Probabilistic Graphical Models Principles

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Bayesian Programming - Pierre Bessiere 2013-12-20
Probability as an Alternative to Boolean LogicWhile logic is the mathematical foundation of rational reasoning and the fundamental principle of computing, it is restricted to problems where information is both complete and certain. However, many real-world problems, from financial investments to email filtering, are incomplete or uncertain in natur

Bayesian Artificial Intelligence

- Kevin B. Korb 2003-09-25
As the power of Bayesian techniques has become more fully realized, the field of artificial intelligence has embraced Bayesian methodology and integrated it to the point where an introduction to Bayesian techniques is now a core course in many computer science programs. Unlike other books on the subject, Bayesian Artificial Intelligence keeps mathematical detail to a minimum and covers a broad range of topics. The authors integrate all of Bayesian net technology and learning Bayesian net technology and apply them both to knowledge engineering. They emphasize understanding and intuition but also provide the algorithms and technical background needed for applications. Software, exercises, and solutions are available on the authors' website.

Probabilistic Graphical Models - Alexander Denev 2015

Computer Vision - Simon J. D. Prince 2012-06-18
A modern treatment focusing on learning and inference, with minimal prerequisites, real-world examples and implementable algorithms.

Reasoning With Probabilistic and Deterministic Graphical Models - Rina Dechter 2019-02-14
Graphical models (e.g., Bayesian and constraint networks, influence diagrams, and Markov decision processes) have become a central paradigm for knowledge representation and reasoning in both artificial intelligence and computer science in general. These models are used to perform many reasoning tasks, such as scheduling, planning and learning, diagnosis and prediction, design, hardware and software verification, and bioinformatics. These problems can be stated as the formal tasks of constraint satisfaction and satisfiability, combinatorial optimization, and probabilistic inference. It is well known that the tasks are computationally hard, but research during the past three decades has yielded

a variety of principles and techniques that significantly advanced the state of the art. This book provides comprehensive coverage of the primary exact algorithms for reasoning with such models. The main feature exploited by the algorithms is the model's graph. We present inference-based, message-passing schemes (e.g., variable-elimination) and search-based, conditioning schemes (e.g., cycle-cutset conditioning and AND/OR search). Each class possesses distinguished characteristics and in particular has different time vs. space behavior. We emphasize the dependence of both schemes on few graph parameters such as the treewidth, cycle-cutset, and (the pseudo-tree) height. The new edition includes the notion of influence diagrams, which focus on sequential decision making under uncertainty. We believe the principles outlined in the book would serve well in moving forward to approximation and anytime-based schemes. The target audience of this book is researchers and students in the artificial intelligence and machine learning area, and beyond.

Graphical Models for Machine Learning and Digital Communication - Brendan J. Frey 1998

Content Description. #Includes bibliographical references and index.

Probabilistic Graphical Models for Genetics, Genomics and Postgenomics - Christine Sinoquet 2014

At the crossroads between statistics and machine learning, probabilistic graphical models (PGMs) provide a powerful formal framework to model complex data. An expanding volume of biological data of various types, the so-called 'omics', is in need of accurate and efficient methods for modelling and PGMs are expected to have a prominent role to play. This book provides an overview of the applications of PGMs to genetics, genomics and postgenomics to meet this increased interest.

Introduction to Bayesian Networks - Finn V. Jensen 1997-08-15

Disk contains: Tool for building Bayesian networks -- Library of examples -- Library of proposed solutions to some exercises.

Graphical Models - Steffen L. Lauritzen 1996-05-02

The idea of modelling systems using graph theory has its origin in several scientific areas: in statistical physics (the study of large particle systems), in genetics (studying inheritable properties of natural species), and in interactions in contingency tables. The use of graphical models in statistics has increased considerably over recent years and the theory has been greatly developed and extended. This book provides the first comprehensive and authoritative account of the theory of graphical models and is written by a leading expert in the field. It contains the fundamental graph theory required and a thorough study of Markov properties associated with various type of graphs. The statistical theory of log-linear and graphical models for contingency tables, covariance selection models, and graphical models with mixed discrete-continous variables in developed detail. Special topics, such as the application of graphical models to probabilistic expert systems, are described briefly, and appendices give details of the multivarate normal distribution and of the theory of regular exponential families. The author has recently been awarded the RSS Guy Medal in Silver 1996 for his innovative contributions to statistical theory and practice, and especially for his work on graphical models.

