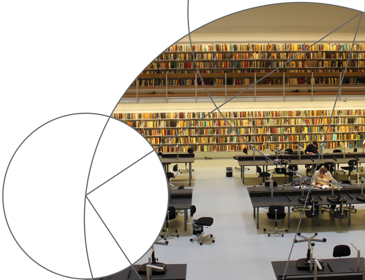
UNIVERSITY OF COPENHAGEN

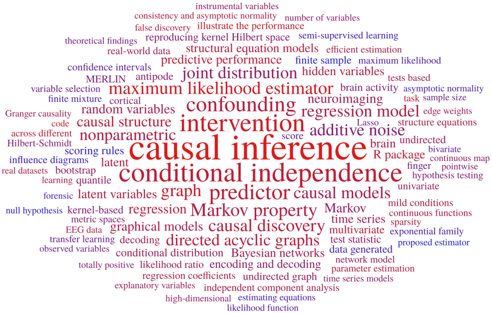
Causal inference in neuroimaging

Sebastian Weichwald
sweichwald.de @sweichwald



Global Excellence Seminar, DRCMR, Hvidovre
2020-01-24


CoCaLab
Copenhagen
Causality


instrumental variables
consistency and asymptotic normality
number of variables
false discovery
illustrate the performance
theoretical findings
reproducing kernel Hilbert space
semi-supervised learning
real-world data
structural equation models
efficient estimation
predictive performance
finite sample
maximum likelihood
confidence intervals
MERLIN
antipode
joint distribution
hidden variables
tests based
variable selection
maximum likelihood estimator
brain activity
asymptotic normality
finite mixture
cortical
confounding
neuroimaging
task
sample size
Granger causality
random variables
regression model
edge weights
code
causal structure
intervention
Lasso
structure equations
across different
nonparametric
additive noise
score
undirected
Hilbert-Schmidt
causal inference
brain
bivariate
scoring rules
R package
continuous map
influence diagrams
latent
finger
pointwise
real datasets
bootstrap
conditional independence
hypothesis testing
learning
quantile
univariate
forensic
latent variables
graph
predictor
causal models
mild conditions
null hypothesis
kernel-based
regression
Markov property
Markov
continuous functions
metric spaces
time series
sparsity
EEG data
graphical models
causal discovery
multivariate
exponential family
transfer learning
decoding
directed acyclic graphs
test statistic
proposed estimator
observed variables
conditional distribution
Bayesian networks
data generated
network model
totally positive
likelihood ratio
encoding and decoding
parameter estimation
regression coefficients
undirected graph
time series models
explanatory variables
independent component analysis
high-dimensional
estimating equations
likelihood function

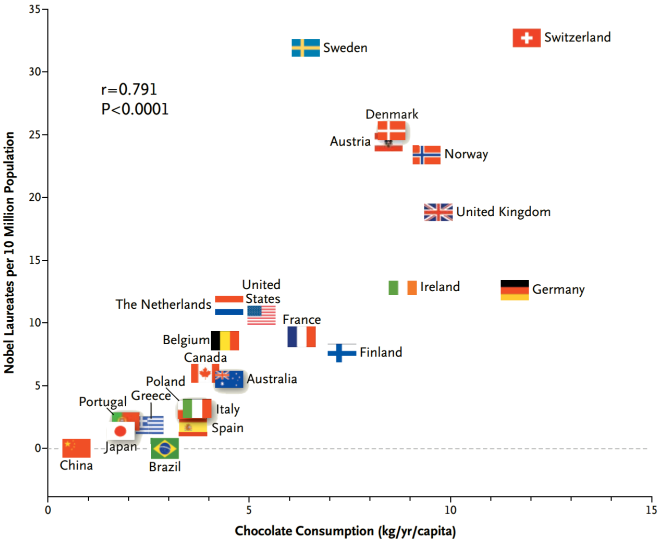
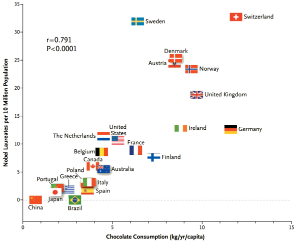


