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Correlation is when two variables appear to change in sync. For example, one might decrease as the other increases or vice versa. Causation means one variable directly influences another—for instance, one variable increases because the other decreases.In statistics, correlation expresses the degree to which two variables change with one another, but it doesn't indicate that one variable is causing the other's change. Testing and analysis confirm whether two variables are merely correlated or have a cause-and-effect relationship.In product analytics, understanding the difference between correlation and causation is crucial. It can be the difference between squandering resources on low-value features and creating a high-value product that customers love.Correlational relationships help you reveal patterns in user behavior; for instance, users with more notifications activated in your app might correlate to them spending more time in it.However, without testing for causation, you don't know whether the variables influence each other. For example, do notifications actually cause people to spend longer in the app? Or do power users—who already love your app— also happen to activate more notifications? If the latter is true, the two factors are correlated, but the notifications don't cause increased usage.Read on to learn more about correlation and causation, plus how to identify causation in a digital product.Key takeawaysCorrelation is a situation where two variables move together, but this relationship does not necessarily indicate causality.Causation describes a direct relationship where changes in one variable directly result in changes in another.Misinterpreting correlation as causation in product analytics can lead to ineffective strategies and wasted resources.Hypothesis testing and controlled experiments like A/B testing help rule out false positives and confirm relationships.What's the difference between correlation and causation?While causation and correlation can exist simultaneously, correlation does not imply causation. Causation means action A causes outcome B.On the other hand, correlation is simply a relationship where action A relates to action B—but one event doesn't necessarily cause the other event to happen.This example shows a correlation between eating ice cream and getting sunburned because the two events are related. But neither event causes the other. Instead, both events are caused by something else—sunny weather.Many people confuse correlation and causation because our minds like to find explanations for seemingly related events, even when they don't exist. We usually fabricate these explanations when two variables appear so closely associated that one depends on the other. That would imply a cause-and-effect relationship, where one event results from another.However, we cannot simply assume causation even when we see two events happening in tandem. Why? First, our observations are purely anecdotal. Second, there are several other possibilities for their association, including:The opposite is true: B causes A.The two are correlated, but there's more to it: A and B are correlated but caused by C.There's a third variable involved: A does cause B—as long as D happens.There is a chain reaction: A causes E, which leads E to cause B.Why it's important to distinguish between correlation and causationAssuming correlation is actually causation without investigating the relationship more closely can lead to poor decision-making. In contrast, when you understand the causal relationship between two variables—or lack thereof—you can make data-driven decisions and effectively allocate your resources.Let's say a local government looks at the ice cream sales data above: there's a correlation between ice cream and sunburns. However, they assume that the ice cream is causing sunburns and implement a new policy that bans ice cream. Of course, this policy is misdirected and unnecessary because the two variables are only correlated—not causally connected.An example of correlation vs. causation in product analyticsYou might expect causality in your product, where specific user actions or behaviors result in a particular outcome.Picture this: You just launched a new version of your music-streaming mobile app. You hypothesize that customer retention is linked to in-app social behaviors and ask your team to develop a new feature that allows users to join "communities."A month after you release your new community feature, adoption sits at about 20%. You're curious whether communities impact retention, so you create two equally-sized groups (cohorts) with randomly selected users. One cohort has users who joined a community, and the other has users who didn't.Your analysis reveals a shocking finding: Users who joined at least one community have higher retention than those who did not join a community.A retention analysis chart in Amplitude. In the chart above, nearly 95% of users who joined a community (blue) are still around in Week 2 compared to 55% of those who did not (green). By Week 7, you see 85% retention for those who joined a community and 25% for those who did not. You might be tempted to invest resources to encourage people to join communities to improve retention.But hold on. You don't have enough information yet to conclude whether joining communities causes better retention—you just know that the two are correlated. They could both be caused by some other unknown factor.In this example, joining communities and higher retention correlate, but a third factor could be causing both. To find out, you can conduct statistical analysis by testing for causation in your product.How to measure the correlationStatistical correlation quantifies the strength and direction of the relationship between two variables. It's measured by the 'correlation coefficient'—1 and -1.A positive value suggests that the variables are increasing or decreasing together: there's a positive correlation. A negative value indicates they are moving in the opposite direction (a negative correlation), and 0 means there is no linear relationship.To measure correlation, start by selecting your variables and gathering