Bayesian And Graphical Models For Biomedical Imaging First International Workshop Bambi 2014 Cambridge Ma Usa September 18 2014 Revised Selected Papers Lecture Notes In Computer Science

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Probabilistic Graphical Models

WILLIAMSON BECKER

Hybrid Random Fields Springer
Bayesian networks have grown to become a dominant type of model within the domain of probabilistic graphical models. Not only do they empower users with a graphical means for describing the relationships among random variables, but they also allow for (potentially) fewer parameters to estimate, and enable more efficient inference. The random variables and the relationships among them decide the structure of the directed acyclic graph that represents the Bayesian network. It is the stasis over time of these two components that we question in this thesis. By introducing a new type of probabilistic graphical model, which we call gated Bayesian networks, we allow for the variables that we include in our model, and the relationships among them, to change overtime. We introduce algorithms that can learn gated Bayesian networks that use different variables at different times, required due to the process which we are modelling going through distinct phases. We evaluate the efficacy of these algorithms within the domain of algorithmic trading, showing how the learnt gated Bayesian networks can improve upon a passive approach to trading. We also introduce algorithms that detect changes in the relationships among the random variables, allowing us to create a model that consists of several Bayesian networks, thereby revealing changes and the structure by which these changes occur. The resulting models can be used to detect the currently most appropriate Bayesian network, and we show their use in real-world examples from both the domain of sports analytics and finance.
Chain Event Graphs IGI Global
This volume constitutes the refereed proceedings of the Second International Workshop on Advanced Methodologies for Bayesian Networks, AMBN 2015, held in Yokohama, Japan, in November 2015. The 18 revised full papers and 6 invited abstracts presented were carefully reviewed and selected from numerous submissions. In the International Workshop on Advanced Methodologies for Bayesian Networks (AMBN), the researchers explore methodologies for enhancing the effectiveness of graphical models including modeling, reasoning, model selection, logic-probability

relations, and causality. The exploration of methodologies is complemented discussions of practical considerations for applying graphical models in real world settings, covering concerns like scalability, incremental learning, parallelization, and so on.
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.
Bayesian Methods in Gaussian Graphical Models Oxford University Press, USA
Bayesian networks and decision graphs are formal graphical languages for representation and communication of decision scenarios requiring reasoning under uncertainty. Their strengths are two-sided. It is easy for humans to construct and to understand them, and when communicated to a computer, they can easily be compiled. Furthermore, handy algorithms are developed for analyses of the models and for providing responses to a wide range of requests such as belief updating, determining optimal strategies, conflict analyses of evidence, and most probable explanation. The book emphasizes both the human and the computer sides. Part I gives a thorough introduction to Bayesian networks as well as decision trees and infulence diagrams, and through examples and exercises, the reader is instructed in building graphical models from domain knowledge. This part is self-contained and it does not require other background than standard secondary school mathematics. Part II is devoted to the presentation of algorithms and complexity issues. This part is also self-contained, but it requires that the reader is familiar with working with texts in the mathematical language. The author also: - provides a well-founded practical introduction to Bayesian networks, decision trees and influence diagrams; - gives several examples and exercises exploiting the computer systems for Bayesian netowrks and influence diagrams; - gives practical advice on constructiong Bayesian networks and influence diagrams from domain knowledge; - embeds decision making into the framework of Bayesian networks; - presents in detail the currently most efficient algorithms for probability updating in Bayesian networks; - discusses a wide range of analyes tools and model requests together with algorithms for calculation of responses; - gives a detailed presentation of the currently most efficient algorithm for solving influence diagrams.
Bayesian Inference in Gaussian Graphical Models When the Underlying Graph is Non-Decomposable Springer Nature
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.
Learning in Graphical Models Linköping University Electronic Press
In recent years probabilistic graphical models, especially Bayesian networks and decision graphs, have experienced

significant theoretical development within areas such as artificial intelligence and statistics. This carefully edited monograph is a compendium of the most recent advances in the area of probabilistic graphical models such as decision graphs, learning from data and inference. It presents a survey of the state of the art of specific topics of recent interest of Bayesian Networks, including approximate propagation, abductive inferences, decision graphs, and applications of influence. In addition, Advances in Bayesian Networks presents a careful selection of applications of probabilistic graphical models to various fields such as speech recognition, meteorology or information retrieval.

