Strategy Changes in Causal Structure Learning: The Role of Task Complexity

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Abstract

Saito and Shimazaki (2012) found that people rely upon covariation information rather than temporal order information as cues to causal structure, whereas Lagnado and Sloman (2006) reported an opposite finding, indicating relatively greater influence of temporal order cues. The present research examines the hypothesis that such conflicting findings result from differences in task complexity. Specifically, it is proposed that covariation information becomes less influential as the number of variables increases. Experiment 1 investigated the relationship between the judgment strategy (i.e., covariation vs. temporal order) and the number of variables comprising a causal structure. As a result, people favored covariation cues primarily in tasks with simple causal structure. Experiment 2 used more complex causal structure. The results demonstrated that the tendency to emphasize covariation cues or to rely upon temporal order cues changes as a function of task complexity. These results were consistent with both previous findings and discussed in terms of causal Bayes net theories and heuristic models.

Keywords: causal structure learning; causal reasoning; covariation; temporal order; task complexity.

Introduction

Many psychological studies have shown that both children and adults easily form representations of causal relations (Sloman, 2005; see also Holyoak & Cheng, 2011 for a review). Causal relations lead to associations of various kinds of events and they may form part of complex causal structures. Knowledge about the causal structure plays an important role in explanations, predictions, control, as well as decision making (Pearl, 2000). Despite its importance, in many cases, actual causal connections among constituent elements are often difficult to discern or to tease out of a complicated pattern of contingencies. For instance, if one hears a bit of gossip from colleague, X, and then hears same story from another colleague, Y, this might lead to the inference that X had passed the rumor to Y (i.e., X→Y) based on the temporal order in which one receives this information. However, it is also possible that, earlier, Y had initially gossiped to X and then it is heard from X prior to seeing Y (i.e., Y→X). Or, a third party, such as the boss, Z, may have spread this rumor (i.e., X←Z→Y). In light of this, how might be people acquire knowledge about causal structure?

As Hume (1739/2000) has argued that causal relations are unobservable and therefore must be induced from observable events, covariation among observable events serves as a fundamental cue to learn causal structure. Covariation is formally represented as a joint probability distribution and is specifically explained as patterns of presence and absence for binary variables. When a causal relation exists, strong covariation between a cause and its effect will be expected except for the possibility that both variables are caused by a common cause. In contrast, the absence of covariation indicates that two variables are not related to each other—except for the effects of other variables. However, there are several limitations to the use of covariation cues. First, covariation information becomes more complex as the number of variables increases. With two binary variables, for example, covariation is represented by a 2 × 2 contingency table of 4 data patterns; however, 32 data patterns result from five binary variables. In addition, covariation itself is inadequate for distinguishing a unique causal structure from models that represent the same joint probability distribution (i.e., Markov equivalent). When event X covaries with event Y, for instance, it is difficult to determine the precise cause. These examples suggest the difficulty of learning causal structure using only covariation cues.

In addition to covariation, another important cue to causal structure is temporal order in which people observe the states of variables. Because causes are often observed to happen prior to their effects, when event X precedes event Y, it is probable that X causes Y. However, the observed temporal order does not always serve as an accurate cue. First, temporal order may mislead people with regard to the direction of causal relations. In situations where people observe effects prior to their causes, temporal order information indicates the opposite causal direction. A second issue concerns spurious correlation. Even if event X precedes event Y, their co-occurrence might be the result of a hidden common cause Z. In this case, a temporal delay between two variables will result in a false belief that the earlier event causes the later, despite the fact that no causal relation exists. Thus, although temporal order cues can facilitate causal structure learning, they may also mislead causal inferences.

Combined with information indicating hidden causes are absent, both kinds of information become more useful. When event X covariates with event Y, three possible causal structures are presumed (i.e., X→Y, X←Y, or X←Z→Y). The absence of hidden causes enables people to exclude the possibility that both events are caused by a hidden cause. If event X occurs alone in this situation, then it is suggested that X causes Y. Since nothing happens without a cause (i.e., necessity), an event that occurs alone must be a cause variable but not an effect variable.

