ISSN 2278-3091
Volume 8, No.1.2, 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse2281.22019.pdf
https://doi.org/10.30534/ijatcse/2019/2281.22019

Bayesian Network Structure Learning Based On Pigeon Inspired Optimization

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ABSTRACT

Bayesian networks are useful analytical models for designing the structure of knowledge in machine learning. Probabilistic dependency relationships among the variables can be represented by Bayesian networks. One strategy of a structure learning Bayesian Networks is the score and search technique. In this paper, present the proposed method for Bayesian network structure learning which is depended on Pigeon Inspired Optimization (PIO). The proposed method is a simple one among a firm concentration rate. In nature, a navigational ability concerning pigeons is unbelievable and impressive. Under the PIO search algorithm, we define a set of directed acyclic graphs. Every graph owns a score which shows its fitness. It iterates the algorithm until it gets the best solution or a satisfactory network structure using a landmark, compass and map operator. During this work, the proposed method compared with Simulated Annealing and Greedy Search using BDe score function. We also investigated the confusion matrix performances of the methods using various benchmark data sets. Specific effects show that a presented algorithm produces excellent performance than Simulated Annealing and Greedy algorithms and produces higher scores and accuracy values.

Key words: Bayesian network, structure learning, pigeon inspired optimization, global search, local search, search and score.

1. INTRODUCTION

The most common analytical methods to construct the probabilistic structure of knowledge in machine learning is Bayesian networks (BN). They can be implemented universally in knowledge design, argumentation, and inference [1]. The network structure of Bayesian is a directed acyclic graph (DAG) they form which of two major parts; parameters and the structure of the network. Parameters describe conditional probabilities, and the structure expresses dependencies among the variables. Bayesian network structure learning is NP-hard [2, 27]. But, they have conducted extensive research to develop approximate strategies for learning network structure. There are two approaches concerning Bayesian networks structural learning. The first is a constraint-based and the second is score and search approach [3]. 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 [4]. The score function method is implemented using two major criteria: Bayesian score and information-theoretic score. The Bayesian score is implemented in some methods like; K2, BD, BDe, and BDeu. The information-theoretic score implemented in other methods like; LL, AIC, BIC/MDL, NML, and MIT [5].

There are various methods to search strategy for achieving the optimization of the structure learning problem. They include Bee Colony [2], Particle Swarm optimization [6], Ant Colony Algorithm [7], Hybrid methods [8,9,10,11], Simulated Annealing Algorithm [12], Bacterial foraging optimization [13], Genetic algorithms [14], Gene-Pool Optimal Mixing Evolutionary Algorithm (GOMEA) [15], Breeding Swarm algorithm [16], binary encoding water cycle [17]. The organization of the remainder of the paper is as follows. Section 2 presents the concept of structure learning in Bayesian Networks. Section 3 includes a brief introduction of Pigeon Inspired Optimization algorithm. We discuss in detail the methodology and present the experimental result in section 4. The conclusion is in section 5.

2. STRUCTURE LEARNING OF BAYESIAN NETWORKS

Fundamentally the Bayesian Network can be expressed using two components: (G, P). The first one, G (V; E) is a DAG covering a calculable group of vertices, V, interconnected over marked edges (or links), E. The second one, P = {P (Xi | Pa (Xi))} represents the collection of conditional probabilistic distributions (CPD), individual to all variables Xi (vertices of the graph), moreover Pa(Xi)) represents the collection of parents of the node Xi in G [1]. Based on this model, common probabilistic combination for a (G; P) network can be represented via:

$$P(X1, \ldots Xn) = \prod_{i=1}^{n} P(Xi|Pa(Xi)) \qquad (1)$$

where Pa(Xi) is the parents of Xi. Focusing on the techniques for Bayesian networks structure learning dependent on score & search method. A score function, on the other hand, depends on several criteria, like Bayesian approaches, information and entropy, and minimum description length [18]. According to Bayesian inference rules, Bayesian network posterior probability can be expressed as:

$$P(G^h|D) = \frac{P(G^h|D)P(G^h)}{\sum P(D|G^h)P(G^{h'})} \quad (2)$$

In (2), P(D|G) is marginal likelihood, which is defined using the normalizing constant P(D) as:

$$P(D|G) = \int P(D|G,\theta)\,P(\theta|G)d\theta \quad (3)$$

P(D) is assumed to be independent of the structure of Bayesian network G. P(G') is the prior probability and θ represents the parameter of the model. Consequently, as long as the marginal probability to all feasible structure is determined, the posterior distribution of the network structure can be calculated [19]. Structure learning methods use score-based techniques by comparing the current and previous scores of the structure. The final expression of the score is [20]:

