



Causal inference in neuroimaging

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



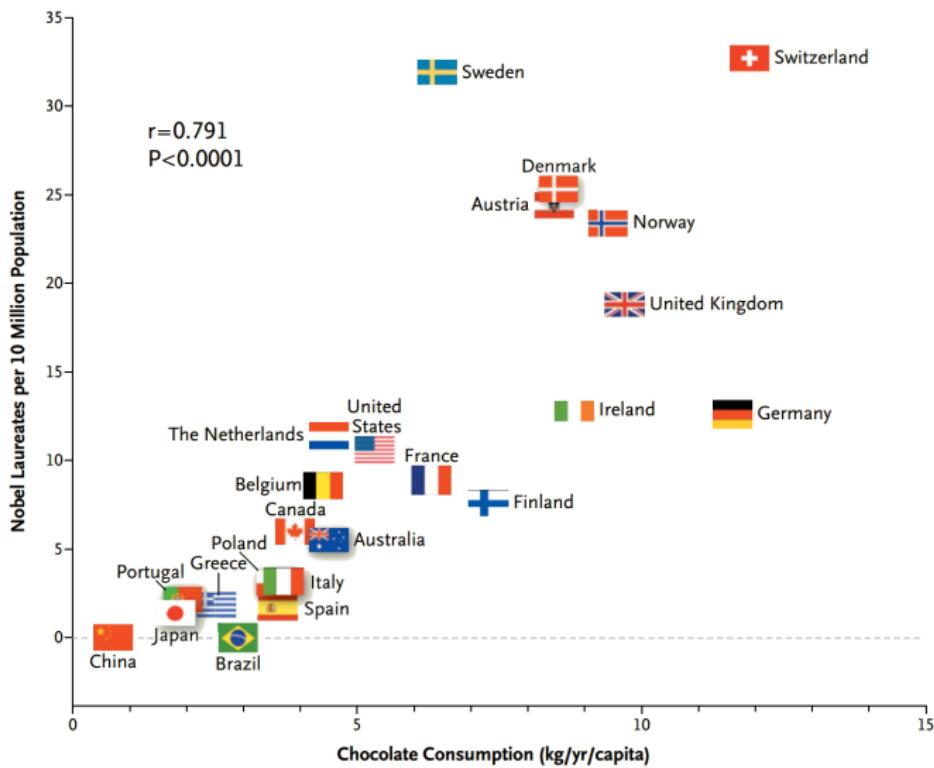


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.



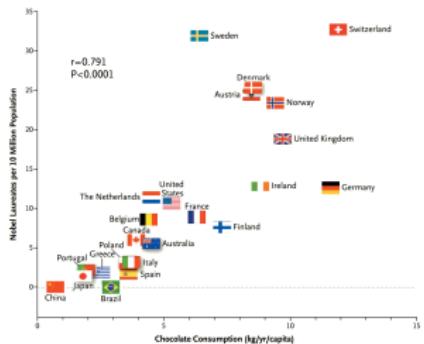


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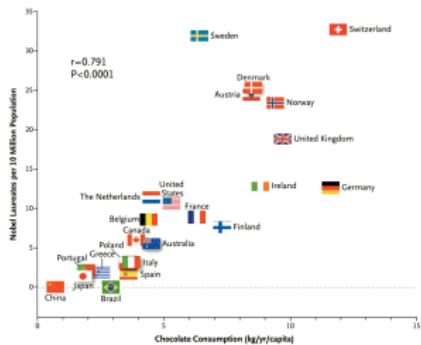


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Bobby goes on a cruise to another country..



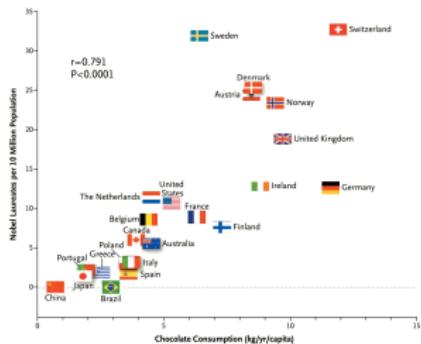


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SEEING: ..and reports back that year's chocolate consumption.