Previous studies on causal structure learning have provided conflicting evidence regarding the use of covariation cues and temporal order cues (e.g., Lagnado & Sloman, 2006; Saito & Shimazaki, 2012; White, 2006). On one hand, Lagnado and Sloman (2006) demonstrated that people preferred temporal order cues to covariation cues. In their experiment, participants were required to send messages from a master computer to one of four computers in a network (e.g., computer A), to observe whether other computers also received the messages (e.g., computer B, C, & D), and then to infer the structure of network. Participants observed the states of the computers in the order different from the causal order (e.g., temporal order: A→D→C→B, causal order: A→B→C & D). Although participants were given instructions including information on the unreliability of temporal order and the absence of hidden causes, their judgments were based on temporal order cues rather than covariation cues. White (2006) reported similar results indicating that participants relied heavily on temporal order information, in spite of the fact that they received explicit instructions regarding the way in which causal structures are induced from covariation information.

On the other hand, Saito and Shimazaki (2012) showed the opposite results that people use covariation cues rather than temporal order cues. The experimental task was to observe occurrences of two types of bacteria and to infer their causal relationship. As in Lagnado and Sloman (2006), participants were instructed that temporal order cues were unreliable and that there were no hidden causes. In the condition in which covariation cues contradicted temporal order cues, participants heavily favored covariation information over temporal order information. Furthermore, these judgments were made after several observations.

A possible interpretation of these conflicting findings involves differences in task complexity, especially as this is reflected by number of variables. It is possible that task complexity modulates an individual's judgment strategy. A critical difference between the preceding experiments is the number of variables that constitute the causal structure. Whereas Lagnado and Sloman (2006) required participants to learn causal directions among four variables, and White (2006) adopted five variables in constituting a causal structure, the design of Saito and Shimazaki (2012) presented a causal structure involving only two variables—the minimum unit for causal structures. Since increasing the number of variables complicates covariation information, it therefore would be difficult to induce a complex causal structure based solely on covariation cues.

Several studies have revealed the role of task complexity in causal learning and inference (e.g., Marsh & Ahn, 2006; Reips & Waldmann, 2008). Marsh and Ahn (2006) demonstrated that the task complexity served as a determinant of a primacy effect and a recency effect. When a few variables were observed, information presented earlier weighted more than information presented later (i.e., primacy effect); in contrast, information presented later was emphasized more than information presented earlier when many kinds of variables existed (i.e., recency effect). In a similar vein, Reips and Waldmann (2008) showed that accurate diagnostic inferences depended on the number of variables in the experimental task. These studies suggest the importance of task complexity in causal judgment.

The purpose of the present study is to investigate the relationship between task complexity and the judgment strategy in causal structure learning. In order to manipulate task complexity, the number of variables composing the causal structures was manipulated in Experiment 1. Experiment 2 employed different forms of causal structures. The hypothesis predicts that people use covariation cues rather than temporal order cues in learning simple causal structures whereas they rely more upon temporal order cues than covariation cues in inferring complex causal structures.

Experiment 1

Experiment 1 was designed to investigate how strategies change as a function of the number of variables in learning a causal structure. The experimental task was to observe states of the variables and to infer causal relations among these variables. The number of variables in the causal structure was varied for the manipulation of task complexity. The authors predicted that when the number of variables was small covariation would be more emphasized rather than temporal order and that when the number of variables was large temporal order would be more reflected than covariation.

Method

Participants and design A total of 24 undergraduates from Kwansei Gakuin University received course credit for taking part in this experiment. The number of variables (three, four, and five) was manipulated within participants. Each participant performed three causal learning tasks with different causal structures.

Instructions Participants received verbal and written instructions in Japanese. An English translation of outlines of the instructions was as follows:

> Imagine that you are a scientist who is attempting to reveal causal relations among several newly discovered bacteria. Whether one bacterium propagates another bacterium, or whether they are irrelevant to each other are unknown to you. In order to investigate the relations among the bacteria, you put one type of bacterium into the 40 containers of liquid nutrient medium. Then you observe the states of other bacteria under the microscope. Before performing each task, you will be informed about which bacterium is put into the nutrient medium. (The bacterium serves as a first cause.)