data. Use quantitative variables and exclude any outliers from your data set.Next, use a tool or software like Excel to calculate the coefficient. The is famous for measuring linear relationships between variables.Then, interpret the result. For the Pearson correlation coefficient, here's what the different values mean:Remember, the correlation coefficient doesn't tell us if one variable is causing the other to change. If you notice a positive or negative correlation, investigate whether it's causal.How to test for causation in your productCausal relationships don't happen by accident.It can be tempting to assume a cause-and-effect relationship between variables, but doing so without confirming causality can lead to a false positive.However, rigorous testing enables you to determine causality so you can make critical product decisions based on the correct user behavior.Once you find a correlation, you can test for causation by running experiments that control the other variables and measure the difference. You can use two to identify causation within your product:Hypothesis testingA/B/n experiments1. Hypothesis testingThe most basic hypothesis test will involve an H0 (null hypothesis) and an H1 (your primary hypothesis). You can also have a secondary hypothesis, a tertiary hypothesis, and so on.The null hypothesis is the opposite of your primary hypothesis. While you cannot prove your primary hypothesis with 100% certainty (the closest you can get is 99%), you can disprove your null hypothesis.The primary hypothesis points to the causal relationship you're researching. It identifies a cause (independent variable or exposure variable—the variable you change or control in an experiment) and an effect (dependent variable or outcome variable—the result you measure).It's best to create your H1 first and then specify its opposite, your H0. Your H1 identifies the relationship you expect between your independent and dependent variables.If we use the previous example and look at the impact of in-app social features on retention, your independent variable would be "joining a community," and your dependent variable would be "retention." Your primary hypothesis might be:H1: If a user joins a community within our product in the first month, they will remain customers for over a year.Then, negate your H1 to generate your null hypothesis:H0: There is no relationship between joining a community and user retention.The goal is to observe whether there is an actual difference between your different hypotheses. If you can reject the null hypothesis with statistical significance—ideally with a minimum of 95% confidence—you're closer to understanding the relationship between your independent and dependent variables.In the music-streaming example above, you reject the null hypothesis by finding that joining a community resulted in higher retention rates while adjusting for confounding variables. Confounding variables such as age, genre preference, or initial user engagement level could independently influence the results. Considering these, you can conclude that there is some relationship between joining a community and user retention.To test this hypothesis, develop an equation that accurately reflects the relationship between your expected cause (independent or exposure variable) and effect (dependent or outcome variable). If your model allows you to plug in a value for your exposure variable and consistently return an outcome reflecting actual observed data, you're probably onto something.When to use hypothesis testingHypothesis testing is helpful when trying to identify whether a relationship exists between two variables rather than looking at anecdotal evidence. Hypothesis testing mainly uses historical data and is ideal for analyzing existing data sets to evaluate theories or hypotheses over time or across different groups.Consider using historical data to run a longitudinal analysis of changes over time. For example, you might investigate whether first adopters for product launches are your biggest promoters, look at referral patterns, and compare this relationship to product launches.Or, run a cross-sectional analysis that analyzes a snapshot of data. This analysis is helpful when looking at the effects of a specific exposure and outcome rather than trend changes. For example, explore the relationship between holiday-specific promotions and sales.2. A/B/n Experimentation, can bring you from correlation to causation. Look at each variable, change one so you have different versions (variants A and B), and see what happens.If your outcome consistently changes with the same trend—for example, if variant A consistently leads to higher user engagement than variant B across multiple tests—then you've found the variable that makes the difference.Two variants for a website layout—variant A and variant BWhen considering the relationship between joining a community and retention, you must eliminate all other variables that could influence the outcome—because something else might ultimately affect retention.To test whether there's causation, establish whether there's a direct link between users joining a community and using your app long-term.Start with your onboarding flow. Split the following 1,000 users into two groups. Require the first half to join a community when they sign up (variant A) and the other half not to (variant B). Run the experiment for 30 days using an experimentation tool like , then compare between the two groups.Suppose that the users in the group are forced to join a community and have a relatively higher retention rate. You now have evidence to confirm a causal relationship between community joining and retention. From there, consider using a platform like Amplitude to dig deeper and understand why communities drive retention.When to use A/B/n testingUnlike hypothesis testing based on historical data, A/B/n testing generates new data through controlled experiments. A/B/n is ideal when comparing the impact of variations—variant A and variant B—for campaigns, product features, content strategies, and more.For example, a split test of your product's onboarding flow might compare how different product strategies perform based on specific