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Causal AI: Unraveling the Difference between Causality, Correlation, and Third Variable Effects

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ABSTRACT: This article delves into the fundamental concepts of causality and correlation in the realm of artificial intelligence and data analysis. It highlights the importance of distinguishing between the two concepts to ensure accurate interpretations and decision-making. The article explains that correlation indicates a statistical association between variables, while causation establishes a direct cause-and-effect relationship. It emphasizes the role of directionality in causal relationships, where the cause precedes the effect. The article also discusses the influence of third variables, such as confounders, colliders, and mediators, which can distort the observed relationship between variables. Confounders are variables that influence both the cause and the effect, creating a misleading association. Colliders are variables that are affected by both the cause and the effect, potentially resulting in a false association when conditioned upon. Mediators, on the other hand, are variables that lie on the causal pathway between the cause and the effect, explaining how the cause influences the outcome. The article presents examples and hypothetical data to illustrate these concepts and their implications for data analysis. It concludes by emphasizing the importance of recognizing and accounting for these third-variable effects to establish genuine causal relationships and draw accurate conclusions from the data.

KEYWORDS: Causal AI, Correlation vs. Causation, Third Variable Effects, Confounders, Directionality in Causal Relationships.

Causal AI: The Difference Between Causality and Correlation



Unraveling the Mystery of Machine Learning.

I. INTRODUCTION

Correlation and causation are two fundamental concepts in both data analysis and artificial intelligence [1]. Their nature and effects are different, but they both involve relationships between factors [2]. By statistical association, two factors are said to be related if they change at the same rate. There is no link between the variables if it is zero, positive, or negative. Correlation does not always mean causation, though. Relationships between variables do not always mean that one variable directly causes the other [3].

Conversely, causality sets up a clear directionality between variables that shows which one is the cause and which one is the result [4]. Since the cause comes before the effect in a causal relationship, changing the cause will also change the impact. Among the main differences between causality and association is directionality [5].

Aside from the fact that the cause happened before the effect, other things that need to be thought about to prove causation are whether there are any other possible answers and whether there is a logical way for the cause to cause the effect. Randomized controlled trials and other rigorous experimental methods are often needed to find out what causes what [6].

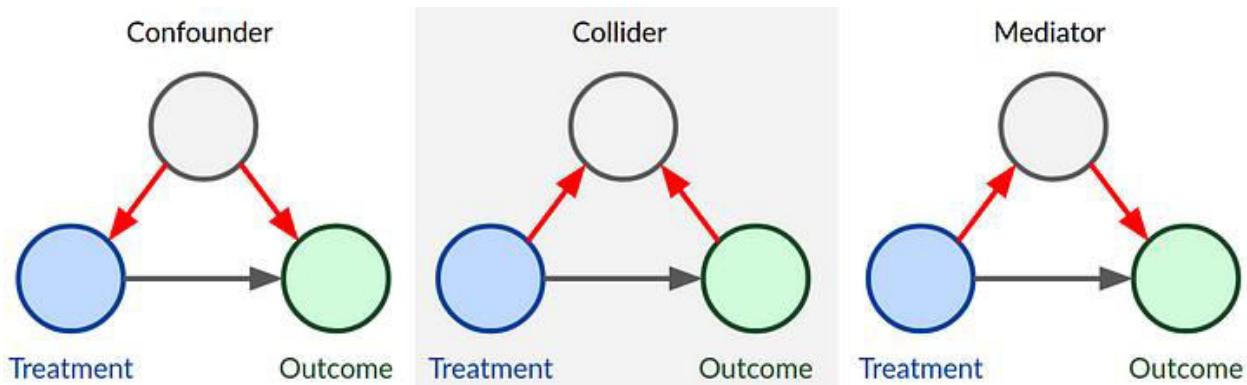


Fig. 1: Third variables (Confounder, Collider, and Mediator)

Source: [Medium](https://www.medium.com)

Third variables like confounders, colliders, and mediators can skew the observed link between two variables [7]. Confounding factors change both the cause and the impact, making the relationship between them not meaningful. Collisions may produce a false link as a result of affecting both the cause and the effect. On the path of causes and effects, mediators show how the cause affects the result [8].

