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KEY=MODELS - JACOB BECKER

Probabilistic Graphical Models

Principles and Techniques

MIT Press *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.*

Probabilistic Graphical Models

Principles and Applications

Springer Nature *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.*

Learning Probabilistic Graphical Models in R

Packt Publishing Ltd *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.*

Mastering Probabilistic Graphical Models Using Python

Packt Publishing Ltd *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.*

Probabilistic Graphical Models for Genetics, Genomics and Postgenomics

Oxford University Press, USA *At the crossroads between statistics and machine learning, probabilistic graphical models provide a powerful formal framework to model complex data. For instance, Bayesian networks and Markov random fields are two of the most popular probabilistic graphical models. With the rapid advance of high-throughput technologies and their ever decreasing costs, a fast-growing volume of biological data of various types - the so-called ''omics'' - is in need of accurate andefficient methods for modeling, prior to further downstream analysis. As probabilistic graphical models* *are able to deal with high-dimensional data, it is foreseeable that such models will have aprominent role to play in advances in genome-wide data analyses. Currently, few people are specialists in the design of cutting-edge methods using probabilistic graphical models for genetics, genomics and postgenomics. This seriously hinders the diffusion of such methods. The prime aim of the book is therefore to bring the concepts underlying these advanced models within reach of scientists who are not specialists of these models, but with no concession on theinformativeness of the book. The target readers include researchers and engineers who have to design novel methods for postgenomics data analysis, as well as graduate students starting a Masters or a PhD. Inaddition to an introductory chapter on probabilistic graphical models, a thorough review chapter focusing on selected domains in genetics and fourteen chapters illustrate the design of such advanced approaches in various domains: gene network inference, inference of causal phenotype networks, association genetics, epigenetics, detection of copy number variations, and prediction of outcomes from high-dimensional genomic data. Notably, most examples also illustrate that probabilistic graphicalmodels are well suited for integrative biology and systems biology, hot topics guaranteed to be of lasting interest.*

Handbook of Graphical Models

CRC 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.*

Probabilistic Graphical Models for Computer Vision.

Academic Press *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*

Probabilistic Graphical Models

A New Way of Thinking in Financial Modelling

Learning in Graphical Models

Springer Science & Business Media *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.*

Graphical Models, Exponential Families, and Variational Inference

Now Publishers Inc *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 with R

Springer Science & Business Media *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.*

Bayesian Networks and Decision Graphs

Springer Science & Business Media *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.*

Building Probabilistic Graphical Models with Python

Packt Pub Limited

Advances in Probabilistic Graphical Models

Springer *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.*

Probabilistic Graphical Models for Computer Vision

Academic Press *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*

Graphical Models

Clarendon Press *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.*

Probabilistic Graphical Models

7th European Workshop, PGM 2014, Utrecht, The Netherlands, September 17-19, 2014. Proceedings

Springer *This book constitutes the refereed proceedings of the 7th International Workshop on Probabilistic Graphical Models, PGM 2014, held in Utrecht, The Netherlands, in September 2014. The 38 revised full papers presented in this book were carefully reviewed and selected from 44 submissions. The papers cover all aspects of graphical models for probabilistic reasoning, decision making, and learning.*

Graphical Models

Foundations of Neural Computation

MIT Press *This book exemplifies the interplay between the general formal framework of graphical models and the exploration of new algorithm and architectures. The selections range from foundational papers of historical importance to results at the cutting edge of research. Graphical models use graphs to represent and manipulate joint probability distributions. They have their roots in artificial intelligence, statistics, and neural networks. The clean mathematical formalism of the graphical models framework makes it possible to understand a wide variety of network-based approaches to computation, and in particular to understand many neural network algorithms and architectures as instances of a broader probabilistic methodology. It also makes it possible to identify novel features of neural network algorithms and architectures and to extend them to more general graphical models.This book exemplifies the interplay between the general formal framework of graphical models and the exploration of new algorithms and architectures. The selections range from foundational papers of historical importance to results at the cutting edge of research. Contributors H. Attias, C. M. Bishop, B. J. Frey, Z. Ghahramani, D. Heckerman, G. E. Hinton, R. Hofmann, R. A. Jacobs, Michael I. Jordan, H. J. Kappen, A. Krogh, R. Neal, S. K. Riis, F. B. Rodríguez, L. K. Saul, Terrence J. Sejnowski, P. Smyth, M. E. Tipping, V. Tresp, Y. Weiss*

