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Editorial

Editorial for the Special Issue on "Bayesian Networks: Inference Algorithms, Applications, and Software Tools"

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In the field of Artificial Intelligence, *Bayesian Networks* (BN) [1] are a well-known framework for reasoning under uncertain knowledge. BNs have been applied in a wide range of real-world domains, such as medical diagnosis, forensic analysis, dependability assessment, risk management, etc. With respect to other types of models, BNs provide relevant advantages: at the modelling level, the compact representation of the joint distribution of the system variables leads to the factorization of the set of possible states, avoiding the generation of the complete state space of the system; at the analysis level, inference algorithms can compute the probability distribution of any variable, possibly conditioned on the observation of the value (state) of other variables, so that predictive and diagnostic measures can be easily evaluated. During the years, BNs have been extended in order to increase their modelling and analysis power; for instance, *Dynamic Bayesian Networks* (DBN) and *Continuous-Time Bayesian Networks* take time into account, *Hybrid Bayesian Networks* deal with both discrete and continuous variables, *Decision Networks* (DN) contain decision nodes and value nodes.

This Special Issue covers a range of case studies examined by means of BNs and their extensions. DBNs are exploited for the risk assessment of a nuclear reactor in [2]. This infrastructure belongs to the class of *Complex Engineering Systems* (CES) and DBNs enable the forward and backward inference of system states, diagnosing current system health, and forecasting future system prognosis. Simulated accident sequence data are used as evidence during DBN inference; the results can serve as a training tool for CES operators to better prepare for accident scenarios. Autonomous vehicles, taking the environmental context into account, are another application field documented in [3], where BNs help in *Fault Detection Isolation and Recovery* (FDIR) in real-time conditions. The models are automatically generated from *Failure Mode and Effects Analysis* (FMEA) and operate online for autonomous vehicles. Then, in the safe mission planning of *Unmanned Aerial Vehicles* (UAV), DNs are experimented as decision-making models; several realistic examples show the benefits.

A BN can be constructed by means of parameter and structure learning from data, as discussed in [4]. When data are incomplete, learning is usually implemented with the *Expectation-Maximization* (EM) algorithm computing the relevant sufficient statistics by belief propagation, or with the *Structural Expectation-Maximization* (Structural EM) algorithm building the network structure from those sufficient statistics. Since practical implementations often impute missing data to compute sufficient statistics, the impact of using imputation instead of belief propagation, is investigated on the quality of the resulting BNs. Given synthetic data, reference BNs, and several scenarios, the better approach is recommended according to the characteristics of the data. As a result, a *Decision Tree* (DT) is built to guide practitioners in choosing the EM algorithm.

Another work about machine learning is presented in [5] and deals with the problem of traffic barrier crashes, with the goal of identifying and optimizing the heights of the barriers, based on the monetary saving and the reduction of frequency and severity of crashes. The paper presents an empirical cost-benefit analysis based on *Bayesian hierarchical machine learning* technique, where a hierarchical model is employed to provide a flexible way of

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addressing the problem. This work is extended in [6] where *Finite Mixture Model* (FMM) is used to find the distribution parameters characterizing the observation dataset. FMM accuracy may be compromised by several problems affecting data, like overdispersion, heterogeneity, loss of information. Thus a new methodology called *Bayesian Hierarchical Finite Mixture*, is implemented, where the FMM parameters are estimated by maximum likelihood technique.

Bootstrap resampling techniques, approximating statistical distributions, are presented in a general Bayesian framework in [7]. Several bootstrap techniques are used and compared in predictive classification and regression models based on ensemble approaches, i.e. bagging models involving DTs. In particular, *Proper Bayesian bootstrap* is used to sample the posterior distribution over trees, introducing prior distributions on the covariates and the target variable. The results obtained on simulated and real data, are compared with respect to other competitive procedures employing different bootstrap techniques.

In summary, this Special Issue covers aspects like learning BN structure and parameters from data, and the utilization of BN modeling and analysis for monitoring, fault diagnosis and future state prediction of safety-critical systems like power plants and autonomous vehicles. Besides BNs, the Special Issue collects works about Bayesian approaches for data analysis, such as machine learning and FMM (both applied to traffic barrier crashes), or bootstrap resampling techniques. We hope that these articles help us advance in our understanding of the capabilities of BNs and Bayesian methods, in particular when exploited for risk and reliability assessment of infrastructures characterized by dependability requirements.

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Abbreviations

The following abbreviations are used in this manuscript:

BN	Bayesian Network
CES	Complex Engineering System
DBN	Dynamic Bayesian Network
DN	Decision Network
DT	Decision Tree
EM	Expectation-Maximization
FDIR	Fault Detection Isolation and Recovery
FMEA	Failure Mode and Effects Analysis
FMM	Finite Mixture Model
UAV	Unmanned Aerial Vehicle

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