Information Theory Inference And Learning Algorithms

Information Theory, Inference and Learning Algorithms **Information Theory , Inference And Learning Algorithms** *Foundations of Probabilistic Logic Programming* **Inference and Learning Systems for Uncertain Relational Data** *Elements of Causal Inference Dynamic Bayesian Networks* **The Elements of Statistical Learning** **Inference and Learning from Data** **Inference and Learning from Data** **Inference and Learning from Data** All of Statistics **Scientific Inference** *Artificial Intelligence and Causal Inference* Targeted Learning in Data Science **Targeted Learning Computer Vision Active Inference Machine Learning Hardware-Aware Probabilistic Machine Learning Models** **Mean-field Approaches for Network Inference and Learning** The Elements of Statistical Learning **Machine Learning for Knowledge Discovery with R** Advanced Lectures on Machine Learning **Grammatical Inference Efficient Inference and Learning in Decimatable Boltzmann Machines** **Visual Inference for IoT Systems: A Practical Approach** *Learning and Inference in Computational Systems Biology* An Introduction to Lifted Probabilistic Inference **Mathematics for Machine Learning** **Emerging Biometrics: Deep Inference and Other Computational Intelligence** **Computer Age Statistical Inference** **Statistical Physics, Optimization, Inference, and Message-Passing Algorithms** An Introduction to Statistical Inference and Its Applications with R Bayesian Reasoning and Machine Learning Statistical Inference and Machine Learning for Big Data Statistical Machine Learning *The Elements of Statistical Learning* **Grammatical Inference: Learning Syntax from Sentences** **Introduction to Statistical Relational Learning** *Grammatical Inference and Applications*

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Visual Inference for IoT Systems: A Practical Approach Sep 03 2020 This book presents a systematic approach to the implementation of Internet of Things (IoT) devices achieving visual inference through deep neural networks. Practical aspects are covered, with a focus on providing guidelines to optimally select hardware and software components as well as network architectures according to prescribed application requirements. The monograph includes a remarkable set of experimental results and functional procedures supporting the theoretical concepts and methodologies introduced. A case study on animal recognition based on smart camera traps is also presented and thoroughly analyzed. In this case study, different system alternatives are explored and a particular realization is completely developed. Illustrations, numerous plots from simulations and experiments, and supporting information in the form of charts and tables make Visual Inference and IoT Systems: A Practical Approach a clear and detailed guide to the topic. It will be of interest to researchers, industrial practitioners, and graduate students in the fields of computer vision and IoT.
An Introduction to Lifted Probabilistic Inference Jul 01 2020 Recent advances in the area of lifted

inference, which exploits the structure inherent in relational probabilistic models. Statistical relational AI (StaRAI) studies the integration of reasoning under uncertainty with reasoning about individuals and relations. The representations used are often called relational probabilistic models. Lifted inference is about how to exploit the structure inherent in relational probabilistic models, either in the way they are expressed or by extracting structure from observations. This book covers recent significant advances in the area of lifted inference, providing a unifying introduction to this very active field. After providing necessary background on probabilistic graphical models, relational probabilistic models, and learning inside these models, the book turns to lifted inference, first covering exact inference and then approximate inference. In addition, the book considers the theory of liftability and acting in relational domains, which allows the connection of learning and reasoning in relational domains.

Computer Age Statistical Inference Mar 29 2020 The twenty-first century has seen a breathtaking expansion of statistical methodology, both in scope and in influence. 'Big data', 'data science', and 'machine learning' have become familiar terms in the news, as statistical methods are brought to bear upon the enormous data sets of modern science and commerce. How did we get here? And where are we going? This book takes us on an exhilarating journey through the revolution in data analysis following the introduction of electronic computation in the 1950s. Beginning with classical inferential theories - Bayesian, frequentist, Fisherian - individual chapters take up a series of influential topics: survival analysis, logistic regression, empirical Bayes, the jackknife and bootstrap, random forests, neural networks, Markov chain Monte Carlo, inference after model selection, and dozens more. The distinctly modern approach integrates methodology and algorithms with statistical inference. The book ends with speculation on the future direction of statistics and data science.

