

Causal Explanation: recursive decompositions and mechanisms

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Outline

- 1 The quest for causal explanation in the social sciences
- 2 The structure of the statistician's explanation
- 3 Explanatory mechanisms
- 4 Case studies

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The quest for causal explanation in the social sciences

- **Durkheim 1897** To explain suicide as a social phenomenon by finding its determinants.
- **Caldwell 1979** To explain child mortality in developing countries by emphasising the role of maternal education.
- **Lopez-Rios *et al.* 1992** To explain a lower mortality rate in Spain as an effect of socio-economic policies.
- ...

Social scientists seek to provide a *causal* explanation.

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Explanation in a stochastic environment

The statistician's explanation is based on a *statistical model* namely:

$$\mathcal{M} = \{\mathbf{S}, P^\theta \mid \theta \in \Theta\} \quad (1)$$

This *stochastic representation* of the observed world is the cornerstone of the statistician's explanation:

- the interpretation of parameter θ provides *the explanation* of the phenomenon
- the stochastic component of the model stands for *the unexplained part* of the phenomenon.

Marginal-conditional decomposition

Consider the bivariate case $X = (Y, Z)$:

$$p_X = p_Z p_{Y|Z} \quad (2)$$

The bivariate process generating $X = (Y, Z)$ is decomposed into two univariate processes

- 1 a marginal process generating Z
- 2 a conditional process generating Y given Z

Structural modelling

Mathematical arbitrariness of the marginal-conditional decomposition: $p_X = p_Z p_{Y|Z}$ or $p_X = p_Y p_{Z|Y}$?

Explanation requires the statistical model to uncover the *structure* of the data generating process

- Background knowledge: the whole body of knowledge we have of a given field
- Invariance: a condition of stability of the marginal-conditional structure of the model and of the characteristics (parameters) of the distribution

Recursive decomposition

Consider a vector of variables X decomposed into p components:

$$X = (X_1, X_2, \dots, X_p)$$

Suppose that the components of X have been ordered thus:

$$\begin{aligned} p_X(x \mid \omega) = & p_{X_p \mid X_1, X_2, \dots, X_{p-1}}(x_p \mid x_1, x_2, \dots, x_{p-1}, \theta_{p \mid 1, \dots, p-1}) \\ & \cdot p_{X_{p-1} \mid X_1, X_2, \dots, X_{p-2}}(x_{p-1} \mid x_1, x_2, \dots, x_{p-2}, \theta_{p-1 \mid 1, \dots, p-2}) \cdot \dots \\ & \cdot p_{X_j \mid X_1, X_2, \dots, X_{j-1}}(x_j \mid x_1, x_2, \dots, x_{j-1}, \theta_{j \mid 1, \dots, j-1}) \cdot \dots \cdot p_{X_1}(x_1) \end{aligned}$$

Each component of the rhs may be considered, as a structural component with mutually independent parameters:

$$\omega = (\theta_{p \mid 1, \dots, p-1}, \theta_{p-1 \mid 1, \dots, p-2}, \dots, \theta_1) \in \Theta_{p \mid 1, \dots, p-1} \times \Theta_{p-1 \mid 1, \dots, p-2} \cdot \dots \times \Theta_1 \quad (4)$$

Under property (4) the conditioning variables X_1, \dots, X_{j-1} of each factor of (3), $p_{X_j \mid X_1, X_2, \dots, X_{j-1}}$, is called *exogenous* for the parameter of the corresponding conditional distribution, $\theta_{j \mid 1, \dots, j-1}$.

Recursive decomposition—cont'ed

Equations (3) and (4) characterize a *completely recursive system*.
A recursive decomposition is not complete when, in equation (3), some components are random vectors rather than random variables.

Difficulties

- Partial observability
- Time delay, dynamic structures, feedback effects
- Causal chain

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Interpreting recursive decompositions

Recursive decompositions as mechanisms:

- Global mechanism: The *whole* recursive decomposition
- Sub-mechanism: Each conditional distribution within the recursive decomposition

A recursive decomposition carries explanatory power insofar as it achieves to disentangle a global mechanism into sub-mechanisms.

Recursive decompositions and mechanisms

Features of mechanisms in the context of structural models:

- Stochastic mechanisms. A mechanism is *not* deterministic but it rather singles out a stable/invariant and contextually meaningful aspect of the phenomenon of interest
- Stable mechanisms. Identifying a mechanism means to separate incidental from structural features of the data generating process. By so-doing, the statistician is also able to distinguish spurious from causal correlations.
- Mixed mechanisms. In social contexts, mechanisms are not necessarily 'physical', that is made of physical processes or physical entities interacting in one way or another.

Mechanisms, structural modelling, and explanation

- 1 the *whole modelling procedure* is explanatory. the marginal-conditional decomposition *alone* does not provide a (causal) explanation of a given phenomenon, but the whole modelling procedure does.
- 2 *no causes in, no causes out*

Causal factors and exogeneity

Why interpreting *exogenous* variables as *causal* factors?

- 1 Structural modelling is not a hunt for the 'true' model nor a device that enables us to discover the 'true' causal relations. Structural modelling is a progressive path toward making intelligible the observed phenomena while adjusting the window of observation to pre-specified targets.
- 2 Exogeneity is a condition of separation of inference. Separating causes from effects mirrors the asymmetry of causation. This last point makes clearer and more precise the familiar expression 'exogenous means generated outside the model'.

Evaluation of explanation

- (i) *statistical* evaluation: measuring how much variability is accounted for, measuring the goodness of fit.
- (ii) *epistemic* evaluation: asking whether results are coherent with background knowledge.
- (iii) *ontological* evaluation: if ontological homogeneity between the variables acting in the mechanism is lacking (for instance if the mixed mechanism includes both economic and health variables), it may be desirable to identify and justify indirect paths from the causes to the effect.

Causal explanations will then be good or bad depending on how well they meet statistical, epistemic, and ontological requirements.

Flexibility of explanation

- 1 'mixed mechanisms': as discussed earlier, we do not need to stick to a *physical* concept of mechanism
- 2 'partial explanation': the available information we base the explanation upon.
- 3 *va et vient* between established theories and establishing theories. Established scientific theories are (and ought to be) used to formulate the causal hypothesis and to evaluate the plausibility of results on theoretical grounds. But causal models also participate in establishing new theories by generalising results of single studies.

HAND WAVING

Thank you for your attention
... and comments!