Computational Science – ICCS 2018 - Yong Shi 2018-06-11

The three-volume set LNCS 10860, 10861 + 10862 constitutes the proceedings of the 18th International Conference on Computational Science, ICCS 2018, held in Wuxi, China, in June 2018. The total of 155 full and 66 short papers presented in this book set was carefully reviewed and selected from 404 submissions. The papers were organized in topical sections named: Part I: ICCS Main Track Part II: Track of Advances in High-Performance Computational Earth Sciences: Applications and Frameworks; Track of Agent-Based Simulations, Adaptive Algorithms and Solvers; Track of Applications of Matrix Methods in Artificial Intelligence and Machine Learning; Track of Architecture, Languages, Compilation and Hardware Support for Emerging ManYcore Systems; Track of Biomedical and Bioinformatics Challenges for Computer Science; Track of Computational Finance and Business Intelligence; Track of Computational Optimization, Modelling and Simulation; Track of Data, Modeling, and Computation in IoT and Smart Systems; Track of Data-Driven Computational Sciences; Track of Mathematical-Methods-and-Algorithms for Extreme Scale; Track of Multiscale Modelling and Simulation Part III: Track of Simulations of Flow and Transport: Modeling, Algorithms and Computation; Track of Solving Problems with Uncertainties; Track of Teaching Computational Science; Poster Papers

Machine Learning - Zhi-Hua Zhou 2021-08-20

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.

Modeling and Reasoning with Bayesian Networks - Adnan Darwiche 2009-04-06

This book provides a thorough introduction to the formal foundations and practical applications of Bayesian networks. It provides an extensive discussion of techniques for building Bayesian networks that model real-world situations, including techniques for synthesizing models from design, learning models from data, and debugging models using sensitivity analysis. It also treats exact and approximate inference algorithms at both theoretical and practical levels. The author assumes very little background on the covered subjects, supplying in-depth discussions for theoretically inclined readers and enough practical details to provide an algorithmic cookbook for the system developer.

Bayesian Reasoning and Machine Learning - David Barber 2012-02-02

A practical introduction perfect for final-year undergraduate and graduate students without a solid background in linear algebra and calculus.

Machine Learning - Sergios Theodoridis 2020-02-19

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

Statistical Relational Artificial Intelligence - Luc De Raedt 2016-03-24

An intelligent agent interacting with the real world will encounter individual people, courses, test results, drugs prescriptions, chairs, boxes, etc., and needs to reason about properties of these individuals and relations among them as well as cope with uncertainty. Uncertainty has been studied in probability theory and graphical models, and relations have been studied in logic, in particular in the predicate calculus and its extensions. This book examines the foundations of combining logic and probability into what are called relational probabilistic models. It introduces representations, inference, and learning techniques for probability, logic, and their combinations. The book focuses on two representations in detail: Markov logic networks, a relational extension of undirected graphical models and weighted first-order predicate calculus formula, and Problog, a probabilistic extension of logic programs that can also be viewed as a Turing-complete relational extension of Bayesian networks.

