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Special issue on the Twelfth International Conference on Probabilistic Graphical Models (PGM 2024)

The International Conference on Probabilistic Graphical Models (PGM) is a biennial conference that brings together researchers interested in all aspects of graphical models for probabilistic reasoning, decision making, and learning. The twelfth edition took place in Nijmegen, The Netherlands, between the 11th and the 13th of September 2024.

The 32 papers presented at the conference and included in the conference proceedings [1] were selected after rigorous reviewing of 40 manuscripts, submitted by authors from around the world. After the conference, the authors of nine papers were invited to submit an extended version of their paper to this special issue of the *International Journal of Approximate Reasoning* (IJAR) devoted to a selection of PGM 2024 papers. Selection of papers was based upon the scientific quality and the potential for extension of the PGM contribution. Eight extended versions were received from these nine invitations, which went through the full reviewing process according to the IJAR standards and were ultimately accepted for publication in this special issue.

The accepted papers illustrate the wide scope of PGM, dealing with different types of probabilistic graphical models such as Bayesian networks, probabilistic circuits, causal networks and credal networks. The focus of the research described in the papers varies from studying foundations to introducing novel approaches to inference and structure learning, to identifying or bounding causal queries, and for handling heavy-tail distributions.

- *Identifying Total Causal Effects in Linear Models Under Partial Homoscedasticity* by David Strieder and Mathias Drton [2] is one of several papers that address the topic of causality. The paper more specifically is concerned with conditions under which total causal effects can be identified from observational data alone. A known setting that allows for this is an underlying linear Gaussian structural causal model with equivalence or all error variances. The authors relax this assumption to shared variances for a restricted set of variables only, and explore how to incorporate structure uncertainty into causal inference under similar conditions.
- *Soft Learning Probabilistic Circuits* by Soroush Ghandi, Benjamin Quost, and Cassio P. de Campos [3] considers learning probabilistic circuits, also known as sum-product networks, from data. The paper analyzes the behaviour of the prominent LearnSPN algorithm, arguing that the repeated greedy hard clustering steps performed during learning can lead to rigid partitioning of marginals, resulting in possible overfitting and poor generalization. The SoftLearn algorithm is proposed to counter the costs of greedy behaviour by taking soft cluster memberships into account in order to obtain greater accuracy in real-world applications.
- *Latent Gaussian and Hüsler-Reiss Graphical Models with Golazo Penalty* by Ignacio Echave-Sustaeta Rodríguez and Frank Röttger [4] focuses on structure learning in the presence of latent variables, for two types of graphical model: multivariate Gaussians, and Hüsler-Reiss graphical models that are suitable for capturing extreme events and their dependences. For both types of model, the authors propose to use the recently introduced Golazo penalty as an alternative to l_1 penalty typically used in learning optimal models.
- *On Fast Arc-Reversal* by Cory Butz, Anders L. Madsen, and Jhonatan S. Oliveira [5] proposes a new inference algorithm for Bayesian networks, Fast Arc-Reversal (FAR), that combines the efficiency of the Variable Elimination (VE) algorithm with the property of preserving sound sub-BN structures of the Arc-Reversal (AR) algorithm. Evaluation on benchmark Bayesian networks shows that the new algorithm is typically more efficient than AR. Moreover, FAR provides for an intuitive visualization of the elimination results of VE, and can help to improve the interpretability of sum-product networks.
- *Cauchy Graph Convolutional Networks* by Taurai Muvunza, Yang Li, and Ercan Engin Kuruoglu [6] considers learning Bayesian networks from data. This paper proposes the use of multivariate Cauchy distributions and shows that such a distribution factor-

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izes as a Bayesian network. The paper also proposes an algorithm for learning these Cauchy graphical models from data. The robustness of this new type of model in real-world settings is evaluated by using the learned structure as the graph topology underlying a graph convolutional network.

- *Divide and Conquer for Causal Computation* by Anna Rodum Bjøru, Rafael Cabañas, Helge Langseth, and Antonio Salmerón [7] proposes a new approach to approximating bounds on unidentifiable causal queries, specifically in case of high-cardinality exogenous variables. Building on a credal network interpretation of Structural Causal models each exogenous variable can be associated with a separate credal set. This allows for a divide-and-conquer approach that enables exact calculation of queries in submodels, providing more accurate bounds at lower computational costs.
- *Stable Structure Learning with HC-Stable and Tabu-Stable Algorithms* by N. Ken Kitson and Anthony C. Constantinou [8] discusses and provides a solution for instability in Bayesian network structure learning algorithms. Instability arises when the order of variables in the dataset influences the choice for directing arcs. This problem was previously addressed for the PC algorithm; this paper considers score-based greedy hill-climbing algorithms for both discrete variable and continuous variable networks.
- *Sensitivity Analysis to Unobserved Confounding with Copula-Based Normalizing Flows* by Sourabh Balgi, Marc Braun, Jose M. Peña, and Adel Daoud [9] extends the state-of-the-art in approaches to stress-testing how causal effect estimates depend on the extent of confoundedness. The authors introduce the ρ-GNF method that suits different types of observational data, uses intuitive sensitivity parameters, and allows for specifying distributional assumptions for the unobserved causes.

We are grateful to both the members of the PGM 2024 Programme Committee and the additional reviewers we recruited, for their detailed and timely reviews. Their efforts and competence have made this special issue possible. We would like to conclude by thanking Elsevier for their support with guiding us through the whole process of managing and editing this special issue. We are particularly grateful to Prof. Thierry Denoeux, Editor-in-Chief of this journal, for the chance to publish this special issue and for his support throughout the reviewing and decision-making process. Thank you!

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