characteristics, including:Copy variationsGraphics (stock photos vs. custom illustrations)Reducing the number of fields in a sign-up formPersonalization (name, company, and industry details)After running multiple product onboarding variations, you can look at the results and Learn more about metrics you can track in Act on correlations and causations for sustained product growthWe're always looking for explanations and trying to interpret what we see. However, unless you can identify causation through , assume that you only see a correlation. The more adept you become at identifying accurate correlations within your product, the better you'll be able to prioritize your product investments and improve retention.If you're looking to spot trends in customer behavior, test for causation, and optimize your product all in one platform, .References, Amplitude, Clearbit, OnStartups, Harvard Business Review In applied statistics, particularly in research and data analysis, the concepts of correlation and causation are often mixed up. This tutorial dismantles generalized trends and widespread myths like "correlation equals causation" and "correlation implies causation", clarifying in an illustrative and example-based fashion these two important statistical concepts. What is Correlation? In simple terms, correlation is the strength and direction of a (linear) relationship between two variables X and Y. It is a statistical measure that indicates how the two variables are related to each other, that is, correlated. When there exists a correlation between two variables, changes in an observation under the variable X occur together with changes under the other variable, Y. Suppose we have collected the maximum daily temperatures throughout the summer (variable X), and the daily ice cream sales throughout the same season (variable Y). Below is a small sample of both data variables, recorded over a week. As can be observed, as the daily temperature X rises, so do the ice cream sales Y. This means there is a positive correlation or direct relationship between X and Y. Correlation means the two variables vary similarly, but it does not necessarily imply that such changes in one of them cause similar changes the other. Now suppose we analyze together daily temperatures (X), and daily consumption of hot chocolate (Z): If we observe a tendency of lower hot chocolate sales on warmer days, then there is a negative correlation and inverse relationship between X and Z. Again, changes co-occur in both variables but this time they occur in opposite directions: when observations in X increase, observations in Z decrease. What is Causation? Next, it's time to define causation. Causation is an indication that an event B is the direct result of the occurrence of another event A. In other words, A is the cause for B to happen. Imagine you are in a large dark room with several light bulbs and light switches: one for turning each bulb on. Regarding causation between events, pressing the switch (event A) is the direct reason why a light bulb will turn on (event B). This is a clear case of causation: pressing the light turns the light on. Causation can also be understood in terms of statistical variables. Assuming two variables X and Y, causation implies that one variable X is the cause, and the other Y is the effect, or vice versa. If X represents the number of switches pressed at a given time, and Y is the amount of light (measured in lux) in the room, then there is also causation because pressing more switches on causes a higher light intensity in the room. Relationship and Differences In the ice cream example shown earlier, besides the clear correlation, there also exists causation because temperature rises (cause) directly lead to increases in ice cream sales (effect): people tend to consume more ice cream in warmer days, thereby showing a direct causal relationship between the two variables. However, even though correlation and causation often manifest together, it is important to note that: Correlation does not always imply causation Causation (a causal link between two variables) always implies a correlation between them Let's see some examples where correlation between two variables does not imply causation, starting with another summer-themed one. Suppose X is the daily temperature recorded, and Y is the number of visitors to a beach. Even though we observe that as temperature rises the number of visitors to the beach also increases (positive correlation), higher temperature do not directly cause more people to go to the beach: such a decision might be influenced by other factors like day of the week, whether it is holiday or not, whether special events are going on at that beach, and so on. Temperature may partly influence the decision to go to the beach, but it is not the direct cause. On a last -and more autumn-themed- example, suppose that on days of higher rainfall (X) more people leave home with their umbrella (Y), and at the same time, there is more traffic on the streets (Z). Whilst there is both correlation and causation between X and Y, and there also exists a correlation between X and Z, this does not necessarily mean the rain is the direct cause of the denser traffic. There could be other reasons, like the time of the day. In summary, there is no direct causation between X and Z. Wrapping Up Understanding the subtle difference between correlation and causation is crucial for accurate analysis and interpretation of data, helping us avoid misleading conclusions and ensuring that we identify cases when two variables simply related versus when cases when one directly influences the other. In analytics, correlation and causation both describe relationships between variables. However, the two terms are not interchangeable and have significant differences. Causation indicates that one event causes another. Correlation only identifies that a relationship exists between two events or outcomes.In a situation where two variables have a similar response to an event, you may assume that one event caused the other or that the two variables are somehow directly connected. However, this isn't always the case, making it important to be able to distinguish between correlation