Probabilistic Graphical Models and Algorithms for Genomic Analysis

Graphical Models for Machine Learning and Digital Communication

MIT Press *Content Description. #Includes bibliographical references and index.*

Probabilistic Graphical Models

Principles and Applications

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.

Graphical Belief Modeling

Routledge *This innovative volume explores graphical models using belief functions as a representation of uncertainty, offering an alternative approach to problems where probability proves inadequate. Graphical Belief Modeling makes it easy to compare the two approaches while evaluating their relative strengths and limitations. The author examines both theory and computation, incorporating practical notes from the author's own experience with the BELIEF software package. As one of the first volumes to apply the Dempster-Shafer belief functions to a practical model, a substantial portion of the book is devoted to a single example--calculating the reliability of a complex system. This special feature enables readers to gain a thorough understanding of the application of this methodology. The first section provides a description of graphical belief models and probablistic graphical models that form an important subset: the second section discusses the algorithm used in the manipulation of graphical models: the final segment of the book offers a complete description of the risk assessment example, as well as the methodology used to describe it. Graphical Belief Modeling offers researchers and graduate students in artificial intelligence and statistics more than just a new approach to an old reliability task: it provides them with an invaluable illustration of the process of graphical belief modeling.*

Appropriate, Accessible and Appealing Probabilistic Graphical Models

Appropriate - Many multivariate probabilistic models either use independent distributions or dependent Gaussian distributions. Yet, many real-world datasets contain count-valued or non-negative skewed data, e.g. bag-of-words text data and biological sequencing data. Thus, we develop novel probabilistic graphical models for use on count-valued and non-negative data including Poisson graphical models and multinomial graphical models. We develop one generalization that allows for triple-wise or k-wise graphical models going beyond the normal pairwise formulation. Furthermore, we also explore Gaussian-copula graphical models and derive closed-form solutions for the conditional distributions and marginal distributions (both before and after conditioning). Finally, we derive mixture and admixture, or topic model, generalizations of these graphical models to introduce more power and interpretability. Accessible - Previous multivariate models, especially related to text data, often have complex dependencies without a closed form and require complex inference algorithms that have limited theoretical justification. For example, hierarchical Bayesian models often require marginalizing over many latent variables. We show that our novel graphical models (even the k-wise interaction models) have simple and intuitive estimation procedures based on node-wise regressions that likely have similar theoretical guarantees as previous work in graphical models. For the copula-based graphical models, we show that simple approximations could still provide useful models; these copula models also *come with closed-form conditional and marginal distributions, which make them amenable to exploratory inspection and manipulation. The parameters of these models are easy to interpret and thus may be accessible to a wide audience. Appealing - High-level visualization and interpretation of graphical models with even 100 variables has often been difficult even for a graphical model expert---despite visualization being one of the original motivators for graphical models. This difficulty is likely due to the lack of collaboration between graphical model experts and visualization experts. To begin bridging this gap, we develop a novel "what if?" interaction that manipulates and leverages the probabilistic power of graphical models. Our approach defines: the probabilistic mechanism via conditional probability; the query language to map text input to a conditional probability query; and the formal underlying probabilistic model. We then propose to visualize these query-specific probabilistic graphical models by combining the intuitiveness of force-directed layouts with the beauty and readability of word clouds, which pack many words into valuable screen space while ensuring words do not overlap via pixel-level collision detection. Although both the force-directed layout and the pixel-level packing problems are challenging in their own right, we approximate both simultaneously via adaptive simulated annealing starting from careful initialization. For visualizing mixture distributions, we also design a meaningful mapping from the properties of the mixture distribution to a color in the perceptually uniform CIELUV color space. Finally, we demonstrate our approach via illustrative visualizations of several real-world datasets.*