The Elements of Statistical Learning Apr 22 2022 During the past decade there has been an explosion in computation and information technology. With it have come vast amounts of data in a variety of fields such as medicine, biology, finance, and marketing. The challenge of understanding these data has led to the development of new tools in the field of statistics, and spawned new areas such as data mining, machine learning, and bioinformatics. Many of these tools have common underpinnings but are often expressed with different terminology. This book describes the important ideas in these areas in a common conceptual framework. While the approach is statistical, the emphasis is on concepts rather than mathematics. Many examples are given, with a liberal use of color graphics. It should be a valuable resource for statisticians and anyone interested in data mining in science or industry. The book’s coverage is broad, from supervised learning (prediction) to unsupervised learning. The many topics include neural networks, support vector machines, classification trees and boosting---the first comprehensive treatment of this topic in any book. This major new edition features many topics not covered in the original, including graphical models, random forests, ensemble methods, least angle regression & path algorithms for the lasso, non-negative matrix factorization, and spectral clustering. There is also a chapter on methods for “wide” data (p bigger than n), including multiple testing and false discovery rates. Trevor Hastie, Robert Tibshirani, and Jerome Friedman are professors of statistics at Stanford University. They are prominent researchers in this area: Hastie and Tibshirani developed generalized additive models and wrote a popular book of that title. Hastie co-developed much of the statistical modeling software and environment in R/S-PLUS and invented principal curves and surfaces. Tibshirani proposed the lasso and is co-author of the very successful An Introduction to the Bootstrap. Friedman is the co-inventor of many data-mining tools including CART, MARS, projection pursuit and gradient boosting.

Machine Learning for Knowledge Discovery with R Jan 07 2021 Machine Learning for Knowledge Discovery with R contains methodologies and examples for statistical modelling, inference, and prediction of data analysis. It includes many recent supervised and unsupervised machine learning methodologies such as recursive partitioning modelling, regularized regression, support vector machine, neural network, clustering, and causal-effect inference. Additionally, it emphasizes statistical thinking of data analysis, use of statistical graphs for data structure exploration, and result presentations. The book includes many real-world data examples from life-science, finance, etc. to illustrate the applications of the methods described therein. Key Features: Contains statistical theory for the most recent supervised and unsupervised machine learning methodologies. Emphasizes broad statistical thinking, judgment, graphical methods, and collaboration with subject-matter-experts in analysis, interpretation, and presentations.

Written by statistical data analysis practitioner for practitioners. The book is suitable for upper-level-undergraduate or graduate-level data analysis course. It also serves as a useful desk-reference for data analysts in scientific research or industrial applications.

Emerging Biometrics: Deep Inference and Other Computational Intelligence Apr 29 2020 This paper aims at identifying emerging computational intelligence trends for the design and modeling of complex biometric-enabled infrastructure and systems. Biometric-enabled systems are evolving towards deep learning and deep inference using the principles of adaptive computing, – the front tides of the modern computational intelligence domain.

Grammatical Inference Nov 05 2020 The problem of inducing, learning or inferring grammars has been studied for decades, but only in recent years has grammatical inference emerged as an independent field with connections to many scientific disciplines, including bio-informatics, computational linguistics and pattern recognition. This book meets the need for a comprehensive and unified summary of the basic techniques and results, suitable for researchers working in these various areas. In Part I, the objects of use for grammatical inference are studied in detail: strings and their topology, automata and grammars, whether probabilistic or not. Part II carefully explores the main questions in the field: What does learning mean? How can we associate complexity theory with learning? In Part III the author describes a number of techniques and algorithms that allow us to learn from text, from an informant, or through interaction with the environment. These concern automata, grammars, rewriting systems, pattern languages or transducers.

Statistical Physics, Optimization, Inference, and Message-Passing Algorithms Feb 26 2020 This text gathers the lecture notes of the Les Houches Summer School that was held in October 2013 for an audience of advanced graduate students and post-doctoral fellows in statistical physics, theoretical physics, machine learning, and computer science.