Probabilistic Graphical Models - Luis Enrique Sucar 2020-12-23

This fully updated new edition of a uniquely accessible textbook/reference provides a general introduction to probabilistic graphical models (PGMs) from an engineering perspective. It features new material on partially observable Markov decision processes, graphical models, and deep learning, as well as an even greater number of exercises. The book covers the fundamentals for each of the main classes of PGMs, including representation, inference and learning principles, and reviews real-world applications for each type of model. These applications are drawn from a broad range of disciplines, highlighting the many uses of Bayesian classifiers, hidden Markov models, Bayesian networks, dynamic and temporal Bayesian networks, Markov random fields, influence diagrams, and Markov decision processes. Topics and features: Presents a unified framework encompassing all of the main classes of PGMs Explores the fundamental aspects of representation, inference and learning for each technique Examines new material on partially observable Markov decision processes, and graphical models Includes a new chapter introducing deep neural networks and their relation with probabilistic graphical models Covers multidimensional Bayesian classifiers, relational graphical models, and causal models Provides substantial chapter-ending exercises, suggestions for further reading, and ideas for research or programming projects Describes classifiers such as Gaussian Naive Bayes, Circular Chain Classifiers, and Hierarchical Classifiers with Bayesian Networks Outlines the practical application of the different techniques Suggests possible course outlines for instructors This classroom-tested work is suitable as a textbook for an advanced undergraduate or a graduate course in probabilistic graphical models for students of computer science, engineering, and physics. Professionals wishing to apply probabilistic graphical models in their own field, or interested in the basis of these techniques, will also find the book to be an invaluable reference. Dr. Luis Enrique Sucar is a Senior Research Scientist at the National Institute for Astrophysics, Optics and Electronics (INAOE), Puebla, Mexico. He received the National Science Prize en 2016.

Probabilistic Graphical Models for Computer Vision.

- Qiang Ji 2019-12-12

Probabilistic Graphical Models for Computer Vision introduces probabilistic graphical models (PGMs) for computer vision problems and teaches how to develop the PGM model from training data. This book discusses PGMs and their significance in the context of solving computer vision problems, giving the basic concepts, definitions and properties. It also provides a comprehensive introduction to well-established theories for different types of PGMs, including both directed and undirected PGMs, such as Bayesian Networks, Markov Networks and their variants. Discusses PGM theories and techniques with computer vision examples Focuses on well-established PGM theories that are accompanied by corresponding pseudocode for computer vision Includes an extensive list of references, online resources and a list of publicly available and commercial software Covers computer vision tasks, including feature extraction and image segmentation, object and facial recognition, human activity recognition, object tracking and 3D reconstruction

Knowledge Graphs - Mayank Kejriwal 2021-03-30

A rigorous and comprehensive textbook covering the major approaches to knowledge graphs, an active and interdisciplinary area within artificial intelligence. The field of knowledge graphs, which allows us to model, process, and derive insights from complex real-world data, has emerged as an active and interdisciplinary area of artificial intelligence over the last decade, drawing on such fields as natural language processing, data mining, and the semantic web. Current projects involve predicting cyberattacks, recommending products, and even gleaning insights from thousands of papers on COVID-19. This textbook offers rigorous and comprehensive coverage of the field. It focuses systematically on the major approaches, both those that have stood the test of time and the latest deep learning methods.

Graphical Models with R - Søren Højsgaard 2012-02-22

Graphical models in their modern form have been around since the late 1970s and appear today in many areas of the sciences. Along with the ongoing developments of graphical models, a number of different graphical modeling software programs have been written over the years. In recent years many of these software developments have taken place within the R community, either in the form of new packages or by providing an R interface to existing software. This book attempts to give the reader a gentle introduction to graphical modeling using R and the main features of some of these packages. In addition, the book provides examples of how more advanced aspects of graphical modeling can be represented and handled within R. Topics covered in the seven chapters include graphical models for contingency tables, Gaussian and mixed graphical models, Bayesian networks and modeling high dimensional data.

