(Research Note)
A Determination Framework for Causal Inference

Abstract

The field of system dynamics operates fundamentally within the realm of causality. However, ambiguity surrounding the colloquial definition of "causal" can make concluding causality from experiments difficult to interpret and a point of contention. When exactly is causal inference justified, and what role does correlation play? We examine this problem using principles of causal experimental design from the physical sciences while acknowledging the inherent indeterminacy in the social sciences that makes these experiments distinct. Jay Forrester provided insight into the role of integrals in specifying causal direction over time with the quote, "Nature only integrates." Building on this understanding, we offer a framework for social scientists to determine when causal inference is justified and provide a mathematical representation of Causality.

Introduction

"The epistemology of causation, and of the scientific method more generally, is at present in a productive state of near chaos"(Cook and Campbell, 1979). In 2024, the situation has not noticeably improved. The causal inference problem is illustrated by the following passage in the general public-facing Wikipedia, 2024, listed under the heading of Causal Inference:

"Despite the advancements in the development of methodologies used to determine causality, significant weaknesses in determining causality remain. These weaknesses can be attributed both to the inherent difficulty of determining causal relations in complex systems but also to cases of scientific malpractice.

Separate from the difficulties of causal inference, the perception that large numbers of scholars in the social sciences engage in non-scientific methodology exists among some large groups of social scientists. Criticism of economists and social scientists as passing off descriptive studies as causal studies are rife within those fields."

Objective

A fundamental problem in defining and determining causality still exists, as Granger (1989: 144) stated, "*there is some disagreement about the use of the word cause*," This paper aims to develop and present a standard reference for drawing conclusions on causal inference in the social sciences.

This discussion will demonstrate why certain classical arguments concerning causal inference are invalid and 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 in the Social Sciences

We present six fundamental premises in determining causal inference in an experiment:

Premise 1: *Knowledge advances through the scientific method;.knowledge from causal inference progresses through continuous approximations and experiments*(Lenzen, 1954; Feynman, 1963).

Premise 2: *System structure is a functional relation between variables which characterize phenomena* (Lenzen, 1954).

Premise 3: *Causal description requires specifying a system structure that moves through temporal system states, where discrete events drive the transition from an initial state to a successor state. (Lenzen, 1954)*

Premise 4: *For causal inference*, *functional relations within system structure must specify time and the direction of causality (Forrester, 1988).*

Premise 5*: *Causal inferences can be falsified, but not definitively proven true (Popper, 1959).

Premise 6: *All causal inferences have inherent indeterminacy, preventing complete control over threats to validity* (Stanford, 2021; Guillen, 1983)

The premises above constitute an axiomatic basis for deducing a solution to the problem of determining when causation can be inferred. This creates an improved basis for arguing the contribution of empirical results incorporating correlation and/or causation, reducing their associated uncertainties.

In this paper we first discuss the ideas behind each of these premises, then from these premises we define Tiers of Causal Inference that are associated with different experimental designs, and finally we draw conclusions on the contribution of different experimental designs in terms of their contribution to advancing knowledge.

Premise Descriptions

Premise 1: *Knowledge advances through the scientific method;.knowledge from causal inference progresses through continuous approximations and experiments*.

“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, and compare it directly with observation to see if it works. If it disagrees with the experiment, it is wrong. In that simple statement is the key to science” (Feynman, 1965; p156).

Premise 2: Causality exists within a system structure, where system structure is a functional relation between variables which characterize phenomena (Lenzen, 1954; p13).

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).

The demarcation between cause and effect: the continuity problem. The continuity 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.

Premise 3: *Causal description of a phenomenon requires specification of states of a system and expression of a functional relation between them. Discrete events occur between initial states that lead to succeeding states. From an initial state of the system one can infer the properties of a succeeding state (Lenzen, 1954; p66).*

Knowledge from causal inference advances in an unending series of successive approximations. Popper viewed progress as a matter of finding corroborated theories exhibiting increasing explanatory and predictive power. Scientific progress can be accounted for in terms of the increasing approximation to the truth of our theories (Popper, 1963).

It is possible progressively to isolate systems and processes. The control of conditions under which a causal law is exemplified proceeds by successive approximation. In preliminary experiments one must presuppose that the conditions are constant and thereby obtained in approximate law. With the aid of approximate laws one can then define conditions of an experiment more precisely, or correct for disturbing the influences, and thus determine a law to a higher order of approximation (Lenzen, 1938: p 41).