Targeted Learning Aug 14 2021 The statistics profession is at a unique point in history. The need for valid statistical tools is greater than ever; data sets are massive, often measuring hundreds of thousands of measurements for a single subject. The field is ready to move towards clear objective benchmarks under which tools can be evaluated. Targeted learning allows (1) the full generalization and utilization of cross-validation as an estimator selection tool so that the subjective choices made by humans are now made by the machine, and (2) targeting the fitting of the probability distribution of the data toward the target parameter representing the scientific question of interest. This book is aimed at both statisticians and applied researchers interested in causal inference and general effect estimation for observational and experimental data. Part I is an accessible introduction to super learning and the targeted maximum likelihood estimator, including related concepts necessary to understand and apply these methods. Parts II-IX handle complex data structures and topics applied researchers will immediately recognize from their own research, including time-to-event outcomes, direct and indirect effects, positivity violations, case-control studies, censored data, longitudinal data, and genomic studies.

Foundations of Probabilistic Logic Programming Aug 26 2022

Elements of Causal Inference Jun 24 2022 A concise and self-contained introduction to causal inference, increasingly important in data science and machine learning. The mathematization of causality is a relatively recent development, and has become increasingly important in data science and machine learning. This book offers a self-contained and concise introduction to causal models and how to learn them from data. After explaining the need for causal models and discussing some of the principles underlying causal inference, the book teaches readers how to use causal models: how to compute intervention distributions, how to infer causal models from observational and interventional data, and how causal ideas could be exploited for classical machine learning problems. All of these topics are discussed first in terms of two variables and then in the more general multivariate case. The bivariate case turns out to be a particularly hard problem for causal learning because there are no conditional independences as used by classical methods for solving multivariate cases. The authors consider analyzing statistical asymmetries between cause and effect to be highly instructive, and they report on their decade of intensive research into this problem. The book is accessible to readers with a background in machine learning or statistics, and can be used in graduate courses or as a reference for researchers. The text includes code snippets that can be copied and pasted, exercises, and an appendix with a summary of the

most important technical concepts.
Grammatical Inference: Learning Syntax from Sentences Aug 22 2019 This book constitutes the refereed proceedings of the Third International Colloquium on Grammatical Inference, ICGI-96, held in Montpellier, France, in September 1996. The 25 revised full papers contained in the book together with two invited key papers by Magerman and Knuutila were carefully selected for presentation at the conference. The papers are organized in sections on algebraic methods and algorithms, natural language and pattern recognition, inference and stochastic models, incremental methods and inductive logic programming, and operational issues.
Inference and Learning from Data Feb 20 2022 Discover techniques for inferring unknown variables and quantities with the second volume of this extraordinary three-volume set.
Inference and Learning from Data Mar 21 2022 Discover data-driven learning methods with the third volume of this extraordinary three-volume set.
Advanced Lectures on Machine Learning Dec 06 2020 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.
Mean-field Approaches for Network Inference and Learning Mar 09 2021
Inference and Learning from Data Jan 19 2022 Discover core topics in inference and learning with the first volume of this extraordinary three-volume set.
Machine Learning May 11 2021 Machine Learning: A Bayesian and Optimization Perspective, 2nd edition, gives a unified perspective on machine learning by covering both pillars of supervised learning, namely regression and classification. The book starts with the basics, including mean square, least squares and maximum likelihood methods, ridge regression, Bayesian decision theory classification, logistic regression, and decision trees. It then progresses to more recent techniques, covering sparse modelling methods, learning in reproducing kernel Hilbert spaces and support vector machines, Bayesian inference with a focus on the EM algorithm and its approximate inference variational versions, Monte Carlo methods, probabilistic graphical models focusing on Bayesian networks, hidden Markov models and particle filtering. Dimensionality reduction and latent variables modelling are also considered in depth. This palette of techniques concludes with an extended chapter on neural networks and deep learning architectures. The book also covers the fundamentals of statistical parameter estimation, Wiener and Kalman filtering, convexity and convex optimization, including a chapter on stochastic approximation and the gradient descent family of algorithms, presenting related online learning techniques as well as concepts and algorithmic versions for distributed optimization. Focusing on the physical reasoning behind the mathematics, without sacrificing rigor, all the various methods and techniques are explained in depth, supported by examples and problems, giving an invaluable resource to the student and researcher for understanding and applying machine learning concepts. Most of the chapters include typical case studies and computer exercises, both in MATLAB and Python. The chapters are written to be as self-contained as possible, making the text suitable for different courses: pattern recognition, statistical/adaptive signal processing, statistical/Bayesian learning, as well as courses on sparse modeling, deep learning, and probabilistic graphical models. New to this edition: Complete re-write of the chapter on Neural Networks and Deep Learning to reflect the latest advances since the 1st edition. The chapter, starting from the basic perceptron and feed-forward neural networks concepts, now presents an in depth treatment of deep networks, including recent optimization algorithms, batch normalization, regularization techniques such as the dropout method, convolutional neural networks, recurrent neural networks, attention mechanisms, adversarial examples and training, capsule networks and generative architectures, such as restricted Boltzman machines (RBMs), variational autoencoders and generative adversarial networks (GANs). Expanded treatment of Bayesian learning to include nonparametric Bayesian methods, with a focus on the