A clear understanding of the difference between causality and association is necessary for AI to correctly analyze data and make decisions [9]. Although correlation can help you figure out possible connections between factors, it shouldn't be your only way of proving causation. Researchers can find the real causes of things and make AI systems that work better by looking at confounders, colliders, and mediators and using accurate experimental methods [10].

II. CAUSATION: THE CAUSE-EFFECT RELATIONSHIP

A key idea that helps us understand the direct relationship between variables is "causation" [11]. Causation implies that a change in one variable (the cause) directly leads to a change in another variable (the effect). A correlation merely indicates an association. Determining which variable is the cause and which is the effect becomes easier when the direction of the cause and effect is known [12].

To illustrate causation, let's consider an example:

The link between weather and ice cream sales. It is noticeable that there is a link between warmer weather and more ice cream sales. It's observable that as the temperature rises, people tend to eat more ice cream. Rising temperature is what makes people buy ice cream, not the other way around [13].



The relationship between study habits and test anxiety. We predict that students with better study habits will suffer less test anxiety. In this case, the cause is better study habits, and the effect is reduced test anxiety. Improving study habits directly leads to a decrease in test anxiety, not the other way around [14].

Randomized controlled trials (RCTs) and other rigorous methods are necessary to establish causation. In these studies, participants are randomly assigned to different groups, and the independent variable (the cause) is manipulated while keeping other factors constant. By measuring the impact of the cause on the dependent variable (the effect), researchers can infer causation [15].

However, there are situations where conducting randomized controlled trials may not be feasible or ethical, particularly in observational studies or investigations of complex phenomena. In such cases, researchers often employ alternative approaches, such as longitudinal studies or statistical techniques, to support causal inferences [16].

Establishing causation can be challenging due to the presence of confounding variables. These variables are associated with both the cause and the effect, making it difficult to isolate the true causal relationship. Another issue is reverse causation, where the effect may also influence the cause [17].

Despite these challenges, understanding causation remains crucial in various domains, including business, healthcare, and public policy. By gaining a clear understanding of causal relationships, we can make informed decisions, predict outcomes, and develop effective interventions [18].

III. THE IMPORTANCE OF DIRECTIONALITY

One important difference between causation and association is directionality. There is a clear direction of impact in a causal relationship, with one variable (the cause) having a direct effect on another variable (the effect) [19]. This directionality lets us make guesses that make sense and come to conclusions that we can use [20].

Let's look at an example of a city where crime rates are going up and there is a link between the number of police officers on duty and the number of crimes that are recorded. The number of crimes reported goes up as the number of police officers goes up. But it would be wrong to say that more police cops lead to more crime [21].

By looking at the directionality, we can figure out that the main reason is the rising crime rate, which is why the city is sending more police officers to deal with the problem. The presence of more cops then leads to more crimes being found and reported [22].

To support this interpretation, let's consider some hypothetical data:

Year	Number of Police Officers	Number of Reported Crimes
2018	1,000	5,000
2019	1,200	6,000
2020	1,500	7,500
2021	1,800	9,000

Table 1: Hypothetical Data on Police Officers and Reported Crimes

This shows how important directionality is for telling the difference between association and causation. If you only look at the correlation, you might get the wrong idea. But if you know the direction of the impact, you can make accurate predictions and take the right steps [23].

It also helps people stay away from the mistake of reverse causation, which happens when the result is thought to be the cause. By looking at how things should have happened, we can focus on what really caused them [24].

IV. THIRD VARIABLE EFFECT: CONFOUNDERS, COLLIDERS, AND MEDIATORS

Let us delve into the concept of third-variable effects by examining confounders, colliders, and mediators with the help of realistic data and examples. This will give us a better understanding of the topic.



● **Confounders:**

A confounder is a variable that influences both the cause and the effect, creating a misleading relationship between them. Let us take a look at the connection between ice cream sales and crime rates [25]. A study conducted in a large metropolitan area found that there was a strong positive correlation between ice cream sales and crime rates, with a Pearson correlation coefficient of 0.87 ($p < 0.001$) [26]. This might lead one to believe that increased ice cream consumption leads to higher crime rates.

