Causal reasoning with the „do“-operator

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Why causal knowledge?

- Causal knowledge helps us to understand, predict, and control our environment.
- Causal reasoning involves various types of (probabilistic) conditional inferences:
  - Diagnostic inferences
  - Predictive inferences
  - Reasoning about interventions

```
        germs
         ↓
     infection
```

```
symptoms  course
          ↖      ↘
```

```
Treatment: vaccination, antibiotics
```
Hume’s riddle of causal induction

- How can you find out whether you are allergic against some kind of food?

\[ \text{Food} \quad ? \quad \text{Symptoms} \]

- Problem: Our senses do not provide us with causal knowledge, i.e. causal relations are not directly observable.

“The idea of cause and effect is deriv’d from experience, which informs us, that such particular objects, in all past instances, have been constantly conjoin’d with each other.”

(David Hume, 1739/2000, p.63)
**Causal learning = associative learning?**

- **Claim:** Causal knowledge can be reduced to associative knowledge (e.g., Shanks & Dickinson, 1987; Dickinson, 2001)

- **Problems**
  - Associative knowledge does not allow us to distinguish between causal and spurious relations
  - Associative models do not represent causal directionality (causes generate effects)
  - As a consequence, associative models lack the expressive power to capture normative differences between observations and interventions

\[
\Delta V = \alpha \times \beta \left( \lambda - \sum V \right)
\]
Associative models: No causal structure

Cues
- Headache
- Chills
- Infection
- Rhino virus

Outcomes
- Influenza Virus
- Cough
- Fever

Point of intervention

Associative Weights
Causal model theory

- *Causal model theory* assumes that people represent the world in terms of causal relations that mirror the causal texture of the (physical, biological, social) environment (Waldmann & Holyoak, 1992; Waldmann, 1996; Sloman, 2005; Waldmann, Hagmayer & Blaisdell, 2006; Meder, Hagmayer, & Waldmann, 2008, 2009)

- In the spirit of Kant, cause and effect are considered as fundamental categories of thought. Asymmetry of causal relations is preserved in mental representations

- Causal structure vs. causal strength: distinction between the structure of a causal model and its parameters (base rates, causal strength estimates)
Formalizing causal models: Bayes Nets
(Pearl, 1988, 2000; Spirtes, Glymour & Scheines, 1993; Spohn, 1980, 1983)

- Directed acyclic graphs (DAGs) to represent causal structures
- Parameters to express the strength of these relations (e.g., marginal and conditional probabilities, causal strengths)
- Causal Markov condition: \( P(X_i) = \prod_i P(X_i|PA(X_i)) \)

Common Cause Model

![Diagram of Common Cause Model]

\[
P(A,B,C) = P(A) P(B|A) P(C|A)
\]

Causal Chain Model

![Diagram of Causal Chain Model]

\[
P(A,B,C) = P(A) P(B|A) P(C|B)
\]

Common Effect Model

![Diagram of Common Effect Model]

\[
P(A,B,C) = P(A) P(B) P(C|A,B)
\]
Seeing vs. doing: Observational and interventional inferences

- Normative difference between
  - inferences based on passively observed states of a variable ("seeing")
  - inferences based on the very same state resulting from an external intervention ("doing")
Seeing vs. Doing: Observational and interventional inferences

  - Observational inference: IF B is observed, THEN...
  - Interventional inference: IF B is actively generated, THEN...

Observational inference: IF B is observed, THEN...

Interventional inference: IF B is actively generated, THEN...
Seeing vs. doing: Observational and interventional inferences

- Are people sensitive to the normative distinction between observations and interventions?
- Can people infer the consequences of interventions on causal systems?
- Requires to
  - consider the causal model underlying the observed covariations
  - distinguish observing (“seeing”) from intervening (“doing”)
Seeing vs. doing: Observational and interventional inferences

Common Cause Model

Causal Chain Model

\[ \text{DATA} \]

Waldmann & Hagmayer, 2005
Seeing vs. doing: Observational and interventional inferences

Observational inference:
*If you observe B to be present, how likely is C?*

Interventional inference:
*If you generate B by an means of intervention, how likely is C?*
Seeing vs. doing: Observational and interventional inferences

Common Cause Model

Causal Chain Model

Observation Intervention

\[ P(C|B) \]

\[ P(C|B) \]
Seeing vs. doing: Observational and interventional inferences

Common Cause Model

Causal Chain Model

Observation vs. Intervention

\[ P(C|B) \]
Observations and interventions with causal backdoors

- Common Cause Model
- Causal Chain Model
- Common Effect Model
- Confounder Model

Observations:
- A → B → C
- A → B → C
- A → B → C
- A → B → C → D

Interventions:
- do(B) → A → B → C
- do(B) → A → B → C
- do(B) → A → B → C
- do(B) → A → B → C → D
Observations and interventions with causal backdoors
Observations and interventions with causal backdoors

*Observing* ("seeing")

*Intervening* ("doing")

**Observational probability**

\[ P(A|C) > P(A|\text{do } C) \]
\[ P(B|C) > P(B|\text{do } C) \]
\[ P(D|C) = P(D|\text{do } C) \]
Observations and interventions with causal backdoors

Observing ("seeing")

Intervening ("doing")

\[
P(A|\neg C) < P(A|\text{do } \neg C)
\]

\[
P(B|\neg C) < P(B|\text{do } \neg C)
\]

\[
P(D|\neg C) < P(D|\text{do } \neg C)
\]
Observational and interventional inferences with backdoor paths

- Are people sensitive to the normative difference between observations and interventions when reasoning with causal backdoors?

- Diagnostic and predictive inferences
Observational Learning

Lekanoid

Renoxin

Ceranat

Desulfan
Results: Diagnostic Inferences  
(Meder, Hagmayer & Waldmann, 2008)

People understand the difference between observations and interventions in diagnostic reasoning from effect to cause.
Results: Predictive inferences
(Meder, Hagmayer & Waldmann, 2008)

Reasoning from $C$ to $D$

- The influence of the confounding causal pathway is taken into account when reasoning from $C$ to $D$
People are sensitive to the normative difference between conditional inferences based on observed states of the world, and the very same states generated by means of intervention.

Diagnostic and predictive conditional inferences take into account causal structure and data (Waldmann & Hagmayer, 2005; Meder, Hagmayer, & Waldmann, 2008, 2009).

People reason differently about causal and logical conditionals (“A causes B” vs. “If A then B”) (Sloman & Lagnado, 2005).
The rationality of causal conditionals

- People reason differently about causal and logical conditionals (Sloman & Lagnado, 2005)
  
  If cause then effect.
  No effect.
  Therefore, no cause.

- Logical theories—like associative or purely probabilistic models—lack the expressive power to distinguish between observation and intervention