Introduction to Natural Language Processing - Jacob Eisenstein 2019-10-01

A survey of computational methods for understanding, generating, and manipulating human language, which offers a synthesis of classical representations and algorithms with contemporary machine learning techniques. This textbook provides a technical perspective on natural language processing—methods for building computer software that understands, generates, and manipulates human language. It emphasizes contemporary data-driven approaches, focusing on techniques from supervised and unsupervised machine learning. The first section establishes a foundation in machine learning by building a set of tools that will be used throughout the book and applying them to word-based textual analysis. The second section introduces structured representations of language, including sequences, trees, and graphs. The third section explores different approaches to the representation and analysis of linguistic meaning, ranging from formal logic to neural word embeddings. The final section offers chapter-length treatments of three transformative applications of natural language processing: information extraction, machine translation, and text generation. End-of-chapter exercises include both paper-and-pencil analysis and software implementation. The text synthesizes and distills a broad and diverse research literature, linking contemporary machine learning techniques with the field's linguistic and computational foundations. It is suitable for use in advanced undergraduate and graduate-level courses and as a reference for software engineers and data scientists. Readers should have a background in computer programming and college-level mathematics. After mastering the material presented, students will have the technical skill to build and analyze novel natural language processing systems and to understand the latest research in the field.

Graphical Models, Exponential Families, and Variational Inference - Martin J. Wainwright 2008

The core of this paper is a general set of variational principles for the problems of computing marginal probabilities and modes, applicable to multivariate statistical models in the exponential family.

Probabilistic Graphical Models - Daphne Koller 2009-07-31

A general framework for constructing and using probabilistic models of complex systems that would enable a computer to use available information for making decisions. Most tasks require a person or an automated system to reason—to reach conclusions based on available information. The framework of probabilistic graphical models, presented in this book, provides a general approach for this task. The approach is model-based, allowing interpretable models to be constructed and then manipulated by reasoning algorithms. These models can also be learned automatically from data, allowing the approach to be used in cases where manually constructing a model is difficult or even impossible. Because uncertainty is an inescapable aspect of most real-world applications, the book focuses on probabilistic models, which make the uncertainty explicit and provide models that are more faithful to reality. Probabilistic Graphical Models discusses a variety of models, spanning Bayesian networks, undirected Markov networks, discrete and continuous models, and extensions to deal with dynamical systems and relational data. For each class of models, the text describes the three fundamental cornerstones: representation, inference, and learning, presenting both basic concepts and advanced techniques. Finally, the book considers the use of the proposed framework for causal reasoning and decision making under uncertainty. The main text in each chapter provides the detailed technical development of the key ideas. Most chapters also include boxes with additional material: skill boxes, which describe techniques; case study boxes, which discuss empirical cases related to the approach described in the text, including applications in computer vision, robotics, natural language understanding, and computational biology; and concept boxes, which present significant concepts drawn from the material in the chapter. Instructors (and readers) can group chapters in various combinations, from core topics to more technically advanced material, to suit their particular needs.

Learning in Graphical Models - M.I. Jordan 2012-12-06

In the past decade, a number of different research communities within the computational sciences have studied learning in networks, starting from a number of different points of view. There has been substantial progress in these different communities and surprising convergence has developed between the formalisms. The awareness of this convergence and the growing interest of researchers in understanding the essential unity of the subject underlies the current volume. Two research communities which have used graphical or network formalisms to particular advantage are the belief network community and the neural network community. Belief networks arose within computer science and statistics and were developed with an emphasis on prior knowledge and exact probabilistic calculations. Neural networks arose within electrical engineering, physics and neuroscience and have emphasised pattern recognition and systems modelling problems. This volume draws together researchers from these two communities and presents both kinds of networks as instances of a general unified graphical formalism. The book focuses on probabilistic methods for learning and inference in graphical models, algorithm analysis and design, theory and applications. Exact methods, sampling methods and variational methods are discussed in detail. Audience: A wide cross-section of computationally oriented researchers, including computer scientists, statisticians, electrical engineers, physicists and neuroscientists.

