Check for updates

RESEARCH ARTICLE

Reducing the Complexity of Casual Representation in Bayesian Belief Network [version 1; peer review: 2 not approved]

Yit Yin Wee , Shing Chiang Tan, KuokKwee Wee

Faculty of Information Science and Technology, Multimedia University, Malacca, Malaysia

V1 First published: 06 Dec 2021, 10:1243
<https://doi.org/10.12688/f1000research.73480.1>

Latest published: 06 Dec 2021, 10:1243
<https://doi.org/10.12688/f1000research.73480.1>

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

Open Peer Review

Approval Status **XX**

	1	2
version 1	×	×
06 Dec 2021	view	view

1. **Bukhoree Sahoh** , Walailak University, Nakhon Si Thammarat, Thailand
2. **Marek J. Druzdzel**, Bialystok University of Technology, Bialystok, Poland

Any reports and responses or comments on the article can be found at the end of the article.

This article is included in the **Research Synergy** Foundation gateway.

Corresponding author: Yit Yin Wee (wyityin@mmu.edu.my)

Author roles: **Wee YY:** Conceptualization, Methodology, Validation, Writing – Original Draft Preparation; **Tan SC:** Supervision, Writing – Review & Editing; **Wee K:** Resources, Writing – Review & Editing

Competing interests: No competing interests were disclosed.

Grant information: The author(s) declared that no grants were involved in supporting this work.

Copyright: © 2021 Wee YY *et al.* This is an open access article distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

How to cite this article: Wee YY, Tan SC and Wee K. **Reducing the Complexity of Casual Representation in Bayesian Belief Network [version 1; peer review: 2 not approved]** F1000Research 2021, **10**:1243 <https://doi.org/10.12688/f1000research.73480.1>

First published: 06 Dec 2021, **10**:1243 <https://doi.org/10.12688/f1000research.73480.1>

Introduction

Knowledge representation in a graphical model eases the knowledge organization and information understanding process. Causal frameworks such as Cognitive Map (CM),¹ Fuzzy Cognitive Map (FCM),² and Bayesian Belief Network (BBN),³ use graphical models to represent domain knowledge and have been widely adopted in various domains in the past few decades.⁴ 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.⁵

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 $(\text{Probability in evidence node} - 0.5)/0.5$
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

$$\text{Posterior probability} = \text{total causal influence} * (1 - \text{posterior probability}) + \text{posterior probability}.$$
 - b. If total causal influence is negative

$$\text{Posterior probability} = \text{total causal influence} * \text{posterior probability} + \text{posterior probability}$$

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.

Table 1. Definition of the causal nodes.

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.

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	+	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

two nodes in the causal models are increased to 1 to observe the changes of probability in other nodes. The reasoning outcomes of both casual 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.

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.

Grant information

The author(s) declared that no grants were involved in supporting this work.

Acknowledgements

This research work was supported by Multimedia University, Malaysia.

References

1. Axelrod R: *Structure of decision: the cognitive maps of political elites*. Princeton, NJ: Princeton University Press; 1976.
2. Kosko B: **Fuzzy Cognitive Maps**. *Int. J. Man-Machine Studies*. 1986; **24**(1): 65–75.
[Publisher Full Text](#)
3. Pearl J: **Fusion, Propagation, and Structuring in Belief Networks**. *Artif. Intell.* 1986; **29**(3): 241–288.
[Publisher Full Text](#)
4. Sedki K, De Beaufort LB: **Cognitive Maps and Bayesian Networks for Knowledge Representation and Reasoning**. *IEEE 24th International Conference on Tools with Artificial Intelligence*. 2012; 1035–1040.
5. Cooper GF: **The computational complexity of probabilistic inference using Bayesian belief networks**. *Artif. Intell.* 1990; **42**(2-3): 393–405.
[Publisher Full Text](#)

Open Peer Review

Current Peer Review Status:

Version 1

Reviewer Report 23 January 2023

<https://doi.org/10.5256/f1000research.77134.r157866>

© 2023 Druzdzel M. This is an open access peer review report distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Marek J. Druzdzel

Białystok University of Technology, Białystok, Poland

The paper proposes a simplification of the Bayesian networks formalism which, according to the authors, makes it easier to construct Bayesian networks/causal graphs and makes them easier to understand.

