Real Possibilities

Utrecht 2011

How to Frame Experimental Possibilities?

★

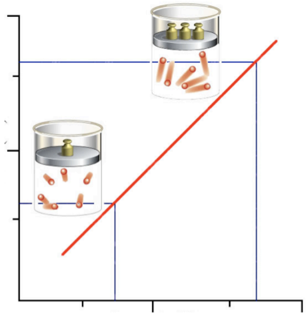
Jan-Willem Romeijn

University of Groningen

Contents

1 Experimental possibilities

Experimentation can be seen as a process of mapping out causal or nomic possibilities.



We systematically vary the states of a system to build up a space of possible states.

A philosophical account of experimentation

Confirmation theory seems a natural place to look for insight into this exploratory process.

- Bayesian treatments of the Duhem-Quine problem, triangulation, and calibration.
- Erotetic approaches, likening scientific experiment to a game of questions and answers.
- General philosophy of science on the role of physically realised models.
- Statistical treatments of experimental design and testing.

Up to date, none of these approaches properly brings the construction of the space of possibilities into view.

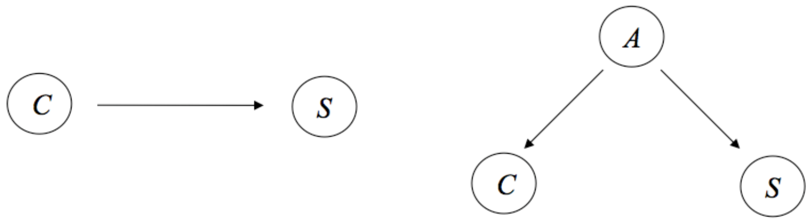
2 Causal Bayesian networks

Bayesian networks are very suitable for modeling experimental interventions.

Example from “The Effect of Country Music on Suicide” in Stack and Gundlach (1992) *Social Forces* 71(2): 211–218.

Causal discovery by intervention

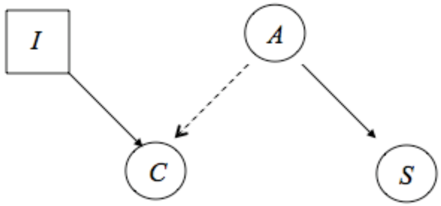
By intervening and then observing we may detect the existence of a causal link between the two, or else the existence of a common cause.

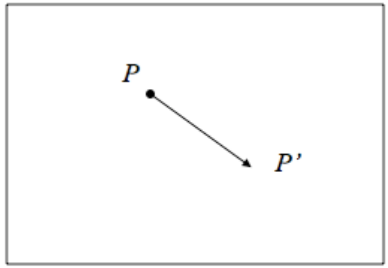


The two candidate networks entail distinct and testable implications for the interventions.

Possibility and causal structure

Every state is a probability over the effect variables for given values of the control variables.

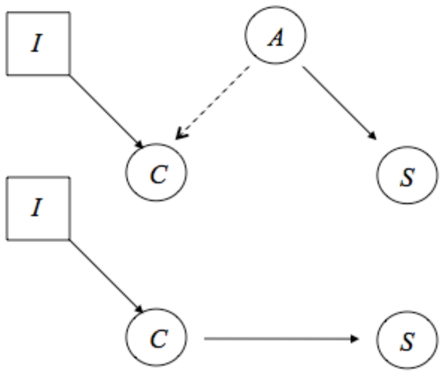


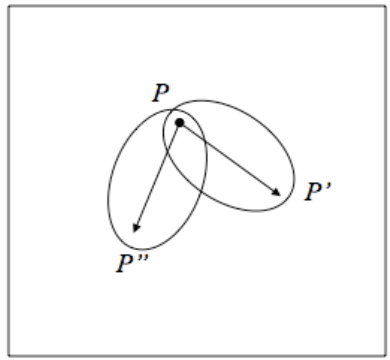


The network structure dictates how a system jumps from one possible state to another under interventions.

Exploiting the possibility structure

In an experiment we determine which jump between probability assignments was made after an intervention.

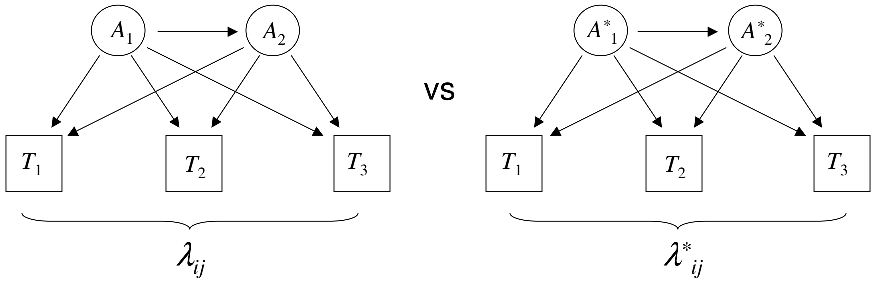




We thereby determine which states of the system, as given by a set of assignments, are possible.