Machine Learning - Kevin P. Murphy 2012-08-24

A comprehensive introduction to machine learning that uses probabilistic models and inference as a unifying approach. Today's Web-enabled deluge of electronic data calls for automated methods of data analysis. Machine learning provides these, developing methods that can automatically detect patterns in data and then use the uncovered patterns to predict future data. This textbook offers a comprehensive and self-contained introduction to the field of machine learning, based on a unified, probabilistic approach. The coverage combines breadth and depth, offering necessary background material on such topics as probability, optimization, and linear algebra as well as discussion of recent developments in the field, including conditional random fields, L1 regularization, and deep learning. The book is written in an informal, accessible style, complete with pseudo-code for the most important algorithms. All topics are copiously illustrated with color images and worked examples drawn from such application domains as biology, text processing, computer vision, and robotics. Rather than providing a cookbook of different heuristic methods, the book stresses a principled model-based approach, often using the language of graphical models to specify models in a concise and intuitive way. Almost all the models described have been implemented in a MATLAB software package—PMTK (probabilistic modeling toolkit)—that is freely available online. The book is suitable for upper-level undergraduates with an introductory-level college math background and beginning graduate students.

Fuzzy Logic and Applications - Francesco Masulli 2013-11-08
This book constitutes the proceedings of the 10th International Workshop on Fuzzy Logic and Applications, WILF 2013, held in Genoa, Italy, in November 2013. After a rigorous peer-review selection process, ultimately 19 regular papers were selected for inclusion in this volume from 29 submissions. In addition the book contains 3 keynote talks and 2 tutorials. The papers are organized in topical sections named: fuzzy machine learning and interpretability; theory and applications.

Programming Languages and Systems - Nobuko Yoshida 2021-03-22
This open access book constitutes the proceedings of the 30th European Symposium on Programming, ESOP 2021, which was held during March 27 until April 1, 2021, as part of the European Joint Conferences on Theory and Practice of Software, ETAPS 2021. The conference was planned to take place in Luxembourg and changed to an online format due to the COVID-19 pandemic. The 24 papers included in this volume were carefully reviewed and selected from 79 submissions. They deal with fundamental issues in the specification, design, analysis, and implementation of programming languages and systems.

Introduction to Graphical Modelling - David Edwards

2012-12-06
A useful introduction to this topic for both students and researchers, with an emphasis on applications and practicalities rather than on a formal development. It is based on the popular software package for graphical modelling, MIM, freely available for downloading from the Internet. Following a description of some of the basic ideas of graphical modelling, subsequent chapters describe particular families of models, including log-linear models, Gaussian models, and models for mixed discrete and continuous variables. Further chapters cover hypothesis testing and model selection. Chapters 7 and 8 are new to this second edition and describe the use of directed, chain, and other graphs, complete with a summary of recent work on causal inference.

Constraint Processing - Rina Dechter 2003-05-05
Constraint reasoning has matured over the last three decades with contributions from a diverse community of researchers in artificial intelligence, databases and programming languages, operations research, management science, and applied mathematics. In Constraint Processing, Rina Dechter synthesizes these contributions, as well as her own significant work, to provide the first comprehensive examination of the theory that underlies constraint processing algorithms.

Learning Probabilistic Graphical Models in R - David Bellot 2016-04-29
Familiarize yourself with probabilistic graphical models through real-world problems and illustrative code examples in R About This Book Predict and use a probabilistic graphical models (PGM) as an expert system Comprehend how your computer can learn Bayesian modeling to solve real-world problems Know how to prepare data and feed the models by using the appropriate algorithms from the appropriate R package Who