The authors seem to be unaware of the existing work on qualitative Bayesian networks (Wellman, Henrion, Druzdzel, van der Gaag), order of magnitude networks (Goldszmidt), CAST formalism (KC Chang), and canonical probabilistic models such as Noisy-OR, Noisy-AND, Noisy-MAX, Noisy-MIN, etc., that allow for specifying the strength of influence of each individual link in a Bayesian network. It is unclear to me how the proposed simplification improves on the existing models, formalisms, and algorithms. QGeNIe software of BayesFusion, available free of charge for academic research and teaching, implements a simplification of Bayesian networks and does it correctly, i.e., according to the rules of probability.

Finally, if the authors demonstrate that the proposed formalism offers advantages over the existing formalisms, they should discuss the effect of the proposed simplification on accuracy of inference. Causal connections can be rather complex and this is reflected in the need for tables that specify precisely the impact of combinations of causes on the effect. Separating influences gets rid of all synergies between causes and will lead to simplified, sometimes incorrect inferences. This is OK but it is important to discuss cases where the proposed simplification will be inadequate.

Is the work clearly and accurately presented and does it cite the current literature?

Partly

Is the study design appropriate and is the work technically sound?

Partly

Are sufficient details of methods and analysis provided to allow replication by others?

No

If applicable, is the statistical analysis and its interpretation appropriate?

No

Are all the source data underlying the results available to ensure full reproducibility?

No

Are the conclusions drawn adequately supported by the results?

No

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Bayesian networks, probabilistic modeling, causality, causal discovery

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.

Reviewer Report 18 May 2022

<https://doi.org/10.5256/f1000research.77134.r136326>

© 2022 Sahoh B. This is an open access peer review report distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Bukhoree Sahoh

School of Informatics, Walailak University, Nakhon Si Thammarat, Thailand

In this article, the authors propose a Bayesian causal model based on Bayesian Belief Network and claim it provides an intuitive and simple graphical representation of causal knowledge. The authors concluded that the representation of the causal strength with a single value in the Bayesian causal model had overcome the complexity of representation in BBN.

I carefully read and consider the details, and my concerns have appeared below:

1. The paper representations are not scientific, and the authors did not explain the problem statements or research contributions in the introduction.
2. The authors did not detail the background knowledge about BBN and related works, how recent approaches are not good enough and why the paper is proposed.
3. The authors introduced Influence Propagation steps but did not well-explain why it is needed. The methodology must be represented in a systematic diagram of how one node changes the belief of the other. The single value in the range of $[-1, +1]$ was not explained how and why they are more special than traditional CPT.
4. The results show nothing relevant to the title Reducing the Complexity of Casual Representation in Bayesian Belief Network. The authors did not discuss how they converged to the problems they had to solve. They did not develop what the number and edge mean.

For example, how results explained the issues, "the Conditional Probability Table (CPT) has increased the complexity and difficulty for the user," as the authors wrote in the abstract. The authors did not describe the meaning of edges in Figure 2, such as S points to G labelled by +0.9, so what is the semantic meaning of +0.9, and how it is relevant to the problem. The authors did not show the results as they claim in the abstract "the complexity and difficulty for the user either in comprehending the causal knowledge" and how this article overcomes that concern. Moreover, the authors did not show how the "Bayesian causal model is able to predict and diagnose the increment and decrement as in BBN". The prediction at least must be represented by a comparison between the predictive performances of the proposed approach and the traditional one.

5. The conclusions have no information concerning current limitations and future works. For example, the authors did not explain what the proposed approach could do and what it could not deal with in recent versions that need more future research contributions. The author must show their expertise in what kinds of techniques, methods, and solutions may be used in the future to solve the current limitations.
6. The references are so poor that the well-known research papers in the present were not researched carefully. For example, the references were published in 1986, 1986, 1990, and 2012. What are the considerations for recent research in 2020, 2021, or 2022?

Is the work clearly and accurately presented and does it cite the current literature?

No

Is the study design appropriate and is the work technically sound?

No

Are sufficient details of methods and analysis provided to allow replication by others?

No

If applicable, is the statistical analysis and its interpretation appropriate?

No

Are all the source data underlying the results available to ensure full reproducibility?

No

Are the conclusions drawn adequately supported by the results?

No

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Explainable Artificial Intelligence, Causality, Complex Event Processing, Causal Machine Learning, Causal Inference

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.

The benefits of publishing with F1000Research:

- Your article is published within days, with no editorial bias
- You can publish traditional articles, null/negative results, case reports, data notes and more
- The peer review process is transparent and collaborative
- Your article is indexed in PubMed after passing peer review
- Dedicated customer support at every stage

For pre-submission enquiries, contact research@f1000.com

F1000Research