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Causal learner: A toolbox for causal structure and Markov blanket learning

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ABSTRACT

Causal Learner is a toolbox for learning causal structure and Markov blanket (MB) from data. It integrates functions for generating simulated Bayesian network data, a set of state-of-the-art global causal structure learning algorithms, a set of state-of-the-art local causal structure learning algorithms, a set of state-of-the-art MB learning algorithms, and abundant functions for evaluating algorithms. The data generation part of Causal Learner is written in R, and the rest of Causal Learner is written in MATLAB. Causal Learner aims to provide researchers and practitioners with an open-source platform for causal learning from data and for the development and evaluation of new causal learning algorithms. The Causal Learner project is available at http://bigdata.ahu.edu.cn/causal-learner.

1. Introduction

Causal networks are graphical models for representing multivariate probability distributions [1]. The structure of a causal network takes the form of a directed acyclic graph (DAG) that captures the causal relationships between variables [2–4]. Thus, causal structure learning has attracted widespread attention from the machine learning community in recent decades [5,6]. Global causal structure learning learns an entire DAG, while local causal structure learning learns only the parents (direct causes) and children (direct effects) of a target variable, as shown in Fig. 1(a) and (b), respectively. The Markov blanket (MB) in a causal network consists of the parents, children, and spouses (other parents of the target variable's children) of a target variable [7], as shown in Fig. 1(c). The MB of a target variable is a minimal set of variables that renders all other variables conditionally independent of the target variable, and thus for a classification problem, the MB of the class attribute is an optimal set for feature selection [8–11].

To facilitate the research and applications of causal structure learning and MB learning, we develop a toolbox named Causal Learner. The current well-known toolbox Causal Explorer [12] represents the state-of-the-art ten years ago. Compared with Causal Explorer, there are three main contributions of Causal Learner. (1) It offers more state-of-the-art algorithms than Causal Explorer. (2) It offers functions for generating simulated data from Bayesian networks (BNs) and functions for evaluating the performance of algorithms, which are not provided by Causal Explorer. (3) It offers a more concise and uniform input format than Causal Explorer, which makes it easier for researchers and practitioners to apply.

2. Architecture

Figure 2 shows the hierarchical architecture of Causal Learner, in comparison with Causal Explorer. As Causal Explorer was developed 10 years ago, it does not contain many new algorithms, and it does not have a data generation or evaluation component. By contrast, Causal Learner conceives a more ambitious blueprint. It aims to support the entire causal structure and MB learning procedure, including data generation, state-of-the-art algorithms, and algorithm evaluation.

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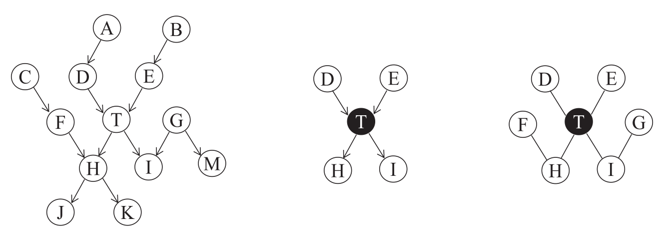
Table 1
Benchmark Bayesian networks.

	Name	#Nodes	#Arcs
Discrete Bayesian Network	CANCER	5	4
	EARTHQUAKE	5	4
	SURVEY	6	6
	ASIA	8	8
	SACHS	11	17
	CHILD	20	25
	INSURANCE	27	52
	WATER	32	66
	MILDEW	35	46
	ALARM	37	46
	BARLEY	48	84
	HAILFINDER	56	66
	HEPAR II	70	123
	WIN95PTS	76	112
	PATHFINDER	109	195
	ANDES	223	338
	DIABETES	413	602
	PIGS	441	592
	LINK	724	1125
	MUNIN (4 subnetworks)	1,861,041	273–1388
Continuous Bayesian Network	SANGIOVESE	15	55
	MEHRA	24	71
	MAGIC-NIAB	44	66
	ECOLI70	46	70
	MAGIC-IRRI	64	102
	ARTH150	107	150



(a) Global causal structure (b) Local causal structure (c) Markov blanket

Fig. 1. Examples of a global causal structure, local causal structure, and Markov blanket (T in black is a target node).

2.1. Data

In the data layer, Causal Learner generates two types of data: discrete data and continuous data. The data are generated based on various benchmark BNs (written in R), and the details of each BN[1] are shown in Table 1. The data can also be generated by the bnlearn [13] toolbox, but the generated data are encapsulated in R language classes and cannot be easily used by researchers using other programming languages. Causal Learner can output the generated data as text for easy and flexible use.