This Book Is For This book is for anyone who has to deal with lots of data and draw conclusions from it, especially when the data is noisy or uncertain. Data scientists, machine learning enthusiasts, engineers, and those who curious about the latest advances in machine learning will find PGM interesting. What You Will Learn Understand the concepts of PGM and which type of PGM to use for which problem Tune the model's parameters and explore new models automatically Understand the basic principles of Bayesian models, from simple to advanced Transform the old linear regression model into a powerful probabilistic model Use standard industry models but with the power of PGM Understand the advanced models used throughout today's industry See how to compute posterior distribution with exact and approximate inference algorithms In Detail Probabilistic graphical models (PGM, also known as graphical models) are a marriage between probability theory and graph theory. Generally, PGMs use a graph-based representation. Two branches of graphical representations of distributions are commonly used, namely Bayesian networks and Markov networks. R has many packages to implement graphical models. We'll start by showing you how to transform a classical statistical model into a modern PGM and then look at how to do exact inference in graphical models. Proceeding, we'll introduce you to many modern R packages that will help you to perform inference on the models. We will then run a Bayesian linear regression and you'll see the advantage of going probabilistic when you want to do prediction. Next, you'll master using R packages and implementing its techniques. Finally, you'll be presented with machine learning applications that have a direct impact in many fields. Here, we'll cover clustering and the discovery of hidden information in big data, as well as two important methods, PCA and ICA, to reduce the size of big problems. Style and approach This book gives you a detailed and step-by-step explanation of each mathematical concept, which will help you build and analyze your own machine learning models and apply them to real-world problems. The mathematics is kept simple and each formula is explained thoroughly.

Building Probabilistic Graphical Models with Python - Kiran Karkal 2014-06-14

Introduction to Statistical Relational Learning - Lise Getoor 2007

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.

Mastering Probabilistic Graphical Models Using Python - Ankur Ankan 2015-08-03

Master probabilistic graphical models by learning through real-world problems and illustrative code examples in Python About This Book Gain in-depth knowledge of Probabilistic Graphical Models Model time-series problems using Dynamic Bayesian Networks A practical guide to help you apply PGMs to real-world problems Who This Book Is For If you are a researcher or a machine learning enthusiast, or are working in the data science field and have a basic idea of Bayesian Learning or Probabilistic Graphical Models, this book will help you to understand the details of Graphical Models and use it in your data science problems. This book will also help you select the appropriate model as well as the appropriate algorithm for your problem. What You Will Learn Get to know the basics of Probability theory and Graph Theory Work with Markov Networks Implement Bayesian Networks Exact Inference Techniques in Graphical Models such as the Variable Elimination Algorithm Understand approximate

Inference Techniques in Graphical Models such as Message Passing Algorithms Sample algorithms in Graphical Models Grasp details of Naive Bayes with real-world examples Deploy PGMs using various libraries in Python Gain working details of Hidden Markov Models with real-world examples In Detail Probabilistic Graphical Models is a technique in machine learning that uses the concepts of graph theory to compactly represent and optimally predict values in our data problems. In real world problems, it's often difficult to select the appropriate graphical model as well as the appropriate inference algorithm, which can make a huge difference in computation time and accuracy. Thus, it is crucial to know the working details of these algorithms. This book starts with the basics of probability theory and graph theory, then goes on to discuss various models and inference algorithms. All the different types of models are discussed along with code examples to create and modify them, and also to run different inference algorithms on them. There is a complete chapter devoted to the most widely used networks Naive Bayes Model and Hidden Markov Models (HMMs). These models have been thoroughly discussed using real-world examples. Style and approach An easy-to-follow guide to help you understand Probabilistic Graphical Models using simple examples and numerous code examples, with an emphasis on more widely used models.

An Introduction to Lifted Probabilistic Inference - David Poole 2021-08-17

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.

Graph Representation Learning - William L. Hamilton 2020-09-16

This book is a foundational guide to graph representation learning, including state-of-the art advances, and introduces the highly successful graph neural network (GNN) formalism. Graph-structured data is ubiquitous throughout the natural and social sciences, from telecommunication networks to quantum chemistry. Building relational inductive biases into deep learning architectures is crucial for creating systems that can learn, reason, and generalize from this kind of data. Recent years have seen a surge in research on graph representation learning, including techniques for deep graph embeddings, generalizations of convolutional neural networks to graph-structured data, and neural message-passing approaches inspired by belief propagation. These advances in graph representation learning have led to new state-of-the-art results in numerous domains, including chemical synthesis, 3D vision, recommender systems, question answering, and social network analysis. It begins with a discussion of the goals of graph representation learning as well as key methodological foundations in graph theory and network analysis. Following this, the book introduces and reviews methods for learning node embeddings, including random-walk-based methods and applications to knowledge graphs. It then provides a technical synthesis and introduction to the highly successful graph neural network (GNN) formalism, which has become a dominant and fast-growing paradigm for deep learning with graph data. The book concludes with a synthesis of recent advancements in deep generative models for graphs -- a nascent but quickly growing subset of graph representation learning.