Score (G,D)=ΣScore (Xi,Pa(Xi), D(Xi,pa(Xi)) (4)

3. PIGEON-INSPIRED OPTIMIZATION

Pigeon-inspired optimization (PIO) denotes a novel optimization algorithm in bio-inspired [20]. PIO technique is depended on the navigational performance from pigeons and introduced foremost through Duan and Qiao [20] and used for air robot path planning. In reality, the pigeons able to detect the targets based on the magnetic field, the sun, including landmarks. The essential PIO owns pair drivers; a map and compass driver, and a landmark driver. The map and compass driver based on the magnetic domain plus a sun, while the landmark driver depends on landmarks. In PIO mode, it applies the behavior of pragmatic pigeons. During the map and compass they establish driver among the location Pi plus the speed Vi from pigeon i including a location plus speeds within D-dimensional exploration area stay renewed during every repetition. We can determine the new location Pi and speed Vi of pigeon i through each tth iteration as follows [21]:

$$Vi(t) = Vi(t-1).e^{-Rt} + \text{rand. (Pg-Pi(t-1))} \quad (5)$$

$$Pi(t) = Pi(t-1) + Vi(t) \quad (6)$$

where R is a factor of map and compass, the random number is a rand, also Pg holds every modern global valid location, that can be achieved through associating each the location amidst a group of pigeons. Figure 1 shown the valid locations of each pigeon are confirmed by utilizing the map and compass [21]. Through analyzing every flown location, that implies clear choice fastened pigeon's location holds an excellent one. Every pigeon is able to establish its path through regarding the special pigeon in proportion to Equation (5), That is shown through the solid indicators. The light indicators continue its recent pathway, that becomes an association with Vi(t-1) * e $^{(-Rt)}$ within Equation (5). The valid location from the pigeons is the right view as shown in Figure 1. A former arrow of some pigeons flying direction is the thin arrows while adjusting the direction based on the best one is the thick arrows. The vector amount of those couple Indicators continues its succeeding routing path. Modern research has shown that pigeons able to receive leader knowledge on natural landmarks [20], like waterways, central roads, including railroads. It supposes a landmark driver, shown in Figure 2 to accord a similar location among the neighboring pigeon within a range. While referred in the Figure2, some pigeon within the core from the figure stands a goal of the remaining pigeons. Some pigeons thereabout the goal preference move to the goal fast. Half of the pigeons rejected within every iteration during the landmark driver [21]. Amount of pigeons in each iteration can be calculated by following:

$$Np = ceil\frac{Np(t-1)}{2} \quad (7)$$

where ceil (A) turns the variable A to the nearest integers bigger than or equivalent to A. Assume that every pigeon can fly directly into the central target. Later, at each iteration, the position of pigeon i is updated as:

$$Xi(t) = Xi(t-1) + rand(Xc(t) - Xi(t-1)) \quad (8)$$

where Xc(t) means a core location in a tth iteration, which described by

$$Xc(t) = \frac{\sum Xi(t).fitness(Xi(t))}{Np\sum fitness(Xi(t))} \quad (9)$$

fitness (•) holds the standard for evaluating a property for all pigeon. This is described as a fitness (Xi (t)) = 1/ (fmin (Xi (t)) + ε) for minimum optimization or fitness (Xi (t)) = fmax (Xi (t)) for maximum optimization.

