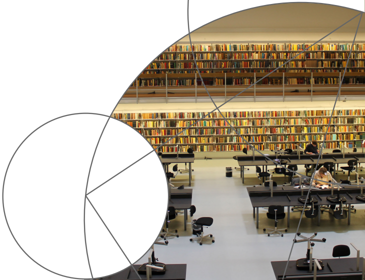
UNIVERSITY OF COPENHAGEN

Causal inference in neuroimaging

Sebastian Weichwald

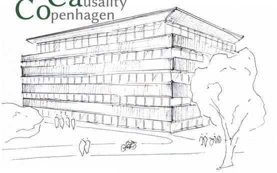
sweichwald.de @sweichwald

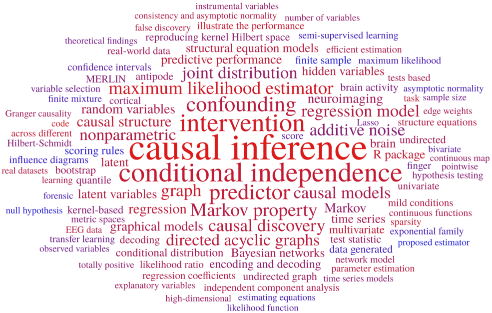


Global Excellence Seminar, DRCMR, Hvidovre

2020-01-24

CoCaLab
Copenhagen Causality Lab





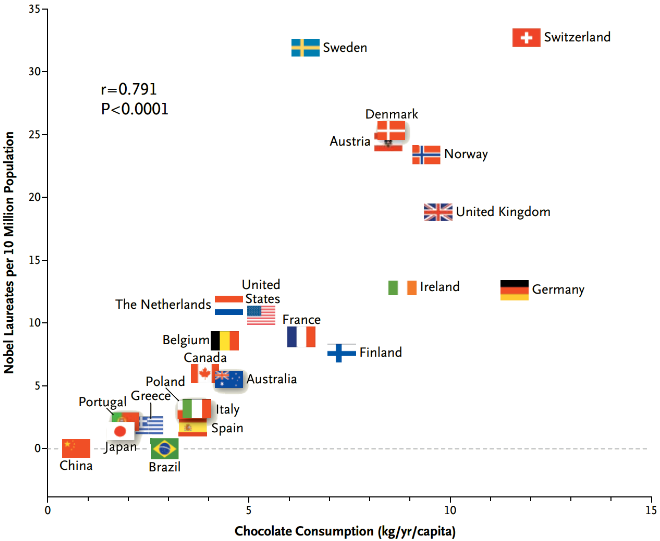
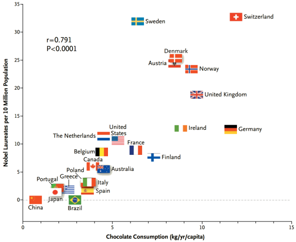


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.



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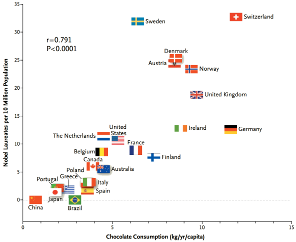

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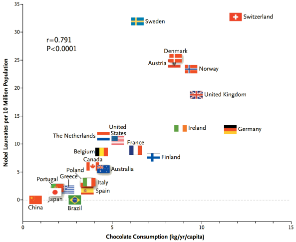

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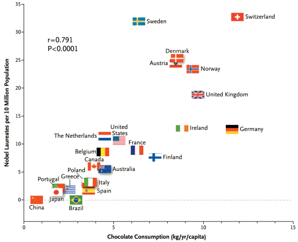

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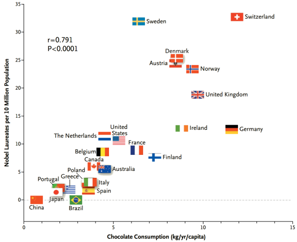

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$\rightsquigarrow$ Can we predict #country's Nobel Laureates?

☹ "Correlation does not imply causation."

☹ “Correlation does not imply causation.” SEEING VS DOING

Hippocampal activity in this study was correlated with amygdala activity, supporting the view that the amygdala ***enhances*** *explicit memory by* ***modulating*** *activity in the hippocampus.*

amygdala → hippocampus → explicit memory

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$$\boxed{\text{amygdala}} \rightarrow \boxed{\text{hippocampus}} \rightarrow \boxed{\text{explicit memory}}$$

Can we enhance explicit memory by amygdala stimulation?