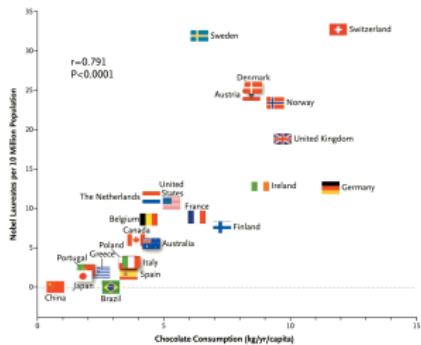


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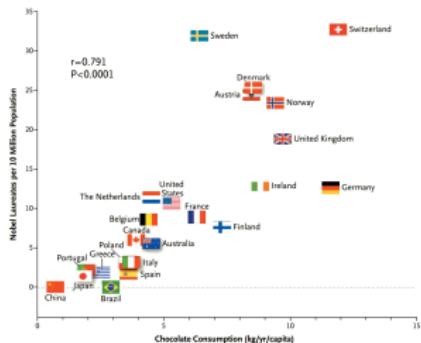


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Bobby goes on a cruise to another country..

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~ Can we predict #country's Nobel Laureates?



⌚ “Correlation does not imply causation.”

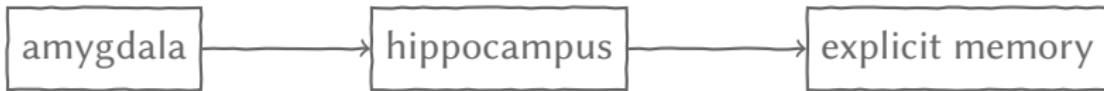




“Correlation does not imply causation.” SEEING VS DOING



*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.*



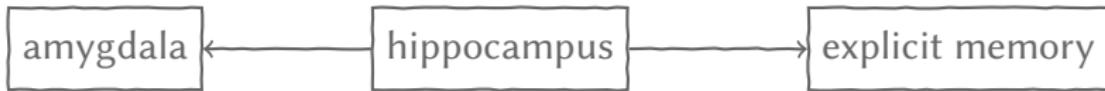
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Can we enhance explicit memory by amygdala stimulation?



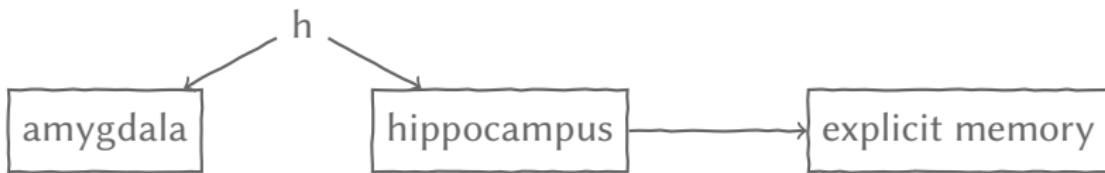
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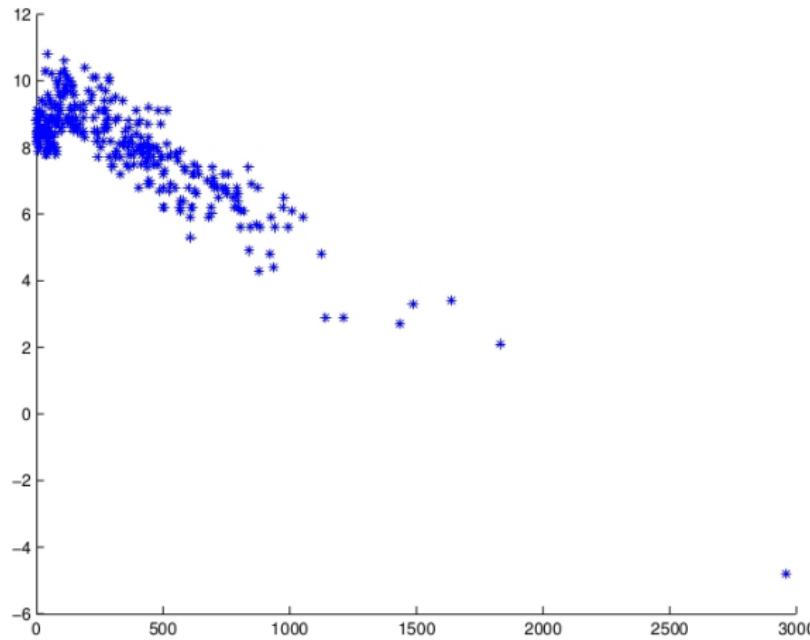


