A Determination Framework for Causation vs Correlation

Abstract

The field of system dynamics operates in causality. However, opaqueness surrounding the colloquial definition of “causal” can make the seemingly simple phrase “correlation does not imply causation” hard to interpret and a point of contention. When is data causal, and when is it correlational? We examine the problem through measurement theory, and offer a measurement-based definition and framework for determining causation.

Introduction

Much of the chaos surrounding causality can be cleared by focusing on measurement issues in experimental designs. Although measurement theory has been widely recognized as a critical aspect of empirical methods (Baird, 1962; Coleman and Steele, 1989; Nunnally, 1978; Pedhauser, 1982), including quasi-experimental designs (Cook and Campbell, 1979; Campbell and Stanley, 1963), it has been usurped in development for specific application to causal inference by experimental design issues of a structural nature; idiographic versus nomothetic, path analytic, random assignment, etc. (Biddle, Slavings and Anderson, 1985; Blalock, 1964; Hicks, 1979; Simon, 1954; Maxwell and Delaney, 1990). Accordingly, LISRAL (Linear Structural Equations) for example, is evidence that substantial progress has been made regarding causal design issues. As powerful as these designs are, they are limited by the measures they incorporate. Thus, we turn to measurement theory to help resolve chronic problems of causal inference, with specific application to determining causality.

The Current Assumption

The current state of knowledge is that correlation does not indicate a causal relationship. It is assumed that correlation may only indicate a causal relationship if a valid argument exists to link the variables in question. The fundamental problem with this situation is: if the correlation is based on the rejection of a random association, then we must accept that the relationship is not random. If the association is not random, and it is not causal because there is no sound argument, then what is it? To label the correlation spurious is a contradiction. This problem requires a fundamental argument that correlation and causation are complementary, in a manner which resolves the contradiction through measurement of temporal-dynamics in experimental designs.

Objective

As Granger (1989: 144) stated, “*there is some disagreement about the use of the word cause*,” there still exists a fundamental problem in defining and determining causality. The objective is to develop and present a measurement-based solution to the “correlation is not causation” problem. This problem begs the following questions: if correlation is not causation, what is the contribution of detecting correlation when it is not causal, under what circumstances does correlation infer causation, and can we assess the generalizability of the findings and the level of indeterminacy in the causal chain? For a clearer understanding of the issue, there are four fundamental problems associated with correlation and causal inference:

Causal inference problems

1) Russell’s mathematical function logic: the causal-symmetry problem
2) Action at a distance: the contemporaneous causality problem
3) The demarcation between cause and effect: the continuity problem
4) Indeterminacy: Heisenberg uncertainty and the manifold problem

Solutions to the four problems above will constitute an axiomatic basis for deducing a solution to the problem of determining when correlation is not causation. This will create an improved basis for arguing the contribution of empirical results incorporating either correlation or causation reducing their associated uncertainties.

Defining the problem will demonstrate why certain classical arguments concerning causal inference are invalid, and therefore misleading. A solution will be developed and presented in an attempt to substantially improve our ability to draw valid causal inferences from empirical research. This should facilitate greater clarification and integration of previous and future empirical work, resulting from an improved understanding of research limitations, and as a consequence, draw stronger causal conclusions.

Premises of Causal Inference

We adopt the following premises for our arguments:

Premise 1 *We advance knowledge with the scientific method*.

"We look for a new law by the following process. First, we guess it. Then we compute the consequences of the guess to see what would be implied if this law that we guessed is right. Then we compare the result of the computation to nature, with experiment or experience, compare it directly with observation to see if it works. If it disagrees with experiment, it is wrong. In that simple statement is the key to science" (Feynman, 1965; p156).

Premise 2. *We cannot prove causal inference to be true, however we can prove it to be false (see Premise 1); asymmetry between confirmation and falsification (Popper, 1959).*

In the social sciences it is not possible to control for all possible threats to valid causal inference. All of our theories are wrong, but many are useful. Causal inference can exist with any degree of confidence except 100%. However, a low degree of confidence, or explanatory power, can deny causal inference.

