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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 44(44)

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Publication Date
2022

Peer reviewed

Causal versus Associative Relations: Do Humans Perceive and Represent Them Differently?

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Abstract

Research has shown that visual diagrams facilitate people's understanding of and communication about abstract relations. In addition, the distinction between causal versus associative relations is important in human reasoning However, previous research has not directly compared how humans represent these two types of relations through visual diagrams. The current study examined whether causal and associative relations differ with respect to how people cognitively represent and interpret them in a spatial context using diagrams. We found that participants perceived relatedness of causal relationships to be stronger than that of associative relationships. This difference was reflected in their drawing of diagrams. Participants connected variables that shared a causal relationship with a shorter line than they did with variables that shared an associative relationship. The results shed light on the difference between causal and associative relations, and suggest new directions for future research to explore the spatial component of causal reasoning.

Keywords: causal reasoning, diagrams, associative relation, spatial representation

Introduction

Humans benefit from the use of visual diagrams to convey abstract knowledge about complex relationships. For example, visual representations in science textbooks scaffold students' comprehension of scientific concepts and subsequent reasoning. One of the most explored types of visual displays in the fields of cognitive psychology and education is a causal diagram. A causal diagram is a type of visual display that uses arrows to represent cause-and-effect relationships among spatially arranged events' (McCrudden et al., 2007), providing a pathway for people to represent and encode rich information. Because of the richness of information a causal diagram can convey, it can improve understanding of causal relationships and support learners' inference making (Ainsworth, 2006).

Previous research has shown that causal diagrams facilitate comprehension and memory of causal relationships (Glenberg & Langston, 1992; McCrudden et al., 2011). Because causal diagrams can show concretely and efficiently in a spatial manner how and why different causes result in certain effects, causal diagrams have been widely utilized in educational contexts to enhance learning of causal knowledge and improve reasoning ability. For example, McCrudden et al. (2007) found that participants who studied causal diagrams during text reading achieved better understanding of the causal sequences described in the text.

In addition, causal diagrams can be used to help learners externalize their mental models of causal relationships, allowing them to identify possible misunderstandings (Gobert, 2000). Causal diagrams thus are a type of useful tool for researchers to understand how people represent different causal relations. By asking participants to generate causal diagrams, researchers can use those participant-generated causal diagrams to study the internal representations of causal structures in the minds of participants. Hence, causal diagrams provide researchers with an important tool to study human causal understanding from raw inputs such as text or videos.

Another type of visual display commonly used in educational settings is a concept map (Gul & Boman, 2006). A concept map provides a visual representation of how knowledge is mentally organized and represented (Torre et al., 2007). Similar to causal diagrams, concept maps enable users to externalize their mental representations, offering users opportunities to examine their understanding critically, and providing researchers with insights into users' thinking and reasoning processes (Novak, 1998). A number of studies have found an effect of both learner-generated and expert-generated concept maps in improving learners' understanding and critical thinking in a variety of domains (Abel & Freeze, 2006; Cutrer et al., 2011; Vacek, 2009).

A concept map shares multiple similarities with a causal diagram, as both use metacognitive approaches to generate spatial displays to facilitate learning; however, the type of relationship and reasoning they support differs. Causal diagrams concern causal representation and reasoning about

In J. Culbertson, A. Perfors, H. Rabagliati & V. Ramenzoni (Eds.), *Proceedings of the 44th Annual Conference of the Cognitive Science Society*.

causal structures, whereas concept maps typically do not distinguish between causal and associative relations. Because causal relations are not differentiated from associative relations in concept maps, concept maps simply treat the cause-effect relation as basically the same as other associative and semantic relations.

However, the distinction between causal versus associative relations is important in human reasoning. We understand that the co-occurrence of two events does not tell the whole story about a relationship (Kurdi et al., 2020). For example, when we observe that crime rates correlate with ice cream sales, we know that the relationship between crime rates and ice cream sales cannot be causal (Fenker et al., 2005). Despite the high correlation between these two variables, we can differentiate this association from causation. Causal reasoning enables us to differentiate between correlation and causation and appropriately interact with our environment (Greville & Buehner, 2010). Without such causal representations of the world, people would be deprived of opportunities to intervene at proper times to control and change our environment.

