Causal Inference from Series of Events

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Abstract

Recent years have witnessed an increased interest, both in statistics and in the social sciences, in time dependent models as a vehicle for the causal interpretation of series of events. The Humean and empiricist tradition in the philosophy of science uses the constant temporal order of cause and effect as a decisive delimitation of causal processes from mere coincidences. To mimic the philosophical distinction, series of events are modelled as dynamic stochastic processes and the precedence of cause over effect is expressed through conditional expectations given the history of the process and the history of the causes. A main technical tool in this development is the concept of conditional independence.

In this article we examine some difficulties in the application of the approach within empirical social research. Specifically, the role of probabilistic concepts of causality and of conditional independence, the nature of events that reasonably qualify as causes or effects, and the time order used in empirical research are considered.

1 The Tradition of Causal Analysis in Sociology

The use of the concept of causality in sociology has been lingering between neglect and over–reliance.[1] Even though the concept was never wholeheartedly accepted by sociologists, it became a cornerstone of arguments in favour of empirical research by the early 1970's. The work of Lazarsfeld, Blalock, Coleman, Duncan, and many others led to the predominance of path models as the paradigmatic form of statistical analyses of causation, which was conceived as a relation between statistical variables. The flowering of structural equation modelling within sociology and psychology strengthened the technical applicability of the approach and gave impetus to the development of statistics in general.[2] But the increased statistical sophistication was accompanied by a growing isolation from the rest of applied social research as well as from statistics (as a branch of applied mathematics). Critical discussions within sociology and across disciplinary boundaries were prematurely cut off. Even the debates in econometrics during the late 50's and early 60's[3] on 'autonomy' of causes, the meaning of simultaneous equations, and the concept of exogeneity are rarely reflected in the textbooks on social statistics from the late 70's onwards. Moreover, developments in statistics, even when originating from concerns for questions of causality from other disciplines, were largely ignored.[4] And within sociology, the connection of causal analysis with certain statistical techniques was met by a general scepticism concerning the role of statistics and of 'variables' in general.

Sociologists outside the tradition of structural equation models often downplay the role of causality in the social sciences in favour of other forms of determination. In fact, the sociological literature abounds with examples of explanations that are not strictly causal in an empiricist or positivistic sense. Historical, functional, structural, teleological explanations—to name just a few of the distinctions used—are often invoked. As far as causal reasoning is granted a place in sociology, many researchers agree with a view of causality that depends on subject-matter considerations. There seems to be wide consensus among sociologists that causality cannot simply and directly be inferred from empirical data, regardless of whether they are obtained from randomised experiments, collected through ingenious research

[1]See Bernert (1983) for an account of its history in the American sociological literature.

[2]See Clogg (1992) for a partial review, including other areas of social statistics.

[3]See e.g. Epstein (1987).

[4]Holland's discussion of Clogg's 1992 paper and Clogg's rejoinder may serve as an illustration.

designs or summarised by particularly advanced statistical models. Blumer's well known early (1956) diatribe against statistical 'variable analysis' is but one example in the sociological tradition asking for more than a statistical analysis of the relation between dependent and independent variables.

More recently, however, statisticians, sociologists, and philosophers have begun to study the relation between statistics and causality more closely. The renewed interest was sparked by advances in the formalisation of concepts related to causation. Most of these developments are well documented in a special volume of Synthese (vol. 121, 1999) and —with emphasis on social science applications— in the proceedings "Causality in Crisis", edited by McKim and Turner (1997). Most of the contributions in these recent publications concentrate on counterfactual or interventionist conceptions of causation. Complementary, we will here investigate the prospects of a classical empiricist criterion of causality in the Humean tradition: the time order of cause and effect.

2 Temporal and Probabilistic Criteria of Causation

Since many theories of causal interdependence rely on empiricist criteria as a prerequisite for the acknowledgement of causality, a strong argument against the assumption of a causal connection can be made if some of the empiricist criteria of causality do not hold. The empiricist conditions for the existence of a causal relation, based on Hume's analysis, require a) spatial and temporal contiguity, b) constant conjunction between cause and effect, and c) temporal succession. We will argue that suitably modified versions of the requirements b) and c) can be used as starting points for empirical arguments concerning causal claims.

The first criterion, that of spatial and/or temporal contiguity, is often disputed. Effects do not need to follow immediately after a cause, nor do they need to be spatially close to the cause. E.g. strikes and demonstrations may be the (efficient) cause of a change of government, but the latter need not follow immediately after the demonstrations, nor need there be any spatial contiguity. Even though criterion a) cannot generally serve as a necessary condition for causation in the social sciences, a formalism of cause–effect relationships should be able to distinguish between 'close' and 'remote' causes of effects. Otherwise it would be difficult to express the ideas of 'spurious cause' and 'causal chain', both considered useful in the construction and criticism of causal explanations.

Condition b) cannot be expected to hold strictly with respect to social interactions. People tend to react differently upon others actions, even in otherwise similar situations. And, as Suppes (1970, p. 92) notes: "Empirical studies of the sort done in psychology, sociology, and medicine hold little hope of establishing complete deterministic chains for the causes of actions. This is true whether we are analysing the sex habits of Eskimos, recidivism among parolees over forty, or church attendance by illiterates."

The 'constant conjunction' condition therefore must be reformulated. Here we will simply replace the 'constant conjunction' condition by a probabilistic relation: that the cause changes the probability of the effect.[5] Note that "[i]t is not a matter of presenting evidence for causality by offering probabilistic considerations but it is part of the concept itself to claim relative frequency of co-occurrence of cause and effect" (Suppes 1970, p. 45). The incorporation of probabilistic aspects is thus not only of an epistemic nature. It is not incorporated because the sociologist does not (yet) know, but because 'constant conjunction' cannot reasonably be claimed in sociology. Consequently, probability statements in this context should generally refer either to frequencies or to propensities, as also fits the needs of an empiricist program.