Definitions

Causality: *Causal description of a phenomenon requires specification of states of a system and expression of a functional relation between them (Lenzen, 1954; p66). In the case of causality, the functional relationship must be event based with respect to time.*

Specification of States*. From an initial state of the system one can infer the properties of a succeeding state (Lenzen, 1954; p66).*

Expression of a functional relation between states. *System structure is a functional relation between variables which characterize phenomena (Lenzen, 1954; p13, Mach, 1919). A criterion of causality is the capacity of a functional relation to serve for the production of results of experience (Schlick, 1931; Lenzen, 1954). That functional relations are reproducible in nature or by experimentation is the basis of the value of the principle of causality (Lenzen, 1954; p19, Feynman, 1963).*

Direct Functional Equivalency*: Causality cannot be determined by defining a direct equivalency function between 2 states without an event. Weight in lbs is a conversion of weight in kg, so lbs cannot cause kg.*

Temporal Dynamics*: Stationary variables are not causal. Causal inference requires dynamics; variance over time in variables comprising functional relation, between states.*

Discrete Events: *Discrete events are happenings in time. Discrete events occur between initial states that lead to succeeding states.*

Statistical Causality*: The causal connection of system states where the probability of connection exhibits statistical regularity.*

Correlation. *A statistical description of the structure of a system state; an expression of structural relation between variables that exhibit statistical regularity for a single point in time.*

Causal Inference Problems

Russell's mathematical function logic: the causal-symmetry problem.

Perhaps the most significant obstacle to valid causal inference is Bertrand Russell's argument that "causality" is a meaningless, or erroneous, term. Mathematical equations may be arranged such that any variable in a given function can be expressed in terms of the other variables in the function, and as a consequence, assuming one causal order would contradict the fundamental mathematical function-order symmetry premise. Accordingly, Russell (1953) stated, *"No doubt the reason why the old 'law of causality' has so long continued to pervade the books of philosophers is simply that the function is unfamiliar to most of them, and therefore they seek an unduly simplified statement."*

The causal axiom states that stationary variables are not causal, only dynamic variables are causal (MacIver, 1942; Nagel, 1951; Feigl, 1953; Russel, 1953; Lenzen, 1954). Accordingly, when variables in a given equation are stationary, the function is structural (in the sense of static equilibrium), as opposed to causal. That is, the mathematical function describes the relative positions, or relationships, of the variables when the system is in equilibrium. Because change is absent, one variable does not cause another, so the order of representation in the equation is a matter of convenience, as long as the relationships are preserved. However, when one of the variables is changing, the relationships are causal and dictated by the temporal order of the changes, the variable that changes dictates the value that the other variable must assume in order to maintain the functional structure. Lenzen (1954: p13) states, "*We have concluded that causality is uniformity of sequence of phenomena; in more precise terms, causality is the functional relation between variables which characterize phenomena*." Accordingly, knowledge of the static structure is important as it allows prediction of the future state of equilibrium. Thus, a distinction is recognized such that functional structure represents variables at rest, or at a single point in time, and causal structure represents only variables in motion over time. Thus, correlations capture the statistical relations between variables in a single point in time; correlations map the structure of the system. When data is drawn from a single point in time (common with nomothetic research designs), there exist no temporal dynamics in the measurement by definition and thus there exists no basis for causal inference. This holds for all types of single observation over time data collection; for example, data reported as an average of three years of performance is still a single point in time measurement. Many discrete events and corresponding dynamics may be occurring within a single data point in time, however the lack of subsequent data observed over time precludes the prediction and observation of a future state, denying causal inference.

Jay Forrester (1988) argues that the solution to the causal symmetry problem is in understanding that causal inference, and the direction of causality, is determined by integral functions, not differential equations, in specifying functional relations. Forrester (1988) explains, "*we focus on systems in the context of integrations, not in the context of differential equations, or differentiation. And this, I think, is very fundamental. Differentiation, I suggest to you, is a figment of the mathematician's imagination. It's been very hard to explain to students. And the reason that it's hard to explain is it doesn't exist. I defy you to find anywhere in nature where nature differentiates. Nature only integrates. Nature only accumulates. There are no processes of differentiation in the natural or social world. And you see this immediately when someone tries to solve differential equations. Going back to Vannevar Bush's differential analyzer-- it wasn't a differential analyzer. It was built out of six integrators. If you want to put differential equations on a digital computer, you always reshape them into integrations. This is important. It's not just a side issue. Because focusing on real life through differential equations and differentiation has an insidious effect on many students. It causes them to get an ambiguous, or even a reversed sense of causality. They do not see what is actually happening in the system or what the direction of causality is. I've had students argue that there is no difference between saying that the water out of the faucet is filling the glass as against saying the rising water in the glass is forcing the water to flow. Now, I gave you a diagram before where there is a control system and the rising water controls the flow rate. But if you just look at a steady flow rate, you don't properly look at it as something where it is the* *rising water that causes the flow. It is the flow, I suggest, that causes the rising water. Unless you get that direction of causality firmly in mind, and so firmly that you can see it in all sorts of physical world and social world situations, then there is a great deal of opportunity for getting things backward*."