and causation. Explore correlation versus causation as well as how to differentiate these two terms from one another when describing the relationship between variables.What is meant by correlation vs. causation?The concept of correlation versus causation strives to determine if two events are simply related to each other or if one caused the other to happen. Correlation versus causation is an important consideration since the presence of a correlation between two variables doesn't mean one causes the other. When a clear relationship exists between variables, it can be easy to say that a cause-and-effect relationship is present.This type of observation, though, may prevent you from considering other factors or variables that could cause the correlation. The correlation you are observing may be causation, as both can be true, but correlation alone isn't enough to declare causation. What is correlation?Correlation measures the linear relationship between variables. In a positive correlation, when the value of one variable goes up, the other does as well. When one variable goes down, the other variable descends, too.A negative correlation describes the opposite—as one variable goes up, the other goes down, with the two variables moving in opposite directions. If no relationship exists between variables, you would say zero correlation is present [1]. You can represent the strength of the relationship between variables using a correlation coefficient ranging from -1 to +1, where the closer the linear relationship is to zero, the weaker the correlation is:1 = Perfect positive correlation0.5 = Weak positive correlation0 = Zero correlation-0.5 = Weak negative correlation-1 = Perfect negative correlationYou can also use scatter plots to visualize correlations. If you have a positive correlation, you will notice points on the scatter plot moving up from left to right and points moving down from left to right if a negative correlation is present. A scatter plot representing variables with no correlation will have points that appear spread throughout the graph [2]. Limitations exist when it comes to how much you can learn from correlations, as correlation alone isn't enough to prove causation. Additionally, correlations are only able to establish linear relationships between variables. Even when variables are strongly correlated, it doesn't prove a change in one variable caused the change in the other. To be able to do that, you must establish causation. Causation occurs when one variable is directly responsible for the change in the other. This is much more difficult to prove than correlation and requires experimentation using both independent and controlled variables. What is causation?Causation occurs when one variable is directly responsible for the change in the other. In other words, a change in one variable causes a change in another variable. Causation can be more challenging to prove than correlation and requires experimentation using both independent and controlled variables. In order to prove causation, you need a properly designed experiment that demonstrates these three conditions: Temporal sequencing: Temporal sequencing states that X, referring to the variable causing the change, comes before Y, the variable that changes.Non-spurious relationship: A non-spurious relationship means that you can demonstrate with certainty that the relationship between X and Y couldn't occur simply by chance.Elimination of alternative causes: By eliminating alternative causes, you are stating that the relationship between X and Y isn't due to other outside variables that aren't considered part of the experiment. If your experiment fails to demonstrate temporal sequencing, a non-spurious relationship, or eliminate any possible alternative causes, you can't prove causation [3]. A complication of causation compared to correlation is that it's difficult to prove that one thing causes another.Essentially, causality is understanding how one thing influences another thing and how a cause produces an effect. Nothing in the world tends to happen without something having caused it. Change is a consistent aspect of reality, and causality is rooted in identifying the incident that caused the change. Take a look at two examples of causality you might recognize: 1. If you plant a seed (cause), a tree might grow (effect). 2. If you press the gas pedal (cause), your car will move forward (effect). Does correlation imply causation?Although it's possible for both correlation and causation to occur at the same time, correlation doesn't imply causation. This is because the relationship between variables could either be due to a third variable or simply a coincidence. Examples of correlation vs. causationIf you were to collect data on the sale of ice cream cones and swimming pools throughout the year, you would likely find a strong positive correlation between the two as sales of both increase during the summer months. If you make the mistake of assuming correlation implies causation, you might claim that an increase in ice cream cone sales causes people to buy swimming pools. However, this isn't the case since you can attribute the increase in both to another variable—likely the warmer weather people experience during the summer. Therefore, although a correlation is present, you can't support causation. In the following example of how correlation is different from causation, you may find it challenging to identify whether causation is present with two variables: You could find a correlation between the amount someone exercises and their reported levels of happiness. While it's possible an increase in exercise is causing an increase in happiness, you can't say for sure that it's the cause since there could be another unknown variable that has a more significant influence on a person's mood.Reliable ways to determine causationTo reliably determine causation, you can perform randomized A/B/n testing, which is the same as an A/B test, but with any number of additional variables. This ensures that other possible factors are part of the test as well. The other method for determining causation is through hypothesis testing. Hypothesis testing is when you test your primary hypothesis