The status of a law may change in the development of science. A law which originates as a generalization from experience may be transformed into a convention that expresses an implicit definition of the concepts it involves (Lenzen, 1938: p 44).

Premise 4: Causal description of a phenomenon requires specification of states of a system and expression of a functional relation between them. Discrete events occur between initial states that lead to succeeding states. From an initial state of the system one can infer the properties of a succeeding state (Lenzen, 1954; p66). The functional relation must specify time and the direction of causality (Forrester, 1988).

Events. Causal inference requires temporal dynamics in the data; a system with entirely stationary variables is not causal. Causal inference requires dynamics (events); variance over time in variables comprising functional relation, between states.

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."*

*Forrester's Nature Only Accumulates: specifying the direction of causality.*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*."

A causal axiom states that stationary variables are not causal (MacIver, 1942; Nagel, 1951; Feigl, 1953; Russel, 1953; Lenzen, 1954). Accordingly, when variables in a given equation are stationary, the function is structural (for example, in the sense of static equilibrium), as opposed to causal. That is, the mathematical function describes the relative positions, or states, 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.

Premise 5:*We cannot prove causal inference to be true, however we can prove it to be false (see Premise 1); the 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 a high degree of confidence but is never 100%.

Premise 6: Indeterminacy is inherent in all causal inference; we can never achieve a complete causal explanation and control for all threats to validity.

However, causal inference can have various degrees of validity in use, if not in precision.(reference) “We must never forget that the truths of political economy are truths only in the rough: they have the certainty, but not the precision, of exact science (Mill, 1871; 428).”

*Indeterminacy - Heisenberg uncertainty.*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.

*Indeterminacy - The Riemann manifold problem.*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 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.

Indeterminacy - 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 problem of contemporaneous causality is nullified in the social sciences, however, by making 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.

Indeterminacy - Feyerabend’s Against Method. Given the extent of indeterminacy in science, Feyerabend argued for intellectual, methodological anarchy. The argument is that what science actually needs is pluralism and unrestrained creativity. That is, rules of science can become obstructive dogma, harmful; too narrow and too stifling of differing perspectives that are (perhaps) needed to achieve a breakthrough understanding of a phenomenon given the deep underlying complexity of the system (Feyerabend, 1987, 1993). Hence, from Premise 1 we include, *knowledge from causal inference progresses through continuous approximations and experiments*(Lenzen, 1954).

Tiers of Causal Inference

Tiers of causal inference efficacy include Premises 1-4.

Tier	0	1	2	3	4
Causality Level	No causal inference	Quasi causal inference	Foundational causal inference	Sequential causal inference	Complex causal inference
Experimental Designs	Cross-Sectional Studies (Single Observation)	Quasi-experimental design; one-shot case study	Experimental design with required minimum structure; pretest:posttest design	Bivariate longitudinal studies and time series analysis	Multivariate longitudinal studies and time series analysis
Experimental Design Diagram*	O	X O	O X O	O O O X O O O	O O O X O O O
Temporal Relationship	Observations are from a single point in time. No temporal dynamics	Single dynamic event occurs prior to observation	Single dynamic event occurs between 2 observed time points	One or more dynamic event(s) occur over multiple observed time points	One or more dynamic event(s) occurs over multiple observed time points, encompassing integrals
Short vs Long-Term Effects	No	No	No	Yes	Yes
Delays	No	No	No	Yes	Yes
Feedback	No	No	No	No	Yes
Insight	Correlational mapping of non temporal functional relations of system structure	Event-outcome connection with no temporal dynamics	Causal outcome specification of temporal system structure without causal process mechanics	Causal outcome specification of temporal system structure with delay causal process mechanics	Causal outcome specification of temporal system structure with delay and feedback causal process mechanics
Example Method	Regression analysis, Correlational analysis	Natural experiments	True experiment when adding randomized selection and a control group.	Granger causality	System dynamics, Agent-based modeling

*O = Observation, X = Event

The Mathematical Essence of Causality

A system is comprised of state variables (stocks in System Dynamics) and control variables (auxiliary variables). State variables are quantities that represent the current state of a dynamic system at any given time and only state variables hold their temporal value across time. Therefore, direct causality, at its most fundamental level, can only occur between state variables.

Consider the system of differential equations:

$$\frac{dx}{dt} = f(x,u,t)$$
$$\frac{dy}{dt} = g(x,y,v,t)$$

where u and v are sets of control (auxiliary) variables.

Taking the integral of both sides, we get:

$$X(t) = \int f(x,u,t)dt$$
$$Y(t) = \int g(x,y,v,t)dt$$

where $X(t)$ and $Y(t)$ represent state variables.