The condition c) requires a temporal framework for causal arguments. This is not normally included in the formulation of 'causal models' in the structural model literature. It is also not included in the formal representation of observational studies[6] in e.g. biometry nor in more recent counterfactual or interventionist accounts. On the other hand, the temporal dimension of causal connections has often been recognised in sociology. Tuma and Hannan, introducing event–history analysis into sociology, acknowledge the interplay between temporal and causal analysis (1984, pp. xi–xii, their italics): "Any attempt at forging a systematic framework for the empirical study of social change must confront two issues. One involves the development of *dynamic* models—models that describe the time paths of change in phenomena. The other involves the development of *causal* models—models that describe how change in some properties induces change in still other properties. . . . we rely

[5] Suppes' (1970) analysis starts from the assumption that causes should *increase* the probability of the effect. The subsequent discussion in the philosohical literature has shown that the concept of 'increase of probability' may not suffice for the analysis of probabilistic causality (e.g. Eells 1991). But since the problem is not central to our discussion we will content ourself with the simple minded principle of a change of probability.

[6] The definition of an observational study is a rather narrow one in this context. Rosenbaum (1995, p. 1) states: "An observational study concerns treatments, interventions, or policies and the effect they cause, and in this respect it resembles an experiment. A study without a treatment is neither an experiment nor an observational study." Following his definition, many empirical sociological studies will not count as observational studies.

heavily on the use of formal models to guide attempts at testing hypotheses about the processes and causes of change." And Blossfeld and Rohwer (1995, p. 20) state: " ... the important task of event history modelling is ... to establish relevant empirical evidence that can serve as a link in a chain of reasoning about causal mechanisms. In this respect, event history models might be particularly helpful instruments because they allow a time-related empirical representation of the structure of causal arguments."

Suppes (1970) proposed one of the best known formalisations of probabilistic causality. His account includes a condition of temporal precedence of cause over effect, in contrast to many later attempts to clarify the concept (e.g. Eells, 1991). His starting point is the theory of probability based on systems of sets, called 'events'. He adjoins a temporal indicator to these sets to indicate temporal sequences. But as witnessed by later contributions (e.g. Davis 1988), this strategy turned out to be rather limited. Savage (1972, p. 10) remarked with respect to the use of the term 'event' in probability theory: " ... the concept of event as here formulated is timeless, though temporal ideas may be employed in the description of particular events." Arjas and Eerola (1993, p. 384) note that in these formulations, "time is present (if at all) only as an index, distinguishing between what comes 'before' and what comes 'after'." Consequently, a more flexible representation of time order is needed. In the absence of condition a), it should at least be possible to formulate the timing of effects with respect to causes. Recent contributions therefore seek to enrich the formulations by borrowing heavily from dynamic theories of stochastic processes.

The program then is clear: to combine probabilistic models —re-expressing the constant conjunction (condition b)— with the idea of 'the cause precedes the effect' (condition c) to facilitate an empirical assessment of claims of causality. Causal statements are translated into the mathematical language of stochastic processes: $Y = \{Y_t, t \in \mathcal{T}\}$ is a stochastic process with values in a finite set $\mathcal{Y}$. The values of Y_t are interpreted as properties of *units* under study and *events* are changes of properties at time points t. At any given point in time t, the description of the evolution of the process may depend on conditions and events that occurred in the past, i.e. before t, but not on what is the case at t or in the future, after t. Causes acting on Y may then be introduced by considering them as changes in a further process $X = \{X_t, t \in \mathcal{T}\}$. The process X may be treated as a time-dependent covariate and causal statements are therefore formulated as probabilistic relations between two (or more) stochastic processes. A time-dependent covariate records when a causal factor has changed its state. It signifies that an event of kind $\mathcal{X}$ has taken place. Consequently, we would not say that a process X is a cause of a process Y, but that a change in X at time t (an event at time t) could be a cause of a change in Y at time $t', t' > t$ (another event at a later time).

Often a canonical dynamic description of the stochastic processes can be given, one relating the 'past' of the processes to their 'future', and encapsulating their relevant probabilistic features. In this case the classical formulation of probabilistic causality (e.g. Suppes 1970) can be enhanced by allowing for an explicit representation of the timing of effects, generalising the Humean requirement of contiguity in time. Approaches along this line were advocated by Granger (1969) in the context of time series analysis and by Schweder (1970, 1986) for general Markov processes. These ideas were taken up more recently by Aalen (1987), Arjas/Eerola (1993), Parner/Arjas (1999), and Keiding (1999), providing a formal framework for probabilistic causality with a clear relation to time order. Many of these articles use genuinely epistemic notions for the interpretation of probabilities. This partly reflects the naming conventions used in the technical literature on stochastic processes and we will follow the convention here. But the mathematical formulation does not force us to accept an epistemic interpretation, and the possibility of interpretations in terms of propensities or frequencies should be kept in mind.

3 Mathematical Models

A dynamic description of stochastic processes fitting the above program can be outlined in the case of processes with discrete time parameters:[7] Let $Y = \{Y_t, t = 0, 1, 2, \dots\}$ be a stochastic process with values in a finite set $\mathcal{Y}$.[8] Suppose one is interested in what happens just after time $t-1$. A good prediction is the conditional expectation of the change of Y_t from Y_{t-1}, con-

[7]Much of the discrete-time theory extends directly to the continuous-time setting. The reason is that a continuous time martingale with respect to a right continuous filtration can be modified to have nice sample path properties, i.e. right-continuous paths with left hand limits. A thorough treatment presupposes a formidable technical machinery without adding much insight to the present discussion. But it should be noted that the continuous-time theory makes heavy use of continuity and of the denseness of the rationals within the real numbers. Many mathematical models of time try to avoid such strong assumptions (see Whitrow 1963, chap. III for an early review). Moreover, the combination of a continuous-time theory using all the properties of the reals may collide with a concept of causality that is based both on the time ordering of cause and effect and on the distinction between direct and indirect causes (see e.g. Suppes 1970, p. 72).