Action at a distance: the contemporaneous causality problem.

The contemporaneous causality problem concerns the assumption that causes and effects may occur simultaneously (Hicks, 1979). Einstein argues that contemporaneous causality violates the special theory of relativity by implying "*action at a distance*" (Popper, 1982b); given that a variable which changes dictates the values of the other variables must assume in order to maintain a given functional structure, the adaptation cannot take place at a speed greater than the speed of light. Thus, some interval of time is necessary to allow the causal chain of events to take place. The assumption of contemporaneous causality is rejected, however, by make explicit the time interval represented in each data point measurement over time. This makes explicit the uncertainty inherent in the structure of the data that limits, absolutely, any causal knowledge that can be inferred (Heisenberg, 1958). For example, data measured annually does not allow the causal inference of effects that resolve in weeks or months.

The demarcation between cause and effect: the continuity problem.

Given the rejection of action at a distance, above, the next problem is one of identifying the point of demarcation between cause and effect. Russell (1953: 389) argued that this problem is insurmountable based on the following: *"…if the cause is a process involving change within itself, we shall require (if causality is universal) causal relations between its earlier and later parts; moreover it would seem that only the later parts can be relevant to the effect, since the earlier parts are not contiguous to the effect, and therefore (by definition) cannot influence the effect. Thus, we shall be led to diminish the duration of the cause without limit, and however much we may diminish it, there will still remain an earlier part which might be altered without altering the effect, so that the true cause, as defined, will not have been reached, for it will be observed that the definition excludes plurality of cases." "This dilemma, therefore, is fatal to the view that cause and effect can be contiguous in time; if there are causes and effects, they must be separated by a finite time-interval."* The finite time interval referred to in this argument is countered by the *time-partition* measurement argument in integral calculus, a pragmatic solution used in the System Dynamics methodology (Forrester, 1961). *"In the mathematical description of motion we may describe the causal process by an integral law which expresses velocity or distance as a function of time"* (Lenzen 1954; p8). That is, integrals contain the sum of "earlier parts" over time (memory) and this means the cause can be partitioned into accumulating, discrete steps which provide the basis for a demarcation of the effect in calculations.

Indeterminacy: Heisenberg uncertainty and the manifold problem.

The indeterminacy problem concerns the extent to which causal knowledge is possible, or feasible. Two fundamental theories of indeterminacy will be emphasized here; Heisenberg indeterminacy and Riemann manifolds. Heisenberg indeterminacy, also referred to as the *uncertainty principle*, argues that human knowledge of causality is ultimately limited, absolutely, by our ability to measure in quantum physics experiments (Feynman, 1963; Popper, 1982a; 1982b). The argument stems from theoretical physics research on the structure of the atom, specifically, from attempts to predict the path of an electron. Heisenberg noted that to conduct an experiment, two fundamental, simultaneous measurements are necessary to "observe" the electron to discover its causal path; measurement of the position and the momentum. He concluded that both measurements could not be made simultaneously, with arbitrarily high accuracy. At the level of the electron, the act of measuring either position or momentum interferes with the simultaneous measurement of the other (Heisenberg, 1953, 1976). *The sole test of the validity of any idea is experiment* (Feynman, 1963). Thus, by experiment, the most knowledge that can be achieved is only a probability estimate of the electron's simultaneous position and momentum (Heisenberg, 1953; Feynman, 1963). Here we accept this idea as an axiom, in a most simple form, to conclude that causal knowledge is always limited by the type and accuracy of measurement in the experiment. Of course, in science it was known, well before Heisenberg, that measurement is a limiting factor in causal inference but Heisenberg's indeterminacy argument indicates that this limit can never be reduced or eliminated by improvements in experimental designs on electrons; this limit to knowledge is absolute (Feynman, 1963). Thus, we credit Heisenberg here for defining the ultimate, limiting case.