In a system, all control (auxiliary) variables seek to define the functional relationships between two or more state variables, and therefore can be classified as ancillary causal. In the natural world, it may be impossible to create a fully complete system of only state and ancillary variables. Therefore, we use single time point static approximations or static snapshots as substitutes for state variables. These approximations are incorporated into our functional relationships to simplify complex systems, making them human-understandable and limiting the scope of our system models. Without these simplifications, most system models would indefinitely increase in scope until they attempt to represent a complete physical model of nature.

Causality is defined within these functional relationships as:

$$X \text{ causes } Y \Rightarrow X(t) = \int_{t_1}^{t_2} f(y,u,t)dt \text{ causes } Y(t) = \int_{t_1}^{t_2} g(x,y,v,t)dt$$

by $\int g(x,y,v,t)dt$, the functional relationship that connects $X(t)$ and $Y(t)$

The directionality of causality is ingrained in the functional relationships between t_1 and t_2 as time progresses forward.

Important Notes:

1. **Time Granularity Consistency**: Causality can only occur between state variables with the same time granularity Δt. Additionally, this means Δt's in the same differential equation must represent the same time interval.

2. **State Variable Order Consistency**: Causality can only occur between state variables with either the same order, or a matched order through the functional relationship.

3. **Self-Causality and Self-variation**: A single state variable cannot be self-causal, but can vary over time with respect to itself if no other state variables are involved.

Self causality implies $X(t)$ is a function of $X(t)$, rewritten as $\frac{dx}{dt} = f(x,u,t)$
This describes the internal behavior of X over time rather than a causal relationship between interacting state variables.

4. **Bi-Causality**: 2 state variables can cause each other if:

$$X(t) = \int f(x,y,u,t)dt$$

$$Y(t) = \int g(x,y,v,t)dt$$

In this case:

X causes $Y \Rightarrow X(t) = \int_{t_1}^{t_2} f(x,y,u,t)dt$ causes $Y(t) = \int_{t_1}^{t_2} g(x,y,v,t)dt$ by $\int g(x,y,v,t)dt$

and

Y causes $X \Rightarrow Y(t) = \int_{t_1}^{t_2} g(x,y,v,t)dt$ causes $X(t) = \int_{t_1}^{t_2} f(x,y,u,t)dt$ by $\int f(x,y,u,t)dt$

5. **Multi-Causality or Component-Causality**: Multiple state variables can all be causes if:

$$X(t) = \int f(x,u,t)dt$$

$$Y(t) = \int g(y,v,t)dt$$

$$\ldots$$

$$Z(t) = \int h(z,w,t)dt$$

and

$$A(t) = \int j(a,x,y,\ldots,z,t)dt$$

In this case:

$X, Y, \ldots, Z$ cause $A \Rightarrow$

$X(t) = \int_{t_1}^{t_2} f(x,u,t)dt,\ Y(t) = \int_{t_1}^{t_2} g(y,v,t)dt, \ldots, Z(t) = \int_{t_1}^{t_2} h(z,w,t)dt$ cause $A(t) = \int_{t_1}^{t_2} j(a,x,y,\ldots,z,t)dt$ by $\int j(a,x,y,\ldots,z,t)dt$

6. **Time Intervals**: The above causality statements can be modified for time interval bounds if necessary, eg. Step Functions or Switching Functions.

   between t_1 and t_2

7. **Systems of Causality**: Since most systems are complex, causality can run between many state variables all at once. These causality statements can be expressed as combinations of the above. (refer to the definitions above)

Conclusions

Correlation is not causation. Correlations, independent of experimental design, never allow causal inference. Causal inference requires an experimental design that meets the Premises (above). It is the experimental design that gives meaning to correlations; without knowledge of the experimental design, the correlation does not allow inference. "*Good experimental design is separable from the use of statistical tests of significance*." (Campbell & Stanley, 1963). Thus, the statement "correlation is not causation" communicates a misunderstanding of the role of statistics in causal inference.