[8]The assumption of a finite state space is not essential for the mathematical formulations used here. But subsequent discussions of the appropriateness of the formal model often presuppose a finite number of states.

ditional on the previous history of the process, that is the random variable

$$V_t = E(Y_t - Y_{t-1}|Y_0, \ldots, Y_{t-1}) \tag{1}$$

Putting

$$U_t = \sum_{s=1}^{t} V_s = \sum_{s=1}^{t} E(Y_s - Y_{s-1}|Y_0, \ldots, Y_{s-1})$$

for the sum of the predicted values, one may write the original process Y_t as a sum of predictions in time and a remainder, the Doob decomposition:[9]

$$Y_t = Y_0 + U_t + M_t \tag{2}$$

The prediction part U_t is a function of the previous history up to and including time $t-1$ only, while M_t is a *martingale*, satisfying

$$E(M_t|Y_0, \ldots, Y_{t-1}) = M_{t-1} \tag{3}$$

In fact, for the *martingale difference* $M_t - M_{t-1}$ one finds

$$\begin{aligned} & E(M_t - M_{t-1}|Y_0, \ldots, Y_{t-1}) \\ &= E((Y_t - Y_{t-1}) - (U_t - U_{t-1})|Y_0, \ldots, Y_{t-1}) \\ &= E(Y_t - Y_{t-1}|Y_0, \ldots, Y_{t-1}) - V_t = V_t - V_t = 0 \end{aligned}$$

The decomposition (2) generalises the additive regression decomposition into a 'structural' part U_t and a 'random' part M_t that is used in much of empirical social research. Accordingly, but somewhat ambiguously, the differences $M_t - M_{t-1}$ are sometimes called the *innovations* of the process. The predictions U_t, depending only on $Y_{t-1}, \ldots, Y_0$, are called *predictable*. Any other process Z_t that depends only on the values of $Y_{t-1}, \ldots, Y_0$, the history of Y strictly before t, will also be called *predictable* with respect to the process Y.

It may be instructive to see how a duration variable T, featuring prominently in event-history analysis, fits into the present framework. In that case one may put $Y_t = 1$ if the event happened at time t or before, 0 otherwise. That is, $Y_t = I[T \leq t]$, where $I[A]$ is the indicator variable of the event A. For simplicity, one may also assume $Y_0 = 0$. The prediction process is then given by $V_t = E(Y_t - Y_{t-1}|Y_0, \ldots Y_{t-1})$. This quantity is 0 if Y_{t-1} takes the value 1, since then both Y_t and Y_{t-1} must be 1. In other words: If the event happened before time t, there will be no change in the prediction of Y_t, because the one possible change in state is known to have occurred.

[9] Williams (1991) provides a thorough and vivid exposition for the discrete time case.

On the other hand, if there was no event at $t-1$ or before, Y_{t-1} as well as $Y_{t-2}, \ldots, Y_0$ are 0 and V_t reduces to the probability $\Pr(Y_t = 1|Y_0 = 0, \ldots, Y_{t-1} = 0) = \Pr(T = t|T \geq t)$. Thus V_t reduces to a random function of the well known hazard function of T. If $\lambda(t) = \Pr(T = t|T \geq t)$ denotes the hazard function of T, $V_t = I[T \geq t]\lambda(t) = (1 - Y_{t-1})\lambda(t)$. Note that V_t in the present discussion is a random variable, depending on $Y_{t-1}, \ldots, Y_0$. In contrast, the hazard function $\lambda(t)$ treated in most texts on event–history analysis is a non-random transform of the distribution function. Furthermore, the accumulated prediction U_t is a random sum of hazard functions, the sum extending over all $s \leq \min(T, t)$, the times s before the event time T or the observation time t, whatever comes first.

Following Aalen (1987), a dynamic statistical model is then defined as a parameterisation of the prediction increments V_t. Since V_t depends on the history of the process up to and including $t-1$ only, it can be interpreted as a description of the future, the likely events at time t, depending only on the knowledge of all past events. Alternatively, it is (an approximation of) the relative frequency of events at t among all sequences with this history.

To introduce concepts of interdependence between several processes, it seems natural to embed the above concepts into a multivariate extension. Basically, the history of the single process is replaced by one based on all relevant information available before time t. In the case of two processes (Y_t, X_t) one might therefore define the conditionally expected increments as

$$V_t^Y = E(Y_t - Y_{t-1}|Y_0, X_0, \ldots, Y_{t-1}, X_{t-1}) \tag{4}$$

and

$$V_t^X = E(X_t - X_{t-1}|Y_0, X_0, \ldots, Y_{t-1}, X_{t-1}). \tag{5}$$

Interpreting the conditional expectations above as an increase in knowledge, V_t^Y will be based not only on the pre-t history of Y itself, but also on the knowledge of the development of X up to and including $t-1$. Thus, the expectation will change depending on the information provided by X. Symmetrically, V_t^X, the prediction of X based on the common history of X and Y before t, will depend on the changes in Y up to t. One may represent the two processes using the Doob decomposition with respect to the joint history of the processes as:

$$Y_t = Y_0 + \sum_{s=1}^{t} V_s^Y + M_t^Y \quad \text{and } X_t = X_0 + \sum_{s=1}^{t} V_s^X + M_t^X \tag{6}$$

Then X_t is defined not to be *causal for Y_t in Aalen's sense* if and only if, first, the prediction errors M_t^X and M_t^Y are uncorrelated, and second, U_t^Y, the prediction of Y_t, may depend on $Y_0, \dots, Y_{t-1}$ but not on $X_0, \dots, X_{t-1}$. We will say that X and Y are *locally autonomous* if the first condition is satisfied.[10] If the second condition holds, Y_t is said to be *locally independent* of X_t. Otherwise, Y_t is said to be *locally dependent* of X_t.[11]

The condition of local (in-)dependence is asymmetric in the two processes. Indeed, in the example of two duration variables $Y_t = I[T_1 \leq t]$ and $X_t = I[T_2 \leq t]$, the process X_{t-1} may enter as a time dependent covariate in the prediction (stochastic hazard) of the other, but not the other way around. This is in accord with the basic asymmetry of causal relations and also respects the notion of 'cause precedes effect'.

