FUJITSU Project:

Title Discoverability with modern AI

Industrial Partner FUJITSU LIMITED

The Fujitsu Group has operations in different regions worldwide, including Japan, providing digital services globally. We have built large-scale, cutting-edge systems that leverage our advanced technologies and extensive track record, garnering the No. 1 market share in Japan and a top-class position worldwide in the IT services field.

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Background

Artificial Intelligence (AI) has been increasingly introduced into various industries. Nevertheless, certain challenges remain in applying AI and machine learning technologies to overcome problems in various fields. To identify key drivers of the difficulties to be overcome, to develop strategies, and to take appropriate actions, it is necessary not merely to assess correlation between attributes A and B, but also to ascertain the causal relation linking A to B, such as "A is the cause of B."

Recently, several methods have been proposed for inferring causal structures from observational data [1,2]. Such methods generally estimate one common causal structure for an entire set of data. However, causality might change or differ depending on circumstances. For example, for cancer treatment in a medical setting, every patient has their own expression of genes, which affects the disease state of cancer. Therefore, to devise appropriate treatment plans for individual patients, doctors must identify those genes which are specific to each patient, not genes that are common to all patients.

Using Fujitsu's Wide Learning technology [3,4], which finds all important combinations without omission, Fujitsu has developed a causal discovery AI technology that can infer causal relations comprehensively under specific conditions.

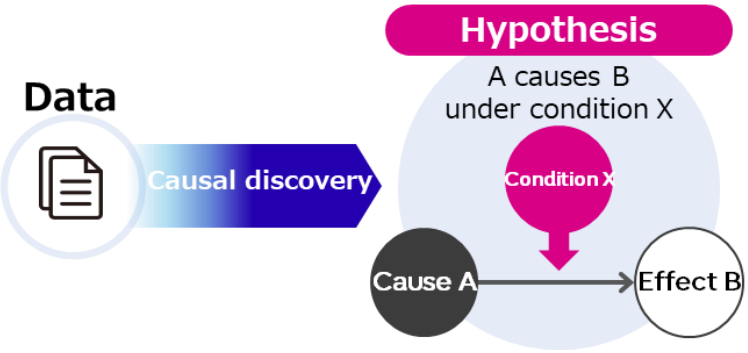
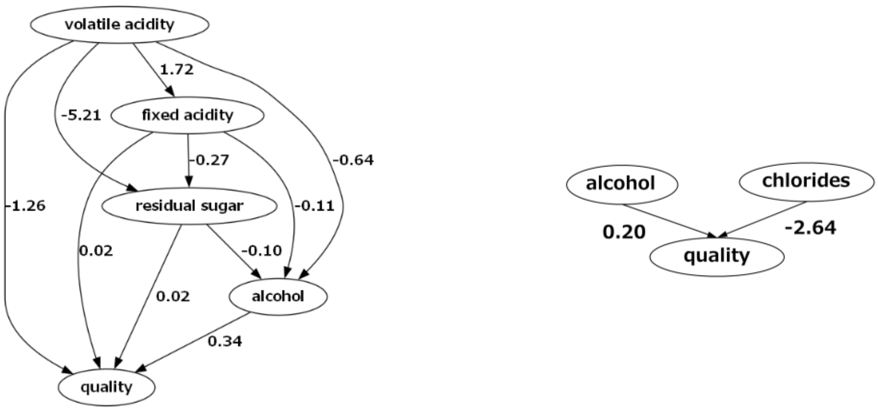


Fig. 1 Fujitsu's causal discovery AI.



(a) Common causal graph

(b) Causal graph under the condition of "alcohol<11.5" ∧ total sulfur dioxide≥130"

Fig. 2 Examples of causal graphs.

Fig. 2 depicts examples of causal graphs for the Wine Quality Data Set [5] from UCI datasets [6]. Whereas Fig. 2(a) shows a common causal graph generated using the DirectLiNGAM method [1], Fig. 2(b) shows a causal graph for a specific condition generated using Fujitsu's causal discovery AI technology. As presented in Fig. 2, a linear non-Gaussian acyclic model (LiNGAM) [7] is assumed, in which the weight attached to an edge from node x_i to node x_j represents the causal effect or the connection strength of x_j on x_i; that is, the weight represents change in the value of x_j corresponding to unit change in the value of x_i. In real-world problems, generally, when the number of nodes is large, each causal graph is complicated. In addition, the number of causal graphs under conditions is large. Therefore, the challenge is to ascertain how to extract important information effectively and how to improve the explainability of causal discovery AI [8].

Project overview

In this project, you will develop an enhanced method of explanations of causal discovery AI assisted by mathematics. For purposes of enhancement, you should consider several aspects such as those presented below.

1. Convincingness: Explanations must be convincing and accepted by users. Therefore, evaluating or estimating the explanations' likelihood of convincing users is important. That evaluation will require mathematical modeling of the explanation's characteristic of "convincingness". The simplest modeling would be to use a length of explanation based on the assumption that a short explanation is easy to understand. However, better modeling might be devised by assuming more practical recognition models.
2. Variety: An explanation for causality is not always unique. Often, more than one perspective is necessary to explain causality. The phenomenon by which many equally good models explain some given data well is called the Rashomon effect [9]. A set of many equally good models is called a Rashomon set [10]. Although a Rashomon set provides variety in explanation, a tradeoff between variety and simplicity (convincingness) should be considered.
3. Discoverability: An explanation that is not convincing to users does not always imply that the explanation is bad. It might include or assert a new finding that users have not noticed before. Therefore, it is also important to remind users that it might be a new discovery even when it is not convincing. In that sense, an explanation must also be evaluated in terms of discoverability.

Among the aspects presented above, you will specifically examine discoverability through this project. However, convincingness and variety are also important factors for improving discoverability.

Expectations

When participating in this project, you will be expected to devise and implement a new user interface of causal discovery AI that is enhanced in terms of discoverability, also improving convincingness and variety.

We look forward to welcoming students who are interested in statistics, graph theory, logic, and the Wide Learning Website "Hello, Wide Learning!" [3]. In addition, students who are interested in answers to the following questions are welcomed.

- ✓ What is explainable AI?
- ✓ What is the gap separating AI and humans?
- ✓ What are good interactions between AI and humans?
- ✓ How can AI help humans discover new findings?

Requirements

Programming skills in Python.

References

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