Hybrid Random Fields

A Scalable Approach to Structure and Parameter Learning in Probabilistic Graphical Models

Springer Science & Business Media *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.*

Fuzzy Logic and Applications

10th International Workshop, WILF 2013, Genoa, Italy, November 19-22, 2013, Proceedings

Springer *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.*

Building Probabilistic Graphical Models with Python

CreateSpace *With the increasing prominence in machine learning and data science applications, probabilistic graphical models are a new tool that machine learning users can use to discover and analyze structures in complex problems. The variety of tools and algorithms under the PGM framework extend to many domains such as natural language processing, speech processing, image processing, and disease diagnosis. You've probably heard of graphical models before, and you're keen to try out new landscapes in the machine learning area. This book gives you enough background information to get started on graphical models, while keeping the math to a minimum. Approach This is a short, practical guide that allows data scientists to understand the concepts of Graphical models and enables them to try them out using small Python code snippets, without being too mathematically complicated. Who this book is for If you are a data scientist who knows about machine learning and want to enhance your knowledge of graphical models, such as Bayes network, in order to use them to solve real-world problems using Python libraries, this book is for you.This book is intended for those who have some Python and machine learning experience, or are exploring the machine learning field.*

Bayesian Reasoning and Machine Learning

Cambridge University 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 Genetics, Genomics, and Postgenomics

OUP Oxford *Nowadays bioinformaticians and geneticists are faced with myriad high-throughput data usually presenting the characteristics of uncertainty, high dimensionality and large complexity. These data will only allow insights into this wealth of so-called 'omics' data if represented by flexible and scalable models, prior to any further analysis. At the interface between statistics and machine learning, probabilistic graphical models (PGMs) represent a powerful formalism to discover complex networks of relations. These models are also amenable to incorporating a priori biological information. Network reconstruction from gene expression data represents perhaps the most emblematic area of research where PGMs have been successfully applied. However these models have also created renewed interest in genetics in the broad sense, in particular regarding association genetics, causality discovery, prediction of outcomes, detection of copy number variations, and epigenetics. This book provides an overview of the applications of PGMs to genetics, genomics and postgenomics to meet this increased interest. A salient feature of bioinformatics, interdisciplinarity, reaches its limit when an intricate cooperation between domain specialists is requested. Currently, few people are specialists in the design of advanced methods using probabilistic graphical models for postgenomics or genetics. This book deciphers such models so that their perceived difficulty no longer hinders their use and focuses on fifteen illustrations showing the mechanisms behind the models. Probabilistic Graphical Models for Genetics, Genomics and Postgenomics covers six main themes: (1) Gene network inference (2) Causality discovery (3) Association genetics (4) Epigenetics (5) Detection of copy number variations (6) Prediction of outcomes from high-dimensional genomic data. Written by leading international experts, this is a collection of the most advanced work at the crossroads of probabilistic graphical models and genetics, genomics, and postgenomics. The self-contained chapters provide an enlightened account of the pros and cons of applying these powerful techniques.*

Graphical Models for Categorical Data

Cambridge University Press *For advanced students of network data science, this compact account covers both well-established methodology and the theory of models recently introduced in the graphical model literature. It focuses on the discrete case where all variables involved are categorical and, in this context, it achieves a unified presentation of classical and recent results.*

Perspectives on Probabilistic Graphical Models

Reasoning With Probabilistic and Deterministic Graphical Models

Exact Algorithms

Synthesis Lectures on Artifici *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 in Applied Multivariate Statistics

Wiley *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.*

Bayesian Time Series Models

Cambridge University Press *The first unified treatment of time series modelling techniques spanning machine learning, statistics, engineering and computer science.*

High-Dimensional Statistics

A Non-Asymptotic Viewpoint

Cambridge University Press *A coherent introductory text from a groundbreaking researcher, focusing on clarity and motivation to build intuition and understanding.*

