FUJITSU Project:

Title Enhancing explainability of causal discovery AI

Industrial Partner FUJITSU LIMITED

The Fujitsu Group provides digital services globally, with operations in different regions around the world, including Japan. Fujitsu’s Information Technology (IT) services business ranks at the top by market share in Japan and is in the top tier worldwide: a record that reflects our outstanding technologies and long track record in building large-scale, cutting-edge systems.

Industrial Mentor

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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 challenges 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 the discovery of 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 the situation. For example, in the case of 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 genes which are specific to each cancer patient, not genes that are common to all cancer 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 comprehensively infer causal relations under specific conditions (Fig. 1).

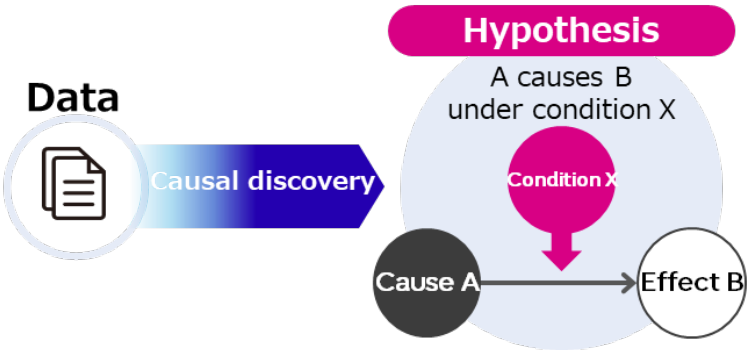
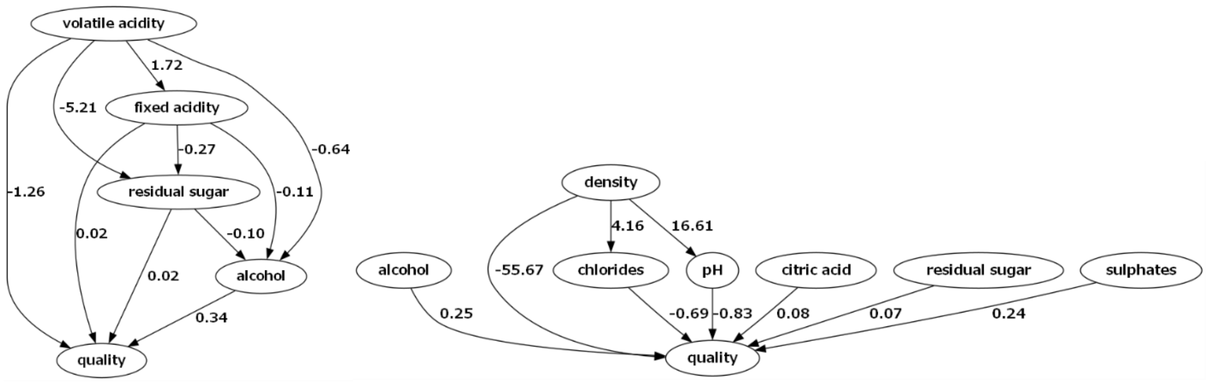


Fig. 1 Fujitsu's causal discovery.



(a) Common causal graph (b) Causal graph under the condition of

$"color = red \ \wedge \ total\ sulfur\ dioxide \geq 130"$

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 shown in Fig. 2, a linear non-gaussian acyclic model (abbreviated as LiNGAM) [7] is assumed, in which the weight attached to an edge from node x_i to node x_j represents the coefficient 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. Also, 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.

Project overview

In the project, you will develop an enhanced view 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 [8]. A set of many equally good models is called a Rashomon set [9]. Although a Rashomon set provides variety in explanation, a tradeoff between variety and simplicity (convincingness) should be considered.
3. Discoverability: When an explanation is not convincing to a user, it is not always because it is a bad explanation. It might be a new finding that a user has never noticed. In that sense, an explanation must also be evaluated in terms of discoverability.

By exploring one or more aspects of enhancement, you will develop a new way of giving explanations of causal discovery AI.

Expectations

When participating in this project, to enhance the explainability of causal discovery AI, you will be expected to devise a new user interface of causal discovery AI and then to implement it. We look forward to welcoming students who are interested in statistical analysis 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, and preferably C or C++.

References

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