The condition of local autonomy is introduced to ensure a certain autonomy of the two processes. When satisfied it is possible to envisage a change in the behaviour of one process after time t without a change in its local relation to the other process or a corresponding immediate change in the other process. This should rule out processes that are merely related by definitions or 'rules of the game'. Consider for example two gamblers throwing dice. Denote by X^1 (X^2) the result of a throw of the first (second) player. If the throws are independent, then also the prediction errors are independent and X^1 and X^2 are autonomous. But one may also look at the result of the play, a win, a draw, or a loss, for each player. Let $Y^1 = I[X^1 > X^2] - I[X^2 > X^1] \in \{-1, 0, 1\}$. Then $Y^2 = -Y^1$ and the processes are clearly not autonomous.

4 Statistical Methods

An empirical strategy to show local dependence of Y on X at t is then to show that the prediction process U_t^Y with respect to the joint history of the process is a non-constant function of $X_{t-1}, \dots, X_0$. In the case of simple duration models, $V_t^Y = I[Y \geq t]\lambda_\theta(t; X_{t-1}, \dots, X_0)$. That is, the process X appears as a time-dependent covariate in the hazard function for Y at t, which is assumed to be parameterised by some $\theta \in \Theta$. One therefore needs to show that the pre-t history of X changes the hazard of Y at t. Often it is possible to factor the likelihood of $(X, Y)_t$ for θ in such a way that only the part $U_t^Y(Y_t | Y_{t-1}, X_{t-1}, \dots, Y_0, X_0; \theta)$ figures in the computation of statistics. This

[10] The notion of 'autonomy' has a long tradition in econometrics, especially in the context of simultaneous equation models. Aldrich (1989) provides a review.

[11] A related concept is Granger non-causality, a concept often used within econometric time series analysis. A process X is said not to cause Y in Granger's sense at t iff $Y_t \perp (X_{t-1}, \dots, X_0) | Y_{t-1}, \dots, Y_0$, i.e. where Y_t and the pre-t history of X, $(X_{t-1}, \dots, X_0)$ are conditionally independent given the pre-t history of Y_t alone. Note that in the context of time series analysis the processes Y_t and X_t need not refer to 'events'. The concept has been explored and extended in a series of papers by Florens and Mouchart (1982, 1985).

is called a *partial likelihood* for θ since it does not depend on the specification of the joint distribution of $(Y, X)_t$. In particular, a model for the covariate process X need not be specified. This allows for an attractive strategy to demonstrate local dependence since one can concentrate on the model for the conditional prediction of Y given X without worrying about the possibly complicated nature of X. In the context of counting process methods, Slud noted (1992, p. 97): " ... that inferences could be made successfully without parametric specification of any probabilistic objects other than the failure counting process intensities. The latter point of view is especially liberating in problems with randomly time-varying covariates, where one is usually interested only in the effect of the covariates on the hazard of failure and where one can usually not provide convincing models of the stochastic variation of the covariates over time."[12]

5 Events and their Descriptions

The formal frame of causal reasoning developed above has many merits with regard to dynamic formulations of causality. Despite some conceptual shortcomings in the reformulation of the 'constant conjunction' condition it may readily be used to formulate claims of (non-) causality. As it stands, it relates to stochastic processes, i.e. collections of random variables. Often, statisticians are satisfied with formal references to variables as causes and effects, especially when arguing in the tradition of structural equation models. E.g. Pearl and Verma (1992, p. 91) speak of "stable causal mechanisms, which on a microscopic level, are deterministic functional relationships between variables, some of which are unobservable." But neither variables nor what they stand for are generally admitted as causes or effects by social scientists. Background variables like sex or religion are not considered to be (representations of) possible causes.

One further prerequisite for the applicability of the above formalism in the social sciences is therefore a restriction on the entities that may be causes or effects. As Bunge (1963, p. 72, his italics) puts it, "*there can be no causal links among states*, nor among any other systems of qualities. States are not *causes*, but simply *antecedents* of later states. To regard states as causes amounts consequently to committing the fallacy of the *post hoc, propter hoc*." Thus neither states nor things nor qualities of things can be causes or effects, only *events* can.[13]

[12] Arjas/Haara (1984), Slud (1992) and Greenwood/Wefelmeyer (1998) have studied the statistical properties of factorisations with time-dependent covariates.

[13] But see e.g. Mellor (1995, p. 129), who argues that "causation mostly links facts . . . .