Figure 1. **Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.**



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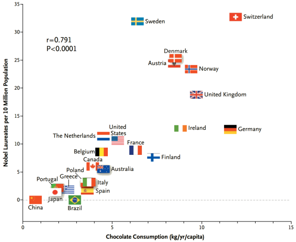

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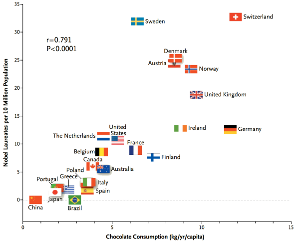
Bobby goes on a cruise to another country..



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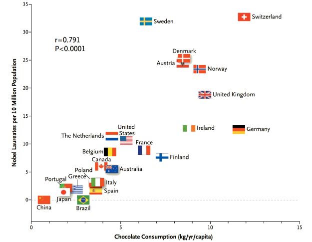
SEEING: ..and reports back that year's chocolate consumption.



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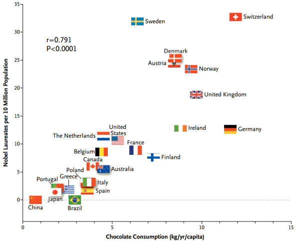

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Bobby goes on a cruise to another country..

SEEING: ..and reports back that year's chocolate consumption.

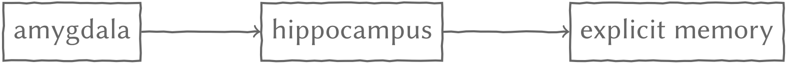
DOING: ..and brings enormous amounts of chocolate for a year.

$\leadsto$ 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.*



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amygdala → hippocampus → explicit memory

Can we enhance explicit memory by amygdala stimulation?

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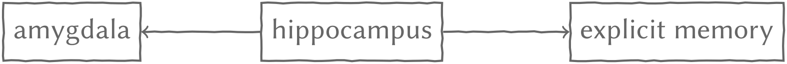

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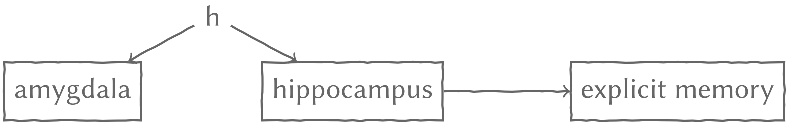

Can we enhance explicit memory by amygdala stimulation?

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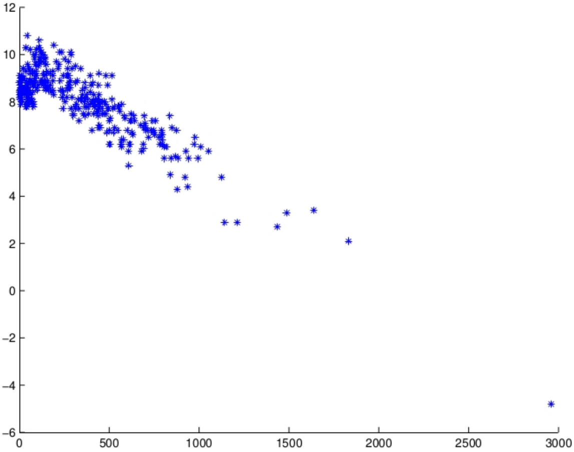
↯ Causal questions require causal answers.

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



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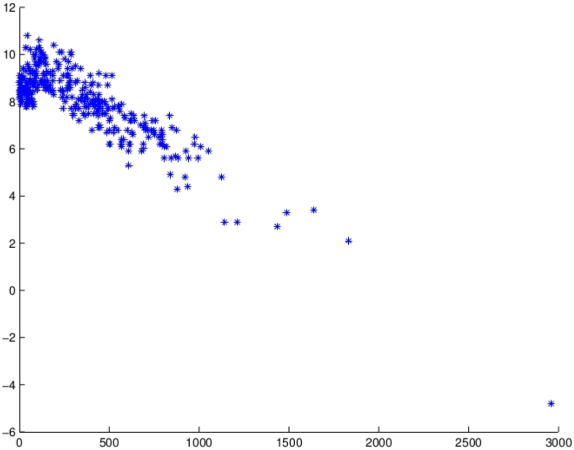

X (Altitude) $\longrightarrow$ Y (Temperature)

Mooij, Janzing, Zscheischler, and Schölkopf (2014). *CauseEffectPairs repository* at webdav.tuebingen.mpg.de/cause-effect/.