3 Experimentation and underdetermination

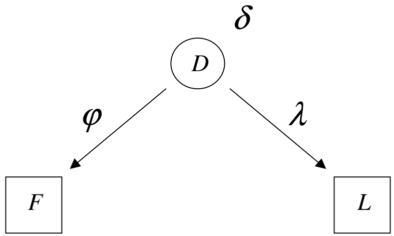
In some cases we do not know the full probability assignment for a system. Romeijn and Williamson (201X) show that experiments resolve such underdetermination.



This is illustrated by a toy example of the so-called rotation problem in factor analysis.

Fear and loathing in Bayesian networks

Say that fear F and loathing L are both binary manifest variables, and consider a single latent cause, depression D.



Observations are of individuals being fearful and loathsome or not, so there are four categories.

Unidentifiability in Bayesian networks

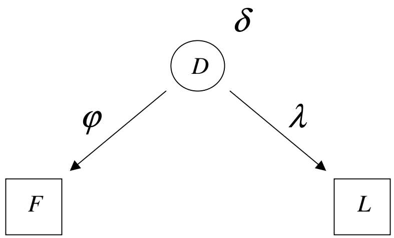
We have a total of five parameters in the statistical model:

- the chance of an individual for being depressed,
- two separate chances for being loathsome, depending on whether the subject suffers from depression or not, and
- two such chances for being fearful.

But we have only 4 observed relative frequencies, with the restriction that they add up to 1. There is a 2-dimensional continuum of hypotheses that fit the data perfectly.

4 Using intervention data

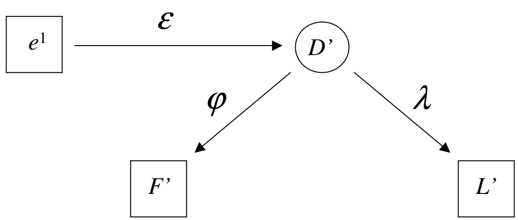
Ideally an intervention changes the probability for depression but keeps the conditional probability of fear and loathing fixed.



To accommodate the intervention data, we therefore have a smaller space of parameters available.

Drugs to the rescue

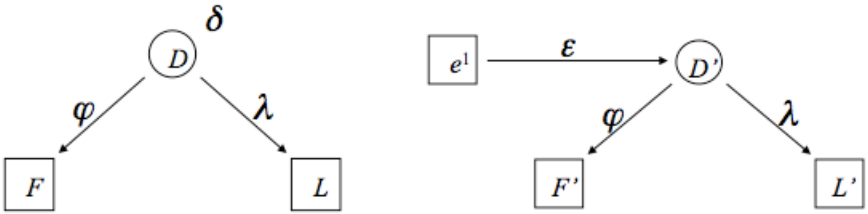
We intervene on the depression by administering a drug E. We model this by an additional node, setting the probability for depression to a new but unknown value $\varepsilon < \delta$.



In order to frame the intervention, we assume that the latent variable model is correct and that we intervene only on the depression node.

Unidentifiability resolved

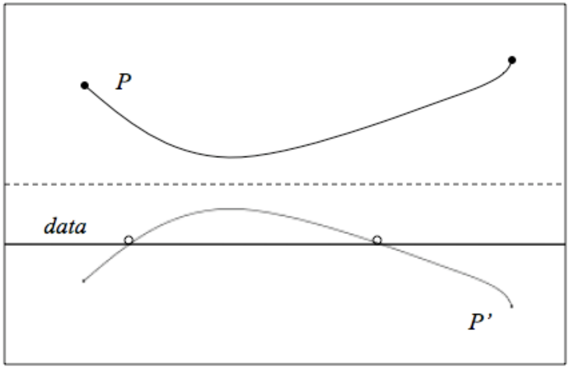
Because we observe the fear and loathing of the individuals after the intervention, we have 3 additional observed relative frequencies.



We have a total of 6 observed relative frequencies. But we have only one additional parameter in our problem: ε. The total number of parameters is 6 as well, so there is a unique best fit!

In the space of possibilities

We are clear on the type of jump that was effected by the experiment while we do not know from where we jumped.