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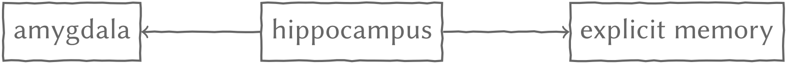

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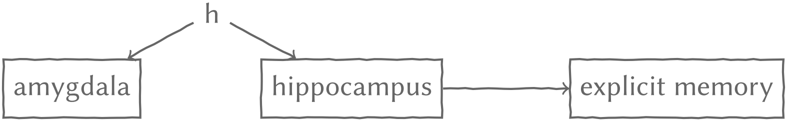

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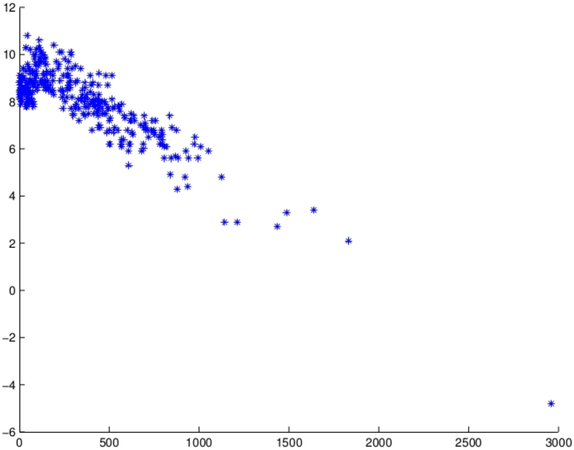
↯ Causal questions require causal answers.

What's the cause and what's the effect?



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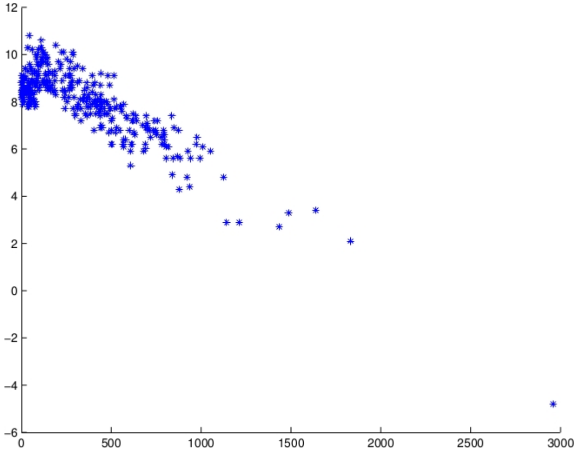

X (Altitude) $\longrightarrow$ Y (Temperature)

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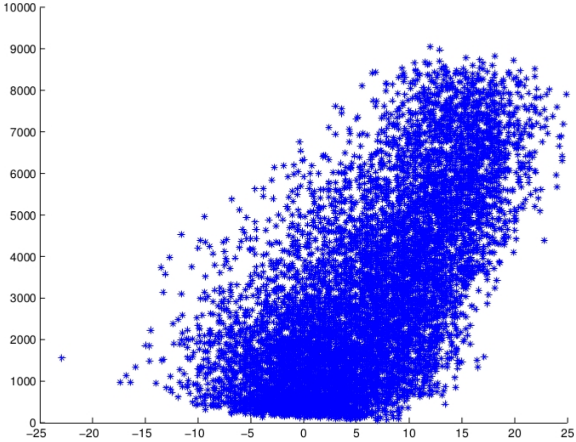

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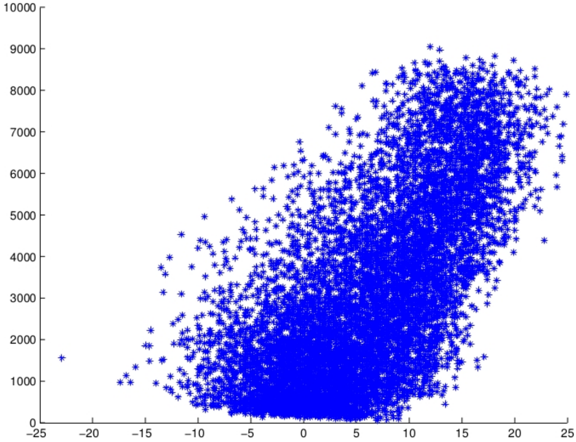

Y (Solar Radiation) $\longrightarrow$ X (Temperature)

