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# Integrated modular Bayesian networks with selective inference for context-aware decision making

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ABSTRACT

As many devices equipped with various sensors have recently proliferated, the fusion methods of various information and data from different sources have been studied. Bayesian network is one of the popular methods that solve this problem to cope with the uncertainty and imprecision. However, because a monolithic Bayesian network has high computational and design complexities, it is hard to apply to realistic problems. In this paper, we propose a modular Bayesian network system to extract context information by cooperative inference of multiple modules, which guarantees reliable inference compared to a monolithic Bayesian network without losing its strength like the easy management of knowledge and scalability. The proposed method preserves inter-modular dependencies by virtual linking and has lower computational complexity in complicated environments. The inter-modular *d*-separation controls local information to be delivered only to relevant modules. We verify that the proposed modular Bayesian network is enough to keep inter-modular causalities in a time-saving manner. This paper shows a possibility that a context-aware system would be easily constructed by mashing up Bayesian network fractions independently designed or leaned in different domains.


## 1. Introduction

With the recent proliferation of devices with various sensors like smartphone, the integration of information and knowledge derived from different sources of data and evidence is an important problem. However, this problem accompanies uncertainty and imprecision, for instance, lack of information, error in sensors, and ambiguous meanings in criteria and assessments. Several researchers have investigated efficient techniques for managing and integrating various types of information in complex decision-making situations. As one solution, Bayesian probabilistic approach is widely adopted to solve these problems.

Bayesian network (BN) can respond flexibly in complex situations which involve high level of uncertainty. However, a monolithic Bayesian network is hard to adopt in large scale domains because it has high computational complexity in accordance with the scale of domain. For these reasons, it is difficult to apply on devices that are limited in the computational power and resource. To cope with this problem, there are two types of approach. One is to conduct additional procedure like junction tree algorithm. While this approach guarantees accurate calculation, it requires additional time. The other is to design the model appropriately. In this way, despite that modularity makes network easier to handle, it does not verify how to maintain causalities between modules and how to evaluate all the modules by minimizing its time complexity.

This paper proposes modular Bayesian networks (MBN) to integrate different types of information for context-awareness. To reduce the time complexity of MBN, the proposed method uses the selective inference algorithm with virtual linking. This algorithm selects the modules that require re-inference and the modules that do not require re-inference by using the previous probability. The virtual linking method connects the modules while maintaining the result of final probability. Using this method, the proposed MBN enables the integration of different types of information on devices which have limited computing power and resources. Experiments are conducted to verify the accuracy and the time reduction of the proposed method.

The organization of this paper is as follows: Section 2 presents the related studies of probabilistic approaches. Section 3 defines the modular Bayesian networks and virtual linking method. Section 4 proposes the selective inference method and Section 5 evaluates the accuracy and time of inference in MBN compared to a monolithic BN to confirm whether the MBN fully maintains the

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causalities and lessens the computation required. Section 6 concludes the paper with summary and future work.

## 2. Related works

### 2.1. Context-awareness using Bayesian network

Many researchers have developed context-aware applications based on a probabilistic approach. Ko et al. utilized Bayesian network to recognize the user's emotion [1]. They showed that the probabilistic approach could be good enough to handle the uncertain information because the EEG data have various noises. Ji et al. proposed an active and dynamic information fusion method for distributed multi-sensor system using dynamic Bayesian networks [2]. They showed that Bayesian network could be applied to a monitoring system where continuous reasoning and diverse information fusion are required. This work gave us glimpse about how Bayesian network could handle, reason, and combine uncertain information in real world. Krause et al. utilized Bayesian network to evaluate a user's situation for providing proper context-aware services [3]. Lifelog was collected from sensors on mobile devices, and used to model several probabilistic modules which classified user's activity reflecting given user's preferences. Brogini and Slanzi used Bayesian network as a tool of explorative analysis [4]. The Markov blanket of a variable is the minimal conditioning set through which the variable is independent from all the others. They used a theory to extract the relevant features for constructing a decision tree. Nazerfard and Cook proposed an activity prediction approach using Bayesian networks, utilizing a novel two-step inference process to predict the next activity [5].