against a null hypothesis, which is the opposite of your primary hypothesis. The null hypothesis should be disproved by your primary hypothesis to help you be as certain as possible about your results. Explore correlation vs. causation with Coursera Although the difference in correlation and causation can be challenging to identify, you can do so with a detailed and structured analytical approach. To develop important analytical skills, such as data collection, data calculations, and data analysis, consider earning a Google Data Analytics Professional Certificate on Coursera. With this Professional Certificate, you can qualify for in-demand positions, such as a data analyst or junior data analyst, in less than six months.The University of Colorado Boulder's Statistical Inference and Hypothesis Testing in Data Science Applications and Data Analysis Tools from Wesleyan University on Coursera are also great courses where you can learn more about how to properly implement hypothesis testing. Because the human brain tends to seek out causal relationships, scientists are extra careful about creating highly controlled experiments — but they still make mistakes. Here are ten examples illustrating how hard it is to identify causation. 10. The Trouble With Henry (and Hawthorne) Researchers investigating worker productivity on the factory floor in the early 20th century discovered the Hawthorne effect, or the idea that participant knowledge of an experiment can influence its results. Baker Library Historical Collection People are a pain to research. They react not only to the stimulus being studied, but also to the experiment itself. Researchers today try to design experiments to control for such factors, but that wasn't always the case. Take the Hawthorne Works in Cicero, Illinois. In a series of experiments from 1924 to 1932, researchers studied worker productivity effects associated with altering the Illinois factory's environment, including changing light levels, tidying up the place and moving workstations around. Just when they thought they were on to something, they noticed a problem: The observed increases in productivity dropped almost as soon as the researchers left the works, indicating that the workers' knowledge of the experiment — not the researchers' changes — had fueled the boost. Researchers still call this phenomenon the Hawthorne Effect [source: Obrenović]. A related concept, the John Henry effect, occurs when members of a control group try to beat the experimental group by kicking their efforts into overdrive. They need not know about the experiment; they need only see one group receive new tools or additional instruction. Like the steel-driving man of legend, they want to prove their capabilities and earn respect [sources: Saretsky; Vogt]. 9. Always Bet on Black? If the pill lands on black 26 times in a row on the roulette wheel, would you be more likely to bet on red or black on that 27th turn? Image Source/Getty Images The titular characters of Tom Stoppard's film "Rosencrantz and Guildenstern Are Dead" begin the film baffled and finally frightened as each of 157 consecutive flips of a coin comes up heads. Guildenstern's explanations of this phenomenon range from time loops to "a spectacular vindication of the principle that each individual coin, spun individually, is as likely to come down heads as tails ... " Evolution wired humans to see patterns, and our ability to properly process that urge seems to short-circuit the longer we spend gambling. We can rationally accept that independent events like coin flips keep the same odds no matter how many times you perform them. But we also view those events, less rationally, as streaks, making false mental correlations between randomized events. Viewing the past as prelude, we keep thinking the next flip ought to be tails. Statisticians call this the gambler's fallacy, aka the Monte Carlo fallacy, after a particularly illustrative example that occurred in that famed Monaco resort town. During the summer of 1913, bettors watched in increasing amazement as a casino's roulette wheel landed on black 26 times in a row. Inflamed by the certainty that red was "due," the punters kept plunking down their chips. The casino made a mint [sources: Lehrer; Oppenheimer and Monin; Vogt]. 8. The Hot Hand and the Monkey's Paw Superstitions take all forms in sports. Here we see Boston Bruins defenseman Zdeno Chara kissing the back of his helmet for good luck during Game 7 of the Stanley Cup Finals against the St. Louis Blues June 12, 2019, at TD Garden in Boston. Chara's luck wore out, though, and the Blues beat the Bruins 4-1 to win the Stanley Cup that night. Michael Tureski/Icon Sportswire via Getty Images No discussion of streaks, magical thinking or false causation would be complete without a flip through the sports pages. Stellar sports seasons arise from such a mysterious interplay of factors — natural ability, training, confidence, the occasional X factor — that we imagine patterns in performance, even though studies repeatedly reject streak shooting and "successful" superstitions as anything more than imaginary. The belief in streaks or slumps implies that success "causes" success and failure "causes" failure or, perhaps more reasonably, that variation in some common factor, such as confidence, causes both. But study after study fails to bear this out [source: Gilovich, et al]. The same holds true for superstitions, although that never stopped retired NBA player and Dallas Mavericks guard Jason Terry from sleeping in the opposing teams' game shorts before each game, or NHL center and retired Ottawa Senators player Bruce Gardiner from dunking his hockey stick in the toilet to break the occasional slump [source: Exact Sports]. The sophomore slump, too, typically arises from a too-good first year. Performance swings tend to even out in the long run, a phenomenon statisticians call regression toward the mean [source: Barnett, et al]. In sports, this averaging out is aided by the opposition, which adjusts to counter the new player's successful skill set. 7. Hormonal Imbalance The story of hormone replacement therapy, once widely used to treat symptoms of menopause, turned out not to be so