> Additionally, the following three facts should help you consider causal relations among bacteria. First, it is not always true that one bacterium is certain to propagate other bacterium even if there is a causal relation between them. That is, a causal relation among bacteria is probabilistic. Second, there are no hidden causes as this is a controlled situation. Therefore, when a bacterium exists, except for the one originally put into the liquid nutrient medium by yourself (i.e., first cause), there is another bacterium that acts to propagate it. Third, the states of bacteria develop in order. This is either because it takes time for a bacterium to propagate another bacterium or because it takes time to identify the presence and absence of bacteria due to their invisibility without the use of microscope. Therefore, it could be that a bacterium has propagated another bacterium before it turned out to be present.
>
> Your task is to observe the occurrences and non-occurrences of these bacteria and to infer causal relations among them. Note that the experimental task does not require any knowledge of biology. (The remaining instructions describe how to progress through the learning phase and test phase.)

After receiving the instructions, participants were asked whether they understood the instructions. In this cover story, the number of variables (three vs. four vs. five) corresponded to the number of bacteria participants observed in each task.

Learning phase At the beginning of the learning phase, participants were taught how many kinds of bacteria would appear (e.g., three, four, or five) and which bacterium would be put into the 40 containers of nutrient medium (i.e., first cause) in each condition. The learning phase consisted of 40 trials that presented information about the presence and absence of the bacteria. Participants were asked to observe the states of the bacteria and to consider their causal relations. First, a button labeled “NEXT” was displayed on a screen. After clicking the button, the shapes of the several number of bacteria labeled with question marks were shown (i.e., they remained unknown). The number of bacteria varied across conditions. There were three bacteria in the three variables condition, four bacteria in the four variables condition, and five bacteria in the five variables condition. Then, information about the state of the bacterium was given in order. The presence of bacteria was indicated by the appearance of bacteria; in contrast, the absence of bacteria was represented by the appearance of bacteria labeled with a cross mark. The inter-stimulus interval was 1s, and the screen was returned to its primary state (i.e., “NEXT”) 2s after the all bacteria appeared.

Figure 1 illustrates the causal order in which causes produced effects and the temporal order in which participants observed the states of variables. Covariation information was arranged based on these causal structures and the causal strength of the relation. As the instructions stated causal relations among bacteria were probabilistic, the probability that causes produced effects was 80 percent. In the three variables condition in which participants observed 40 cases, for example, 26 cases included the presence of bacteria A, B, and C. In 6 cases, bacteria A and B were present; bacteria A and C were present in additional 6 cases. The remaining 2 cases included the presence of bacterium A and the absence of bacteria B and C. While the first cause was always present, other variables did not occur unless their specific cause was present. As the number of variables increased, covariation information became more complex. As is evident in Figure 1, temporal order was inconsistent with causal order. Arranging the temporal order to be different from the causal order enabled assessment of the degree to which covariation cues and temporal order cues were used to infer causal structure.

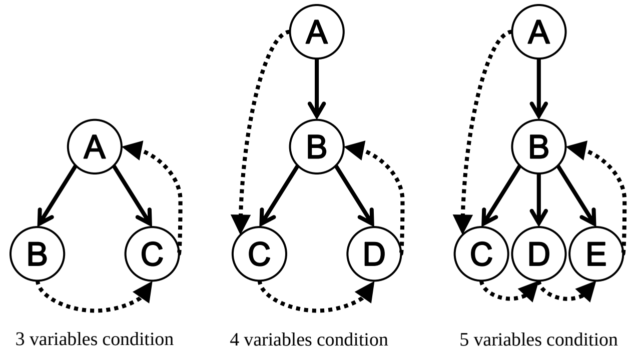

Figure 1: Causal structures in Experiment 1. Continuous lines represent causal relations, whereas dotted lines indicate temporal orders.

Test phase After observing 40 cases, participants were told to infer causal structure in the test phase. Participants received a sheet in which bacteria were displayed in the same way as they were shown in the learning phase, with light gray lines between the bacteria. The instructions required participants to judge whether a casual relation existed and to draw an arrow from a cause to an effect on the line when a causal relation was assumed. Participants had to consider three lines in the three variables condition, six lines in the four variables condition, and ten lines in the five variables condition.