The manifold problem concerns the intractable nature of determining "absolutely" the causal structure of any open system in the social sciences. The problem is well presented by Guillen (1983; 85), "*According to Riemann, mathematical dimension need not refer only to sensible space; it could just as logically refer to purely conceptual spaces, which he named manifolds." "Thought of in this way, a human is a manifold of an extraordinary number of dimensions – some might even say an infinite number." "So pity the social scientists. One of the reasons their track record looks so miserable compared to that of the physical scientists is simply because their job is much more difficult, and perhaps even impossible*." The implication is that an infinite number of measures would be necessary to "observe" each dimension and determine the causal structure. Here we accept the premise of the manifold problem and argue the resolution is found in terms of measurement theory by incorporating *economy in science* arguments of Mach (1919), Pareto (1898), Poincare (1905), Popper (1959; 1983; 1989), and Forrester (1961); we measure the fewest variables possible to explain the phenomenon in a manner that is incomplete, but useful to the actual decision maker solving the problem.

Conclusion

The distinction between correlation and causality involves the presence, or absence, of temporal dynamics in the experiment data measurement. When experiment data is measured for only a single point in time, the significant statistical relationships in correlation analysis capture structural relations of the variables; this maps the structure of the system state for that point in time. Understanding the structural relations of the variables is important because it helps the researcher to seek and define the functional relations, over time, that determine a future state when an event shocks the system. Causal inference occurs only when temporal dynamics are present in the experiment data; there exists measurement on the state of the system for more than one time period and this allows the researcher to predict the subsequent state given a discrete event, treatment, or cause.

References

Baird, D.C. (1962). ***Experimentation: An Introduction to Measurement Theory and Experimental Design***. Prentice-Hall.

Berk, R. (2004). ***Regression Analysis: A Constructive Critique***. Sage Publ.

Biddle, B. Slavings, R. and Anderson, D. (1985). *Methodological Observations on Applied Behavioral Science: Panel Studies and Causal Inference*. ***The Journal of Applied Behavioral Science***. 21, 1: 79-93.

Blalock, H. (1964). ***Causal Inferences in Nonexperimental Research***. University of North Carolina Press.

Blaug, M. (1992). ***The Methodology of Economics: or How Economists Explain***. 2nd Edition. Cambridge University Press.

Bollen, K. & Pearl, J. (2013). *Eight Myths About Causality and Structural Equation Models.* In S.L. Morgan (Ed.), ***Handbook of Causal Analysis for Social Research***, *Chapter 15, 301-328, Springer.*

Born, M. (1964). ***Natural Philosophy of Cause and Chance***. Dover Publ.

Campbell, D. and Stanley, J. (1963). ***Experimental and Quasi-Experimental Designs for Research***. Rand McNally & Co.

Coleman, H and Steele, G. (1989). ***Experimentation and Uncertainty Analysis for Engineers***. John Wiley & Sons.

Cook, T. and Campbell, D. (1979). *Causal Inference and the language of Experimentation*. Chapter 1 in ***Quasi-Experimentation: Design & Analysis Issues for Field Settings***. Houghton Mifflin.

Dranove, D. (2012). *Practical Regression: Convincing Empirical Research in 10 Steps*. ***Technical Note***. Harvard Business Publ: KEL635.

Feigl, H. (1953). *Notes on Causality*. In ***Readings in the Philosophy of Science.*** Edited by Herbert Feigl and May Brodbeck. Appleton-Century-Crofts.

Feyerabend, P. (1993). ***Against Method***. 3rd Edition. Verso Publ.

Feyerabend, P. (1987). ***Farewell to Reason***. Verso Publ.

Feynman, R. Leighton, R. and Sands, M. (1963). ***The Feynman Lectures on Physics***. Addison-Wesley Publ. Co. 2nd Printing 1964.

Feynman, R. (1965). ***The Character of Physical Law***. MIT Press.

Forrester, J. (1961) *Industrial Dynamics*. Cambridge, MA: Productivity Press.

Forrester, J. (1988) *Applications of System Dynamics*. MIT 16th Annual Killian Award Lectures. https://killianlectures.mit.edu/jay-forrester. Accessed in March, 2022.