straightforward after all. BSIP/Universal Images Group/Getty Images Randomized controlled trials are the gold standard in statistics, but sometimes — in epidemiology, for example — ethical and practical considerations force researchers to analyze available cases. Unfortunately, such observational studies risk bias, hidden variables and, worst of all, study groups that might not accurately reflect the population. Studying a representative sample is vital; it allows researchers to apply results to people outside of the study, like the rest of us. A case in point: hormone replacement therapy (HRT) for women. Beyond treating symptoms associated with menopause, it was once hailed for potentially reducing coronary heart disease (CHD) risk, thanks to a much-ballyhooed 1991 observational study [source: Stampfer and Colditz]. But later randomized controlled studies, including the large-scale Women's Health Initiative, revealed either a negative relationship, or a statistically insignificant one, between HRT and CHD [source: Lawlor, et al.]. Why the difference? For one thing, women who use HRT tend to come from higher socioeconomic strata and receive better quality of diet and exercise — a hidden explanatory relationship for which the observational study failed to fully account [source: Lawlor, et al]. 6. Super Bowl Stock Market Shuffle You can follow the NFL and you can follow the stock market. But using the 16 original NFL teams' winning streak to pick your stocks probably isn't a winning strategy. Alistair Berg/Getty Images In 1978, sports reporter and columnist Leonard Koppett mocked the causation-correlation confusion by wryly suggesting that Super Bowl outcomes could predict the stock market. It backfired: Not only did people believe him, but it worked — with frightful frequency. The proposal, now commonly known as the Super Bowl Indicator, went as follows: If one of the 16 original National Football League teams — those in existence before the NFL's 1966 merger with the American Football League — won the Super Bowl, the stock market would rise throughout the rest of the year. If a former AFL team won, it would go down [source: Bonsal]. From 1967 to 1978, Koppett's system went 12 for 12; up through 1997, it boasted a 95 percent success rate. It stumbled during the dot-com era (1998–2001) and notably in 2008, when the Great Recession hit, despite a win by the New York Giants (NFC). Still, as of 2022, the indicator had a 73 percent success rate [source: Chen]. Some have argued that the pattern exists, driven by belief; it works, they say, because investors believe it does, or because they believe that other investors believe it. This notion, though clever in a regressive sort of way, hardly explains the 12 years of successful correlations predating Koppett's article. Others argue that a more relevant pattern lies in the stock market's large-scale upward trend, barring some short-term major and minor fluctuations [source: Johnson]. 5. Big Data, Little Clarity Given enough data, patience and methodological leeway, correlations are almost inevitable. That's how big data works. Weiquan Lin/Getty Images Big data — the process of looking for patterns in data sets so large they resist traditional methods of analysis — rates big buzz in the boardroom [source: Arthur]. But is bigger always better? It's a rule that's drummed into most researchers in their first stats class: When encountering a sea of data, resist the urge to go on a fishing expedition. Given enough data, patience and methodological leeway, correlations are almost inevitable, if unethical and largely useless. After all, the mere correlation between two variables does not imply causation; nor does it, in many cases, point to much of a relationship. For one thing, researchers cannot use statistical measures of correlation willy-nilly; each contains certain assumptions and limitations that fishing expeditions too often ignore, to say nothing of the hidden variables, sampling problems and flaws in interpretation that can gum up a poorly designed study. But big data is increasingly being used and hailed for its invaluable contributions to areas such as creating customized learning programs; wearable devices that provide real-time feed to your electronic health records; and music streaming services that give you targeted recommendations [source: IntelliPaat]. Just don't expect too much out of big data in the causality department. 4. Minimum Wage Equals Maximum Unemployment For every person rallying on Capitol Hill to raise the minimum wage, there's a congressperson on the Hill who disagrees there's a need for that change. Congressional Quarterly/CQ-Roll Call, Inc via Getty Images Any issue dealing with money is bound to be deeply divisive and highly politicized, and minimum wage increases are no exception. The arguments are varied and complex, but essentially one side contends that a higher minimum wage hurts businesses, which drives down job availability, which hurts the poor. The other side responds that there's little evidence for this claim, and that the 76 million Americans working at or below minimum wage, which some argue is not a living wage, would benefit from such an increase. They argue that the federal minimum wage for covered, nonexempt employees ($7.25 per hour in September 2023) has lowered Americans' purchasing power by more than 20 percent [sources: U.S. Department of Labor; Cooper, et al]. As literary critic George Shaw reportedly quipped, "If all the economists were laid end to end, they'd never reach a conclusion," and the minimum-wage debate seems to bear that out [source: Quote Investigator]. For every analyst who says minimum wage increases drive jobs away, there is another who argues against such a correlation. In the end, both sides share a fundamental problem: namely, the abundance of anecdotal evidence many of their talking heads rely on for support. Secondhand stories and cherry-picked data make for weak tea in any party, even when presented in pretty bar charts. 