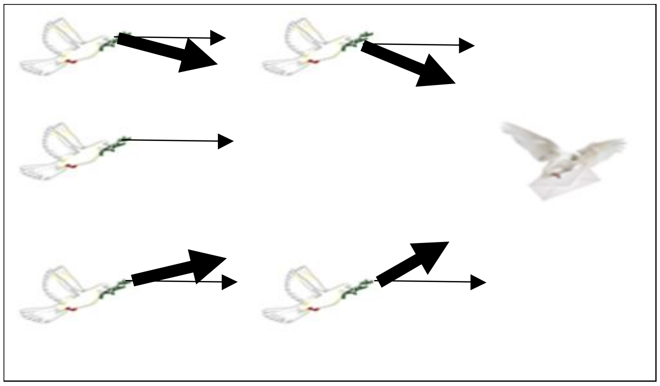

Figure 1: Operator of Map and Compass [20].

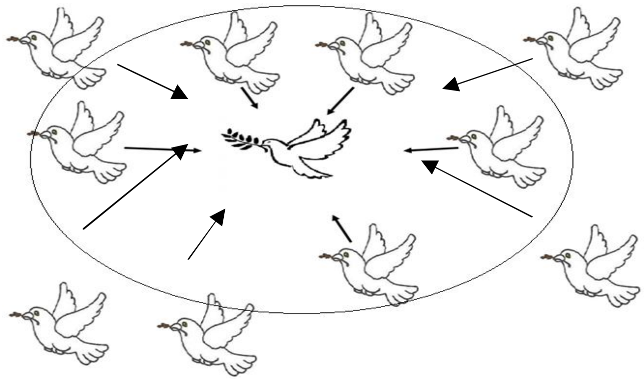

Figure 2: Operator of Landmark [20]

4. PIO FOR BAYESIAN NETWORK STRUCTURE LEARNING

The proposed method uses PIO approach as a search method for structural learning of Bayesian networks. The BDe metric was used as score function for measuring the Bayesian network structure. The PIO algorithm is effectively an iterated procedure that consists of a population of individuals where every pigeon encodes a potential position and velocity in a given space. This space is held to be the search space. The proposed method is based on two techniques. The first technique uses map and compass operator model for local search through the necessary process. The second one uses landmark operator model for global search. Figure 3 shows the pseudo code of this technique. PIO algorithm's solution construction utilizes different neighbourhood than local search. The expectation that local search updates a solution formed by a Pigeon is actually high. The Bayesian network structure learning solution area is formed for each potential DAGs. Every pigeon inside the swarm initiates a possible solution which is represented as a DAG having empty arcs. A pigeon later examines the exploration area for finding the approximately near-optimal or optimal solution which is known as the BDe score. Equation (4) is used to calculate the BDe score as the goal function of the optimization. The exploration aims for obtaining a higher BDe score for the network structure. All initial solutions are produced through iterative operations. Starting with a blank graph (G0), the arcs are appended one after another, provided that they are not included in the current graph solution. The append operation is performed If the new solution score function is higher than the current result, the new solution also satisfies the DAG constraint.

This process continues until the quantity of the arcs equals the quantity defined in advance. In the model, the solution starts assigning a population for each operator and picks the solution which has a higher score function. Pigeon continues according to the selected operator until the process has performed a maximum number of iterations or the BDe score not increased anymore. Typically, the processes hold four separate operations in local optimization: Deletion, Addition, Reversion, Movement. The first three are simple operations within this domain, involve just replacing an individual edge every time from a competitor solution. This allows the inclusion of a comparatively small area near the solution. With every movement operation, on the other hand, the existing edges change the set of parents which can make a

Algorithm PIOSB (pigeon inspired optimization for structure learning of Bayesian network)
INPUT: - datasets
NP: pigeons number.
D: search space dimension
P: factor of the map and compass
Search range: the border of search space
Nc1max: maximum number of iteration number for the map and compass operation is carried out
Nc2max: maximum number of iteration number for the landmark operation is carried out.
OUTPUT: - learning Bayesian Network