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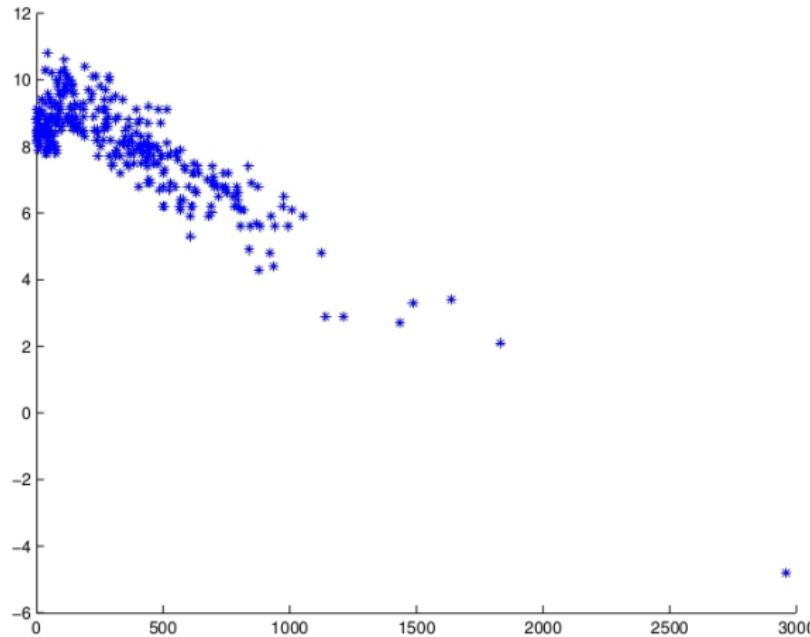
⚡ Causal questions require causal answers.



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



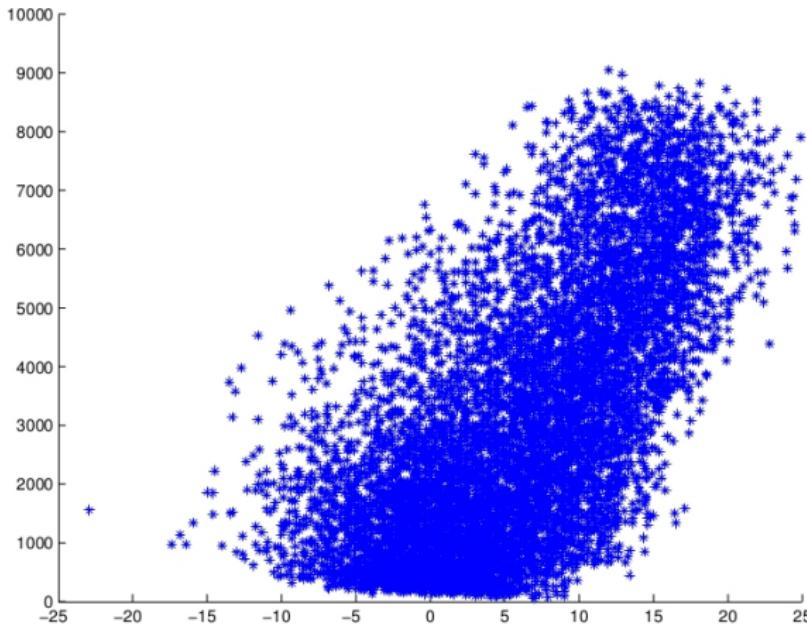
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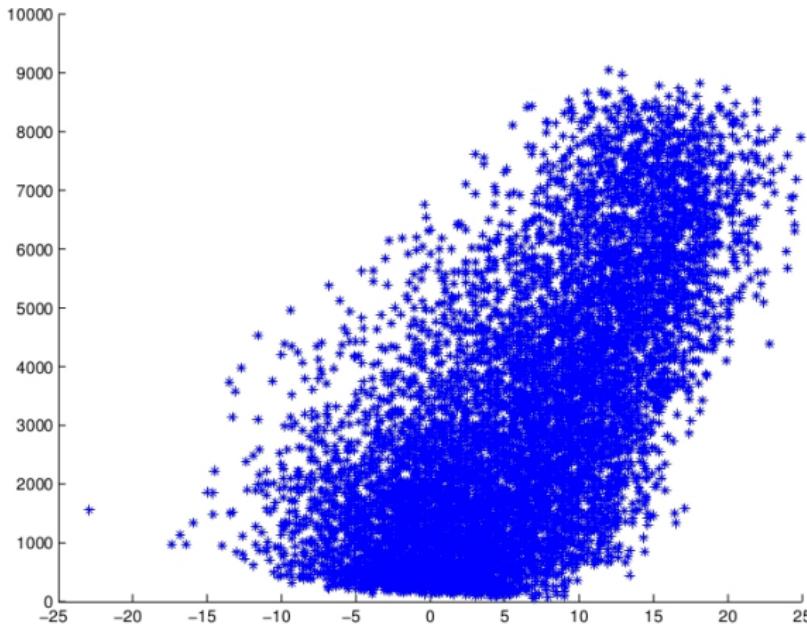
X (Altitude) \rightarrow Y (Temperature)