Correlation is not required for causal inference. As described in Premise 2; Causal description of a phenomenon requires specification of states of a system and expression of a functional relation between them. Discrete events occur between initial states that lead to succeeding states. The functional relation must specify time and the direction of causality (Forrester, 1988). Thus, we can define an experimental design that meets the absolute minimum requirements as follows:

Observation, followed by an event, followed by another observation. This design may be diagrammed as (Campbell & Stanley, 1963):

O X O

If the future state is observed to conform to the prediction of specified functional relation (hypothesis), having an event that altered the system from the initial state, then the experiment meets the minimum criteria for causal inference. Thus, statistics are not required for casual inference. An example is the test of Einstein's Theory of General Relativity. Einstein argued that, as a test, we should be able to see a slight alteration in the position of stars lined up on either side of the sun during a solar eclipse; event = the deflection of light by the Sun. In 1919 Arthur Stanley Eddington, an English astronomer and mathematician, and The Astronomer Royal of England, Frank Watson Dyson conducted an experiment by observing the positions of stars before and then during a total solar eclipse, predicting that when the Moon blocks the Sun's light it might be possible to photograph the eclipse and record the positions of stars whose light passes near the Sun. Measurements (observations) were recorded using photographs, to determine to what extent the stars were out of position, and whether it accorded with Newtonian theory, or with Einstein, or neither. The results were consistent with Einstein's argument from General Relativity. This experimental design allowed causal inference, and this experiment did not use statistics. Adding a control group comparison helps minimize threats to internal validity, especially in the social sciences, but is not required for causal inference.

In general, in terms of threats to internal and external validity of casual inference, Premise 7 is required; successive experiment replications will reveal weaknesses in validity. The social sciences do not currently have a strong record of publishing replications. Rather, authors are expected to build immediate confidence in their projects by conducting their experiments on a large number of organization/individuals and use statistics on that sample size to justify confidence in the results. This approach has the benefit of speed in building confidence, but at the expense of rigor; testing by non-affiliated authors in independent settings and contexts. So, we conclude that improving publishing opportunities for causal inference experiment replications would be strategic in strengthening these scientific conclusions and overcoming the public outcry for rigorous and reliable results as mentioned in our introduction.

Any experimental designs that meet the requirements of Premise 2 allow causal inference. For example:

$O_1O_2O_3O_4$ X $O_5O_6O_7O_8$ (Time series experimental designs meet the criteria for causal inference)

In contrast, any experimental design that does not meet the requirements of Premise 2 do not allow causal inference. This is true regardless of any statistical or mathematical methodology applied in the experiment. For example, the following quasi-experimental design example described in Campbell & Stanley, 1963 does not allow causal inference:

X O (Pre-Experimental Designs are missing an observation of the initial state)

In the case above, for example, it becomes clear why causal inference is not allowed; with only one point in time measured, the hypothesis is prevented from specifying a functional relation between the initial state and the subsequent state.

X O (Pre-Experimental Designs are missing an observation of the initial state)
—-—-
O (adding a proxy for observing the initial state; perhaps a group of similar firms)

Quasi-Causal Inference. In the case of Pre-Experimental designs, even with experimental design modifications such as adding a proxy for observing the initial state (see above), the design fails to meet the criteria for causal inference, however, the outcomes of this approach may provide strong indicators of causality. Accordingly, we follow the example of Campbell and Stanley (1963) and Cook and Campbell (1979) and conclude that these designs are designated "Quasi-Causal Inference."

Contribution to social science in causal inference occurs when:

1. *The model (the expression of the functional relation between states) replicates real behavior with enough precision to be useful in solving the problem.*
2. *The model provides deeper (or different) insight, than previously published models, in understanding the system's behavior, or models, but with a significantly less complex model.*
3. *The model provides a similar level of insight, or even less insight, as compared to previously published.*

Finally, we present the following definitions to help clarify these arguments and discussions:

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.*

System State*: The set of observations for all variables in the system at a specific point in time.*

System Structure*: The set of all functional relationships between the variables that define the system.*

Static System Structure*: System structure in which the functional relationships are time-independent and do not contain temporal dynamics.*

Temporal System Structure*: System structure in which the functional relationships are time-dependent, contain directional temporal dynamics.*

Temporal Dynamics*: A set of System States can only exhibit temporal dynamics if it possesses a temporal system structure and progresses through time according to that structure.*

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*: 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. An event is a shock to the system of relatively short duration, the shortness depending on the precision with which one intends to describe the phenomena (Lenzen, 1938).*

Statistical Causality*: The causal connection of system states where the probability of connection exhibits statistical regularity. There is a finite probability that a result will be observed which is characteristic of one component state, and a finite probability that the result will be characteristic of another component state. If the system is initially in one of the component states, the result of an observation is predictable with certainty (Lenzen, 1938: p57).*

Cross-Sectional Correlation*: A statistical description of the structure of a system state; an expression of structural relation between variables that exhibit statistical regularity.*

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