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Structure Learning of Bayesian Networks Using Elephant Swarm Water Search Algorithm

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ABSTRACT

Bayesian networks are useful analytical models for designing the structure of knowledge in machine learning. Bayesian networks can represent probabilistic dependency relationships among the variables. One strategy of Bayesian Networks structure learning is the score and search technique. The authors present the Elephant Swarm Water Search Algorithm (ESWSA) as a novel approach to Bayesian network structure learning. In the algorithm; Deleting, Reversing, Inserting, and Moving are used to make the ESWSA for reaching the optimal structure solution. Mainly, water search strategy of elephants during drought periods is used in the ESWSA algorithm. The proposed method is compared with simulated annealing and greedy search using BDe score function. The authors have also investigated the confusion matrix performances of these techniques utilizing various benchmark data sets. As presented by the results of the evaluations, the proposed algorithm has better performance than the other algorithms and produces better scores and accuracy values.

KEYWORDS

Bayesian Network, Elephant Swarm, Global Search, Local Search, Search and Score Structure Learning, Water Search

INTRODUCTION

Bayesian networks (BN) are one of the simplified analytical methods for constructing the probabilistic structure of knowledge in machine learning (Ji, Wei, & Liu, 2012). They can be implemented universally in knowledge design, argumentation, and inference (Fortier, Sheppard, & Pillai, 2013). The structure of the Bayesian network is a direct acyclic graph (DAG) which is formed concerning two significant parts; the parameters and the structure of the network. The parameters describe conditional probabilities, and the structure expresses dependencies among the variables. Solving the learning structure of the Bayesian network without a suitable search method is difficult. The challenges for learning the structure of Bayesian network (BN) from a dataset to achieve the optimal is NP-hard optimization problem (Li & Chen, 2014); however, extensive research has been conducted

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to develop approximate strategies for learning network structure. Essentially, there are two procedures for Bayesian networks structural learning. The first is a constraint-based procedure while the second is score and search procedure (Margaritis, 2003). The score and search method is used to explore the space of BN structures and continuously evaluate all applicant network structures until the valid metric value achieved.

Score-based procedures rely on a function to evaluate the network, the available data, and they search for a structure that optimizes the score, which is the goal (Fast, 2010). The score function method is implemented using two primary criteria: Bayesian score and information-theoretic score. The information-theoretic score implemented in methods like; Log-likelihood (LL), Akaike information criterion (AIC), Bayesian Information Criterion (BIC), Minimum Description Length (MDL), Normalized Minimum Likelihood (NML), and Mutual Information Tests (MIT). The Bayesian score implemented in some other methods like; BD (Bayesian Dirichlet), BDe (Bayesian Dirichlet ("e" for likelihood-equivalence)), BDeu (Bayesian Dirichlet equivalent uniform ("u" for uniform joint distribution)), and K2 (Cooper & Herskovits, 1992).

There are several methods of the search strategy for achieving the optimization of the structure learning problem. They include Particle Swarm Intelligence (Cowie, Oteniya, & Coles, 2007), Ant Colony Optimization Algorithm (Salama & Freitas, 2012), Bee Colony (Li & Chen, 2014), Hybrid Algorithm (He & Gao, 2018; Li & Wang, 2017; Kareem & Okur, 2018), Simulated Annealing Algorithm (Hesar, 2013), Bacterial Foraging Optimization (Yang, Ji, Liu, Liu, & Yin, 2016), Genetic Algorithms (Larraiiaga & Poza, 1996), Gene-Pool Optimal Mixing Evolutionary Algorithm (GOMEA) (Orphanou, Thierens, & Bosman, 2018), Breeding Swarm Algorithm (Khanteymoori, Olyaee, Abbaszadeh, & Valian, 2018), Binary Encoding Water Cycle (Wang & Liu, 2018), Pigeon Inspired Optimization (Kareem & Okur, 2019), Tightening Bounds (Fan, Yuan, & Malone, 2014), A* Search Algorithms (Yuan, Malonean, & Wu, 2011), Scatter Search Documents (Djan-Sampson & Sahin, 2004), Cuckoo Optimization Algorithm (Askari & Ahsaee, 2018), Quasi-Determinism Screening (Rahier, Marie, Girard & Forbes, 2019), and Minimum Spanning Tree Algorithm (Sencer, Oztemel, Taskin, & Torkul, 2013). Another state-of-the-art metaheuristic method that can be used for structure learning in Bayesian networks is the elephant swarm optimization. This paper proposes and presents a comparative evaluation of this method as a novel approach to Bayesian network structure learning.

The organization of the remainder of this paper is as follows. Section 2 presents the concept of structure learning in Bayesian Networks. Section 3 includes a brief introduction of Elephant Swarm Water Search Algorithm. We discuss in detail the methodology and present the experimental result in section 4. The conclusions are in section 5.

STRUCTURE LEARNING OF BAYESIAN NETWORKS

Fundamentally the Bayesian Network can be expressed using two components: (G, P). The first one, G(V; E) is the DAG covering the calculable group of vertices (or nodes), V, interconnected over marked edges (or links), E . The second one, $P = \{P(X_i \mid Pa(X_i))\}$ represents the collection of conditional probabilistic distributions (CPD), individual to all variables X_i (vertices from a graph). Moreover, $Pa(X_i)$ represents the collection of parents of the node X_i in G (Cowie, Oteniya, & Coles, 2007). Based on this model, a simple probabilistic combination for a (G; P) network can be represented via:

$$P\left(X_i,\ldots X_n\right)\prod_{i=1}^{n}P\left(X_i \mid Pa\left(X_i\right)\right) \tag{1}$$

A score function, on the other hand, depends on several criteria, including Bayesian approaches, information and entropy, and minimum description length (Campos, 2006). According to Bayesian inference rules, Bayesian - network posterior probability can express as:

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