Chinese restaurant and the Indian buffet processes. Presents the physical reasoning, mathematical modeling and algorithmic implementation of each method Updates on the latest trends, including sparsity, convex analysis and optimization, online distributed algorithms, learning in RKH spaces, Bayesian inference, graphical and hidden Markov models, particle filtering, deep learning, dictionary learning and latent variables modeling Provides case studies on a variety of topics, including protein folding prediction, optical character recognition, text authorship identification, fMRI data analysis, change point detection, hyperspectral image unmixing, target localization, and more

Efficient Inference and Learning in Decimatable Boltzmann Machines Oct 04 2020 Abstract: "Inference and learning in general Boltzmann machines are NP-hard problems. Several restricted Boltzmann machines can be handled efficiently with the decimation technique known from statistical mechanics. A set of thus decimatable Boltzmann machines is defined. We show that the Fourier-Stieltjes transformation of the probability distribution given by a Boltzmann machine is closely related to its partition sum. Decimation allows for the efficient calculation of the partition sum with the help of an adjoint deterministic feedforward network. We exploit this structure in order to specify powerful algorithms for exact inference and learning. The original stochastic Boltzmann machine may be disregarded, since all relevant probability computations can be performed exactly in the corresponding adjoint networks."

Dynamic Bayesian Networks May 23 2022

The Elements of Statistical Learning Feb 08 2021

Learning and Inference in Computational Systems Biology Aug 02 2020 Tools and techniques for biological inference problems at scales ranging from genome-wide to pathway-specific. Computational systems biology unifies the mechanistic approach of systems biology with the data-driven approach of computational biology. Computational systems biology aims to develop algorithms that uncover the structure and parameterization of the underlying mechanistic model--in other words, to answer specific questions about the underlying mechanisms of a biological system--in a process that can be thought of as learning or inference. This volume offers state-of-the-art perspectives from computational biology, statistics, modeling, and machine learning on new methodologies for learning and inference in biological networks.The chapters offer practical approaches to biological inference problems ranging from genome-wide inference of genetic regulation to pathway-specific studies. Both deterministic models (based on ordinary differential equations) and stochastic models (which anticipate the increasing availability of data from small populations of cells) are considered. Several chapters emphasize Bayesian inference, so the editors have included an introduction to the philosophy of the Bayesian approach and an overview of current work on Bayesian inference. Taken together, the methods discussed by the experts in Learning and Inference in Computational Systems Biology provide a foundation upon which the next decade of research in systems biology can be built. Florence d'Alch e-Buc, John Angus, Matthew J. Beal, Nicholas Brunel, Ben Calderhead, Pei Gao, Mark Girolami, Andrew Golightly, Dirk Husmeier, Johannes Jaeger, Neil D. Lawrence, Juan Li, Kuang Lin, Pedro Mendes, Nicholas A. M. Monk, Eric Mjolsness, Manfred Opper, Claudia Rangel, Magnus Rattray, Andreas Ruttor, Guido Sanguinetti, Michalis Titsias, Vladislav Vyshemirsky, David L. Wild, Darren Wilkinson, Guy Yosiphon

Mathematics for Machine Learning May 31 2020 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.