But we can find this out because we know the characteristics of the intervention, and we have constraints on the results of the interventions.

5 Framing experimental possibilities

These results might lead the way to a full understanding of scientific experimentation in formal terms.

Would that do justice to the often messy practice of experimentation?

6 Externalism and ignorance

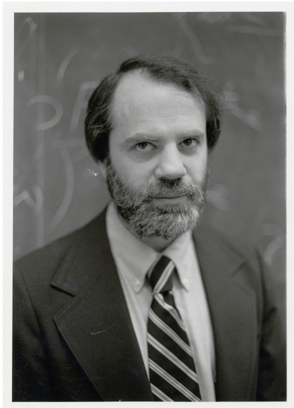
As illustrated by the example, the exploration of possibility relies on the presupposition of a causal structure.

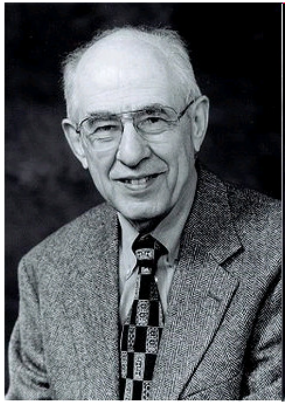
- It determines how the system under scrutiny is affected, by framing the intervention action.
- It thereby provides the link between the data sets before and after intervention.

I argue that the presupposition that is at work in actual experimentation cannot be represented in terms of variables, edges, and real numbers.

Meaning externalism

The meaning of terms in our language may well be fixed by states of affairs in the world rather than facts of the matter about the world.





In our use of language, we rely on the world having a particular but unknown structure.

Externalism regarding modality

Experimental science also relies on external structure: it need not be clear to the experimenter what exactly is being manipulated.

- It may not yet be clear in what ontology the system should be located.
- And even if it is, it need not be structured according to a fixed set of variables yet.

In a formal model, such ignorance is captured in an uncertainty measure over a parameterised domain. Formal models kick in when most of the work is already done.

7 Modality and agency

Taken on their own terms the data ultimately concern the same system, but we frame these data as pertaining to different states, associated by interventions.

- We assume that if we had not intervened, nothing out of the ordinary would have happened.
- We attribute the divergence of the system from this null option to the intervention we made.

This isolation of different states seems to clash with the empiricist outlook of formal models of experimentation.

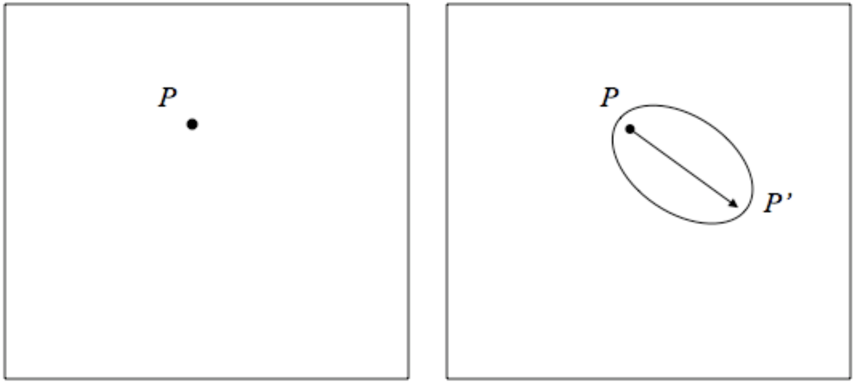
The experimenter as control?

The data are assumed to be given, and the experimenter is external and independent. Hence she can frame the data as pertaining to multiple states of the system.

But in practice the experimenter is often internal to the expertimental setup. Experimenter and experiment respond to each other to arrive at stable phenomena.

Natural experiments

Say that we accept that experimenters are internal to the system. In a sense, then, all experiments are "natural experiments".



The problem then is that we do not know when the data are supposed to concern a different state of the system. Why not say that we look at the same state all the time?

8 Formal models in philosophy

To my mind these problems are not idiosyncratic for modelling experimentation by Bayesian networks. They are endemic to much of formal philosophy of science.

- The priority of language in formal modelling flies in the face of the externalist aspects of much of scientific activity.

- The traditional empiricist backdrop of formal models is at variance with the role of agency in scientific knowledge.

Of course, this is a rather negative reading of the foregoing. Instead, the audience is welcome to consider the criticisms as challenges!

Thank you

The slides for this talk will be available at

http://www.philos.rug.nl/∼romeyn

and the full paper will also be posted there. For comments and questions, email

j.w.romeijn@rug.nl