

# 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 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>.

**Keywords:** Causal structure learning, Markov blanket, Bayesian network

## 1. Introduction

Causal networks are graphical models for representing multivariate probability distributions (Pearl, 2009). The structure of a causal network takes the form of a directed acyclic graph (DAG) that captures the causal relationships between variables (Spirtes et al., 2000; Koller et al., 2009). Thus, causal structure learning has attracted widespread attention from the machine learning community in recent decades. 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 Figure 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 (Pearl, 2009), as shown in Figure 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 (Guyon et al., 2007; Aliferis et al., 2010a,b; Yu et al., 2020).

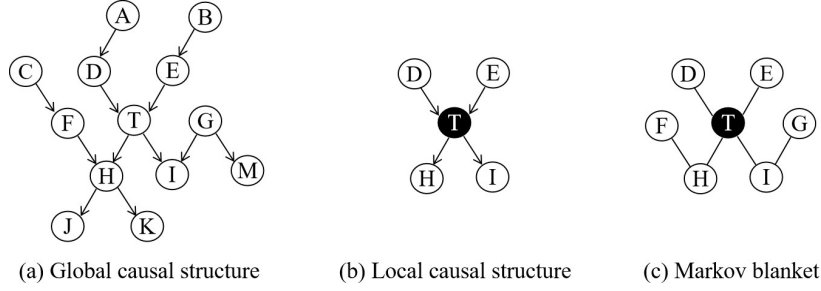


Figure 1: Examples of a global causal structure, local causal structure, and Markov blanket ( $T$  in black is a target node).

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 (Statnikov et al., 2010) 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 is completely open-source, which makes it easier for researchers and practitioners to understand, modify, and apply, while the source code of Causal Explorer is not provided.

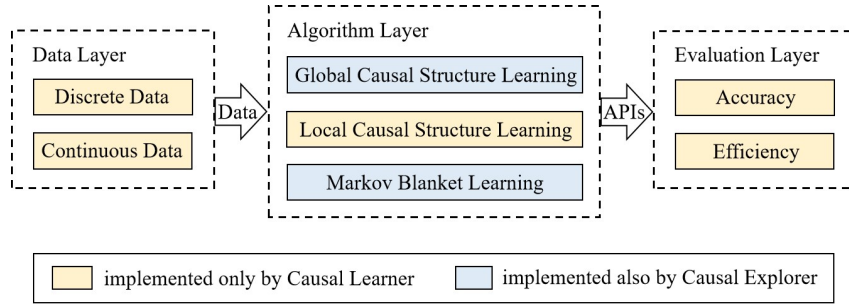


Figure 2: The architecture of Causal Learner.

## 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.

	Name	#Nodes	#Arcs	Name	#Nodes	#Arcs
Discrete Bayesian Network	CANCER	5	4	BARLEY	48	84
	EARTHQUAKE	5	4	HAILFINDER	56	66
	SURVEY	6	6	HEPAR II	70	123
	ASIA	8	8	WIN95PTS	76	112
	SACHS	11	17	PATHFINDER	109	195
	CHILD	20	25	ANDES	223	338
	INSURANCE	27	52	DIABETES	413	602
	WATER	32	66	PIGS	441	592
	MILDEW	35	46	LINK	724	1125
	ALARM	37	46	MUNIN (4 subnetworks)	186 -1041	273 -1388
Continuous Bayesian Network	SANGIOVESE	15	55	ECOLI70	46	70
	MEHRA	24	71	MAGIC-IRRI	64	102
	MAGIC-NIAB	44	66	ARTH150	107	150

Table 1: Benchmark Bayesian networks.

## 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<sup>1</sup> are shown in Table 1. The data can also be generated by the bnlearn (Scutari, 2010) 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 15 MB learning algorithms (written in MATLAB). Table 2 lists all of these algorithms. To ensure the correctness of the algorithms implemented in Causal Learner, unless the original implementations of the algorithms are not released, we always try to integrate the original versions rather than re-implement them. Additionally, we have used the same data to evaluate the algorithms in Causal Learner. Compared with Causal Explorer, the results of Causal Learner are comparable in accuracy and much 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 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.

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1. <https://www.bnlearn.com/bnrepository>

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

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

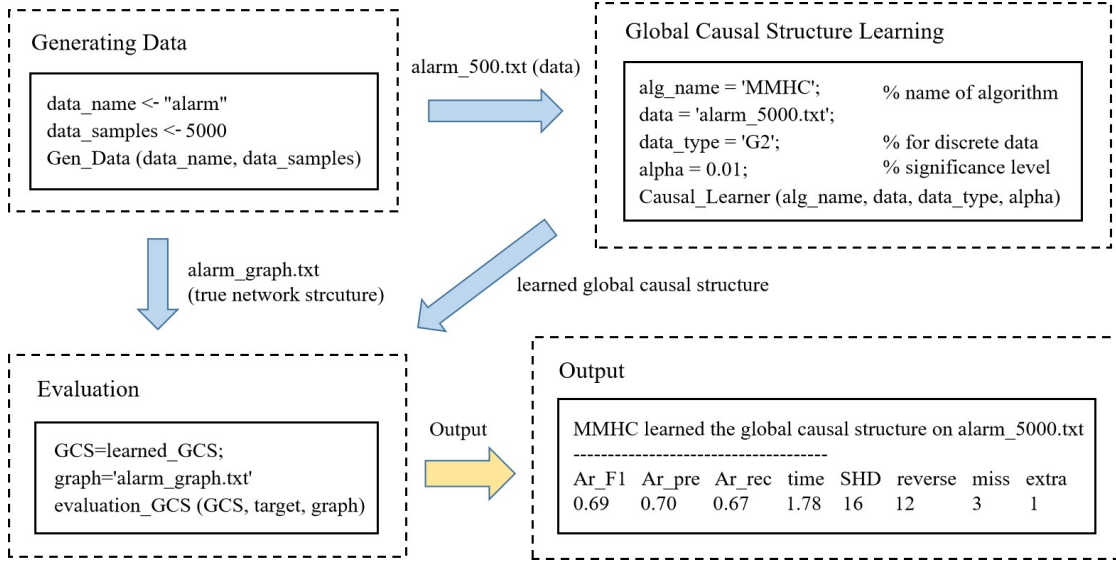


Figure 3: An example of using Causal Learner to learn a global causal structure.

### 3. Usage Example

Causal Learner comes with a manual that details the BNs, 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”. Thus, Causal Learner uses a cleaner input format than that of Causal Explorer.

## 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 field 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.

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