Probabilistic Graphical Models Solutions

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Topics in Probabilistic Graphical Models
Exact Algorithms, Second Edition
7th European Workshop, PGM 2014, Utrecht, The Netherlands, September 17-19, 2014. Proceedings
Bayesian Reasoning and Machine Learning
Probabilistic Graphical Models for Computer Vision.
Machine Learning and Statistical Models

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PRECIOUS JEFFERSON

Decision Theory Models for Applications in Artificial Intelligence: Concepts and Solutions
Packt Publishing Ltd
The Wiley Paperback Series makes valuable content more accessible to a new generation of statisticians, mathematicians and scientists. Graphical models--a subset of log-linear models--reveal the interrelationships between multiple variables and features of the underlying conditional independence. This introduction to the use of graphical models in the description and modeling of multivariate systems covers conditional independence, several types of independence graphs, Gaussian models, issues in model selection, regression and decomposition. Many numerical examples and exercises with

solutions are included. This book is aimed at students who require a course on applied multivariate statistics unified by the concept of conditional independence and researchers concerned with applying graphical modelling techniques.
Graphical Models with R Springer Science & Business Media
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
Principles and Applications Cambridge University Press
Reviews the use of factor graphs for the

modeling and solving of large-scale inference problems in robotics. Factor graphs are introduced as an economical representation within which to formulate the different inference problems, setting the stage for the subsequent sections on practical methods to solve them.
A New Way of Thinking in Financial Modelling Cambridge University Press 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.

with Applications in Systems Biology Academic Press

This book brings together important topics of current research in probabilistic graphical modeling, learning from data and probabilistic inference. Coverage includes such topics as the characterization of conditional independence, the learning of graphical models with latent variables, and extensions to the influence diagram formalism as well as important application fields, such as the control of vehicles, bioinformatics and medicine.

Algorithms, Worked Examples, and Case Studies Springer Nature

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.

Graphical Models, Exponential

Families, and Variational Inference
Springer Science & Business Media
One of the goals of artificial intelligence (AI) is creating autonomous agents that must make decisions based on uncertain and incomplete information. The goal is to design rational agents that must take the best action given the information available and their goals. Decision Theory Models for Applications in Artificial Intelligence: Concepts and Solutions provides an introduction to different types of decision theory techniques, including MDPs, POMDPs, Influence Diagrams, and Reinforcement Learning, and illustrates their application in artificial intelligence. This book provides insights into the advantages and challenges of using decision theory models for developing intelligent systems.

Topics in Probabilistic Graphical Models
CRC Press
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.
Exact Algorithms, Second Edition Morgan & Claypool Publishers
This book presents an exciting new synthesis of directed and undirected, discrete and continuous graphical models. Combining elements of Bayesian networks and Markov random fields, the newly introduced hybrid random fields are an interesting approach to get the best of both these worlds, with an added promise of modularity and scalability. The authors have written an enjoyable book---rigorous in the treatment of the mathematical background, but also enlivened by interesting and original historical and philosophical perspectives. -- Manfred Jaeger, Aalborg Universitet
The book not only marks an effective direction of investigation with significant experimental advances, but it is also---and perhaps primarily---a guide for the reader through an original trip in the space of probabilistic modeling. While digesting the book, one is enriched with a very open view of the field, with full of stimulating connections. [...] Everyone specifically interested in Bayesian networks and Markov random fields should not miss it. -- Marco Gori, Università degli Studi di Siena Graphical models are sometimes regarded---incorrectly---as an impractical approach to machine learning, assuming that they only work well for low-dimensional applications and discrete-valued domains. While guiding the reader

through the major achievements of this research area in a technically detailed yet accessible way, the book is concerned with the presentation and thorough (mathematical and experimental) investigation of a novel paradigm for probabilistic graphical modeling, the hybrid random field. This model subsumes and extends both Bayesian networks and Markov random fields. Moreover, it comes with well-defined learning algorithms, both for discrete and continuous-valued domains, which fit the needs of real-world applications involving large-scale, high-dimensional data.
7th European Workshop, PGM 2014, Utrecht, The Netherlands, September 17-19, 2014. Proceedings Wiley
A detailed and up-to-date introduction to machine learning, presented through the unifying lens of probabilistic modeling and Bayesian decision theory. This book offers a detailed and up-to-date introduction to machine learning (including deep learning) through the unifying lens of probabilistic modeling and Bayesian decision theory. The book covers mathematical background (including linear algebra and optimization), basic supervised learning (including linear and logistic regression and deep neural networks), as well as more advanced topics (including transfer learning and unsupervised learning). End-of-chapter exercises allow students to apply what they have learned, and an appendix covers notation. Probabilistic Machine Learning grew out of the author’s 2012 book, Machine Learning: A

Probabilistic Perspective. More than just a simple update, this is a completely new book that reflects the dramatic developments in the field since 2012, most notably deep learning. In addition, the new book is accompanied by online Python code, using libraries such as scikit-learn, JAX, PyTorch, and Tensorflow, which can be used to reproduce nearly all the figures; this code can be run inside a web browser using cloud-based notebooks, and provides a practical complement to the theoretical topics discussed in the book. This introductory text will be followed by a sequel that covers more advanced topics, taking the same probabilistic approach.