Given the importance of causal reasoning, research in cognitive psychology has endeavored to understand how people perceive, represent, interpret, and reason with causal relationships. However, studying such reasoning is hard because causal relations are neither directly nor immediately detectable by our sensory modalities (Greville & Buehner, 2010). The processes by which people comprehend causal relations are not easily captured. Thus, one of the purposes of the current study is to explore the differences between how people perceive and represent causal versus associative relationships.

A major characteristic distinguishing causal reasoning from associative reasoning stems from the basic asymmetry in causal relations. (Hausman & Simon, 1998; Waldmann, 1996). Unlike associative relations, causal relations have a fixed temporal order: the cause has to temporally precede its effect. However, there have been debates about whether this asymmetry is mirrored in our cognitive perception and representation. Some researchers argue that humans do not capture this asymmetry in their causal representation (Cobos et al., 2002; Shanks & Lopez, 1996), whereas others support a causal model theory, which hypothesizes that causal relations explicitly manifest themselves through asymmetries in people's cognitive representations (Waldmann & Holyoak, 1992; Waldmann et al., 1995; Waldmann, 1996, 2000, 2001;) and uses special integration rules for causal influences (Yuille & Lu, 2007; Lu et al., 2016). For example, Waldmann and Holyoak (1992) showed that although cue competition occurs when people learn from predictive contexts (cause to effect), multiple possible effects do not compete with each other in diagnostic contexts (effect to cause). The difference between people's predictive and diagnostic reasoning suggests that people not only construct causal models but also explicitly represent the link from cause to effect in the model.

Waldmann (2000) demonstrated a similar cognitive representation of causal relationships when asking participants to categorize artificial diseases based on the presence of different substances in patients' blood. Participants were randomly assigned different information about the same set of substances and diseases — they were either told that these substances in patients' blood caused their disease or that the substances are just effects of the disease. The study similarly observed cue competition only when the substances were presented as the cause: multiple causes (i.e., substances) but not multiple effects compete for explanatory strength.

Research has mainly explored causal relations and their cognitive representation in the context of semantic memory (e.g., Fenker et al., 2005). However, it remains unclear how causal information is spatially represented and stored in spatial memory. Based on the literature, it is possible to hypothesize a relationship between causal strength and physical proximity. Specifically, the studies on causal judgment and distance metaphors provide support to this relationship (Chae et al., 2013). Research has shown that people can make causal judgments about a mechanical process based on spatial proximity (Michotte, 1963; Yela, 1952).

Beyond mechanical processes, the reliance on proximity to make inferences about causal strength has also been observed in non mechanical contexts, known as the metaphor, "closeness is strength of effect" (Lakoff & Johnson, 1980; Landau et al., 2010). The metaphor describes the mapping of a concrete experience as a source to an abstract concept as a target (e.g., warm as an embodied, concrete feeling to friendliness as an abstract concept, Landau et al., 2010). Then, similarly, spatial proximity is seen as the source, the features of which map to the target, people's abstract judgment of causal strength. This argument is supported by our daily use of language (e.g., closely regulated) as well as the literature in embodied cognition, which suggests that our embodied experience in the world impacts our cognition (Barsalou, 2008). In this way, the link between spatial proximity and causal strength suggests that people can judge the causal strength of relatedness between two things through the special proximity of the two objects, which has been demonstrated in a number of studies (e.g., Chae et al., 2013).

However, the literature has only shown a clear link between spatial proximity and perception of causal strength. It is still unknown if the link between proximity and causal strength is one-directional or if people will also naturally use spatial proximity to represent strength of causal relations in the mental representations. In addition, given the difference between causal and associative relations, we ask if people would use proximity to indicate strength of relatedness only for causal relations but not for associative relations.

In the current study, participants were randomly assigned two passages written in causal language and two passages written in associative language. After reading each passage and answering some questions to ensure a solid understanding of the content, participants were asked to draw a diagram that they thought would best represent the relationships described in the passage. After drawing, they rated the strength of those relationships on a numerical scale.

We hypothesized that there would be differences between the causal and associative passages in terms of both people's self-rated strength of relationships and distances between the variables they drew on the diagram. Specifically, we hypothesized that people would rate causal relationships to be stronger than associative ones, and that they would reflect this difference in their diagram drawings. If causal relations are viewed as drawing linked variables "closer together", then the lines drawn to connect variables in a causal relationship will e in general be shorter than lines that connect variables in an associative relationship.