(1) *The initialized empty structure and initialize PIO parameters (dimension space D, population size of Np, factor R for map and compass, the number of iteration Nc1 max and Nc2 max for two operators, and Nc2 max>Nc1 max.*
(2) *Set the velocity and position for all Pigeon randomly. Comparing each Pigeon by BDe score function, and find the best in the current position.*
(3) *Assign the value of velocity and location according to the Equations (5) and (6) for each pigeon in operator of the map and compass.*
(4) *Find a new best position, by comparing the BDe score function of each pigeon.*
(5) *If Nc2> Nc1 max, halt a map and compass driver plus operate next driver. Oppositely, move into Step 3.*
(6) *List every pigeon depended on the values of the fitness. Half from a pigeons that score function lows preference attend those pigeons including a large score based on the Equation (7).*
    a) *Get a core for every pigeon based on Equation (9), plus the core is the desired goal. Every pigeon fly toward the goal through setting their flying path based on Equation (8).*
    b) *Later, save the valid solution parameters including the best value of the score.*
    c) *If Nc1> Nc2 max, end the diver of a landmark, also store the results. Otherwise, move to Step 5.*
(7) *Return a maximum BDe score.*

Figure-3: PIO Algorithm for Structure learning Bayesian Network.

moderately big modification for the current solution. Therefore, if the solution is not changed after applying simple operators, the move operator may improve it. Flying is the major force utilizing the chosen operation in local optimization, which grows further widespread while a pigeon approaches the desirable solution. Flying directions, the switch with various local optimization operators, grows extra widespread as a pigeon flies continuously of a solution through exploration toward a better one. Therefore, the current velocity is renewed in accordance with either pigeon's best global or best local solution. The velocity of pigeon is renewed based on the current best position of the pigeon in the local search. On the other hand, the global velocity depends on the best global solution concerning pigeon in a global search, near a global best position. As shown in Figure.4, Pigeon G0, which describes a DAG with arcs, tries reversion, move, addition, and deletion, and reaches new solutions G1, G2, G3, and G4, respectively. Assuming the best score is in G3, it will be selected and the pigeon will proceed to examining some equivalent process to get G+3 as the new solution. If the BDe score of G+3 is higher than that of G+1, it will continue to perform the corresponding operator. The operations will be repeated until the BDe score stabilities, or iteration loop reaches maximum. In the whole process, the pigeon selects among the directions as Deletion, Addition, Movement and Reversion.

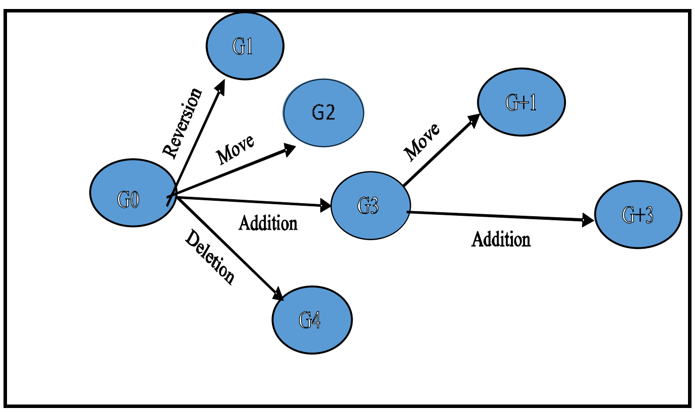

Figure 4: Map and compass steps for one Pigeon

5. EXPERIMENTAL EVALUATION

To assess the performance of the algorithm (PIOSBN), a standard evaluation technique was used to experiment with the algorithm upon datasets extracted of well-known benchmarks about Bayesian networks using probabilistic representations. The test platform is the PC among Core i3, 2.1GHz CPU, 4GB RAM, plus Windows 7, including a method implies executed by Java. We experiment proposed algorithms on various datasets; Alarm, Adult, Epigenetics, Heart, Hepatitis, Imports, Letter, Parkinsons, Sensors, WDBC, Water, win95pts, Andes, Hepar, Hail, static banjo, and mushroom. We compared the results with Simulated Annealing and Greedy Search a technique utilizing the similarly metric on the corresponding datasets. After defining all the parameters of PIO algorithms, local and global search applied to the datasets. We compared the results with Simulated Annealing and Greedy Search methods by utilizing corresponding metrics for the datasets. After defining the parameters of PIO algorithm, local and global search are applied to the datasets. The parameters of Simulated Annealing algorithms are as follows: Temperature of Reannealing = 500, cooling factor= 0.8, Initial temperature= 1000. Greedy search parameters are as follows: Recommended minimum networks before reboot = 3000, minimum recommended networks after highest score = 1000, maximum recommended networks before reboot = 5000, the maximum parent count for operations Reboot=5, restart by random network = yes. The algorithms have been implemented in three different execution times: 2 minutes, 5 minutes and 60 minutes.

