recommendations are provided for further study in order to build advanced skills in tackling important data problem domains. The R statistical environment was chosen for use in this book. R is a growing phenomenon worldwide, with many data scientists using it exclusively for their project work. All of the code examples for the book are written in R. In addition, many popular R packages and data sets will be used.

Advanced Lectures on Machine Learning SAS Institute

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 Bayesian and Optimization Perspective Springer Science & Business Media
Concise description of classical statistics, from basic dice probabilities to modern regression analysis. Equal stress on theory and applications. Moderate difficulty; only basic calculus required. Includes problems with answers.
Statistical Learning with Math and Python Cambridge University Press
A self-contained and coherent account of probabilistic techniques, covering: distance measures, kernel rules, nearest neighbour rules, Vapnik-Chervonenkis theory, parametric classification, and feature extraction. Each chapter concludes with problems and exercises to further the readers understanding. Both research workers and graduate students will benefit from this wide-ranging and up-to-date account of a fast- moving field.
The Nature of Statistical Learning Theory CRC Press
This book is concerned to explore the changing role of the Parole Board across the range of its responsibilities, including the prediction of risk and deciding on the release (or continued detention) of the growing number of recalled prisoners and of those subject to indeterminate sentences. In doing so it aims to rectify the lack of attention that has been given by lawyers, academics and practitioners to back door sentencing (where the real length of a sentence is decided by those who take the decision to release) compared to front door sentencing' (decisions taken by judges or magistrates in court). Particular attention is given in this book to the important changes made to the role and working of the Parole Board as a result of the impact of the early release scheme of the Criminal Justice Act 2005, with the Parole Board now deciding in Panels concerned with determinate sentence prisoners, lifers and recalled prisoners. A wide range of significant issues, and case law, has arisen as a result of these changes, which the contributors to this book, leading authorities in the field, aim to explore.
Statistical Foundations of Data Science Technics Publications
This book presents the Statistical Learning Theory in a detailed and easy to understand way, by using practical examples, algorithms and source codes. It can be used as a textbook in graduation or undergraduation courses, for self-learners, or as reference with respect to the main theoretical concepts of Machine Learning. Fundamental concepts of Linear Algebra and Optimization applied to Machine Learning are provided, as well as source codes in R, making the book as self-contained as possible. It starts with an introduction to Machine Learning concepts and algorithms such as the Perceptron, Multilayer Perceptron and the Distance-Weighted Nearest Neighbors with examples, in order to provide the necessary foundation so the reader is able to understand the Bias-Variance Dilemma, which is the central point of the Statistical Learning Theory. Afterwards, we introduce all assumptions and formalize the Statistical Learning Theory, allowing the practical study of different classification algorithms. Then, we proceed with concentration inequalities until arriving to the Generalization and the Large-Margin bounds, providing the main motivations for the Support Vector Machines. From that, we introduce all necessary optimization concepts related to the implementation of Support Vector Machines. To provide a next stage of development, the book finishes with a discussion on SVM kernels as a way and motivation to study data spaces and improve classification results.
a Concise Introduction Springer Science & Business Media
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.
Who to Release? Springer
Advanced statistical modeling and knowledge representation techniques for a newly emerging area of machine learning and probabilistic reasoning; includes introductory material, tutorials for different proposed approaches, and applications. Handling inherent uncertainty and exploiting compositional structure are fundamental to understanding and designing large-scale systems. Statistical relational learning builds on ideas from probability theory and statistics to address uncertainty while incorporating tools from logic, databases and programming languages to represent structure. In Introduction to Statistical Relational Learning, leading researchers in this emerging area of machine learning describe current formalisms, models, and algorithms that enable effective and robust reasoning about richly structured systems and data. The early chapters provide tutorials for material used in later chapters, offering introductions to representation, inference and learning in graphical models, and logic. The book then describes object-oriented approaches, including probabilistic relational models, relational Markov networks, and probabilistic entity-relationship models as well as logic-based formalisms including Bayesian logic programs, Markov logic, and stochastic logic programs. Later chapters discuss such topics as probabilistic models with unknown objects, relational dependency networks, reinforcement learning in relational domains, and information extraction. By presenting a variety of approaches, the book highlights commonalities and clarifies important differences among proposed approaches and, along the way, identifies important representational and algorithmic issues. Numerous applications are provided throughout.
Additive Logistic Regression "O'Reilly Media, Inc."
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.

An Introduction to Statistical Learning Simon and Schuster

Discover New Methods for Dealing with High-Dimensional Data A sparse statistical model has only a small number of nonzero parameters or weights; therefore, it is much easier to estimate and interpret than a dense model. Statistical Learning with Sparsity: The Lasso and Generalizations presents methods that exploit sparsity to help recover the underlying signal in a set of data. Top experts in this rapidly evolving field, the authors describe the lasso for linear regression and a simple coordinate descent algorithm for its computation. They discuss the application of l1 penalties to generalized linear models and support vector machines, cover generalized penalties such as the elastic net and group lasso, and review numerical methods for optimization. They also present statistical inference methods for fitted (lasso) models, including the bootstrap, Bayesian methods, and recently developed approaches. In addition, the book examines matrix decomposition, sparse multivariate analysis, graphical models, and compressed sensing. It concludes with a survey of theoretical results for the lasso. In this age of big data, the number of features measured on a person or object can be large and might be larger than the number of observations. This book shows how the sparsity assumption allows us to tackle these problems and extract useful and reproducible patterns from big datasets. Data analysts, computer scientists, and theorists will appreciate this thorough and up-to-date treatment of sparse statistical modeling.