Method

Participants

A total of 102 undergraduate students (N = 102, 75 female, 27 male) were recruited from University of California, Los Angeles (M_{age} = 21.15 years, SD = 4.21). Students participated in this study for extra credit toward their final course grades.

Material and Apparatus

Four popular science contexts were used in this research, each presenting a set of statistical interactions of variables. The four contexts had different topics and differed in complexity regarding the number of variables and their interactions. The topics were chosen from a variety of biology and ecology contexts, about which people usually do not hold strong beliefs.

The simplest topic contained three variables with two pairwise relationships. The most complex topic involved seven variables with six pairwise relationships. Our rationale was that the level of complexity might influence participants' perceived strength on causal and associative relationships. We constructed two articles for each topic — one causal version and one associative version. In total, eight articles were used in the study. For the same topic, the two versions were roughly the same in length and shared the same structure (i.e., the same number of variables and number of possible interactions among variables). The only difference was the type of relationships between variables. In the causal versions, all relationships between key variables were causal, and they were described by expressions such as "A determines B" or "The strongest predictor of A is B." In the associative versions, all relationships were associative, and were expressed by phrases such as "A is correlated with B" or "The strongest association of A is B".

The first article discussed how two factors lead to one type of ice movement: deformation. The second article presented how six different factors influence the population change of CoT starfish. The third article discussed six factors that contributed to the survival of desert plants. Lastly, the fourth article discussed how two environmental factors influenced the population of two animal species in the forest. Figure 1 shows a sample article (causal versus associative) for one of the four articles for illustration purposes.

Causal	**Associative**
One type of ice movement is called deformation… there are a couple of factors that affect the amount of deformation that takes place or the speed of the glacier's movement, but the strength of the factors is very different. The thickness of the ice is the number one factor...Deformation is much more likely to occur …because of the gravity of the weight of the ice. Another factor is temperature, though the impact … less likely and also less powerful. Temperature plays a role here because ...	One type of ice movement is called deformation… there are a couple of factors that are associated with the amount of deformation that takes place or the speed of the glacier's movement, but the strength of the factors is very different. The size of the ice is the number one factor ... Deformation is much more likely to be observed … considering the size of the ice is associated with the gravity of the weight of the ice. Another factor is the latitude, though the association is a lot weaker. Latitude is relevant here because …

Figure 1: Sample article for the causal (left) versus associative context (right)

We developed a website to conduct the experiment. (For more information about the website: https://cvlstudy.psych.ucla.edu/shuhao/causal_diagram).

Procedure

This experiment used a within-subject design, such that all participants were randomly assigned to read two articles written in causal language and two articles written in associative language, each from a different topic. The distances between variables on participants' drawing and the self-rated strength of the relationships between variables were measured for each of the four articles.

Figure 2 presents a flow chart visualization of study procedure. Participants ran the experiment using their personal computers with internet access and completed the study individually. During the experiment, the participants progressed through the pages and responded to the questions by clicking on and dragging texts on the page using the mouse. Once the participants entered the survey, they were informed that the experiment was concerned with how people process and represent text information and they would answer questions based on the passages and draw diagrams to represent the key variables and their relations. If they answered the validation question incorrectly, they would be sent back to the instruction page. The validation question was "What you will need to do in this study? (choose all that apply)". The participants had to select "Read 4 passages," "Draw 4 diagrams," and "Answer some questions based on the passages" from four choices. After correctly answering the validation questions regarding the tasks, the participants were randomly assigned to four articles, two of which were written in a causal language and the other two associative. We controlled for the effect of the article content. (i.e., for each article, it was written in both causal and associative languages.)

In each article, the participants were first instructed to read a passage carefully and informed that there would be a quiz after reading the passage. They were given as much time as they needed to read. Once they finished reading, they were asked to answer two multiple-choice questions as validation problems, which were intended to show whether they had grasped the relationships in the passage. If they selected the wrong answers, the page would direct them to the passage again. The process was repeated until they answered the two validation questions correctly. Then, the participants entered the next page and were instructed to draw a diagram based on their understanding of relationships between the variables in the passage they had just read. The variables were presented as keywords in the middle of an 800 × 600-pixel whiteboard, and participants were able to move the keywords to anywhere within the whiteboard and draw straight lines with arrows to connect the keywords.