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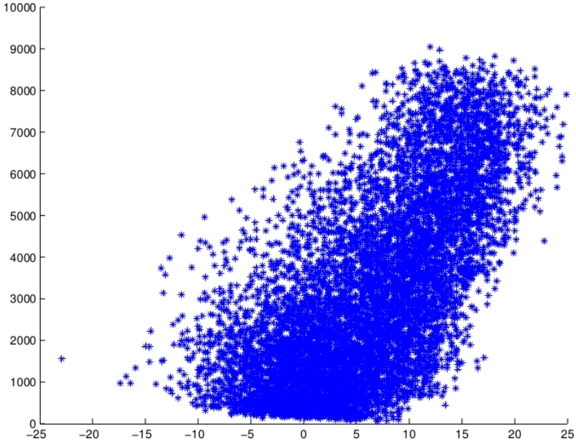

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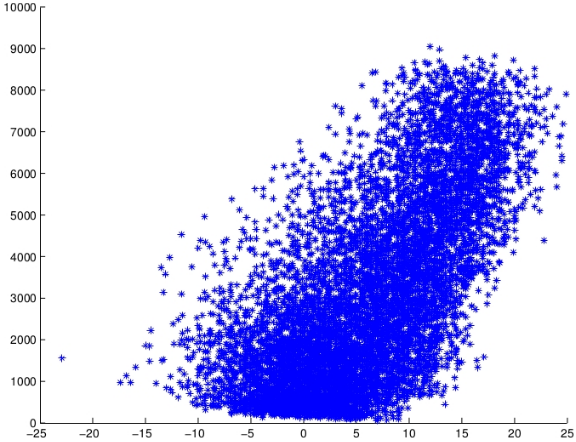

Y (Solar Radiation) $\longrightarrow$ X (Temperature)

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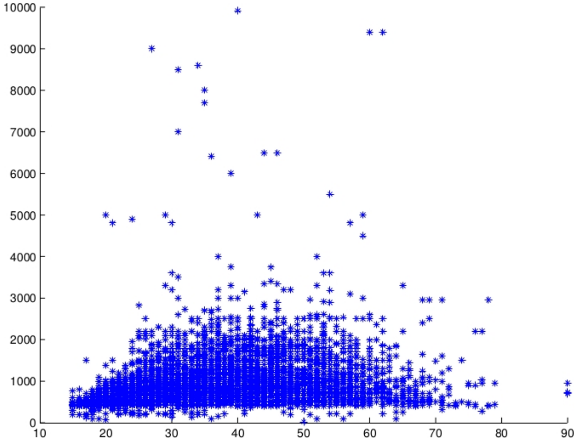

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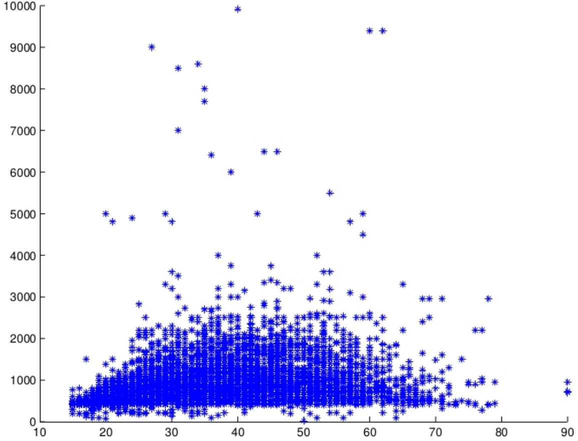

X (Age) $\longrightarrow$ Y (Income)

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☺ Correlation(s) may tell us something about causation.