Advances in Probabilistic Graphical Models Springer Nature

Abstract: "A personal information filtering system monitors an incoming document stream to find the documents that match information needs specified by user profiles. The most challenging aspect in adaptive filtering is to develop a system to learn user profiles efficiently and effectively from very limited user supervision. In order to overcome this challenge, the system needs to do the following: use a robust learning algorithm that can work reasonably well when the amount of training data is small and be more effective with more training data; explore what a user likes while satisfying the user's immediate information need and trade off exploration and exploitation; consider many aspects of a document besides relevance, such as novelty, readability and authority; use multiple forms of evidence, such as user context and implicit feedback from the user, while interacting with a user; and handle various scenarios, such as missing data, in an operational environment robustly. This dissertation uses the Bayesian graphical modelling approach as a unified framework for filtering. We customize the framework to the filtering domain and develop a set of solutions that enable us to build a filtering system with the desired characteristics in a principled way. We evaluate and justify these solutions on a large and diverse set of standard and new adaptive filtering test collections. Firstly, we develop a novel technique to incorporate an IR expert's heuristic algorithm as a Bayesian prior into a machine learning classifier to improve the robustness of a filtering system. Secondly, we derive a novel model quality measure based on the uncertainty of model parameters to trade off exploration and exploitation and do active learning. Thirdly, we carry out a user study with a real web-based personal news filtering system and more than 20 users. With the data collected in the user study, we explore how to use existing graphical modeling algorithms to learn the causal relationships between multiple forms of evidence and improve the filtering system's performance using this evidence."

Online Bayesian Learning in Probabilistic Graphical Models Using Moment Matching with Applications Springer

Scientific studies in many fields involve understanding and characterizing dependence relationships among large numbers of variables. This can be challenging in settings where data is limited and noisy. Take survey data as an example, understanding the associations between questions may help researchers better explain themes amongst related questions and impute missing values. Yet, such data typically contains a combination of binary, continuous, and categorical variables, high proportions of missing values, and complex data structures. In this dissertation, we develop flexible models and algorithms to estimate Gaussian and latent Gaussian graphical models from noisy data. First, we develop a latent Gaussian graphical model for mixed data that takes advantage of informative prior beliefs on the marginal distribution of variables. Next, we propose several shrinkage priors for precision matrices and develop estimation procedures for fast posterior explorations of a single and multiple graphical models. This work is motivated by modeling survey-based cause of death instruments, known as verbal autopsies (VAs). Our methods provide new perspectives in improving model performance while recovering useful dependencies in the VA data.

Advances in Bayesian Networks MIT 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.

Probabilistic Graphical Models for Computer Vision Packt Publishing Ltd

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.

Advances in Probabilistic Graphical Models Springer Science & Business Media

In this dissertation we investigate the problem of network inference. The statistical frame- work tailored to this task is that of graphical models, in which the (in)dependence relation- ships satis ed by a multivariate distribution are represented through a graph. We consider the problem from a Bayesian perspective and focus on a subset of graphs making structure inference possible in an exact and e cient manner, namely spanning trees. Indeed, the integration of a function de ned on spanning trees can be performed with cubic complexity with respect to number of variables under some factorisation assumption on the edges, in spite of the super-exponential cardinality of this set. A careful choice of prior distributions on both graphs and distribution parameters allows to use this result for network inference in tree-structured graphical models, for which we provide a complete and formal framework.We also consider the situation in which observations are organised in a multivariate time- series. We assume that the underlying graph describing the dependence structure of the distribution is a ected by an unknown number of abrupt changes throughout time. Our goal is then to retrieve the number and locations of these change-points, therefore dealing with a segmentation problem. Using spanning trees and assuming that segments are inde- pendent from one another, we show that this can be achieved with polynomial complexity with respect to both the number of variables and the length of the series.

Bayesian Inference in Nonparanormal Graphical Models John Wiley & Sons

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.