Inference and Learning Systems for Uncertain Relational Data Jul 25 2022 With the advent of the

Semantic Web, which makes use of formalisms based on Description Logics (DLs) for knowledge representation, it has become increasingly important to tackle the problem of managing uncertain information. The main goal of this book is to propose inference and (distributed) learning algorithms for Probabilistic Logic Programs (PLPs) and Probabilistic Description Logics (PDLs). Moreover two web applications are presented: cplint on SWISH (http://www.cplint.eu/) and TRILL on SWISH (http://trill-sw.eu/) that allow, with just a web browser, to perform inference over PLPs and PDLs respectively. The book provides guidelines for using all these systems. The book is self-contained and progresses from the most basic concepts of First-Order Logic to the most advanced issues of Statistical Relational Learning. It is structured in such a way that it will be of interest to both beginners and experts who want to learn about the state-of-the-art of inference and learning systems for probabilistic logics.

Computer Vision Jul 13 2021 A modern treatment focusing on learning and inference, with minimal prerequisites, real-world examples and implementable algorithms.

The Elements of Statistical Learning Sep 22 2019 This book describes the important ideas in a common conceptual framework. While the approach is statistical, the emphasis is on concepts rather than mathematics. Many examples are given, with a liberal use of color graphics. It should be a valuable resource for statisticians and anyone interested in data mining in science or industry.

All of Statistics Dec 18 2021 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.

Hardware-Aware Probabilistic Machine Learning Models Apr 10 2021 This book proposes probabilistic machine learning models that represent the hardware properties of the device hosting them. These models can be used to evaluate the impact that a specific device configuration may have on resource consumption and performance of the machine learning task, with the overarching goal of balancing the two optimally. The book first motivates extreme-edge computing in the context of the Internet of Things (IoT) paradigm. Then, it briefly reviews the steps involved in the execution of a machine learning task and identifies the implications associated with implementing this type of workload in resource-constrained devices. The core of this book focuses on augmenting and exploiting the properties of Bayesian Networks and Probabilistic Circuits in order to endow them with hardware-awareness. The proposed models can encode the properties of various device sub-systems that are typically not considered by other resource-aware strategies, bringing about resource-saving opportunities that traditional approaches fail to uncover. The performance of the proposed models and strategies is empirically evaluated for several use cases. All of the considered examples show the potential of attaining significant resource-saving opportunities with minimal accuracy losses at application time. Overall, this book constitutes a novel approach to hardware-algorithm co-optimization that further bridges the fields of Machine Learning and Electrical Engineering.

Targeted Learning in Data Science Sep 15 2021 This textbook for graduate students in statistics, data science, and public health deals with the practical challenges that come with big, complex, and dynamic data. It presents a scientific roadmap to translate real-world data science applications into formal statistical estimation problems by using the general template of targeted maximum likelihood estimators. These targeted machine learning algorithms estimate quantities of interest while still providing valid inference. Targeted learning methods within data science area critical component for solving scientific problems in the modern age. The techniques can answer complex questions including optimal rules for assigning treatment based on longitudinal data with time-dependent confounding, as well as other estimands in dependent data structures, such as networks. Included in Targeted Learning in Data Science are demonstrations with soft ware packages and real data sets that present a case that targeted learning is crucial for the next generation of statisticians and data scientists. Th is book is a sequel to the first textbook on machine learning for causal inference, Targeted Learning, published in 2011. Mark van der

Laan, PhD, is Jiann-Ping Hsu/Karl E. Peace Professor of Biostatistics and Statistics at UC Berkeley. His research interests include statistical methods in genomics, survival analysis, censored data, machine learning, semiparametric models, causal inference, and targeted learning. Dr. van der Laan received the 2004 Mortimer Spiegelman Award, the 2005 Van Dantzig Award, the 2005 COPSS Snedecor Award, the 2005 COPSS Presidential Award, and has graduated over 40 PhD students in biostatistics and statistics. Sherri Rose, PhD, is Associate Professor of Health Care Policy (Biostatistics) at Harvard Medical School. Her work is centered on developing and integrating innovative statistical approaches to advance human health. Dr. Rose's methodological research focuses on nonparametric machine learning for causal inference and prediction. She co-leads the Health Policy Data Science Lab and currently serves as an associate editor for the Journal of the American Statistical Association and Biostatistics.

