A Theory Of Inferred Causation

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Our Task

Find cause-effect relationships (causal model).

Use only the information from uncontrolled observation of nature.
(No controlled experiments!)

empirical joint distribution over observable variables $\rightarrow$ causal model

Should be possible because humans can do it.

Our Problems

- statistical dependence ≠ causality
  (← but not →)
- causal relationship vs spurious covariance
- hidden information/nodes
  (for example hidden common cause)

first thoughts

- Use temporal information, helps with:
  direction of causality
  common causes
- Identify statistical patterns and associate them with a causal interpration:
  no need for temporal information

Definitions

<u>2.2.1</u> causal structure D = DAG, blueprint

<u>2.3.2</u> latent structure <D,O> = D with Observables

<u>2.2.2</u> causal model <D,Θ> = full model

What now? Just find the causal model which can generate the observed joint distribution?

removing some ambiguity

basic idea:
Use the simplest working model that you can find.
(The simpler the explanation the better.)

less basic idea:
The simpler the model the smaller its „expressive power“.

$L \leq L'$: A latent structure L is simpler than L' if L' can mimic L (only looking at the observables).

the big thing

Find (one) minimal L=<D,O> which is consistent:

$$P_O(L) = P_{empirical}$$

<u>2.3.6</u> **inferred causation**

Given $P_{empirical}$, C has a *causal influence* on E iff there is a directed path from C to E in *every minimal L consistent with $P_{empirical}$*

yet another concept ...

... to remove ambiguity:

stability

Some independencies are structural and others are only „numerical“.

Don't use models that allow „numerical“ indepencies (they are unstable).

recovering DAG structures inductive causation (IC)

1. For all a,b in V find S_{ab} which renders a and b independent if conditioned on.
   Construct undirected graph with a,b connected if no such S_{ab} exists.
2. For all a,b with common neighbor c:
   if c is in S_{ab}, do nothing
   else, construct $a \rightarrow c \leftarrow b$
3. In the resulting directed partially graph, orient as many edges as possible.
   Don't create new v-structures.
   Don't create directed cycles.

recovering latent structures

Stability is no longer needed over O.
Minimal latent structures don't have to be DAG structured.

<u>2.6.1</u> Projection

$L_{[o]}$ is a projection of L iff
hidden variables are parentless common causes of two observables and
$L_{[o]}$ and L have the same conditional indepencies

IC with latent variables (IC*)

1. Find S_{ab} again and construct a-b if no S_{ab} exists.
2. Construct $a \rightarrow c \leftarrow b$ again if possible.
3. Add arrows as long as the rules permit it.

local criteria for causal relations

Certain statistical patterns allow us to infer causal relationships.

There is always a third variable which allows us to do „an uncontrolled experiment“. („no causation without manipulation“)

local criteria for causal relations

<u>2.7.1</u> Potential Cause: It's not the only cause.

<u>2.7.2</u> Genuine Cause: Controlling X is controlling Y and X can screen Y from any further control. (+ closure)

<u>2.7.3</u> Spurious Association: Leaves only a latent common cause as explanation.

using temporal information

2.7.4 Genuine Causation: Temporal precedence replaces potential cause.

2.7.5 Spurious Association: Only check for one direction of causality.

„inferred time“ / statistical time

We expect causation to follow the timeline.

Most techniques today didn't use temporal information.

A correct DAG should hopefully give us a statistical time which coincides with the physical time.
(May not always be the case.)