Bayesian Reasoning and Machine Learning CRC Press

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

Probabilistic Graphical Models for Computer Vision. MIT Press

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

Machine Learning and Statistical Models Cambridge University Press

The second edition of a comprehensive introduction to machine learning approaches used in predictive data analytics, covering both theory and practice. Machine learning is often used to build predictive models by extracting patterns from large datasets. These models are used in predictive data analytics applications including price prediction, risk assessment, predicting customer behavior, and document classification. This introductory textbook offers a detailed and focused treatment of the most important machine learning approaches used in predictive data analytics, covering both theoretical concepts and practical applications. Technical and mathematical material is augmented with explanatory worked examples, and case studies illustrate the application of these models in the broader business context. This second edition covers recent developments in machine learning, especially in a new chapter on deep learning, and two new chapters that go beyond predictive analytics to cover unsupervised learning and reinforcement learning.

Machine Learning Cambridge University Press

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.

Bayesian Networks in R Now Publishers Inc

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.

Deep Learning on Graphs Cambridge University Press

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.

Machine Learning MIT Press

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.
Principles and Techniques MIT Press
Complex networks involve interplay of several entities with each other that results in dependence in these entities. This dependence has often a modular structure that should be exploited for efficient inference and decision making. We present a survey of inference, learning, and decision making in such complex networks depicted as probabilistic graphical models. In particular, we focus on four particular problems in graphical models: (i) efficient computation of marginal and conditional probabilities; (ii) efficient parameter estimation; (iii) efficient structural learning; and (iv) decision making. We present the models in which exact solution is tractable and elucidate on the associated algorithms. We also present approximate solution techniques for general graphical models.
Advances in Probabilistic Graphical Models Springer
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.

Probabilistic Graphical Models for Computer Vision Springer Science & Business Media

Mixed constraint and probabilistic graphical models occur quite frequently in many real world applications. Examples include: genetic linkage analysis, functional/software verification, target tracking and activity modeling. Query answering and in particular probabilistic inference on such graphical models is computationally hard often requiring exponential time in the worst case. Therefore in practice sampling algorithms are widely used for providing an approximate answer. In presence of deterministic dependencies or hard constraints, however, sampling has to overcome some principal challenges. In particular, importance sampling type schemes suffer from what is known as the rejection problem in that samples having zero weight may be generated with probability arbitrarily close to one yielding useless results. On the other hand, Markov Chain Monte Carlo techniques do not converge at all often yielding highly inaccurate estimates. In this thesis, we address these problems in a two fold manner. First, we utilize research done in constraint satisfaction and satisfiability communities for processing constraints to reduce or eliminate rejection. Second, mindful of the time overhead in sample generation due to determinism, we both make and utilize advances in statistical estimation theory to make the "most" out of the generated samples. Utilizing constraint satisfaction and satisfiability research, we propose two classes of sampling algorithms - one based on consistency enforcement and the other based on systematic search. The consistency enforcement class of algorithms work by shrinking the domains of random variables, by strengthening constraints, or by creating new ones, so that some or all zeros in the problem space can be removed. This improves convergence because of dimensionality reduction and also reduces rejection because many zero weight samples will not be generated. Our systematic search based techniques called SampleSearch manage the rejection problem by interleaving sampling with backtracking search. In this scheme, when a sample is supposed to be rejected, the algorithm continues instead with systematic backtracking search until a strictly positive-weight sample is generated. The strength of this scheme is that any state-of-the-art constraint satisfaction or propositional satisfiability search algorithm can be used with minor modifications. Through large scale experimental evaluation, we show that SampleSearch outperforms all state-of-the-art schemes when a significant amount of determinism is present in the graphical model. Subsequently, we combine SampleSearch with known statistical techniques such as Sampling Importance Resampling and Metropolis Hastings yielding efficient algorithms for sampling solutions from a uniform distribution over the solutions of a Boolean satisfiability formula. Unlike state-of-the-art algorithms, our SampleSearch-based algorithms guarantee convergence in the limit. As to statistical estimation, we make two distinct contributions. First, we propose several new statistical inequalities extending the one-sample Markov inequality to multiple samples which can be used in conjunction with SampleSearch to probabilistically lower bound likelihood tasks over mixed networks. Second, we present a novel framework called "AND/OR importance sampling" which generalizes the process of computing sample mean by exploiting AND/OR search spaces for graphical models. Specifically we provide a spectrum of AND/OR sample means which are defined on the same set of samples but derive different estimates trading variance with time. At one end is the AND/OR sample tree mean which has smaller variance than the conventional OR sample tree mean and has the same time complexity. At the other end is the AND/OR graph sample mean which has even lower variance but has higher time and space complexity. We demonstrate empirically that AND/OR sample means are far closer to the exact answer than the conventional OR sample mean.

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