Statistical Inference and Machine Learning for Big Data Nov 24 2019 This book presents a variety of advanced statistical methods at a level suitable for advanced undergraduate and graduate students as well as for others interested in familiarizing themselves with these important subjects. It proceeds to illustrate these methods in the context of real-life applications in a variety of areas such as genetics, medicine, and environmental problems. The book begins in Part I by outlining various data types and by indicating how these are normally represented graphically and subsequently analyzed. In Part II, the basic tools in probability and statistics are introduced with special reference to symbolic data analysis. The most useful and relevant results pertinent to this book are retained. In Part III, the focus is on the tools of machine learning whereas in Part IV the computational aspects of BIG DATA are presented. This book would serve as a handy desk reference for statistical methods at the undergraduate and graduate level as well as be useful in courses which aim to provide an overview of modern statistics and its applications.

Information Theory , Inference And Learning Algorithms Sep 27 2022 Information theory and inference, taught together in this exciting textbook, lie at the heart of many important areas of modern technology - communication, signal processing, data mining, machine learning, pattern recognition, computational neuroscience, bioinformatics and cryptography. The book introduces theory in tandem with applications. Information theory is taught alongside practical communication systems such as arithmetic coding for data compression and sparse-graph codes for error-correction. Inference techniques, including message-passing algorithms, Monte Carlo methods and variational approximations, are developed alongside applications to clustering, convolutional codes, independent component analysis, and neural networks. Uniquely, the book covers state-of-the-art error-correcting codes, including low-density-parity-check codes, turbo codes, and digital fountain codes - the twenty-first-century standards for satellite communications, disk drives, and data broadcast. Richly illustrated, filled with worked examples and over 400 exercises, some with detailed solutions, the book is ideal for self-learning, and for undergraduate or graduate courses. It also provides an unparalleled entry point for professionals in areas as diverse as computational biology, financial engineering and machine learning.

Grammatical Inference and Applications Jun 19 2019 This volume presents the proceedings of the Second International Colloquium on Grammatical Inference (ICGI-94), held in Alicante, Spain in September 1994. Besides 25 research papers carefully selected and refereed by the program committee, the book contains a survey by E. Vidal. The book is devoted to all those aspects of automatic learning that explicitly focus on principles, theory, and applications of grammars and languages. The papers are organized in sections on formal aspects; language modelling and linguistic applications; stochastic approaches, applications and performance analysis; and neural networks, genetic algorithms, and artificial intelligence techniques.

Artificial Intelligence and Causal Inference Oct 16 2021 Artificial Intelligence and Causal Inference address the recent development of relationships between artificial intelligence (AI) and causal inference. Despite significant progress in AI, a great challenge in AI development we are still facing is to understand mechanism underlying intelligence, including reasoning, planning and imagination. Understanding, transfer and generalization are major principles that give rise intelligence. One of a key component for understanding is causal inference. Causal inference includes intervention, domain shift learning, temporal structure and counterfactual thinking as major concepts to understand causation and reasoning. Unfortunately, these essential components of the causality are often overlooked by machine learning, which leads to some failure of the deep learning. AI and causal inference involve (1) using AI techniques

as major tools for causal analysis and (2) applying the causal concepts and causal analysis methods to solving AI problems. The purpose of this book is to fill the gap between the AI and modern causal analysis for further facilitating the AI revolution. This book is ideal for graduate students and researchers in AI, data science, causal inference, statistics, genomics, bioinformatics and precision medicine. Key Features: Cover three types of neural networks, formulate deep learning as an optimal control problem and use Pontryagin's Maximum Principle for network training. Deep learning for nonlinear mediation and instrumental variable causal analysis. Construction of causal networks is formulated as a continuous optimization problem. Transformer and attention are used to encode-decode graphics. RL is used to infer large causal networks. Use VAE, GAN, neural differential equations, recurrent neural network (RNN) and RL to estimate counterfactual outcomes. AI-based methods for estimation of individualized treatment effect in the presence of network interference.