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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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$$X \longrightarrow Y$$

I

Reichenbach's principle of common cause (1956)

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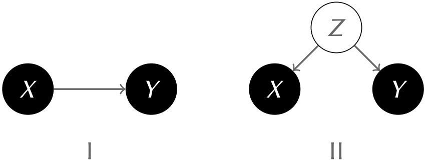

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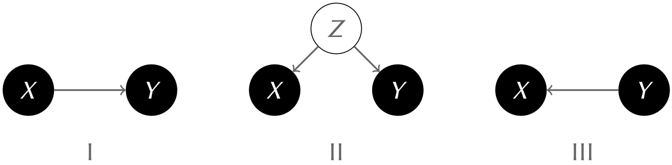

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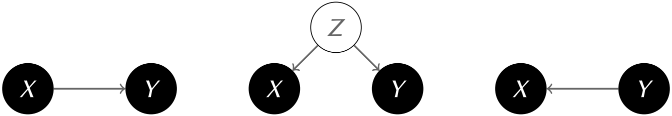

I II III

- every statistical dependence is due to a causal relation

Reichenbach's principle of common cause (1956)

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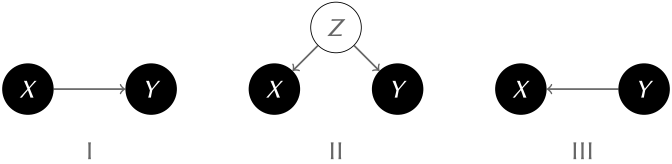

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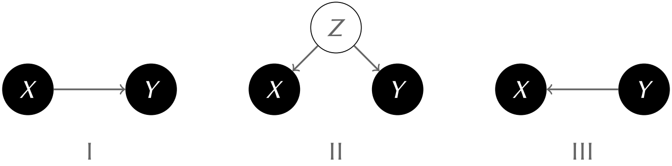
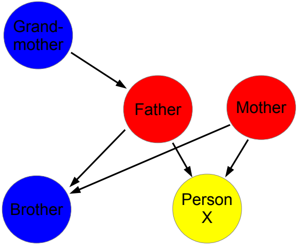


- every statistical dependence is due to a causal relation
- cases I, II, and III can also occur simultaneously
- distinction between the 3 cases is a key problem in scientific reasoning

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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- Randomised stimulus S

Hidden confounding and constraint-based CI in NI

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- Observe neural activity X and Y

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  - $S \not\perp\!\!\!\perp X$

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  - $S \not\perp\!\!\!\perp X \underset{\text{(Markov)}}{\implies}$ path between S and X w/o collider

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Weichwald et al. (2015). *NeuroImage*; Grosse-Wentrup et al. (2016). *NeuroImage*; Weichwald et al. (2016). *IEEE Selected Topics in Signal Processing.*

Hidden confounding and constraint-based CI in NI

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- Can formally prove that X indeed is a cause of Y

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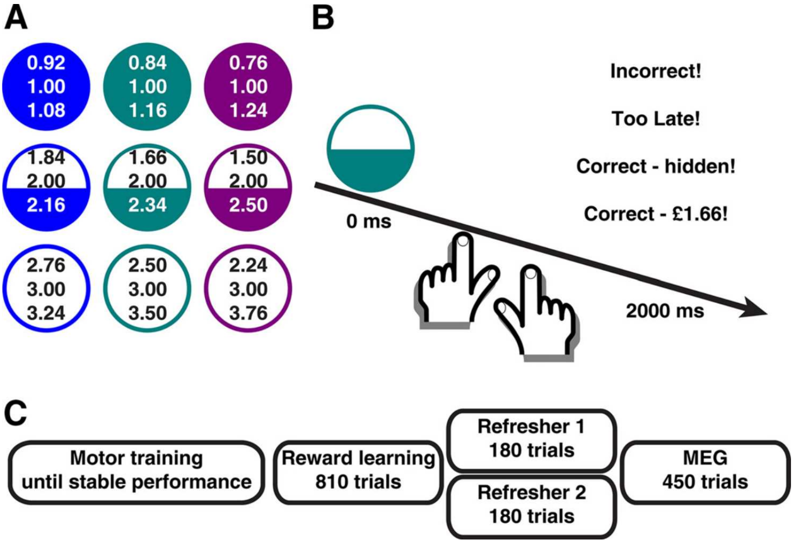
$\rightsquigarrow$ Robust against hidden confounding

