Reducing the Complexity of Casual Representation in Bayesian Belief Network [version 1; peer review: awaiting peer review]

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Abstract

**Background:** Bayesian Belief Network (BBN) is a well-established causal framework that is widely adopted in various domains and has a proven track record of success in research and application areas. However, BBN has weaknesses in causal knowledge elicitation and representation. The representation of the joint probability distribution in the Conditional Probability Table (CPT) has increased the complexity and difficulty for the user either in comprehending the causal knowledge or using it as a front-end modelling tool.

**Methods:** This study aims to propose a simplified version of the BBN — Bayesian causal model, which can represent the BBN intuitively and proposes an inference method based on the simplified version of BBN. The CPT in the BBN is replaced with the causal weight in the range of [-1, +1] to indicate the causal influence between the nodes. In addition, an inferential algorithm is proposed to compute and propagate the influence in the causal model.

**Results:** A case study is used to validate the proposed inferential algorithm. The results show that a Bayesian causal model is able to predict and diagnose the increment and decrement as in BBN.

**Conclusions:** The Bayesian causal model that serves as a simplified version of BBN has shown its advantages in modelling and representation, especially from the knowledge engineering perspective.

**Keywords**
Bayesian Belief Network, Causal Model, Causal representation

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**Introduction**

Knowledge representation in a graphical model eases the knowledge organization and information understanding process. Causal frameworks such as Cognitive Map (CM), Fuzzy Cognitive Map (FCM), and Bayesian Belief Network (BBN) use graphical models to represent domain knowledge and have been widely adopted in various domains in the past few decades. BBN is a graphical model that used nodes to represent domain variables and links to represent the causal relationship among the nodes. However, the causal strengths of the causal relationship are represented in a tabular format. The complexity of the representation is increased with the growth of the size of conditional probability tables in BBN. The size of the CPT in BBN is growth in exponential proportion to the number of variables and the number of discrete states for each variable. Although high precision of inference outcome can be provided in BBN, such precision is often not needed or not necessary to the purpose of application. Moreover, elicitation of conditional probabilities from domain experts during the BBN modelling process is an unnatural and tedious job. BBN lacks intuitiveness in terms of representation and suffers from complexity problems in inference.

This paper introduces a simplified BBN, namely the Bayesian causal model. A Bayesian causal model improves the representation of BBN by replacing the CPT with a single numeric value that is attached to the causal link. Moreover, a new inferential algorithm is proposed to propagate the influence in the Bayesian causal model. The proposed causal framework shows its advantages in modelling and representation, especially from the knowledge engineering perspective. Incremental updates in the model can be done easily because no reconstruction of the causal model is needed when a component is added/removed. To show the validity of the Bayesian causal model, a procedure to represent a Bayesian causal model as a BBN and comparison of the inference outcome in the Bayesian causal model corresponds to a specific probability in the Bayesian network are carried out in this study.

**Methods**

The Bayesian causal model is formally defined in this section. Figure 1 shows the representation of the causal influence between nodes in the Bayesian causal mode.

Instead of CPT, causal strength between the nodes is represented as a single value in the range of $[-1, +1]$. $-1$ represents the decrease of 100% of the probability value and $+1$ denotes the increase of 100% of the probability value. The initial probability of each node is pre-determined as 0.5.

The propagation steps of the newly available evidence in the Bayesian causal model are as follows.

**Influence Propagation steps**

1. Start from either one of the nodes with evidence
2. Calculate the change in the evidence node
   a. The change of evidence increase/decrease can obtain by (Probability in evidence node – 0.5)/0.5
3. Propagate the evidence AGAINST the arc.
   a. Causal weight = causal weight/no. of cause node
   b. Influence = the change of evidence increase/decrease * (causal weight/no. of cause node)
4. Continue to propagate until further propagation is impossible.
5. Back to the node with completed causal influence from all effect nodes. Calculate the total influence.
   a. Total backward influence = sum of causal influence from all effect node
6. Start propagating the influence FOLLOW the arc
   a. The influence from the cause node needs to exclude the previous backward influence from this effect node to the cause node.
   b. Total forward influence = sum of causal influence from all cause nodes
7. Once the node obtains complete backward and forward influence,
   a. Total influence = total backward influence + total forward influence
8. Back to 4.
9. Stop when all nodes obtain the total causal influence.
10. Calculate the posterior probability of each node
    a. Posterior probability = total causal influence * 0.5 + initial probability.
11. Start from the other node with evidence.
12. Continue steps 2-9.
13. Calculate the posterior probability of each node
    a. If total causal influence is positive
       Posterior probability = total causal influence * \( \frac{1}{C_{\text{posterior probability}}} \) + posterior probability.
    b. If total causal influence is negative
       Posterior probability = total causal influence * posterior probability + posterior probability