Results and Discussion

To investigate judgment strategy in causal structure learning, the authors defined usage rates as measures of the degree to which participants used covariation cues and temporal order cues. The usage rate of covariation was calculated by dividing the number of links drawn by participants to be consistent with covariation cues by the number of all links suggested by covariation information. In the three variables condition, for example, the link from A to B and the link from A to C were supported by covariation cues (see Figure 1). If participants gave these two links as their answer, their covariation usage rates were 100 percent; in contrast, when they failed to answer both links, the usage rates were 0 percent. The usage rate of temporal order was calculated in a similar manner. In the above example, temporal order cues sustained the link from B to C and the link from C to A respectively (see Figure 1). If participants responded either of the links, their temporal order usage rates were 50%. These indices represent the amount of use of each cue by participants.

Figure 2 shows the usage rates of two types of cues in each condition. When the number of variables was three or four, participants used covariation rather than temporal order; however, there seemed to be no difference in the five variables condition. A two-way repeated measures ANOVA with the type of cue (covariation vs. temporal order) and the number of variables (three vs. four vs. five) as within-participants factors revealed a significant main effects of the type of cue, $F(1, 23) = 14.01$, $p < .01$, and the number of variables, $F(2, 46) = 4.43$, $p < .05$. The interaction between the type of cue and the number of variables was also significant, $F(2, 46) = 6.76$, $p < .01$. Subsequent tests of the simple main effect of the type of cue were significant in the three and four variables condition, $F(1, 69) = 21.03$, $p < .001$, $F(1, 69) = 10.11$, $p < .01$ respectively, but not in the five variables condition, $F < 1$, indicating the task complexity served as the modulator of the judgment strategy.

Although the judgment strategy varied across the number of variables, the result of the four variables condition was inconsistent with previous findings in which the temporal order information had a greater impact than covariation in learning the causal structure composed of four variables (Lagnado & Sloman, 2006). In their experiment, the 58% usage rate of temporal order cues was higher than the 39% usage rate of covariation cues when the causal order (A→B→C & D) differed from the temporal order (A→D→C→B). The opposite results might stem from differences in cover stories. Whereas the present study dealt with the causal relations of several types of bacteria, the previous study used computer networks in which participants sent a message to one computer and observed whether other computers received. Prior knowledge and experience about computer message would give more

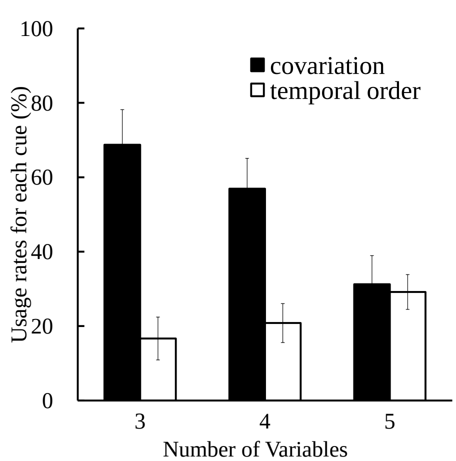

Figure 2: Usage rates for covariation cues and temporal order cues in Experiment 1. Error bars reflect standard errors.

weight to temporal order cues. In fact, Saito and Shimazaki (2012) have reported that the use of temporal order cues depends on its reliability.

In summary, Experiment 1 showed that covariation cues were used more often than temporal order cues when participants learned causal relations among three or four variables. However, when the causal structure consisted of five variables, the preference for covariation disappeared. This pattern of results supports the claim that judgment strategy changes as a function of increasing the number of variables.

Experiment 2

The results of Experiment 1 demonstrated that task complexity modulates participant's judgments about causal structures. However, these findings did not reveal a tendency to rely upon temporal order rather than covariation. The goal of Experiment 2 was to provide further evidence about the relationship between task complexity and the judgment strategy. In order to ascertain whether temporal order cues were more influential than covariation cues in learning complex causal structures, different forms of causal structures were used. Specifically, causal structures with multiple causal links were adopted. This is because increasing the number of causal links leads to more complicated covariation information. Again, the authors predicted that participants' judgments will be based more on covariation than on temporal order when the causal structure was relatively simple, whereas temporal order cues should be more influential than covariation cues when participants inferred the complex causal structure.

Method

Participants and design A total of 24 undergraduates from Kwansei Gakuin University participated for course credit. None of them took part in Experiment 1. As in Experiment 1, the number of variables (three, four, and five) was varied within participants. Participants were asked to perform three causal learning tasks with different causal structures.