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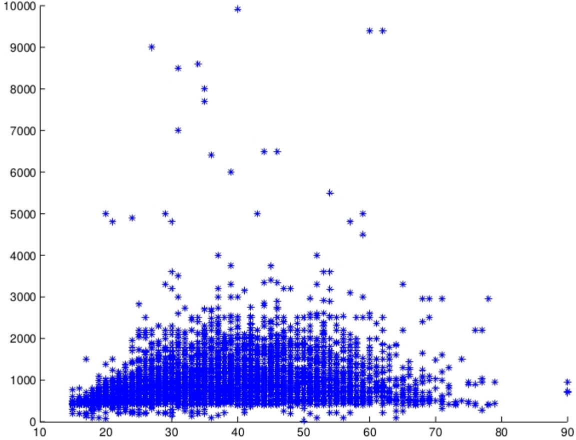

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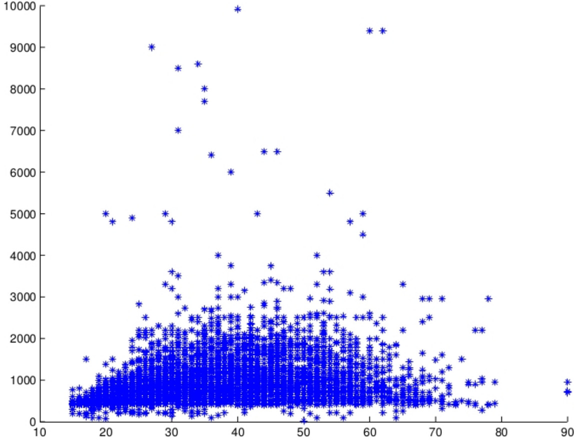

X (Age) $\longrightarrow$ Y (Income)

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Causal inference: assumptions & data $\rightsquigarrow$ causal hypotheses

Reichenbach's principle of common cause (1956)

If two variables X and Y are statistically dependent then either

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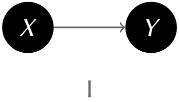

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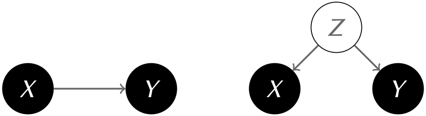

I II

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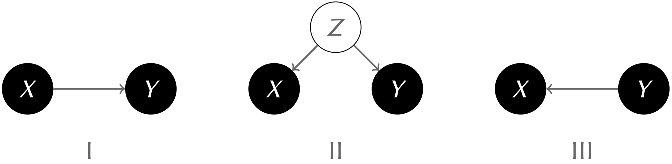

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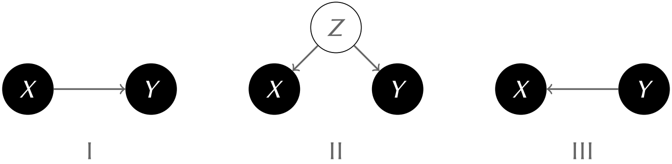

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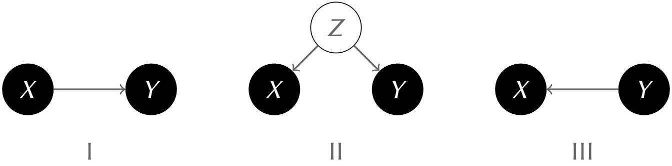

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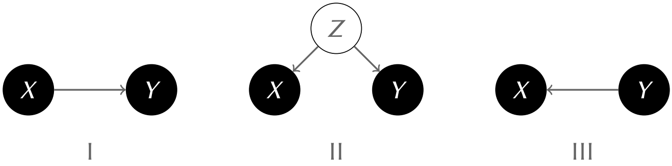
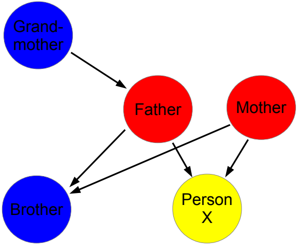


- every statistical dependence is due to a causal relation
- cases I, II, and III can also occur simultaneously
- distinction between the 3 cases is a key problem in scientific reasoning

Metaphor for the local Markov condition



If someone knows the genes of X's parents, neither the genes of the grandmother nor the genes of the brother contain additional information about X

Hidden confounding and constraint-based CI in NI

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- Observe neural activity X and Y

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$\rightsquigarrow$ Robust against hidden confounding