The results in Table 1 present the score for each algorithm in the mentioned datasets and time values. From this table, it can be noted that, the proposed method produces better score values than the default Greedy Search plus simulated Annealing Algorithms for all situations. This indicates that, the PIO finds the best score with minimum time required.

To evaluate the success of structure discovery, the confusion matrix has been computed for each data set and its known network structure. The metrics TP, TN, FN, and FP have been calculated for each network per algorithm as well as the criteria; Sensitivity (SE), Accuracy (Acc), F1_Score, and AHD which are described by:

$$\text{sensitivity} = \frac{TP}{TP+FN} \tag{10}$$

$$\text{accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

$$\text{F1\_Score} = \frac{2*TP}{2TP+FP+FN} \tag{12}$$

$$\text{AHD} = \frac{FP+FN}{TP+TN+FP+FN} \tag{13}$$

The meanings of these metrics are as follows: A TP is an arc (vertex or edge) in the right position inside the learning network, TN is the arc inside neither the learning network nor the regular network, FP is the arc inside the learning network just not in the regular network, the FN is the arc in the regular however not in the learning network. The Sensitivity for PIO, Simulated Annealing and Greedy are shown Figure 5. The proposed method produces better values than the Simulated Annealing and Greedy in the different datasets. Similarly, the proposed method in most dataset have high accuracy than simulated Annealing and Greedy algorithms. The proposed PIO Learning Algorithm performs well in finding the appropriate structure, and presented a relatively low time complexity because the global search decreases by half the number of pigeons. As a result, it was shown that from the point of prediction accuracy, the Iterative PIO algorithm is the best algorithm compared to other algorithms in most datasets,

and from the point of construction times also the PIO is better than the other algorithms. For performance metrics, in addition
to the best score in Bayesian results, we applied F1 as the metric regarding the accuracy model.
For performance metrics, in addition to the best score in Bayesian results, we applied F1 essentially a metric of the model's accuracy.
The Recall, Precision, and F1- score are used to evaluate the performance of the proposed algorithm. In these circumstances, precision is the number of directed edges that are found correctly divided by the number of all edges in the expected BN. Recall represents the division of the number of directed edges that are found by the number of edges in the actual BN. It is known that, F1 is the harmonic average of accuracy and recall. The Figure 5 presents the comparison of PIO, simulated Annealing, and Greedy search. As presented in the Figure-5- the proposed methods is successful than the Greedy search and Simulated Annealing Methods. Furthermore, the final purpose of the model is to present a convenient representation of the real world, so accuracy is a useful measure of model performance evaluation. The proposed algorithm is also preferable from the point of view of the Hamming distances, which are always considerably lower than the ones obtained by using the DAG space. Hamming distances is one of the most widely used evaluation metrics for BN structure learning, which directly matches the structure of learners and local networks also is directed entirely towards exploration rather than inference. Figure 5 also shows the Average Hamming Distances for the mentioned algorithms. The results demonstrate that the proposed method produces better performance values than the other methods that we have considered.
Figure-5 Sensitivity, Accuracy, F1_Score, and Average Hamming Distance for PIO, Simulated Annealing and Greedy.

Table 1:calculation the score function for PIO with Simulated Annealing in 2, 5, and 60 minutes Execution time