2.2. Algorithm

In the algorithm layer, Causal Learner implements 7 global causal structure learning algorithms, 4 local causal structure learning algorithms, and 16 MB learning algorithms (written in MATLAB). Table 2 lists all of these algorithms. Moreover, we take the following two measures to ensure the correctness of the algorithms implemented in Causal Learner: (1) For algorithms that have released the original implementations, we directly integrated them into the Causal Learner without any changes. (2) For other algorithms that have not released the original implementations, we re-implemented them based on the ideas of these algorithms, and used the same data and evaluation metrics to evaluate the performance of these algorithms in Causal Learner and Causal Explorer, respectively. Compared with Causal Explorer, the results of Causal Learner are comparable in accuracy and more efficient.

2.3. Evaluation

In the evaluation layer, Causal Learner provides abundant metrics for evaluating causal structure and MB learning algorithms (written in MATLAB). In terms of accuracy, global and local causal

[1] https://www.bnlearn.com/bnrepository

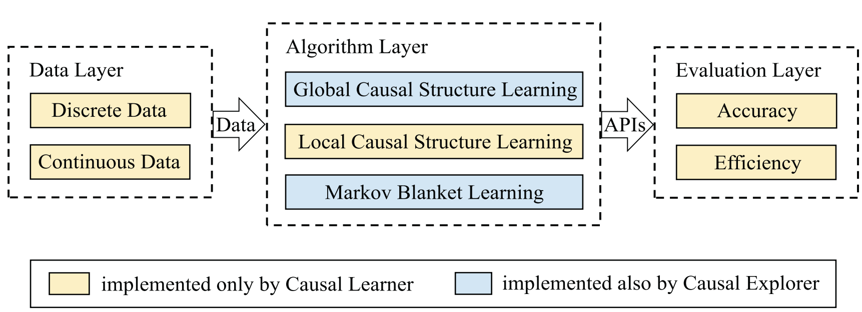


Fig. 2. The architecture of Causal Learner.

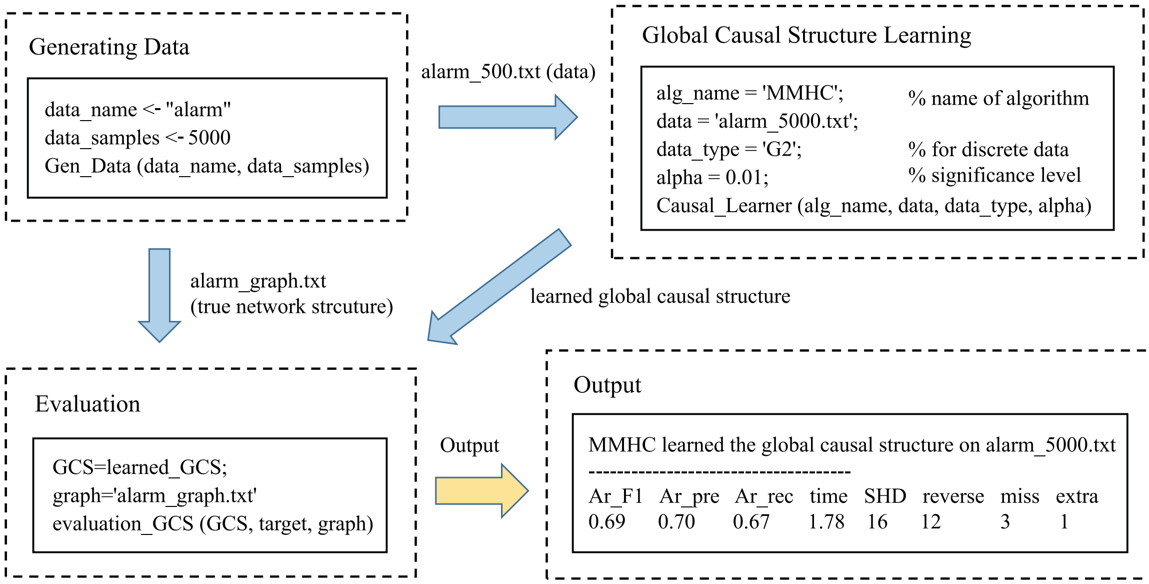


Fig. 3. An example of using Causal Learner to learn a global causal structure.

Table 2
Algorithms included in (indicated by •) and absent from (indicated by ○) Causal Learner and Causal Explorer.