Introduction to Graph Theory - Richard J. Trudeau 2013-04-15

Aimed at "the mathematically traumatized," this text offers nontechnical coverage of graph theory, with exercises. Discusses planar graphs, Euler's formula, Platonic graphs, coloring, the genus of a graph, Euler walks, Hamilton walks, more. 1976 edition.

Handbook of Graphical Models - Marloes Maathuis 2018-11-12

A graphical model is a statistical model that is represented by a graph. The factorization properties underlying graphical models facilitate tractable computation with multivariate distributions, making the models a valuable tool with a plethora of applications. Furthermore, directed graphical models allow intuitive causal interpretations and have become a cornerstone for causal inference. While there exist a number of excellent books on graphical models, the field has grown so much that individual authors can hardly cover its entire scope. Moreover, the field is interdisciplinary by nature. Through chapters by leading researchers from different areas, this handbook provides a broad and accessible overview of the state of the art. Key features: * Contributions by leading researchers from a range of disciplines * Structured in five parts, covering foundations, computational aspects, statistical inference, causal inference, and applications *

Balanced coverage of concepts, theory, methods, examples, and applications * Chapters can be read mostly independently, while cross-references highlight connections The handbook is targeted at a wide audience, including graduate students, applied researchers, and experts in graphical models.

Learning Bayesian Networks - Richard E. Neapolitan 2004

This book serves as a textbook or reference for anyone with an interest in probabilistic modeling in the fields of computer science, computer engineering, and electrical engineering. This text is also a resource for courses on expert systems, machine learning, and artificial intelligence. Beginning with a basic theoretical introduction, the author then provides a discussion of inference, methods of learning, and applications based on Bayesian networks and beyond.

Deep Learning on Graphs - Yao Ma 2021-09-23

A comprehensive text on foundations and techniques of graph neural networks with applications in NLP, data mining, vision and healthcare.

Bayesian Networks and Decision Graphs - Thomas Dyhre Nielsen 2009-03-17

This is a brand new edition of an essential work on Bayesian networks and decision graphs. It is an introduction to probabilistic graphical models including Bayesian networks and influence diagrams. The reader is guided through the two types of frameworks with examples and exercises, which also give instruction on how to build these models. Structured in two parts, the first section focuses on probabilistic graphical models, while the second part deals with decision graphs, and in addition to the frameworks described in the previous edition, it also introduces Markov decision process and partially ordered decision problems.

Boosting - Robert E. Schapire 2014-01-10

An accessible introduction and essential reference for an approach to machine learning that creates highly accurate prediction rules by combining many weak and inaccurate ones. Boosting is an approach to machine learning based on the idea of creating a highly accurate predictor by combining many weak and inaccurate “rules of thumb.” A remarkably rich theory has evolved around boosting, with connections to a range of topics, including statistics, game theory, convex optimization, and information geometry. Boosting algorithms have also enjoyed practical success in such fields as biology, vision, and speech processing. At various times in its history, boosting has been perceived as mysterious, controversial, even paradoxical. This book, written by the inventors of the method, brings together, organizes, simplifies, and substantially extends two decades of research on boosting, presenting both theory and applications in a way that is accessible to readers from diverse backgrounds while also providing an authoritative reference for advanced researchers. With its introductory treatment of all material and its inclusion of exercises in every chapter, the book is appropriate for course use as well. The book begins with a general introduction to machine learning algorithms and their analysis; then explores the core theory of boosting, especially its ability to generalize; examines some of the myriad other theoretical viewpoints that help to explain and understand boosting; provides practical extensions of boosting for more complex learning problems; and finally presents a number of advanced theoretical topics. Numerous applications and practical illustrations are offered throughout.