Procedure Each participant completed the tasks of observing states of the bacteria and inferring their causal relations. The procedure was identical to Experiment 1 with the exception that different forms of causal structures were used. Although the number of variables was constant across two experiments, the number of causal links in Experiment 2 was larger than that in Experiment 1 (see Figure 1 and 3). Increasing causal links resulted in more complex patterns of covariation information. For example, the four variables condition in Experiment 2 provided seven types of co-occurrence information, whereas there were five kinds of co-occurrence information in the four variables condition in Experiment 1.

Instructions explained the cover story and indicated to the participants that they were required to judge causal relations among bacteria. As in Experiment 1, participants were informed that causal relations were probabilistic, that there were no hidden causes, and that temporal order was

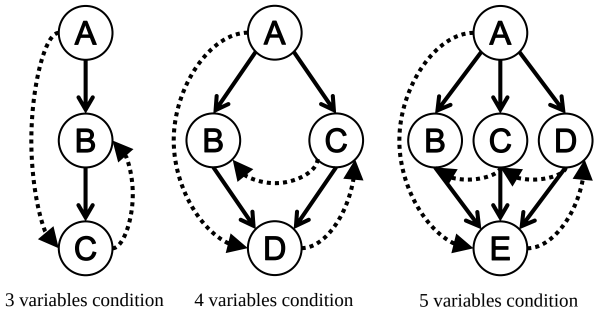

Figure 3: Causal structures in Experiment 2. Continuous lines represent causal relations, whereas dotted lines indicate temporal orders.

not always an accurate cue. In the learning phase, participants received information on 40 cases of bacteria states through observation. Each condition differed in the number of bacteria participants observed. As can be seen in Figure 3, there were three variables with two causal links in the three variables condition, four variables with four causal links in the four variables condition, and five variables with six causal links in the five variables condition. Moreover, the causal order differed from the temporal order in each condition, allowing assessment of the degree to which each cue was used. In the test phase, participants were told to infer the causal structure in the same way as in Experiment 1.

Results and Discussion

Participants' responses were analyzed in a manner similar to Experiment 1. Figure 4 shows the usage rates of covariation cues and temporal order cues in each condition. The results of the three variables condition indicated that covariation cues were emphasized over temporal order cues, replicating this effect in Experiment 1. In contrast, participants in the four and five variables conditions based their judgment more upon temporal order than upon covariation. A 2 (the type of cue: covariation vs. temporal order) × 3 (the number of variables: three vs. four vs. five) repeated measures ANOVA yielded a significant main effect of the number of variables, $F(2, 46) = 9.31$, $p < .001$, and a significant interaction between the type of cue and the number of variables, $F(2, 46) = 9.66$, $p < .001$. To explore the interaction, an analysis of the simple main effect of the type of cue was conducted for each condition. The tendency to emphasize covariation rather than temporal order was marginally significant in the three variables condition, $F(1, 69) = 3.36$, $p < .10$. There was no significant difference in the four variables condition, $F(1, 69) = 1.75$, *ns*. In the five variables condition, however, the usage rate of temporal order cues was reliably higher than that of covariation cues, $F(1, 69) = 7.94$, $p < .01$. These results suggest that task complexity determines whether participants rely on covariation cues or temporal order cues.

In order to investigate effects of forms of causal relations on judgment strategy, a 2 (causal structure: Exp.1 vs. Exp.2) × 2 (the type of cue: covariation vs. temporal order) × 3 (the

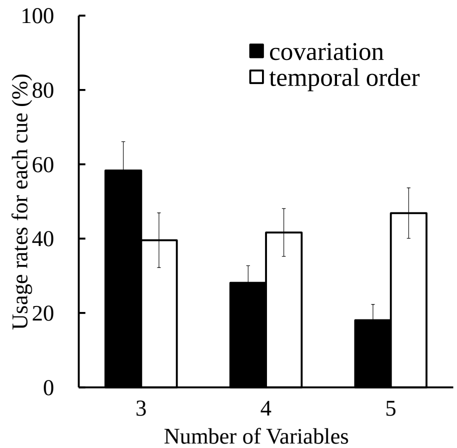

Figure 4: Usage rates for covariation cues and temporal order cues in Experiment 2. Error bars reflect standard errors.