We did not impose any time pressure on participants, and they could advance the page once they had finished drawing. Next, participants read a page of multiple rating questions asking them to rate perceived strengths of relations between each pair of variables, with "1" being not related at all and "7" being strongly related. After finishing these questions, the participants were instructed to proceed and read the next passage. Once participants finished all four passages, they were asked to provide answers to indicate if they were distracted and/or experienced any issues during the study and some additional demographic information.

Measures

Rating of Relatedness Strength Participants' perceived strength of the relatedness between each pair of variables was coded as a continuous variable. We used standardized rating scores (since individual participants may use rating scales differently). Specifically, we normalized ratings by subtracting each value from the average rating of each participant for all questions and then dividing by the standard deviation of each participant's rating: $rating_{normalized} = \frac{rating_i - \overline{rating_i}}{SD\ rating_i}$. In this way, the standardized ratings were centered to 0 for each subject.

After standardizing rating scores, we computed participants' average rating of relatedness strength for all variables in each diagram that they drew by dividing the sum of the strength rating by the total number of variables in that diagram.

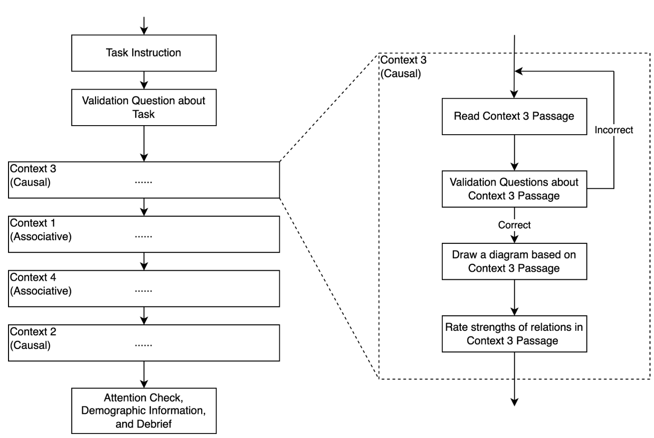

Figure 2: Flowchart of study procedure. The order of context and condition were randomized for each participant.

Spatial Distance of a Relation in Diagrams Raw distance was defined as the spatial distance (in the unit of pixel) between two variables in the causal diagram that participants drew. It was coded as the distance from the middle of the first variable keyword to the middle of the second variable keyword (i.e., the length of that straight line). We normalized distance using the same standardization method as for rating judgments for each participant. Distances were not included in analyses if the two keywords did not have a relation but participants still drew lines between them.

Results

17 out of the 102 participants were removed from analysis either because they indicated they were not serious, or because they did not draw lines in every causal diagram. Thus, data from a total of 85 participants were included in analyses.

Rating of Relatedness Strength

For each participant's rating of perceived strength, we computed two means: the average of each participant's ratings of relatedness between variables in the two causal contexts, and the average of their ratings in the associative contexts.

Figure 3 provides a histogram of relatedness ratings for associative passages and causal passages. A paired-sample t test showed that relatedness ratings in the causal condition were significantly higher than ratings in the associative condition ($t(84) = 4.43$, $p < .001$). Meanwhile, rating histograms in Figure 3 showed the large variability of judgments on relatedness. This is not surprising given some relations are likely judged as being more causal than other relations. Hence, in the following analyses, we focus on distances for individual relations of two variables in the diagrams.

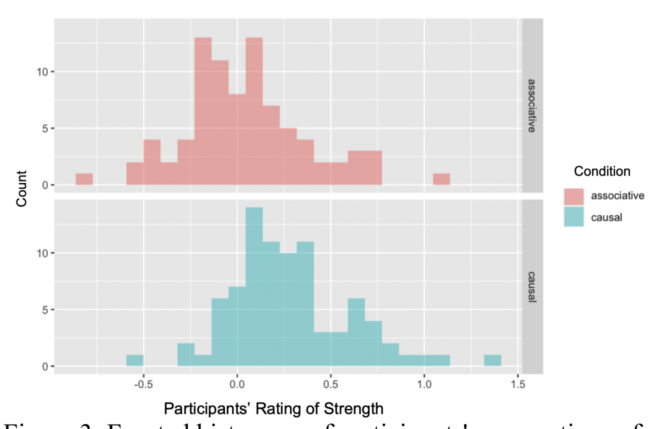

Figure 3: Faceted histogram of participants' mean ratings of strength by condition