But what are events? Hacker (1982, p. 17) says that "[e]vents, unlike objects, are directly related to time. They occur before, after, or simultaneously with other events. They may be sudden, brief or prolonged ... None of these temporal predicates apply in the same way to objects." But this special connection with time implies a difficulty for probabilistic theories of causality: "it is manifest that no event ever happens more than once, so that the causes and effects cannot be the same in *all* respects."[14] Therefore one cannot speak about the constant conjunction of cause and effect unless it is possible to also speak of *kinds of events*. While an event is something unique, events of the same kind can occur several times. But how can one define kinds of events? One possibility would be to delete some temporal descriptions from propositions about events. Such propositions might then be said to be about kinds of events.[15] The obvious shortcoming of this approach is that it concerns propositions, not events, and propositions do not qualify as causes, at least not in a realist account of causality. "Events presumably are not linguistic entities; like trees and molecules, events can be talked about, referred to, and described but they are not themselves statements, sentences, descriptions, or any other kind of linguistic units. Nor are events propositions; propositions are supposed to be abstract entities, whereas events are spatio-temporally bounded particulars."(Kim 1969, p. 198.) An alternative is to relate events to changes in things. An *event* "is a 'movement' by an object from the having of one to the having of another property, where those properties belong to the same quality space, and where those properties are such that the object's successive havings of them implies that the object changes non-relationally."[16] This fits nicely with the proposed mathematical formalisation: The random variables Y_t refer to properties of things. These properties are represented by a definite set $\mathcal{Y}$, the 'property space'. And events are changes in things represented by variables, $\{Y_t - Y_{t-1} \neq 0\}$. Events occur at a definite point in time.[17] Kinds of events may than be described by certain transitions between elements of the set $\mathcal{Y}$, or as classes of such transitions.

But this approach may be at once too general and too specific to serve its purpose as a general guideline in the social sciences. It may be too specific

So no causation would be lost even if there were no particular events."

[14]Maxwell, cited in Bunge 1963, p. 50

[15]See e.g. Scheffler 1994.

[16]Lombart 1986, p. 114. He argues that *all* events should be treated in this way.

[17]Since an event in general takes some time, it seems inappropriate to say that they occur at a point in time. This creates considerable problems for a formalisation of time sequences, especially if it is based on the continuous-time theory of stochastic process. Hamblin argues that "the time-continuum, modelled on the real numbers, is richer than we need for the modelling of empirical reality." (cited in Galton 1984, p. 19)

because the translation of 'event' into 'change of property' does not capture the most general idea of event playing the role of an efficient cause. Parties, strikes, wars etc. are certainly events, and they generally are considered to have causal efficiency. Still, the notion of an event as a change of a property can only be adapted to such events at the price of some distortion of the event under study.

On the other hand, the notion of events and their probabilistic interdependence in time does still not capture the realist notion that causes should reflect mechanisms (Sørensen 1996), capacities (Cartwright 1989) or productivity (Bunge 1963). Events as changes of state may not involve mechanisms. They may only be sequences like sunset after sunrise, so that the concept of events as changes of properties of things is too general.

6 Agents, Actions, and Events

In the words of Bunge (1963, p. 46, his italics), "the reduction of causation to regular association, as propounded by Humeans, amounts to mistaking causation for one of its tests .... What we need is a statement expressing the idea—common to both the ordinary and the scientific usage of the word—that causation, far more than a relation, is a category of genetic connection, hence of change, that is a way of *producing* things, new if only in number, out of other things." In statistical discussions, the exhibition of productivity of proposed causes is often side stepped. Instead, many accounts view causality through an analogy with planned, isolated experiments. Experiments are seen as a deliberate manipulation of causes with the goal to provide a magnitude of their effects. This magnitude is perceived as the difference between the value of a measurement on a subject in the presence of the cause and the value of the measurement on the same subject in the absence of the cause. The difference can never be observed and so relates to a counterfactual question. The theory therefore involves constructions of 'similar worlds' to identify such magnitudes.[18]

Since all the criteria for deriving magnitudes of effects rest on empirically untestable assumptions, they are met with scepticism from statisticians (e.g. Dawid 2000) and sociologists alike. Furthermore, counterfactual accounts are deterministic in that they refer to what would necessarily happen in the

[18] See Holland (1986), Pratt/Schlaifer (1984), Dempster (1990), Rubin (1990), Galles/Pearl (1998), Pearl (1999) and Robins (1999) for discussions and refinements. These approaches are closer in spirit to J.S. Mill's attempts to codify methods of causal inquiry (Holland, 1986, p. 950) than to elaborations of Humean criteria for the existence of causal links.

presence or absence of the cause. But such a deterministic outlook cannot easily adapt to the variability generally observed in the social sciences.

On the other hand, the insistence on the experimental analogy points to the importance of action based interpretations of causality. In fact, it is sometimes suggested that causality should be defined in terms of human actions and their impact on other humans. Von Wright (1972, chap. 2.9) distinguishes between doing something and bringing about something and goes on to define P as a cause relative to Q, and Q as an effect relative to P, if and only if by doing P one could bring about Q, or by suppressing P one could prevent Q from happening. Such a view partly reconciles Bunge's search for productivity with counterfactual analysis: The capacity of a human agent to act and thereby to bring about certain events can hardly be denied. And this capacity includes the possibility of deliberately abstaining from that action. But the power to act and thereby to bring about an event is normally understood to mean that, counterfactually, if the agent would not have acted as, in fact, he did, then the event would not have happened.[19]

Many social phenomena are directly based on actions of individuals or organisations (see e.g. Blossfeld/Prein 1998). As far as sociology is concerned with these phenomena, there is no need to refer to an omnipotent experimenter or to seek rescue in designs that—always imperfectly—mimic the experimental setup of other sciences. Within these fields, sociology does not deal with associations among variables per se, but with events brought about or done by acting people. And claims for causal connection among events brought about by agents can be based on the causal capacities of the agents themselves.

It is tempting to seek the causal connection directly in sequences of actions. But actions should not be treated like events that enter into causal relations as causes and effects. There cannot be a similar connection between actions. Otherwise, as Alvarez/Hyman (1998) point out, one would be led to the idea that agents cause their actions, that actions are events caused by agents. But then "an agent who performs one action performs an infinite series of actions: he causes his action; he causes the causing of his action; he causes the causing of the causing of his action; and so on." (p. 222) We will therefore say that agents cause the result of their action, that they bring about events and that causal connection exist, not between actions, but between events done or brought about by actions.

[19] Kelsen (1982) argues that the notion of cause and effect originated from idealised human action and reaction in society, that its origins lie in the projection of crime and punishment, guilt and retaliation, onto nature. An action based reasoning about causal connection would therefore be close to the ancient origins of the idea, but without projecting human capacities on God or nature.