The proposed inference algorithm for Bayesian causal model is implemented using C++ programming language and Code::Blocks 20.03.

Results
An example of a sprinkler is used to demonstrate and validate the inference method in the Bayesian causal model. Table 1 illustrates the description of nodes in the causal model. There are a total of five nodes and five links in the causal model. The Bayesian causal model of sprinkler example is constructed as shown in Figure 2. Then, the Bayesian causal model is encoded into a BBN as shown in Figure 3. To validate the inference algorithm in Bayesian causal model, reasoning processes are performed in the Bayesian causal model and the BBN that are constructed earlier. The probabilities of any

![Figure 1. Representation of causal influence in Bayesian causal model.](image)

| Node | Description                                      |
|------|--------------------------------------------------|
| S    | SPRINKLER                                       |
| R    | RAIN                                             |
| G    | WETNESS OF MY GARDEN                             |
| N    | WETNESS OF MY NEIGHBOUR’S GARDEN                 |
| P    | HEALTH OF MY PLANTS                              |
Figure 2. Bayesian causal model of a sprinkler.

Figure 3. BBN of a sprinkler.
two nodes in the causal models are increased to 1 to observe the changes of probability in other nodes. The reasoning outcomes of both causal models are then recorded and compared as shown in Table 2.

According to the inference results shown in Table 2, the Bayesian causal model has shown its ability to predict and diagnose as in BBN because the reasoning outcome of both causal models are not differed too much.

**Conclusions**

In this paper, a new causal model — the Bayesian causal model is introduced and defined. The causal strength in the Bayesian causal model is represented by a numeric value from −1 to +1. Whereas the value in each node is interpreted as probabilities. The semantics of the variables and influences are defined in this study. Moreover, the computation of the propagated influence from a node to another one in the causal model is proposed. The Bayesian causal model has provided an intuitive and simple graphical representation of causal knowledge. The representation of the causal strength with a single value in the Bayesian causal model has overcome the complexity of representation in BBN. Moreover, the construction of a Bayesian causal model from domain experts is less laborious and the user could easily understand the causal knowledge from the Bayesian causal model.

| Table 2. Comparison results of BBN with Bayesian causal model. |
|---|---|---|---|---|
| R | N | S | G | P |
| BBN | 1 | 1 | + | + | + |
| BCM | 1 | 1 | + | + | + |
| R | N | S | G | P |
| BBN | 1 | + | 1 | + | + |
| BCM | 1 | + | 1 | + | + |
| R | N | S | G | P |
| BBN | 1 | + | + | 1 | + |
| BCM | 1 | + | + | 1 | + |
| R | N | S | G | P |
| BBN | + | 1 | 1 | + | + |
| BCM | + | 1 | 1 | + | + |
| R | N | S | G | P |
| BBN | + | 1 | + | 1 | + |
| BCM | + | 1 | + | 1 | + |
| R | N | S | G | P |
| BBN | + | + | + | 1 | + |
| BCM | + | + | + | 1 | + |
| R | N | S | G | P |
| BBN | + | + | 1 | 1 | + |
| BCM | + | + | 1 | 1 | + |
| R | N | S | G | P |
| BBN | + | + | 1 | + | 1 |
| BCM | + | + | 1 | + | 1 |
| R | N | S | G | P |
| BBN | + | + | + | 1 | 1 |
| BCM | + | + | + | 1 | 1 |
Data availability
All data underlying the results are available as part of the article and no additional source data are required.

Competing interests
No competing interests were disclosed.

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