These studies successfully dealt with context information using Bayesian probability model while they did not consider the computational complexity of Bayesian network.

### 2.2. Bayesian network

Bayesian networks are models that express large probability distributions with relatively small cost in statistical mechanics. The structure is a directed acyclic graph (DAG) that represents the link relationship of each node and includes conditional probability table (CPT). It consists of two components: structure and parameters. The network can identify the structure and parameters through learning algorithms using real-world data as well as constructing it with expert's domain knowledge.

- Definition 1 (Bayesian network). Bayesian network is a probabilistic graphical model that represents casual relationships between random variables in real-world problem. BN consists of variables $V$ and directed edges $E=(V_{i,}V_j)$, and where $Pa(V_i)$ indicates the set of parent nodes of $V_i$, conditional probability table $P(V_i)$ defines the set of $P(V|Pa(V_i))$. Given the evidence $e=\{e_{1,}\ e_{2,\dots,}e_m\}$ the posterior probability $P(V_u|e)$ is calculated by applying the chain rule as Eq. (1).

$$P(V_u|e)=\prod P(V_u|Pa(V_u))\times e=\prod P(V_u|Pa(V_u))\prod_{e_i\in e} e_i \tag{1}$$

- Definition 2 ($d$-separation). The connections of the variables have three types in BN: Serial connections, diverging connections, and converging connections [6]. Two distinct variables $V_i$ and $V_j$ in a BN are $d$-separated if, for all paths between $V_i$ and $V_j$, there is an intermediate variable $V_k$ such that either the connection is serial or diverging and $V_k$ is instantiated or the connection is converging, and neither $V_k$ nor any of $V_k'$ descendants have received evidence.

The time complexity of Bayesian network can be calculated using the Lauritzen Speifelhalter (LS) algorithm, as given in Eq. (2), where $n$ is the number of nodes, $k$ is the maximum number of parents for each node, $r$ is the number of values for each node, and $w$ is the maximum clique [7].

$$CMPX=O(k^3n^k+wn^2+(wr^w+r^w)n) \tag{2}$$

### 2.3. Reduction of computational complexity in Bayesian network

Table 1 summarizes the related works on reducing the computational complexity of BN, which includes the three approaches: an approach to modularize the network, an approach to modify the structure based on the dependency of nodes when the network updates its probabilities, and an approach to reduce the size of the conditional probability table. The Noisy-OR model was proposed by Pearl [8]. This can compute the distributions required for the CPT from a set of distributions, elicited from the expert, the magnitude of which grows linearly with the number of parents. Heckerman and Breese proposed an extended version of the method called Noisy-MAX Gate [9]. This method showed a collection of conditional independence assertions and functional relationships and removed the representation of the uncertain interactions between cause and effect.

Zhang et al. removed weak dependencies before inference [10]. The method evaluated the relation of each node with query node and modified the structure of network through removing the nodes and edges. Kjaerulff presented a method for reducing the computational complexity through removal of weak depe-

**Table 1**
Related researches of reducing the computational complexity of BN.

| Author | Modular approach | Structure modification | CPT modification | Description |
|---|---|---|---|---|
| Pearl [8] | X | X | O | Computing the distributions needed for the CPT from a set of distributions |
| Heckerman and Breese [9] | X | X | O | Removing the uncertain interaction between causes and effects |
| Zhang and Poole [10] | X | O | X | Modifying the structure before inference |
| Kjaerulff [11] | X | O | X | Removing weak dependencies before inference |
| Koller and Pfeffer [12] | O | X | X | Applying object concept to BN |
| Das [13] | X | X | O | Reducing conditional probability table using weighted-sum algorithm |
| Tu et al. [14] | O | X | X | Hybridization of BN and HMM for high, and low-level information, respectively |
| Oude et al. [15] | O | X | X | Hierarchical modular approach designed for multiple agents |
| Baker and Mendes [16] | X | X | O | Verification of WSA and calculation method of weight |
| Villanueva and Maciel [17] | X | O | X | Two optimized constraint-based method for the task of super-structure estimation |
| Zhang et al. [18] | X | O | X | Consideration of conditional independence tests and maximum information coefficient |