Scientific Inference Nov 17 2021 Providing the knowledge and practical experience to begin analysing scientific data, this book is ideal for physical sciences students wishing to improve their data handling skills. The book focuses on explaining and developing the practice and understanding of basic statistical analysis, concentrating on a few core ideas, such as the visual display of information, modelling using the likelihood function, and simulating random data. Key concepts are developed through a combination of graphical explanations, worked examples, example computer code and case studies using real data. Students will develop an understanding of the ideas behind statistical methods and gain experience in applying them in practice.

Statistical Machine Learning Oct 24 2019 The recent rapid growth in the variety and complexity of new machine learning architectures requires the development of improved methods for designing, analyzing, evaluating, and communicating machine learning technologies. Statistical Machine Learning: A Unified Framework provides students, engineers, and scientists with tools from mathematical statistics and nonlinear optimization theory to become experts in the field of machine learning. In particular, the material in this text directly supports the mathematical analysis and design of old, new, and not-yet-invented nonlinear high-dimensional machine learning algorithms. Features: Unified empirical risk minimization framework supports rigorous mathematical analyses of widely used supervised, unsupervised, and reinforcement machine learning algorithms Matrix calculus methods for supporting machine learning analysis and design applications Explicit conditions for ensuring convergence of adaptive, batch, minibatch, MCEM, and MCMC learning algorithms that minimize both unimodal and multimodal objective functions Explicit conditions for characterizing asymptotic properties of M-estimators and model selection criteria such as AIC and BIC in the presence of possible model misspecification This advanced text is suitable for graduate students or highly motivated undergraduate students in statistics, computer science, electrical engineering, and applied mathematics. The text is self-contained and only assumes knowledge of lower-division linear algebra and upper-division probability theory. Students, professional engineers, and multidisciplinary scientists possessing these minimal prerequisites will find this text challenging yet accessible. About the Author: Richard M. Golden (Ph.D., M.S.E.E., B.S.E.E.) is Professor of Cognitive Science and Participating Faculty Member in Electrical Engineering at the University of Texas at Dallas. Dr. Golden has published articles and given talks at scientific conferences on a wide range of topics in the fields of both statistics and machine learning over the past three decades. His long-term research interests include identifying conditions for the convergence of deterministic and stochastic machine learning algorithms and investigating estimation and inference in the presence of possibly misspecified probability models.

Introduction to Statistical Relational Learning Jul 21 2019 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.

Bayesian Reasoning and Machine Learning Dec 26 2019 A practical introduction perfect for final-year undergraduate and graduate students without a solid background in linear algebra and calculus.

Active Inference Jun 12 2021 The first comprehensive treatment of active inference, an integrative perspective on brain, cognition, and behavior used across multiple disciplines. Active inference is a way of understanding sentient behavior—a theory that characterizes perception, planning, and action in terms of probabilistic inference. Developed by theoretical neuroscientist Karl Friston over years of groundbreaking research, active inference provides an integrated perspective on brain, cognition, and behavior that is increasingly used across multiple disciplines including neuroscience, psychology, and philosophy. Active inference puts the action into perception. This book offers the first comprehensive treatment of active inference, covering theory, applications, and cognitive domains. Active inference is a "first principles" approach to understanding behavior and the brain, framed in terms of a single imperative to minimize free energy. The book emphasizes the implications of the free energy principle for understanding how the brain works. It first introduces active inference both conceptually and formally, contextualizing it within current theories of cognition. It then provides specific examples of computational models that use active inference to explain such cognitive phenomena as perception, attention, memory, and planning.

Information Theory, Inference and Learning Algorithms Oct 28 2022 Table of contents

An Introduction to Statistical Inference and Its Applications with R Jan 27 2020 Emphasizing concepts rather than recipes, An Introduction to Statistical Inference and Its Applications with R provides a clear exposition of the methods of statistical inference for students who are comfortable with mathematical notation. Numerous examples, case studies, and exercises are included. R is used to simplify computation, create figures