number of variables: three vs. four vs. five) mixed ANOVA was performed, with causal structure as a between-participants factor and the type of cue and the number of variables as within-participants factors. As a result, a main effect of the number of variables, $F(2, 92) = 12.03$, $p < .001$, an interaction between causal structure and the type of cue, $F(1, 46) = 11.21$, $p < .01$, and an interaction between the type of cue and the number of variables, $F(2, 92) = 15.11$, $p < .001$ were significant. To explore the interaction between causal structure and the type of cue in greater detail, the simple main effects of causal structure were tested. The usage rate of covariation cues in Experiment 1 was higher than that in Experiment 2, $F(1, 92) = 5.92$, $p < .05$. On the contrary, the usage rate of temporal order cues in Experiment 1 was lower than that in Experiment 2, $F(1, 92) = 8.14$, $p < .01$. These results indicate that forms of causal structures also modulate judgment strategy.

Taken together with the results of Experiment 1, Experiment 2 provides further evidence on the relationship between task complexity and the judgment strategy. Participants in the three variables condition emphasized covariation over temporal order; on the other hand, temporal order cues were given more weight than covariation cues in the five variables condition. These results bridge the gap between the findings about the preferential use of covariation (Saito & Shimazaki, 2012) and about the preferential use of temporal order (Lagnado & Sloman, 2006; White, 2006). In addition, the comparison between experiments demonstrates that judgment strategy is affected not only by the number of variables but also by the form of the causal structure.

General Discussion

The present study clarifies conflicting evidence concerning the use of covariation cues and temporal order cues in causal structure learning. Lagnado and Sloman (2006) showed temporal order to be more influential on judgments than covariation; however, Saito and Shimazaki (2012) reported that covariation was favored over temporal order. In the present study, the authors interpreted these results from the viewpoint of the task complexity and manipulated the number of variables which consisted of a causal structure. Experiment 1 demonstrated that covariation cues were carried more weight than temporal order cues in learning simple causal structure and that this preference disappeared as the number of variables increased. In addition, Experiment 2 investigated the relationship between the judgment strategy and the number of variables with different forms of causal structures. The results of Experiment 2 are consistent with both findings concerning the preferential use of covariation cues in a simple task (Saito & Shimazaki, 2012) and the preferential use of temporal order cues in a complex task (Lagnado & Sloman, 2006; White, 2006). These results show the task complexity, composed of the number of variables and the form of the causal structure, serves as a modulator of the judgment strategy in causal structure learning.

The results of the present study can be interpreted in terms of salience and validity in multiple-cue probability learning (Kruschke & Johansen, 1999). According to Kruschke and Johansen (1999), irrelevant cues have a deleterious effect on the use of valid cues and this effect becomes more apparent as the salience of irrelevant cues increase. In the present experiment, covariation served as valid cue whereas temporal order was high salient but less reliable cue. Increasing the number of variables in the causal structure brought lower salience of covariation and higher salience of temporal order, which resulted in a deleterious effect on the use of covariation cues. These similar findings imply the tight coupling between causal learning and category learning.

The present study has several implications for models in causal structure learning. The use of covariation cues is easily explained by constraint-based methods (Gopnik, Glymour, Sobel, Schulz, Kushnir, & Danks, 2004) and Bayesian methods (Steyvers, Tenenbaum, Wagenmakers, & Blum, 2003) in causal Bayes nets and broken link heuristics (Mayrhofer & Waldmann, 2011). Whereas Constraint-based methods compute independence and dependence in bottom-up process, Bayesian methods make probabilistic inferences for each causal model using Bayes' theorem in top-down process. Broken link heuristics offers a simple explanation with a determinism bias and a sufficiency bias. In contrast, the use of temporal order cues is well accounted for by local computations (Fernbach & Sloman, 2009). According to this heuristic model, people focused not on covariation cues but instead on temporal order cues because of their quick accessibility and lower computational demands. The tendency to use temporal order cues is also explained by temporal strategy (Rottman & Keil, 2012), which induces causal directionality from temporal change over time. Although these models focus on either covariation cues or temporal order cues, the present results suggest the importance of both cues in causal learning. An intriguing question for future research concerns how people integrate covariation with temporal order for inferring causal structure.

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