As Bach (1980) points out, the distinction between actions and events also relieves us from specifying times and places for actions. "Once we have specified all the relevant events in the act sequence and have described them as stemming from a mental episode in the way appropriate to action, we have said all we need to say about which actions were performed and what the agent did." (p. 118)

It is sometimes argued that since human actors act intentionally and behaviour is goal-oriented, the intentions or motives of actors to bring about some effect in the future causes the actor to behave in a specific way in the present. Marini and Singer (1988, p. 377) say that "[a] major problem with use of the criterion of temporal order in which behavior occurs, or in which events resulting from behavior occur, is often not a good indication of causal priority. Because human beings can anticipate and plan the future, much human behavior follows from goals, intentions, and motives; i.e., it is teleologically determined. As a result, causal priority is established in the mind in a way that is not reflected in the temporal sequence of behavior or even in the temporal sequence of the formation of behavioral intentions." But the connection of goals, intentions, and motives to acts and events seems to be much looser than Marini and Singer suggest. In fact, von Wright (1972, chap. 3) argues that in the 'practical syllogism' of the form: a) person P wants to achieve Y; b) P believes that Y can be brought about when he is doing X; c) Therefore P tries to do X; the antecedences a) and b) cannot be understood as causes of the person's doing X. Based on observations of goals, intentions, and motives one may try to give a *teleological* explanation of behaviour. But such explanations are not causal, and they can coexist with causal connections between events that are done and brought about by agents. The fact that social agents can behave intentionally, based on expectations, does not reverse the time order underlying causal statements. The explanandum envisaged by Marini and Singer—why a certain person acts as she chooses to act—is simply different from the explanandum of causal analysis.

7 Conceptual Problems

In summary, we propose to investigate causal relations among events employing the concepts of local independence and local autonomy in those cases where one is concerned with events brought about or done by agents. However, the execution of such a program is hampered as well by technical as by philosophical problems. The latter concern the basic concepts of independence and autonomy themselves and we will exhibit some of the more disturbing aspects below.

7.1 Local Independence

In his "Foundations of the Theory of Probability" Kolmogorov (1950, p. 9) says that "one of the most important problems in the philosophy of the natural sciences is—in addition to the well-known one regarding the essence of the concept of probability itself—to make precise the premises which would make it possible to regard any given real events as independent." The same applies, we think, to the concept of local independence or similar attempts to provide models for causal independence. Local independence cannot be demonstrated from observations alone.[20] Even though conditional independence as well as local independence are not empirical concepts, it does not follow that they cannot be used in an empiricist program for the assessment of causality. They are needed as regulative ideas in modelling. The role of local and conditional independence is to suggest the kind of relations one needs to take into account, but not to describe the likely results of an investigation.

Second, observed relations between stochastic processes generally depend on the number of processes that are considered. If a further process is included, the local dependence between all processes may change. The theoretical background on which an analysis is grounded will to a certain extent determine the variables and histories to be considered in an analysis. In the words of Suppes (1970, pp. 74) "It is important to emphasise ... that what is to be taken as background or field will always be relative to the conceptual framework under discussion. In one theoretical approach to the causal analysis of phenomena, the field will include only the consideration of macroscopic bodies and their characteristics, but in another, it will go deeper and consider as well atomic objects and their properties." In this sense, there may exist several valid causal analyses based on different sets of stochastic processes. Arguments for the exclusion of certain processes will partly rely on ideas of causal non-dependence, which can be translated into local independence within the mathematical model. On the other hand, the theoretical background will rarely be specific enough to determine exactly what processes are to be considered. In consequence, results cannot be expected to be unique.

Third, and perhaps most disturbingly, the probabilistic concept of local independence does not fully conform with most notions of 'explanations'[21]:

[20] A similar point has often been made in connection with the role of conditional independence in structural equation models. See e.g. Sobel (1997) and Holland in his discussion of Clogg (1992, p. 199).

[21] See Dawid 1979a, 1979b, 1980 for some examples concerning the 'unexpected' be-

- There may be two different histories $H_1 = \{Y_{t-1}, A_{t-1}, \dots\}$ and $H_2 = \{Y_{t-1}, B_{t-1}, \dots\}$ that make the respective predictions for Y_t locally independent of $\{X_{t-1}, \dots, X_0\}$, showing that X_t is at most an indirect cause of Y_t. But neither $H_1 \subseteq H_2$ nor $H_2 \subseteq H_1$ need to hold so that explanations (of spuriousness) are not unique.

- Perhaps even worse, it may happen that Y_t is locally independent of X_t with respect to a history $H_1 = \{Y_{t-1}, A_{t-1}, \dots\}$, but that it ceases to be so with respect to a larger history, say $H_2 = \{Y_{t-1}, A_{t-1}, B_{t-1} \dots\}$. Including more information for the prediction of Y_t might destroy local independence. The work of Clogg and Haritou (1997) contains some valuable examples.

- Finally, local dependence is not antisymmetric. Both processes may be locally dependent on each other. In this respect, the concept is weaker than many accounts of causality would require. On the other hand, if X and Y are mutually locally independent, then under slight regularity conditions (including uncorrelated innovations) X and Y are stochastically independent (e.g. Schweder 1979, p. 404). But stochastic independence is a much stronger concept than causal unrelatedness would seem to require.