Neural Dynamics of Probabilistic Reward Prediction

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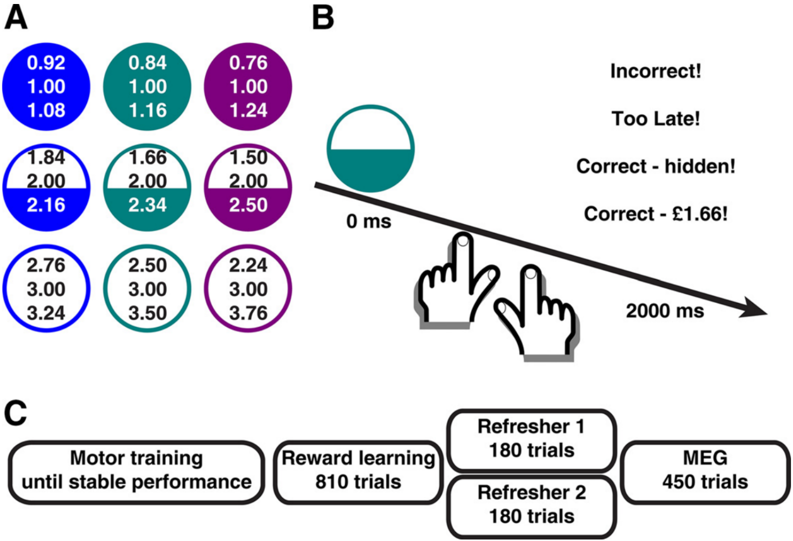

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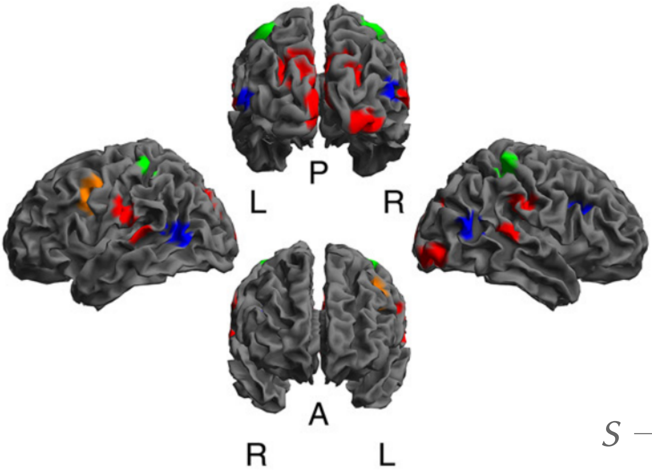
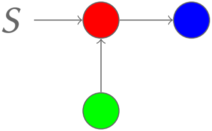
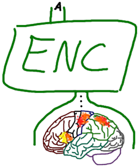




Causal interpretation of encoding and decoding models



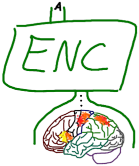
$X_i \not\perp\!\!\!\perp C$

"Significant variation explained by experimental condition?"

$X_i \not\perp\!\!\!\perp C | X_{\neg i}$

"Does removal impair decoding performance?"

Causal interpretation of encoding and decoding models



$X_i \not\perp\!\!\!\perp C$ **MARGINAL CORR**

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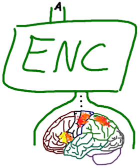

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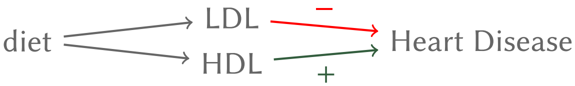
relevant feature $\overset{?}{\rightsquigarrow}$ cognitive process

What else can go wrong? Cholesterol and Heart Disease



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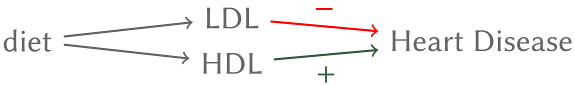

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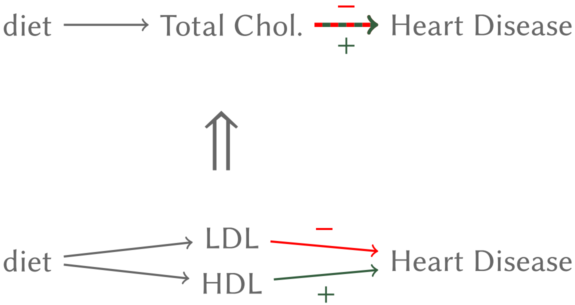

Macro-variables can be problematic.

Causal inference: assumptions & data $\rightsquigarrow$ causal hypotheses

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- 4 lectures on causality by J Peters (8 h)
  MIT Statistics and Data Science Center, 2017
  `stat.mit.edu/news/four-lectures-causality`
- causality tutorial by D Janzing and S Weichwald (4 h)
  Conference on Cognitive Computational Neuroscience 2019
  `sweichwald.de/ccn2019`
- course on causality by D Janzing and B Schölkopf (3 h)
  Machine Learning Summer School 2013
  `mlss.tuebingen.mpg.de/2013/speakers.html`

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- Come and talk to us at the CoCaLa b Copenhagen Causality Lab 🚲☕☺