Global Causal Structure Learning			Markov Blanket Learning		
Algorithms	Learner	Explorer	Algorithms	Learner	Explorer
SCA	○	•	GS	•	•
PC	•	•	IAMB	•	•
TPDA	○	•	interIAMB	•	•
GES	•	○	IAMBnPC	•	•
GSBN	•	○	interIAMBnPC	•	•
MMHC	•	•	Fast-IAMB	•	○
PC-stable	•	○	FBED	•	○
F2SL-c	•	○	MMMB	•	•
F2SL-s	•	○	HITON-MB	•	•
Local Causal Structure Learning			PCMB	•	○
			IPCMB	•	○
Algorithms	Learner	Explorer	MBOR	•	○
PCD-by-PCD	•	○	STMB	•	○
MB-by-MB	•	○	BAMB	•	○
CMB	•	○	EEMB	•	○
LCS-FS	•	○	CFS-MI	•	○

structure learning algorithms are evaluated using the same 7 metrics: Ar_F1 (Ar denotes arrow), Ar_precision, Ar_recall, SHD, Miss, Extra, and Reverse. MB learning algorithms are evaluated using 3 metrics: Adj_F1 (Adj denotes adjacent), Adj_precision, and Adj_recall. In terms of efficiency, global causal structure learning algorithms are evaluated using running time, while both local causal structure and MB learning algorithms are evaluated using running time and the number of conditional independence tests.

3. Usage example

Causal Learner comes with a manual that details the data generation, algorithms, evaluation metrics, and how each function is used, https://github.com/z-dragonl/Causal-Learner. Figure 3 shows an example of global causal structure learning using Causal Learner. As shown in the figure, Causal Learner needs only 4 input parameters when learning a global causal structure, while Causal Explorer requires additional parameters such as "domain_count". Furthermore, Causal Learner unifies the input parameters of causal structure learning and MB learning. Thus, Causal Learner provides a more concise and uniform input format than Causal Explorer, to facilitate its use by researchers and practitioners.

4. Conclusion and future work

Causal Learner is an easy-to-use open-source toolbox for causal structure learning and MB learning, which aims to promote and accelerate research progress in the filed of causal learning. The current version of Causal Learner includes simulated BN data generation functions, causal structure and MB learning algorithms, and algorithm evaluation functions. Causal Learner is still growing. Future work includes extending Causal Learner with causal structure and MB learning algorithms without causal sufficiency or faithfulness assumptions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejps.2020.105216.

References

[1] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, Elsevier, 2014.
[2] G.F. Cooper, A simple constraint-based algorithm for efficiently mining observational databases for causal relationships, Data Min. Knowl. Discov. 1 (2) (1997) 203–224.
[3] I. Tsamardinos, C.F. Aliferis, Towards principled feature selection: relevancy, filters and wrappers, AISTATS, 2003.
[4] D. Koller, N. Friedman, F. Bach, Probabilistic Graphical Models: Principles and Techniques, MIT Press, 2009.
[5] P. Spirtes, C.N. Glymour, R. Scheines, Causation, Prediction, and Search, MIT Press, 2000.
[6] I. Tsamardinos, L.E. Brown, C.F. Aliferis, The max-min hill-climbing Bayesian network structure learning algorithm, Mach. Learn. 65 (1) (2006) 31–78.

[7] J. Pearl, Causality, Cambridge University Press, 2009.
[8] I. Guyon, C. Aliferis, et al., Causal feature selection, in: Computational Methods of Feature Selection, Chapman and Hall/CRC, 2007, pp. 75–97.
[9] C.F. Aliferis, A. Statnikov, I. Tsamardinos, S. Mani, X.D. Koutsoukos, Local causal and Markov blanket induction for causal discovery and feature selection for classification part i: algorithms and empirical evaluation, J. Mach. Learn. Res. 11 (Jan) (2010) 171–234.
[10] C.F. Aliferis, A. Statnikov, I. Tsamardinos, S. Mani, X.D. Koutsoukos, Local causal and Markov blanket induction for causal discovery and feature selection for classification Part II: analysis and extensions, J. Mach. Learn. Res. 11 (Jan) (2010) 235–284.
[11] K. Yu, X. Guo, L. Liu, J. Li, H. Wang, Z. Ling, X. Wu, Causality-based feature selection: methods and evaluations, ACM Comput. Surv. (CSUR) 53 (5) (2020) 1–36.
[12] A. Statnikov, I. Tsamardinos, L.E. Brown, C.F. Aliferis, Causal explorer: a matlab library of algorithms for causal discovery and variable selection for classification, Causation Prediction Challenge ChallengesMach. Learn. 2 (2010) 267–278.
[13] M. Scutari, Learning Bayesian networks with the bnlearn R package, J. Stat. Softw. 35 (3) (2010) 1–22.