Individual Distance in Diagram versus Individual Rating of Perceived Strength

Figure 4 showed sample diagrams from causal and associative conditions for each context. We investigated whether distance and rating of perceived strength is correlated in the item-level. In this analysis, we considered each pair of distance and rating as an entry and performed a correlation analysis on the two variables. Figure 5 visualized the relationship between participants' individual ratings of strength and individual distances on diagram by condition. The overall correlation between distance and rating of perceived strength was significant in this analysis ($r(981) = -.13$, $p < .001$). The two variables are strongly negatively correlated in causal condition ($r(518) = -.19$, $p < .001$), but not significantly correlated in associative condition ($r(461) = -.08$, $p = .095$). However, a Fisher's z-test of the two correlations for causal versus associative condition did not reveal a significant difference between the two correlations ($z = -1.72$, $p = .085$).

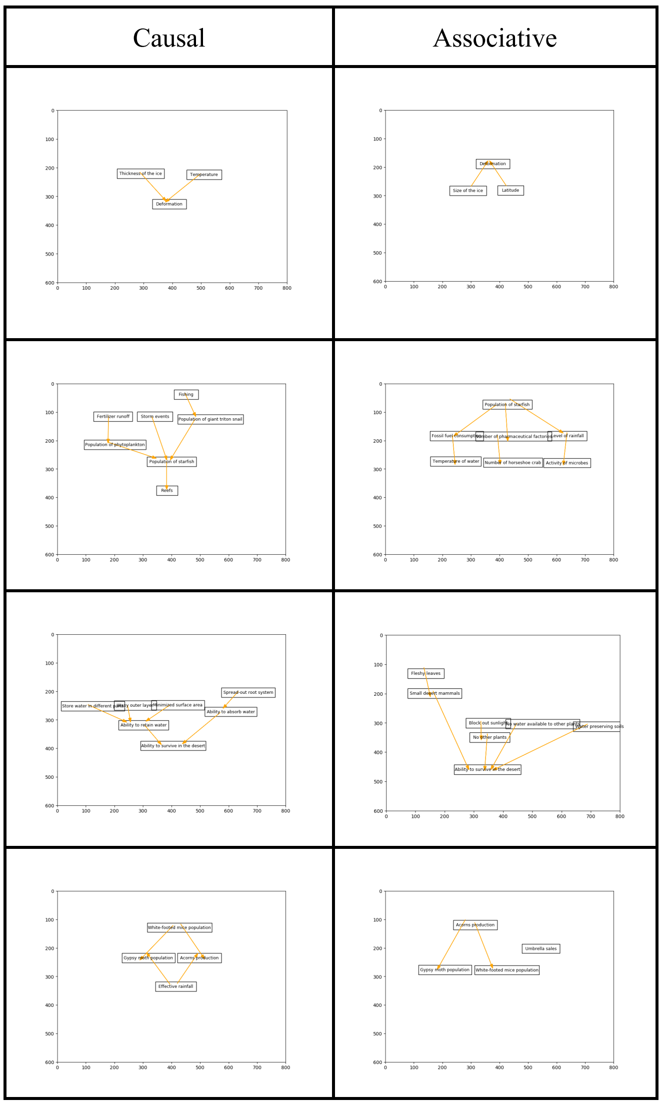

Figure 4: Sample diagram for each context (causal versus associative condition)

Individual Distance in Diagram Predicted by Individual Rating of Perceived Strength

Because distances between two variables showed large variability from one passage to the other, analysis with aggregated mean measures lacks a way of taking into consideration individual differences and item-level variability. Hence, we used a mixed effect model to examine the relationship between individual ratings of perceived strength and distances for each pair of variables. The model included a fixed effect of participants' rating of perceived strength, context (i.e. four different contents from the passage), and variable pairs (i.e., the pair of variables participants were asked to rate). It also included a random effect of participants to account for the within-subject design. We dropped random intercepts in the model because these complex models with random intercepts produced very small random effects.