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



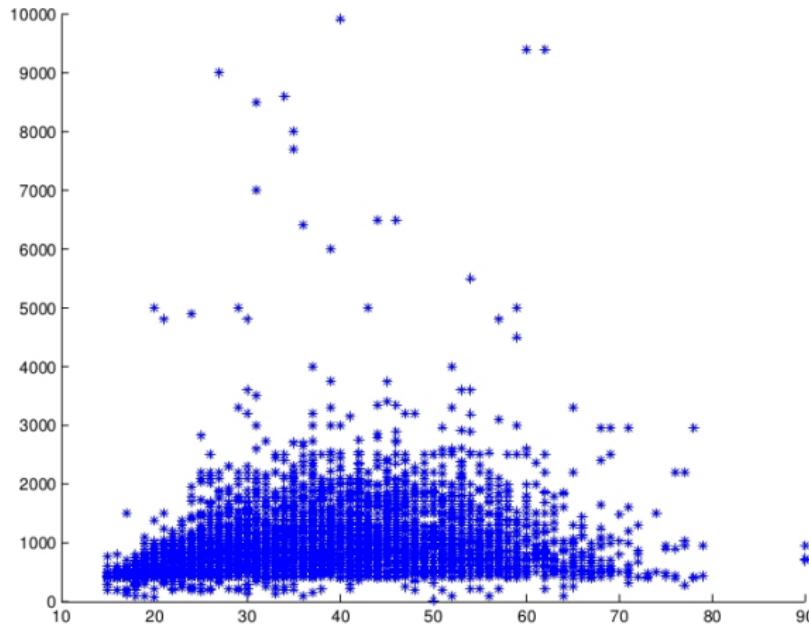
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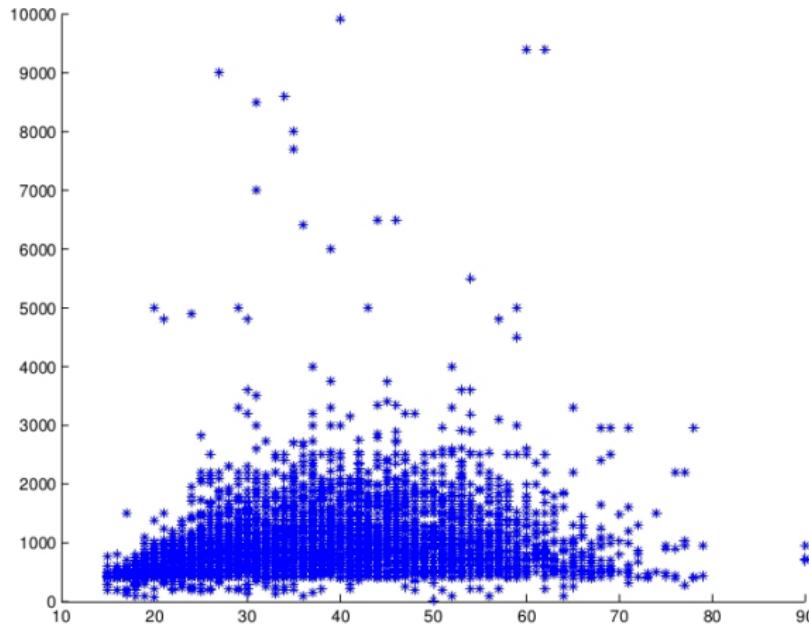
$Y \text{ (Solar Radiation)} \rightarrow X \text{ (Temperature)}$



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



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



X (Age) \rightarrow Y (Income)



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- 😊 Correlation(s) may tell us something about causation.



