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Editorial

Special issue on PGM'04: Second European workshop on probabilistic graphical models 2004

1. Introduction

Probabilistic graphical models, such as Bayesian networks and Markov networks, have been around for some time by now, and have seen a remarkable rise in their popularity within the scientific community during the past decade. This community is strikingly broad and includes computer scientists, statisticians, mathematicians, physicists, and, to an increasing extent, researchers from various fields of application, such as psychology, biomedicine and finance. It is not surprising that these researchers have developed a need for having their own specialised meetings to discuss progress in their area of research.

The biennial European workshop on probabilistic graphical models (PGM) currently serves this purpose. The workshop was an instant success in 2002 when it was held for the first time in Cuenca, Spain, as it was able to attract interest from the entire research community in probabilistic graphical models in Europe, and, to some extent, also from outside Europe. The papers included in this special issue are from the second, equally successful, workshop PGM'04, held from 4th to 8th October, 2004 in Leiden, The Netherlands. Of the 29 papers that were presented at PGM'04, eight were selected for inclusion in this special issue after revision. Each paper was reviewed by at least two independent reviewers, and based on their reviews revised versions of the papers were submitted. This special issue will, therefore, give a good, representative impression of the state of the art of the research in probabilistic graphical models.

2. Content of the special issue

Below, we give a brief summary of the content of the papers included in this special issue. Roughly, the papers focus on either Bayesian networks or influence diagrams, and either deal with problems related to probabilistic or decision-theoretic inference or structure and parameter learning. To start, we summarise the two papers dealing with

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inference in Bayesian networks, followed by four papers that discuss methods for structure and parameter learning; the special issue is rounded-off by the two papers on learning and inference in influence diagrams.

The paper by Mark Chavira, Adnan Darwiche and Manfred Jaeger, titled "Compiling relational Bayesian networks for exact inference" describes work on the PRIMULA system, a system that allows specifying Bayesian networks as logical constructs, so-called relational Bayesian networks. In the paper it is shown that these can be compiled into arithmetic circuits through a number of intermediate steps, which allows exploiting the local structure present in probability tables. In the next paper, titled "Operations for inference in continuous Bayesian networks with linear deterministic variables", by Barry Cobb and Prakash Shenoy an inference method for dealing with continuous Bayesian networks is described, where continuous variables are a linear deterministic function of their parent variables in the Bayesian network. Inference is carried out using the theory of mixtures of truncated exponentials, also discussed in another paper included in this special issue (see below).

The subsequent four papers are concerned with various approaches to learning Bayesian networks. The first paper, by Ad Feelders and Linda van der Gaag, titled "Learning Bayesian network parameters under order constraints", deals with the problem of how to incorporate knowledge about qualitative probabilistic relationships, expressed by signs, into the parameter learning process. It is shown that the incorporation of such prior qualitative knowledge into the learning process leads to an improved fit of the learnt probability distribution to the true distribution. The proposed method, therefore, alleviates the life of Bayesian-network developers, as it allows them to exploit information of various kinds in the development process. The paper titled "Learning hybrid Bayesian networks using mixtures of truncated exponentials" by Vanessa Romero, Rafael Rumí and Antonio Salmerón proposes a new algorithm for learning hybrid Bayesian networks from data using the theory of mixtures of truncated exponentials. Both structure and parameter learning are investigated in this context. When learning Bayesian networks from real-life data, one is normally confronted with the fact that data are missing. In the paper by Carsten Riggelsen, titled "Learning Bayesian network parameters from incomplete data via importance sampling", a new statistically valid algorithm is proposed that supports parameter learning for discrete Bayesian networks in the face of missing data. The algorithm is compared to earlier algorithms that are able to deal with missing data, such as the EM algorithm. Probabilistic decision graphs are a relatively new representation language that allows representing joint probability distributions compactly by exploiting local structure. In the paper, " Learning probabilistic decision graphs" by Manfred Jaeger, Jens Nielsen and Tomi Silander, the problem of learning probabilistic decision graphs from data is studied. The learning method is compared to a standard method of learning Bayesian networks from data, and the paper also discusses a mixed method, where probabilistic decision graphs and Bayesian-network learning are combined.

The last two papers included in this special issue concern influence diagrams. The first paper on influence diagrams, titled "Sequential influence diagrams: a unified asymmetry framework", by Finn Jensen, Thomas Nielsen and Prakash Shenoy is about the representation of decision-making knowledge in influence diagrams. Influence diagrams provide a convenient representation formalism for decision-making; however, in the standard influence-diagram formalism only symmetric decision problems can be represented. This normally leads to some representational overhead. The proposed formalism of sequential influence diagrams is influence-diagram like, yet offers means to encode asymmetry. The second paper on influence diagrams by Andrés Cano, Manuel Gómez and Serafín Moral, titled "A forward–backward Monte-Carlo method for solving influence diagrams" deals with influence diagram reasoning, in particular its efficiency. As influence diagrams for real-life problem can be very large, it is usually hard or even impossible to solve them. The authors propose a new, approximate anytime algorithm that is able to handle such large influence-diagram problems.

This special issue on probabilistic graphical models offers a good cross-section of the topics that are currently attracting attention from researchers. We therefore hope that it assists the researchers who were unable to attend PGM'04 to get up to date. Those researchers, whom we met at PGM'04, hopefully appreciate the fact that the included papers have been extended and improved and, thus, offer an even better account of the mentioned research than already was the case at PGM'04.

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Peter J.F. Lucas
Institute for Computing and Information Sciences
Radboud University
Toernooiveld 1
6525 ED Nijmegen
The Netherlands

José A. Gámez
Computer Science Department
University of Castilla-La Mancha
Spain

Antonio Salmerón
Department of Statistics and Applied Mathematics
University of Almería
Spain

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