Granger, C. (1980). *Testing for Causality: A personal Viewpoint*. ***Journal of Economic Dynamics and control***.

Grant, A. & Wall, T. (2009). *The Neglected Science and Art of Quasi-Experimentation; Why-to, When-to, and How-to Advice for Organizational Researchers*. ***Organizational Research Methods***, Volume 12 , Number 4, October: 653-686.

Guillen, M. (1983). ***Bridges to Infinity***. Houghton Mifflin.

Hayashi, A. (2014). *Thriving in a Big Data World*. ***MIT Sloan Management Review***. Winter, Vol. 55, No. 2. SMR472.

Heisenberg, W. (1953). ***Nuclear Physics***. The Philosophical Library, Inc.

Hicks, J. (1979). ***Causality in Economics***. Basic Books.

Hume, D. (1748). ***An Enquiry Concerning Human Understanding***. Edited by Antony Flew, reprinted 1988. Open Court.

Kant, I. (1787). ***Critique of Pure Reason***. Translated from the 2nd Edition by Norman Kemp Smith, reprinted in 1929. MacMillan Co. Ltd.

Kennedy, P. (1992). ***A Guide to Econometrics***. The MIT Press.

Lenzen, V. (1954). ***Causality in Natural Science***. Charles C. Thomas Publ.

Mach, E. (1919). *The Economy of Science*. In ***The World of Mathematics***, Volume 3, Part XII. Simon and Schuster.

MacIver, R. (1942). ***Social Causation***. Ginn & Co.

Makin, T. (2019). *Science Forum: Ten common statistical mistakes to watch out for when writing or reviewing a manuscript.* **eLife** 2019;8:e48175 DOI: 10.7554/eLife.48175. https://elifesciences.org/articles/48175

Mill, J.S. (1843). ***A System of Logic Ratiocinative and Inductive; Being a Connected View of the Principles of Evidence and the Methods of Scientific Investigation***. Longmans, Green and Co. 8th Edition, printed in 1941.

Maxwell, S. & Delaney, H. (1990). ***Designing Experiments and Analyzing Data***. Wadsworth Co.

Nagel, E. (1951). *The Causal Character of Modern Physical Theory*. In ***Readings in the Philosophy of Science***. Edited by Herbert Feigl and May Brodbeck. Appleton-Century-Crofts.

Nunnally, J. (1978). ***Psychometric Theory***. McGraw-Hill.

Pareto, V. (1897). ***Manual of Political Economy***. Translated by Ann S. Schwier from the French Edition of 1927, and published in 1971. Augustus M. Kelley Publ.

Pedhauser, E. (1982). ***Multiple Regression in Behavioral Research, Explanation and Prediction***. 2nd Edition. Holt, Reinhart and Winston, Inc.

Poincare, H. (1905). ***Science and Hypothesis***. Dover Publications Inc. Reprinted 1952.

Popper, K. (1959). ***The Logic of Scientific Discovery***. Basic Books.

Rothman, P. & Greenland, S. (2005). *Causation and Causal Inference in Epidemiology*. ***American Journal of Public Health***. Supplement 1, Vol. 95, No. S1.

Russell, B. (1953). *On the Notion of Cause, With Applications to the Freewill Problem*. In ***Readings in the Philosophy of Science***. Edited by Herbert Feigl and May Brodbeck. Appleton-Century-Crofts.

Simon, H. (1954). *Spurious Correlation: A Causal Interpretation*. Chapter 1 in Blalock, H. ***Causal Inferences in Nonexperimental Research***. University of North Carolina Press, 1964: 5-17.

Stanford, K. (2021). "*Underdetermination of Scientific Theory*", ***The Stanford Encyclopedia of Philosophy*** (Winter 2021 Edition), Edward N. Zalta (ed.), URL = <https://plato.stanford.edu/archives/win2021/entries/scientific-underdetermination/>.

Tanner, J. (2014). *The Elements of Dynamic Customer Strategy*. Chapter 2 in ***Dynamic Customer Strategy: Today's CRM***. A Business Expert Press Book. Digital chapter in Harvard Business Publ: BEP236.

Vroom, V. (1966). *A Comparison of Static and Dynamic Correlational Methods in the Study of Organizations*. ***Organizational Behavior and Human Performance***, 1, 56-70.