Query-specific Learning and Inference for Probabilistic Graphical Models

Abstract: "In numerous real world applications, from sensor networks to computer vision to natural text processing, one needs to reason about the system in question in the face of uncertainty. A key problem in all those settings is to compute the probability distribution over the variables of interest (the query) given the observed values of other random variables (the evidence). Probabilistic graphical models (PGMs) have become the approach of choice for representing and reasoning with high-dimensional probability distributions. However, for most models capable of accurately representing real-life distributions, inference is fundamentally intractable. As a result, optimally balancing the expressive power and inference complexity of the models, as well as designing better approximate inference algorithms, remain important open problems with potential to significantly improve the quality of answers to probabilistic queries. This thesis contributes algorithms for learning and approximate inference in probabilistic graphical models that improve on the state of the art by emphasizing the computational aspects of inference over the representational properties of the models. Our contributions fall into two categories: learning accurate models where exact inference is tractable and speeding up approximate inference by focusing computation on the query variables and only spending as much effort on the remaining parts of the model as needed to answer the query accurately. First, for a case when the set of evidence variables is not known in advance and a single model is needed that can be used to *answer any query well, we propose a polynomial time algorithm for learning the structure of tractable graphical models with quality guarantees, including PAC learnability and graceful degradation guarantees. Ours is the first efficient algorithm to provide this type of guarantees. A key theoretical insight of our approach is a tractable upper bound on the mutual information of arbitrarily large sets of random variables that yields exponential speedups over the exact computation. Second, for a setting where the set of evidence variables is known in advance, we propose an approach for learning tractable models that tailors the structure of the model for the particular value of evidence that become known at test time. By avoiding a commitment to a single tractable structure during learning, we are able to expand the representation power of the model without sacrificing efficient exact inference and parameter learning. We provide a general framework that allows one to leverage existing structure learning algorithms for discovering high-quality evidence-specific structures. Empirically, we demonstrate state of the art accuracy on real-life datasets and an order of magnitude speedup. Finally, for applications where the intractable model structure is a given and approximate inference is needed, we propose a principled way to speed up convergence of belief propagation by focusing the computation on the query variables and away from the variables that are of no direct interest to the user. We demonstrate significant speedups over the state of the art on large-scale relational models. Unlike existing approaches, ours does not involve model simplification, and thus has an advantage of converging to the fixed point of the full model. More generally, we argue that the common approach of concentrating on the structure of representation provided by PGMs, and only structuring the computation as representation allows, is suboptimal because of the fundamental computational problems. It is the computation that eventually yields answers to the queries, so directly focusing on structure of computation is a natural direction for improving the quality of the answers. The results of this thesis are a step towards adapting the structure of computation as a foundation of graphical models."*

New Trends in Probabilistic Graphical Models

Graphical Models

Representations for Learning, Reasoning and Data Mining

John Wiley & Sons *Graphical models are of increasing importance in applied statistics, and in particular in data mining. Providing a self-contained introduction and overview to learning relational, probabilistic, and possibilistic networks from data, this second edition of Graphical Models is thoroughly updated to include the latest research in this burgeoning field, including a new chapter on visualization. The text provides graduate students, and researchers with all the necessary background material, including modelling under uncertainty, decomposition of distributions, graphical representation of distributions, and applications relating to graphical models and problems for further research.*

A Probabilistic Graphical Models Approach to Model Interconnectedness

In this paper, we show that using multiple models when executing a specific task almost unavoidably gives rise to interaction between them, especially when their number is large. We show that this interaction can lead to biased and incomplete results if treated inappropriately (which we believe is the current standard in the financial industry). We propose the use of Probabilistic Graphical Models - a machine learning technique as a remedy to this problem. We discuss some numerical aspects of our approach that will be present in any practical implementation. We then examine, in detail, a practical example of using this method in a stress testing context.

Elements of Causal Inference

Foundations and Learning Algorithms

MIT Press *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.*

Probabilistic Graphical Models in RapidMiner