7.2 Autonomy

The principle of local autonomy was introduced to ensure that the processes under consideration are not just expressions of a sole underlying process, so that it is meaningful to assess the properties of one process without regard to the other. The condition is formulated in terms of the uncorrelatedness of the martingales M_t^X and M_t^Y, expressing the intuitive notion that what happens next to X, say, should not be directly related to what happens to Y at the same time. The condition excludes two stochastic processes that are functionally related. In that case it may well be that the first process is locally independent of the second, while the second is locally dependent on the first, but it would contradict common sense to say that the first process is a cause of the second.[22]

But the condition fails in deterministic situations: Granger (1969, p. 430) used two deterministic processes as an example: If $Y_t = bt$ and $X_t = c(t+1)$, then $V_t^Y = b$ (independent of $X_0, \dots, X_{t-1}$). But one can as well write $V_t^Y = (b/c)(X_{t-1} - X_{t-2})$, which is dependent on $X_0, \dots, X_{t-1}$. Certainly one would

haviour of conditional independence relations.

[22] See Aalen (1987, p. 188) for an example.

not like to call X_t a cause for Y_t even though the martingales corresponding to the two processes are trivially uncorrelated.

Second, in the context of counting process models, the assumption of autonomy is often replaced by the assumption of no common jumps of the two processes. This in turn implies that the martingales M_t^Y and M_t^X are uncorrelated and that $M_t^X M_t^Y$ is again a martingale (Fleming/Harrington 1991, p. 75). The condition of no common jumps is often easy to handle, but it may obscure somewhat the role of the condition. Schweder (1970), who starts with a common (Markov–) process with state space $\mathcal{X} \times \mathcal{Y}$, uses the assumption of no common jumps in X and Y explicitly as a condition for the existence of processes that can formally be partitioned into processes X and Y.

On the other hand, the condition of no common jumps is often used for quite a different purpose: It can justify the construction of partial likelihoods. But the statistical considerations that lead to the use of only $U_t^Y(Y_t|Y_{t-1}, X_{t-1}, \ldots, Y_0, X_0; \theta)$ for likelihood construction and statistical inference should be carefully distinguished from considerations of the role of the two processes within a causal connection. If one is only willing to specify $U_t^Y(Y_t|Y_{t-1}, X_{t-1}, \ldots, Y_0, X_0; \theta)$ for statistical purposes one cannot analyse or simulate the dynamics of the compound process even if one might be willing to impute values for all X_t. This point was stressed both by Strotz and Wold (1960) and Cox (1992). Solving the estimation problem by concentrating on only a part of the system, even if justified, need not suffice to answer causal questions.

8 Conclusions

The discussions on causality, whether originating from a statistical perspective or from the methodology of the social sciences, have only rarely reflected the philosophical insight that a causal connection is a relation between events but not between variables, things, or qualities. Similarly, an agent based theory of causes that suggests itself in many parts of sociology was largely ignored in favour of counterfactual or system theoretic accounts. We have argued here that an agent based idea of causal connections between events can be supplemented by dynamic descriptions of series of events. When series of events of different kinds are represented by autonomous stochastic processes, the absence of a causal connection can be explicated by the concept of local independence. These concepts should be useful at least in those areas of empirical social research that are directly concerned with events brought about by agents.

We have not treated here a problem of central importance: the problem of spurious causes and of confounding. While the dynamic characterisation of series of events seems to allow for a better understanding and a more flexible formulation of these rather intuitive concepts (e.g. Parner and Arjas 1999), the variety of background conditions and situations generally encountered in social research may well preclude a comprehensive theoretical treatment of confounding. An examination of earlier attempts of demonstrating non-spuriousness in sociology, similar to Goldenberg's (1998) article, will certainly enrich further theoretical developments.

References

Aalen, O.O. (1987) Dynamic modelling and causality. *Scand. Actuar. J.*, 177–190.

Aldrich, J. (1989) Autonomy. *Oxford Ec. Papers*, **41**, 15–34.

Alvarez, M. and Hyman, J. (1998) Agents and their actions. *Philosophy*, **73**, 219–245.

Arjas, E. and Eerola, M. (1993) On predictive causality in longitudinal studies. *J. Statist. Plann. Inference*, **34**, 361–386.

Arjas, E. and Haara, P. (1984) A marked point process approach to censored failure data with complicated covariates. *Scand. J. Statist.*, **11**, 193–209.

Bach, K. (1980) Actions are not events. *Mind*, **89**, 114–120.

Bernert, C. (1983) The career of causal analysis in American sociology. *British J. Sociol.*, **34**, 230–254.

Blossfeld, H.-P. and Prein, G. (1998) *Rational choice theory and large scale data analysis*. Westview, Boulder (CO).

Blossfeld, H.-P. and Rohwer, G. (1995) *Techniques of Event History Modeling. New Approaches to Causal Analysis*. Erlbaum, Hillsdale.

Blumer, H. (1956) Sociological analysis and the 'variable'. *Am. Soc. Rev.*, **21**, 683–690.

Bunge, M. (1963) *Causality*. Meridian Books, Cleveland.

Cartwright, N. (1989) *Nature's Capacities and their Measurement.* Clarendon Press, Oxford.

Cartwright, N. (1999) Causal diversity and the Markov condition. *Synthese*, **121**, 3–27.

Clogg, C.C. (1992) The impact of sociological methodology on statistical methodology (with discussion). *Statist. Sci.*, **7**, 183–207.

Clogg, C.C. and Haritou, A. (1997) The regression method of causal inference and a dilemma confronting this method. In McKim, V.R. and Turner, S.P. (eds) *Causality in Crisis? Statistical Methods and the Search for Causal Knowledge in the Social Sciences*. University of Notre Dame Press, Notre Dame, pp. 83–112.

Cox, D.R. (1992) Causality: Some statistical aspects. *J. Roy. Statist. Soc.*, A, **155**, 291–301.

Davis, W.A. (1988) Probabilistic theories of causation. In Fetzer, J.H. (ed) *Probability and Causality. Essays in Honor of Wesley C. Salmon*. D. Reidel, Dordrecht, pp. 133–160.

Dawid, A.P. (1979a) Conditional independence in statistical theory. *J. Roy. Statist. Soc.*, B, **41**, 1–31.