Neural Dynamics of Probabilistic Reward Prediction

Bach, Symmonds, Barnes, and Dolan (2017). Whole-brain neural dynamics of probabilistic reward prediction. *Journal of Neuroscience*.

Neural Dynamics of Probabilistic Reward Prediction



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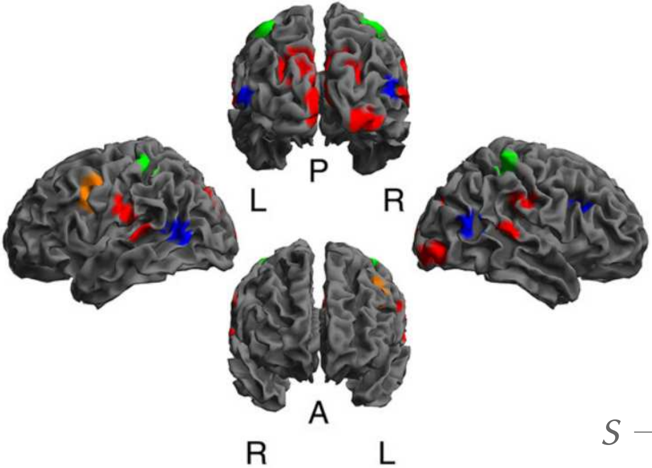
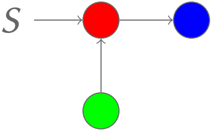
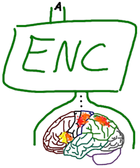




Causal interpretation of encoding and decoding models



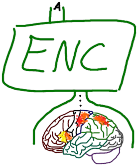
$X_i \not\perp\!\!\!\perp C$

"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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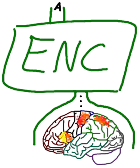
Causal interpretation of encoding and decoding models



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"Significant variation explained by experimental condition?"

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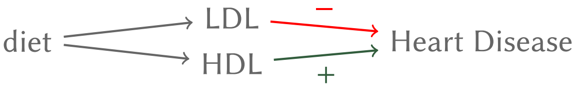
"Does removal impair decoding performance?"

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

What else can go wrong? Cholesterol and Heart Disease



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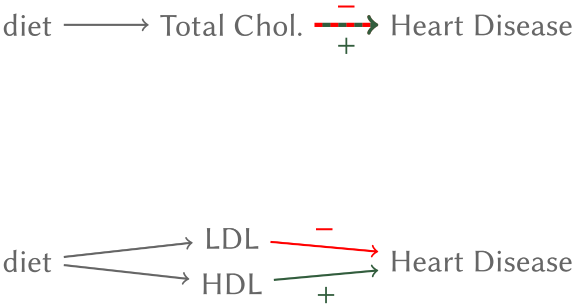

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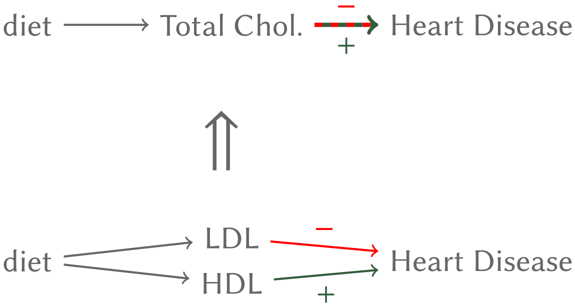

Macro-variables can be problematic.

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 CoCaLab (Copenhagen Causality Lab) 🚲☕☺