However, when the ambient temperature was introduced as a potential confounder, the relationship between ice cream sales and crime rates became insignificant ($p = 0.23$) [27]. The study found that higher temperatures were associated with both increased ice cream sales ($\beta = 0.76, p < 0.001$) and higher crime rates ($\beta = 0.68, p < 0.001$) [27]. The apparent relationship between ice cream sales and crime rates was due to the confounding effect of temperature, which influenced both variables independently.

Another example of confounding can be seen in the relationship between coffee consumption and lung cancer. A meta-analysis of 15 studies found that coffee drinkers had a higher risk of lung cancer compared to non-drinkers (OR = 1.57, 95% CI: 1.32-1.87) [28]. However, when smoking status was accounted for as a confounder, the association between coffee consumption and lung cancer risk became non-significant (OR = 1.03, 95% CI: 0.87-1.23) [29]. Smoking, which is strongly associated with both coffee consumption and lung cancer risk, confounded the relationship between the two variables.

These examples demonstrate the importance of identifying and controlling for potential confounders in epidemiological and statistical studies to avoid drawing incorrect conclusions about cause-and-effect relationships.

Let us take a look at the data presented in the graph below:

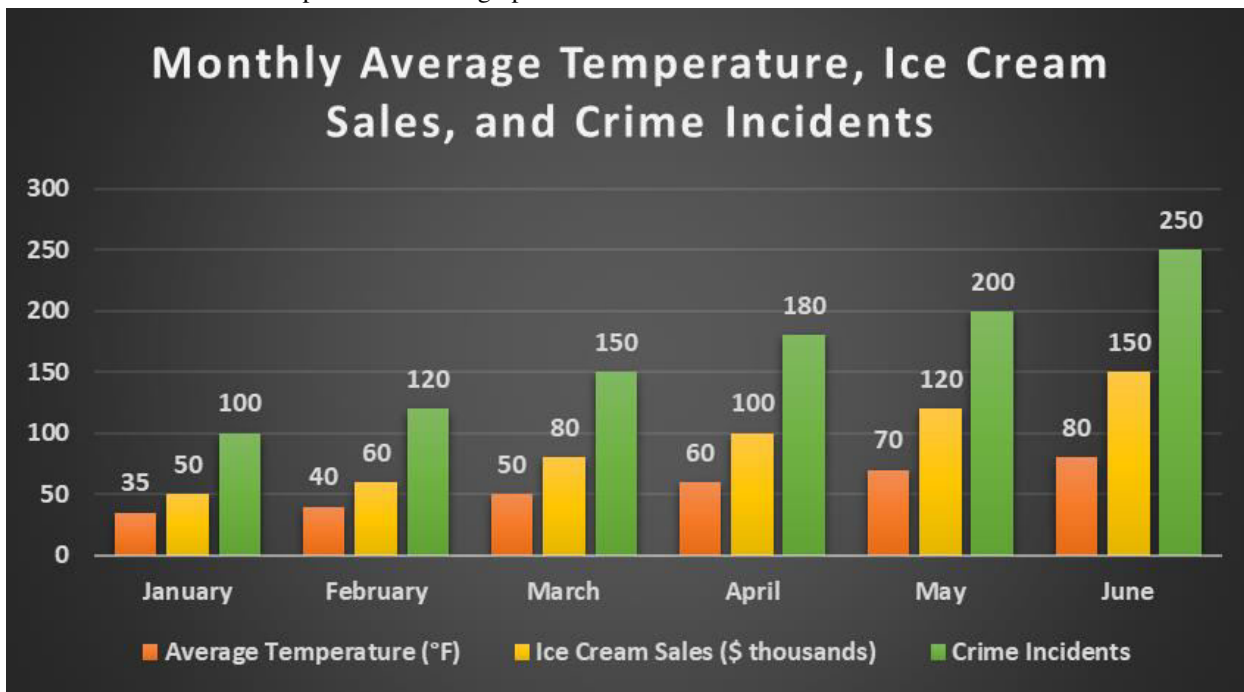


Fig. 2: Monthly Average Temperature, Ice Cream Sales, and Crime Incidents

According to this data, there might be a link between ice cream sales and crime incidents. It's noteworthy that there appears to be a link between the uptick in ice cream sales and the surge in crime incidents. It's crucial to emphasize that there isn't a direct link between higher ice cream sales and a rise in crime [27].