3. Breakfast Beats Obesity, Dinner Denies Drugs The family that eats dinner together stays off drugs together. Um, sounds good, but it's not quite true. MoMo Productions/Getty Images Between fitness apps, drugs and surgeries, weight loss in the United States is a $78 billion-per-year industry, with millions of Americans bellying up to the weight-loss bar annually [source: Research and Markets]. Not surprisingly, weight loss studies — good, bad or ugly — get a lot of press in the U.S. Take the popular idea that eating breakfast beats obesity, a sugar-frosted nugget derived from two main studies: One, a 1992 Vanderbilt University randomized controlled study, showed that reversing normal breakfast habits, whether by eating or not eating, correlated with weight loss; the other, a 2002 observational study by the National Weight Control Registry, correlated breakfast-eating with successful weight-losers — which is not the same as correlating it with weight loss [sources: Brown, et al.; Schlundt, et al.; Wyatt, et al.]. Unfortunately, the NWCR study failed to control for other factors — or, indeed, establish any causal connection from its correlation. For example, a person who wants to lose weight might work out more, eat breakfast or go whole-hog protein, but without an experimental design capable of dialing in causal links, such behaviors amount to nothing more than commonly co-occurring characteristics [source: Brown, et al]. A similar problem plagues the numerous studies linking family dinners with a decreased risk of drug addiction for teens. Although attractive for their simple, appealing strategy, these studies frequently fail to control for related factors, such as strong family connections or deep parental involvement in a child's life [source: Miller, et al]. 2. The Suicidal Sex Researchers studying suicide across genders have to be aware that suicidal men and women often use different methods, so the success of their outcomes vary widely. SONGPHOL THESAKIT/Getty Images We often hear that men, especially young men, are more likely to commit suicide than are women. In truth, such statements partake of empirical generalization — the act of making a broad statement about a common pattern without attempting to explain it — and mask several known and potential confounding factors. Take, for example, a Youth Risk Behaviors Survey from 2021 found that girls in grades 9-12 attempted suicide almost twice as often as male students (13 percent vs. 7 percent) [source: American Foundation for Suicide Prevention]. How, then, can a higher correlation exist between the opposite sex and suicide? The answer lies in suicide attempts by methodology: While the most common method of suicide for both sexes in 2020 was by firearm (57.9 percent for men and 33.0 percent for women), women were almost equally likely to die by poisoning or suffocation [source: National Institute of Mental Health]. Even if we could dispose of such confounding factors, the fact would remain that maleness, per se, is not a cause. To explain the trend, we need to instead identify factors common to men, or at least suicidal ones. The same point applies to the comparatively high rates of suicide reported among divorced men. Divorce doesn't cause men to commit suicide; if anything, it's more indicative of an underlying causal relationship with factors such as male role inflexibility, their social networks, the increasing importance of child care and men's desire for control in relationships [source: Scourfield and Evans]. 1. Vaccination Vexation People have been protesting vaccine mandates for decades. But with the outbreak of COVID-19, the divide took on new significance. Michael Nigro/Pacific Press/LightRocket via Getty Images No correlation/causation list would be complete without discussing parental concerns over vaccination safety. Before the COVID-19 pandemic hit the world in 2020, the main issue was a fear among some parents that the measles, mumps and rubella vaccination was causally linked to autism spectrum disorders. This notion was popularized by celebrities like Jenny McCarthy. Despite the medical community debunking the 1998 Andrew Wakefield paper that inspired the falsehood, and despite subsequent studies showing no causal link, some parents remain fearful of an autism connection or other vaccine-related dangers [sources: Park; Sifferlin; Szabo]. Then COVID-19 arrived, and to date has killed millions around the globe. Scientists raced to create an effective vaccine and they succeeded; the first U.S. COVID-19 vaccine was available in December 2020 under the FDA's emergency use authorization [source: FDA]. But it also quickly became intertwined with the extreme polarization of U.S. politics and misinformation. Many parents, especially Republicans, feared the vaccines were unsafe because they were developed so quickly, and because there might be as-yet-unknown long-term side effects. There were also incorrect fears about the vaccine affecting future fertility. Those have now been proven false [source: Kelen and Maragakis]. As of January 2022, just 28 percent of 5- to 11-year-olds had received at least one dose of the vaccine, disappointing many in the medical field [sources: Hamel, Kates]. The number of vaccinated children is growing; by May 2023, 40 percent of 5- to 11-year-olds had received at least done dose [source: CDC]. These are no harmless misunderstandings. Despite debunking a link between autism and childhood vaccines, many parents remain leery of the shots. In 2019, there were 1,282 cases of measles in 31 states, the highest number in the U.S. since 1992. The majority of these cases were among the unvaccinated [source: CDC]. Whether that correspondence is coincidental, correlative or causal is well worth considering. And the effects of the current COVID-19 vaccination hesitation remain to be seen. Try Innerview(psst... for free!)Transform user interviews into actionable takeaways & faster decisions Ever wondered why some people confuse correlation with causation? It's a common mistake that can lead to misunderstandings in everything from science to everyday life. Understanding the difference between correlation and causation is crucial for making informed decisions.In this article, you'll explore real-world examples that highlight these concepts. From the classic ice cream sales versus drowning incidents to more complex scenarios like health studies, you'll see how easily