Reasoning with Probabilistic and Deterministic Graphical Models

Springer Nature

This research monograph is highly contextual in the present era of spatial/spatio-temporal data explosion. The overall text contains many interesting results that are worth applying in practice, while it is also a source of intriguing and motivating questions for advanced research on spatial data science. The monograph is primarily prepared for graduate students of Computer Science, who wish to employ probabilistic graphical models, especially Bayesian networks (BNs), for applied research on spatial/spatio-temporal data. Students of any other discipline of engineering, science, and technology, will also find this monograph useful. Research students looking for a suitable problem for their MS or PhD thesis will also find this monograph beneficial. The open research problems as discussed with sufficient references in Chapter-8 and Chapter-9 can immensely help graduate researchers to identify topics of their own choice. The various illustrations and proofs presented throughout the monograph may help them to better understand the working principles of the models. The present monograph, containing sufficient description of the parameter learning and inference generation process for each enhanced BN model, can also serve as an algorithmic cookbook for the relevant system developers.

Bayesian Regularization for Graphical Models and Variants: Theory and Algorithms Springer

Probabilistic Graphical Models are often used to e fficiently encode uncertainty in real world problems as probability distributions. Bayesian learning allows us to compute a posterior distribution over the parameters of these distributions based on observed data. One of the main challenges in Bayesian learning is that the posterior distribution can become exponentially complex as new data becomes available. Secondly, many algorithms require all the data to be present in memory before the parameters can be learned and may require retraining when new data becomes available. This is problematic for big data and expensive for streaming applications where new data arrives constantly. In this work I have proposed an online moment matching algorithm for Bayesian learning called Bayesian Moment Matching (BMM). This algorithm is based on Assumed Density Filtering (ADF) and allows us to update the posterior in a constant amount of time as new data arrives. In BMM, after new data is received, the exact posterior is projected onto a family of distributions indexed by a set of parameters. This projection is accomplished by matching the moments of this approximate posterior with those of the exact one. This allows us to update the posterior at each step in constant time. The eff ectiveness of this technique has been demonstrated on two real world problems. - Topic Modelling: Latent Dirichlet Allocation (LDA) is a statistical topic model that examines a set of documents and based on the statistics of the words in each document, discovers what is the distribution over topics for each document. - Activity Recognition: Tung et al have developed an instrumented rolling walker with sensors and cameras to autonomously monitor the user outside the laboratory setting. I have developed automated techniques to identify the activities performed by users with respect to the walker (e.g.,walking, standing, turning) using a Bayesian network called Hidden Markov Model. This problem is signi cant for applied health scientists who are studying the eff ectiveness of walkers to prevent falls. My main contributions in this work are: - In this work, I have given a novel interpretation of moment matching by showingthat there exists a set of initial distributions (di erent from the prior) for which exact Bayesian learning yields the same first and second order moments in the posterior as moment matching. Hence the Bayesian Moment matching algorithm is exact with respect to an implicit posterior. - Label switching is a problem which arises in unsupervised learning because labels can be assigned to hidden variables in a Hidden Markov Model in all possible permutations without changing the model. I also show that even though the exact posterior has n! components each corresponding to a permutation of the hidden states, moment matching for a slightly di fferent distribution can allow us to compute the moments without enumerating all the permutations. - In traditional ADF, the approximate posterior at every time step is constructed by minimizing KL divergence between the approximate and exact posterior. In case the prior is from the exponential family, this boils down to matching the "natural" moments. This can lead to a time complexity which is the order of the number of variables in the problem at every time step. This can become problematic particularly in LDA, where the number of variables is of the order of the dictionary size which can be very large. I have derived an algorithm for moment matching called Linear Moment Matching which updates all the moments in O(n) where n is the number of hidden states. - I have derived a Bayesian Moment Matching algorithm (BMM) for LDA and compared the performance of BMM against existing techniques for topic modelling using multiple real world data sets. -I have developed a model for activity recognition using Hidden Markov Models (HMMs). I also analyse existing parameter learning techniques for HMMs in terms of accuracy. The accuracy of the generative HMM model is also compared to that of a discriminative CRF model. - I have also derived a Bayesian Moment Matching algorithm for Activity Recognition. The e ffectiveness of this algorithm on learning model parameters is analysed using two experiments conducted with real patients and a control group of walker users.

Mastering Probabilistic Graphical Models Using Python Packt Publishing Ltd

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.

Bayesian Methods for Graphical Models with Limited Data CRC 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

Exact Bayesian Inference in Graphical Models MIT Press
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.
Bayesian Networks and Decision Graphs 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.
Enhanced Bayesian Network Models for Spatial Time Series Prediction MIT Press 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.
Bayesian Network Technologies: Applications and Graphical Models Springer Science & Business Media 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.