	2Minutes			5Minutes			60Minutes		
Dataset	PIO	Simulated Annealing	Greedy	PIO	Simulated Annealing	Greedy	PIO	Simulated Annealing	Greedy
Adult	-207809	-211677.72	-211844	-207809	-211678	-211781	-207809	-211678	-211762
Epigenetics	-176657	-179910.33	-225346	-176657	-179300	-224172	-176657	-179300	-217246
Heart	-2423.8	-2432.1878	-2576.93	-2423.8	-2423.8	-2560.43	-2423.8	-2432.19	-2527.44
Hepar	-160095	-161086.42	-169497	-160095	-161086	-169881	-160095	-161086	-168871
Hepatitis	-1327.73	-1330.4645	-1350.16	-1327.73	-1330.46	-1350.16	-1327.73	-1330.46	-1350.16
Imports	-1811.99	-1828.9059	-1994.15	-1811.99	-1828.91	-2012.21	-1811.99	-1828.91	-1995.76
Letter	-175200	-178562.22	-184307	-175200	-178562	-184916	-175200	-178562	-184118
Parkinsons	-1598.91	-1601.2968	-1732.76	-1598.91	-1601.3	-1721.16	-1598.91	-1601.3	-1700.36
Sensors	-60343.3	-60710.499	-69200.3	-60343.3	-60710.5	-69150	-60343.3	-60710.5	-68364
WDBC	-6666.04	-6682.7161	-8089.41	-6666.04	-6682.72	-7954.65	-6666.04	-6682.72	-7841.35
Water	-13269.5	-13290.828	-14619.1	-13269.5	-13290.8	-14644.7	-13269.5	-13290.8	-14272
win95pts	-46779.5	-47085.1	-83749.3	-46779.5	-47085.1	-83150.7	-46779.5	-47085.1	-81779.5
mushroom	-3372.51	-3375.3104	-3734.22	-3372.51	-3375.31	-3706.66	-3372.51	-3375.31	-3588.69

6.CONCLUSION

We focused on Bayesian network structure learning problem and applied the Pigeon Inspired Optimization approach for structure learning Bayesian network. We used score and search technique, using PIO approach as search and BDeu as score function. PIO can be described as a stochastic search

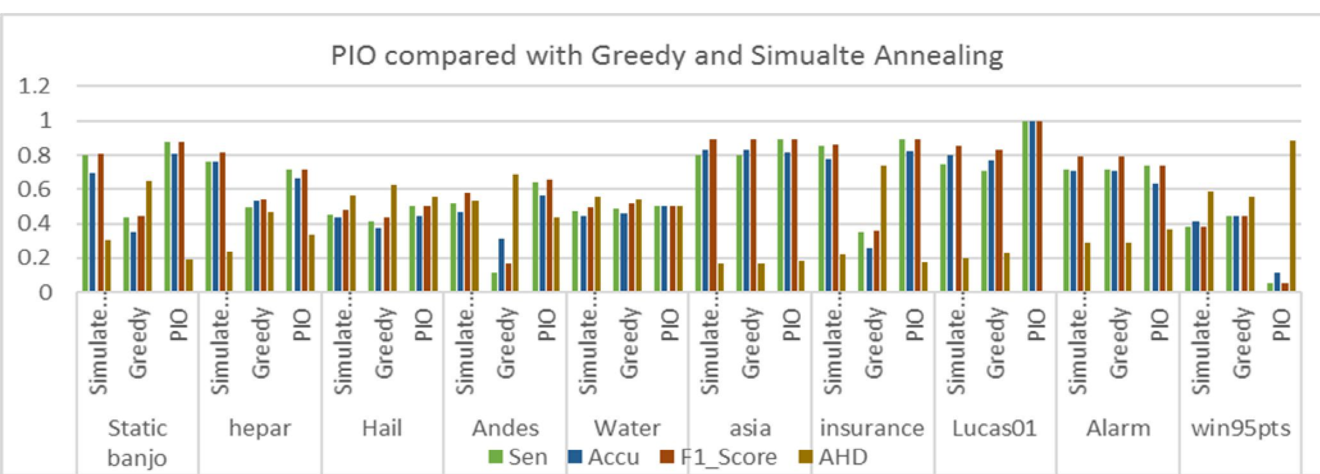

Figure-5 Sensitivity, Accuracy, F1_Score, and Average Hamming Distance for PIO, Simulated Annealing and Greedy.

technique based on navigational behaviors of a pigeon. PIO is a usual methodology for searching discrete solution space. PIO is a common framework which can be adjusted to suit for any application region. Concentration control in PIO presents quickened concentration to global extremum through allowing pigeon to fly to short useful solution space, probabilistically in position to become expected to more effective solution space since the extra control afforded by including a pigeon parameter allows leaving out problems on different scales. The proposed method has more competence for searching, that indicates it can detect great structure solution, calculate higher score function and excellent approximation to the network and more accurate. The algorithms improve the global search and lead rapidly to the global convergence. The proposed approach can be inspected as the parallel implementation which indicates the stability for use in parallel processing.

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