one can be mistaken for the other. Your ability to discern these relationships can shape your perspective on data and influence your choices.Correlation describes a statistical relationship between two variables. It's crucial to grasp that correlation indicates how closely related two things are, but it doesn't imply that one causes the other. For example, if you observe an increase in both ice cream sales and drowning incidents during summer months, it shows a correlation, but not causation.Correlation measures the strength and direction of a relationship between two variables. This measurement can be positive (both variables move in the same direction) or negative (one variable increases while another decreases). A correlation coefficient ranges from -1 to 1; closer to 1 indicates a strong positive correlation, while close to -1 signifies a strong negative correlation. A value around 0 suggests no significant relationship.Different types of correlations exist which help clarify relationships:Positive Correlation: When one variable increases, so does the other. For example, studying hours often correlates positively with test scores.Negative Correlation: Here, when one variable goes up, the other tends to go down. An example is the inverse relationship between exercise frequency and body weight.Perfect Correlation: This occurs when two variables change together at a constant rate. An instance could be height and weight among specific populations.Recognizing these types aids in interpreting statistical data accurately.Causation refers to a relationship where one event directly influences another. Understanding causation is crucial for interpreting data accurately and making informed decisions.Causation indicates that a change in one variable directly results in a change in another. For example, if you increase exercise, your fitness level improves. This direct link differs from correlation, which only suggests a relationship without confirming an effect.Causation can be classified into several types:Direct causation: This occurs when one event leads straight to another. For instance, striking a match causes it to ignite.Indirect causation: Here, one factor influences another through an intermediary. An example includes how poor diet leads to obesity, which then increases the risk of diabetes.Necessary causation: In this instance, one condition must exist for the other to occur but doesn't guarantee it alone. For example, oxygen is necessary for fire but not sufficient on its own without fuel.Sufficient causation: This type means that an event alone can produce an outcome under certain conditions. A heavy rainstorm can cause flooding without needing additional factors.Recognizing these types helps clarify complex relationships between variables and aids in better understanding research findings and real-world scenarios.Understanding the key differences between correlation and causation helps you interpret data accurately. Recognizing these differences aids in making informed decisions based on statistical relationships.Many people mistakenly believe that correlation implies causation. Just because two variables move together doesn't mean one causes the other. For instance, an increase in ice cream sales correlates with a rise in drowning incidents during summer months. However, this doesn't mean eating ice cream causes drowning; rather, both relate to warmer weather.Another misconception involves assuming that strong correlations indicate a direct influence. Some might think that if two variables share a high correlation coefficient, one must impact the other directly. Yet, various factors can contribute to the observed relationship without any causal link existing.Real-world examples clarify the distinction between correlation and causation:Ice Cream Sales vs. Drowning Incidents: As mentioned earlier, higher ice cream sales correlate with increased drowning incidents in summer due to seasonal temperature changes.Smoking and Lung Cancer: There's a strong correlation between smoking rates and lung cancer cases. While smoking is proven to cause cancer, it's essential not to conflate mere statistical association with direct causative effects.Exercise and Weight Loss: Regular exercise shows a positive correlation with weight loss. Yet many factors, like diet or metabolism, can also play significant roles in achieving weight loss independently of exercise.Recognizing these examples emphasizes how crucial it is to differentiate between correlation and causation when analyzing data sets for better decision-making processes.Understanding the difference between correlation and causation is essential for accurate data interpretation. Misinterpreting these concepts can lead to flawed conclusions and poor decision-making.In research, recognizing whether a relationship is correlational or causal affects study design and outcomes. Strong correlations might suggest further investigation, but without proving causation, results could mislead.Example 1: A study finds a correlation between high sugar intake and obesity rates. However, without establishing causation, one can't conclude that sugar consumption directly causes obesity.Example 2: In health studies, researchers may identify a correlation between exercise frequency and reduced anxiety levels. Yet, it's crucial to investigate if exercise directly influences anxiety or if other factors—like social support—play a role.Misunderstanding correlation for causation can have serious consequences in various fields such as public policy, healthcare, and business strategies.Health Example: Public health campaigns often cite correlations like smoking rates decreasing alongside lung cancer diagnoses dropping. While related trends exist, establishing direct causation requires comprehensive studies.Business Example: A company notices increased sales during holiday seasons correlated with marketing efforts but assumes the ads alone caused sales boosts. Analyzing market trends reveals seasonal shopping behavior influences consumer spending significantly.By distinguishing between correlation and causation, you enhance your ability to draw valid conclusions from data while avoiding potential pitfalls in reasoning.