Figure 5: Scatter plot of participants' individual ratings of strength and individual distances on diagram by condition

The mixed-effects model showed that participants' ratings of perceived strength of relatedness significantly predicted individual distances in the diagram ($t(979) = 3.76$, $p < .001$), as did passage context ($t(979) = 3.24$, $p = .001$) and variable pairs ($t(979) = 2.77$, $p = .006$). These results suggest that controlling for the random effect of each participant, when participants gave higher ratings of relatedness strength to a pair of variables, they also tended to draw these two variables closer together in the diagram (i.e. connecting them with a shorter line).

Mediation Analysis

To investigate the question of whether condition (causal versus associative) impacted participants' drawing of the diagram through participants' perceived strength of relationship, we performed a mediation analysis using the mediation package in R (Tingley et al., 2014). In the analysis, we accounted for the random effect of participants. The indirect effect of condition on distance through perceived strength was statistically significant (Effect = .03, 95% CI of 5,000 bootstrapped estimates = [.012, .060]). That is to say, after reading associative contexts, the lines between variables that participants drew were on average .03 longer than those drawn by participants in the causal condition as a result of participants in the causal condition rating the relationships between variables to be stronger, which in turn affected the distance in the diagram to be shorter.

Discussion

In summary, we found that participants rated relatedness for causal relations to be stronger than associative relations. Importantly, this difference in perceived strength of relations was also revealed in their drawing of diagrams. Participants connected variables that shared a cause-effect relation with a shorter line (i.e., placing variables closer to each other) than they did with variables that instantiate mere association. The mediation analysis showed that participants' perceived strength of relationship mediated the impact of condition (i.e., causal versus associative) on the distance between variables drawn in the diagram.

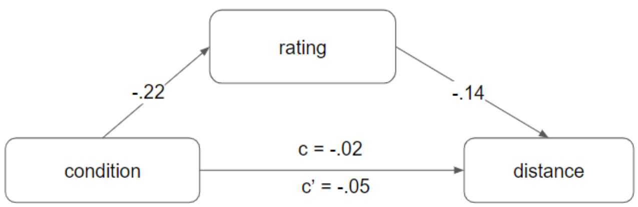

Figure 6. Mediation diagram showing the impact of condition through perceived relatedness ratings on distance participants drew on diagrams.

These findings reveal that causal and associative relations are perceived differently in terms of the strength of relatedness, which is consistent with evidence from the causal learning literature on the uniqueness of causal reasoning (e.g., its asymmetry) (McCrudden et al., 2005; Waldmann & Holyoak, 1992). In addition, we explored how this differentiation between causal and associative relations is related to changes in people's spatial representation for those relations when drawing diagrams. Our findings showed that people tended to draw causal variables closer together when they thought the variables were causally related with strong connection strength. When prompted to draw, people naturally placed two causally related variables closer to each other and used shorter lines to connect them than they would do for associatively related variables. The observed differences together suggest that there might be something fundamentally unique about how people perceive and represent causal relationships.

The current study, nevertheless, has some limitations. One limitation is that, for the mediation analysis, it is unclear the influence direction between relatedness rating and spatial distances in the diagram. It could also be that causal relations lead to shorter distance in mental representation of causal structures, (revealed by shorter distances on the diagram), which resulted in higher rating of relatedness in the subsequent rating tasks. In addition, it is important to highlight that we only tested the university population, who probably understand causal versus associative relations better than the general population or children. Furthermore, although we found a significant correlation between individual distance and individual rating of relatedness strength in only the causal condition, the current study could not be sure if causal and associative relations differ in this aspect. In other words, we still lack understanding of whether people's perceived strength of relatedness and their spatial representation of the relationship are correlated differently in causal versus associative condition.

Despite the aforementioned limitations, the findings of this paper provide a new direction for future research, which extends beyond semantic memory or causal judgments to explore the spatial aspect of mental representation of causal knowledge. Research on causal reasoning and spatial reasoning have been largely isolated from one another, each focusing on different theories and applications. The present study suggests that it may be useful to consider a spatial component of causal reasoning. Based on our findings, causal diagrams can provide a unique window for studying human causal reasoning in complex situations.

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