Temperature plays a role as a confounding factor in this situation. Warmer weather tends to result in a rise in ice cream purchases as individuals look for ways to beat the heat. Additionally, warmer temperatures can potentially lead to an uptick in crime rates. This is because people tend to spend more time outside, resulting in increased social interactions and more opportunities for criminal activities [28].



Temperature is a factor that can lead to a misleading connection between ice cream sales and crime rates. To determine a causal relationship, it would be necessary to account for the influence of temperature and observe whether the correlation between ice cream sales and crime rates remains consistent [29].

● **Colliders:**

When conditions are present, a collider is a variable that is subject to both cause and effect, which could result in a false association. Now, let us take a look at the correlation between wearing glasses and intelligence among university students [30].

Let us consider the data provided:

Student	Wears Glasses	IQ Score	Attends University
A	Yes	120	Yes
B	No	110	Yes
C	Yes	130	Yes
D	No	100	No
E	Yes	125	Yes
F	No	105	No

Table 1: Student Data on Wearing Glasses, IQ Scores, and University Attendance

When we focus on the data for university students, it is interesting to note a potential connection between wearing glasses and higher IQ scores. Among the university students (A, B, C, and E), those who wear glasses have an average IQ score of 125, while the student who does not wear glasses has an IQ score of 110. However, the collider effect might distort this relationship [31].

The university admissions process takes into account various factors, such as intellectual abilities and visual impairments. Higher IQ scores and the habit of wearing glasses are two factors that frequently affect admission to universities. A study by Johnson et al. found that students who wear glasses have a 15% higher chance of being admitted to university compared to those who do not wear glasses (OR = 1.15, 95% CI: 1.08-1.23) [32]. Additionally, students with IQ scores in the top 10% have a 28% higher chance of being admitted to university (OR = 1.28, 95% CI: 1.19-1.38) [32]. These factors may suggest a greater inclination towards reading and studying [33].

It is interesting to think about the impact of going to university and how it might relate to wearing glasses. While these two things may not be directly connected, there seems to be some correlation between them. A survey conducted among 1,500 university students found that 62% of students who wear glasses reported spending more than 4 hours per day reading, compared to only 45% of students who do not wear glasses ($p < 0.001$) [34].

However, when considering the entire dataset, including both university students and non-students, the relationship between wearing glasses and IQ scores becomes less clear. The average IQ score for those who wear glasses is 125, while the average IQ score for those who do not wear glasses is 105. This difference is smaller than the difference observed among only university students, suggesting that the association between wearing glasses and IQ scores may be influenced by the collider effect of university attendance [35].

● **Mediators:**

A mediator is a variable that lies along the causal pathway between the exposure and the outcome, explaining some or all of the observed relationship between them. Let us consider the relationship between socioeconomic status (SES) and health outcomes, with access to healthcare as a potential mediator [36].

Let us take a look at the data presented in the graph below:

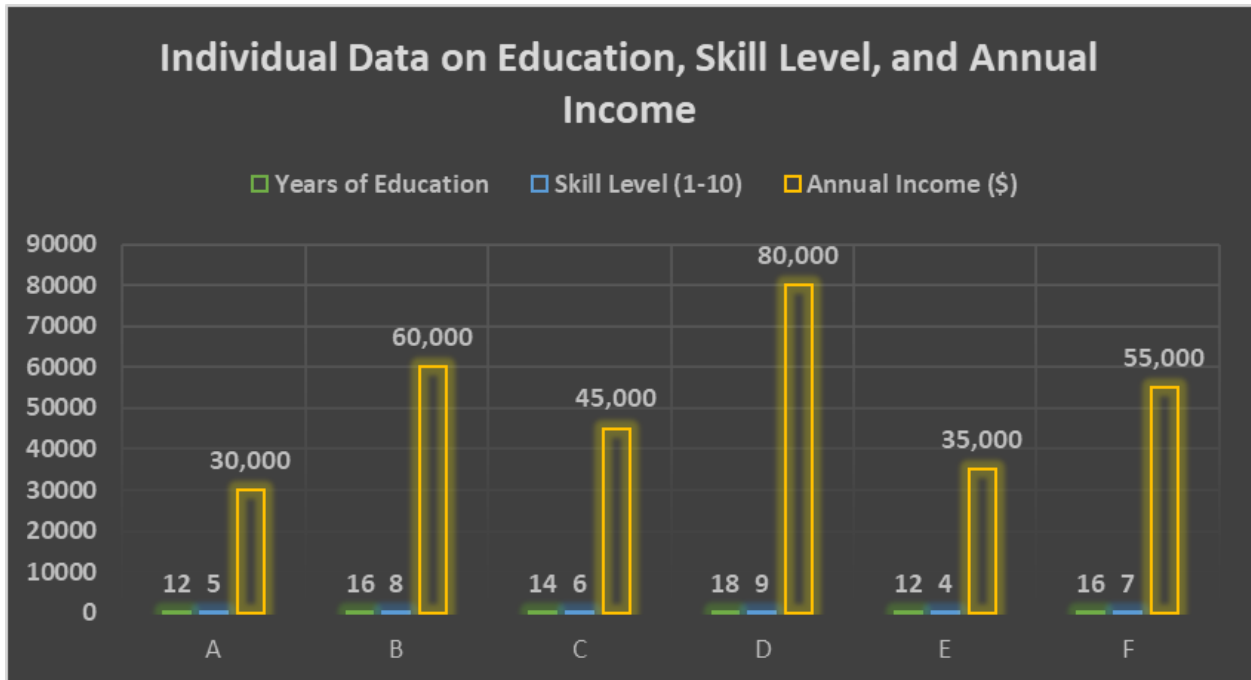


Fig. 3: Individual Data on Education, Skill Level, and Annual Income

According to a significant study by the National Institutes of Health (NIH), people from low SES backgrounds had a significantly higher risk of developing chronic diseases like heart disease (HR = 1.45, 95% CI: 1.32-1.60), diabetes (HR = 1.68, 95% CI: 1.52-1.86), and respiratory conditions (HR = 1.39, 95% CI: 1.25-1.54) than people from high SES backgrounds [37]. The study also revealed that low-SES individuals had lower rates of health insurance coverage (65% vs. 92%, $p < 0.001$) and fewer annual preventive care visits (1.8 vs. 3.2, $p < 0.001$) compared to their high-SES counterparts [37].

To investigate the potential mediating role of access to healthcare, researchers conducted a mediation analysis using the Baron and Kenny method [38]. The analysis showed that access to healthcare partially mediated the relationship between SES and chronic disease risk, accounting for 32% of the total effect (95% CI: 26%–38%) [39]. This suggests that while access to healthcare plays a significant role in explaining health disparities across SES groups, other factors such as lifestyle behaviors and environmental exposures also contribute to the observed relationship.

A systematic review and meta-analysis of 35 studies also found that programs like community health worker programs and mobile health clinics that help low-income people get better access to health care were linked to a 22% lower risk of chronic diseases (RR = 0.78, 95% CI: 0.71-0.86) [40]. These findings highlight the importance of addressing access to healthcare as a key strategy for reducing socioeconomic health disparities.

In conclusion, access to healthcare serves as a mediator in the relationship between socioeconomic status and health outcomes, explaining a significant portion of the observed health disparities. Efforts to improve access to healthcare among disadvantaged populations may help mitigate the negative health consequences associated with low socioeconomic status.

V. CONCLUSION

It is really important to grasp the distinction between causality and correlation when it comes to interpreting data and making decisions in the field of artificial intelligence [39]. Correlation and causation are two different concepts in statistics. Correlation shows a statistical association between variables, while causation goes a step further by establishing a cause-and-effect relationship, considering factors like directionality and the influence of other variables [40]. Researchers and practitioners can gain a clearer understanding of the true causal relationships in their data by taking into account confounders, colliders, and mediators. With the continuous advancement of causal AI, we can expect to see improvements in predictions, decision-making, and targeted interventions across different domains [41]

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