Dawid, A.P. (1979b) Some misleading arguments involving conditional independence. *J. Roy. Statist. Soc.*, B, **41**, 249–252.

Dawid, A.P. (1980) Conditional independence for statistical operations. *Ann. Statist.*, **8**, 598-617.

Dawid, A.P. (2000) Causal inference without counterfactuals. *J. Am. Statist. Assoc.*, **95**, in press.

Dempster, A.P. (1990) Causality and statistics. *J. Statist. Plann. Inference*, **25**, 261–278.

Eells, E. (1991) *Probabilistic Causality*. Cambridge University Press, Cambridge.

Florens, J.P. and Mouchart, M. (1982) A note on noncausality. *Econometrica*, **50**, 583–589.

Florens, J.P. and Mouchart, M. (1985) A linear theory for noncausality. *Econometrica*, **53**, 157–175.

Epstein, R.J. (1987) *A History of Econometrics*. North–Holland, Amsterdam.

Fleming, T.R. and Harrington, D.P. (1991) *Counting Processes and Survival Analysis*. Wiley, New York.

Galles, D. and Pearl, J. (1998) An axiomatic characterization of causal counterfactuals. *Foundations of Science*, **3**, 151–182.

Galton, A. (1984) *The Logic of Aspect*. Clarendon Press, Oxford.

Goldenberg, S. (1998) Rediscovering and confronting critical ambiguities in the determination of causality. *Quality & Quantity*, **32**, 181–200.

Granger, C.W.J. (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, **37**, 424–438.

Greenwood, P.E. and Wefelmeyer, W. (1998) Cox's factoring of regression model likelihoods for continuous-time processes. *Bernoulli*, **4**, 65–80.

Hacker, P.M.S. (1982) Events and objects in space and time. *Mind*, **91**, 1–19.

Holland, P.W. (1986) Statistics and causal inference. *J. Am. Statist. Assoc.*, **81**, 945–970.

Keiding, N. (1999) Event history analysis and inference from observational epidemiology. *Statist. Med.*, **18**, 2353–2363.

Kelsen, H. (1982) *Vergeltung und Kausalität*. Böhlau, Graz.

Kim, J. (1969) Events and their descriptions: Some considerations. In Rescher, N. (ed) *Essays in Honor of Carl G. Hempel*. D. Reidel, Dordrecht, pp. 198–215.

Kolmogorov, A.N. (1950) *Foundations of the Theory of Probability*. Chelsea, New York.

Lombard, L.B. (1986) *Events. A Metaphysical Study*. Routledge & Kegan Paul, London.

Lübbe, W. (1994) Structural causes: On causal chains in social sciences. In Faye, J. and Scheffler, U. and Urchs, M. (eds) *Logic and Causal Reasoning*. Akademie Verlag, Berlin, pp. 91–108.

Marini, M.M. and Singer, B. (1988): Causality in the social sciences. In Clogg, C.C. (ed) *Sociological Methodology*. **18**, Jossey-Bass, San Francisco, pp. 347–409.

McKim, V.R. and Turner, S.P. (eds) (1997) *Causality in Crisis? Statistical Methods and the Search for Causal Knowledge in the Social Sciences.* University of Notre Dame Press, Notre Dame.

Mellor, D.H. (1995) *The Facts of Causation*. Routledge, London.

Parner, J. and Arjas, E. (1999) Causal reasoning from longitudinal data. Research Reports A27, Rolf Nevanlinna Institute, Helsinki.

Pearl, J. (1999) Probabilities of causation: Three counterfactual interpretations and their identification. *Synthese*, **121**, 93–149.

Pearl, J. and Verma, T.S. (1992) A statistical semantics for causation. *Statist. & Computing*, **2**, 91–95.

Pratt, J.W. and Schlaifer, R. (1984) On the nature and discovery of structure. *J. Am. Statist. Assoc.*, **79**, 9–33.

Robins, J.M. (1999) Association, causation, and marginal structural models. *Synthese*, **121**, 151–179.

Rosenbaum, P.R. (1995) *Observational Studies*. Springer, New York.

Savage, L.J. (1972) *The Foundations of Statistics*. Dover, New York.

Scheffler, U. (1994) Token versus type causation. In Faye, J. and Scheffler, U. and Urchs, M. (eds) *Logic and Causal Reasoning*. Akademie Verlag, Berlin, pp. 91–108.

Schweder, T. (1970) Composable Markov processes. *J. Appl. Probab.*, **7**, 400–410.

Schweder, T. (1986) Kan sosialstatistikeren skille årsak fra virkning?. *Tidsskr. f. Samfunnsforskning*, **27**, 357–369.

Slud, E. (1992) Partial likelihood for continuous-time stochastic processes. *Scand. J. Statist.*, **19**, 97–109.

Sobel, M. (1997) Measurement, causation, and local independence in latent variable models. In M. Berkane (ed) *Latent Variable Modeling and Applications to Causality*. Springer, New York, pp. 11–28.

Sørensen, A.B. (1996) Theoretical mechanisms and the empirical study of social processes. Preprint, Dept. Sociology, Harvard University.

Strotz, R.H. and Wold, H.O.A. (1960) Recursive vs. nonrecursive systems: An attempt at sysnthesis. *Econometrica*, **28**, 417–427.

Suppes, P. (1970) *A Probabilistic Theory of Causality*. North–Holland, Amsterdam.

Suppes, P. (1999) The noninvariance of deterministic causal models. *Synthese*, **121**, 181–198.

Tuma, N.B. and Hannan, M.T. (1984) *Social Dynamics*. Academic Press, Orlando.

von Wright, G.H. (1972) *Explanation and Understanding*. Cornell University Press, Ithaca.

Whitrow, G.J. (1963) *The Natural Philosophy of Time*. Harper, New York.

Williams, D. (1991) *Probability with Martingales*. Cambridge University Press, Cambridge.