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Causal inference: assumptions & data \leadsto causal hypotheses



Reichenbach's principle of common cause (1956)

If two variables X and Y are statistically dependent then either



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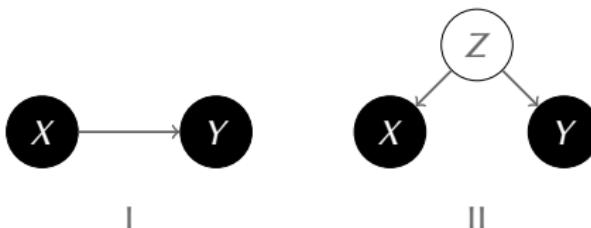


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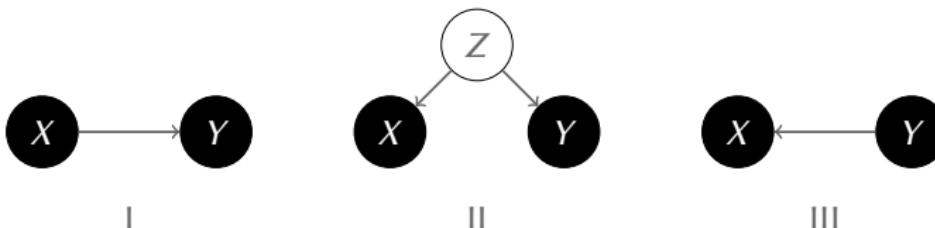
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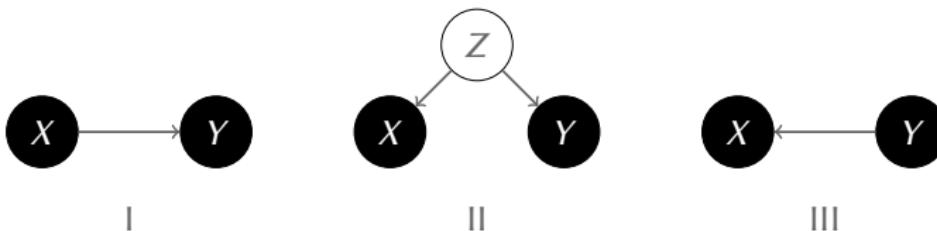
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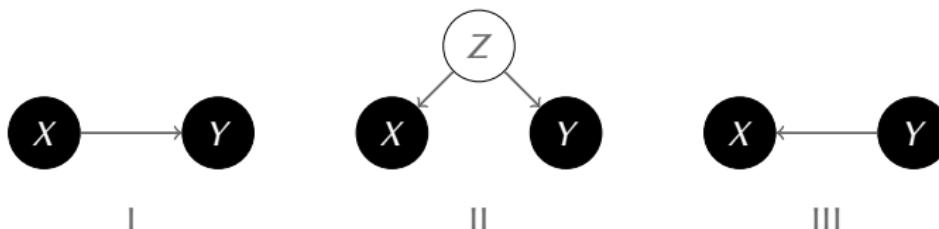


- every statistical dependence is due to a causal relation



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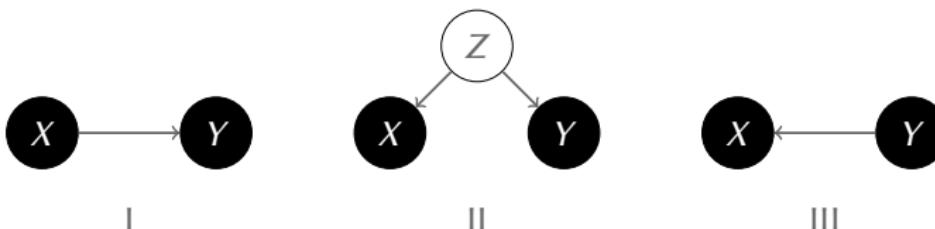


- every statistical dependence is due to a causal relation
- cases I, II, and III can also occur simultaneously



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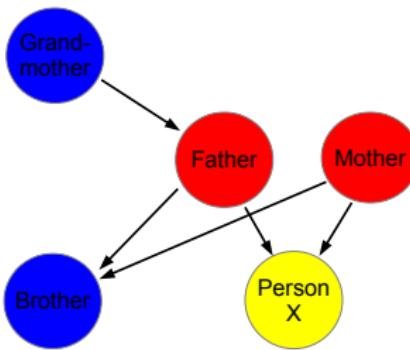
If two variables X and Y are statistically dependent then either



- 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



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- Observe neural activity X and Y



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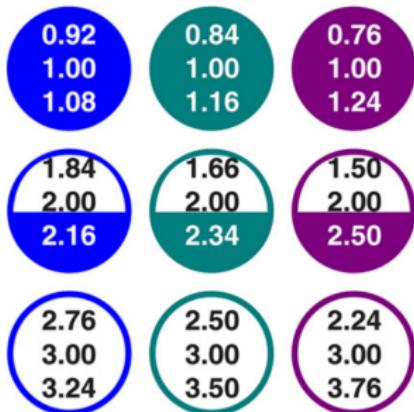
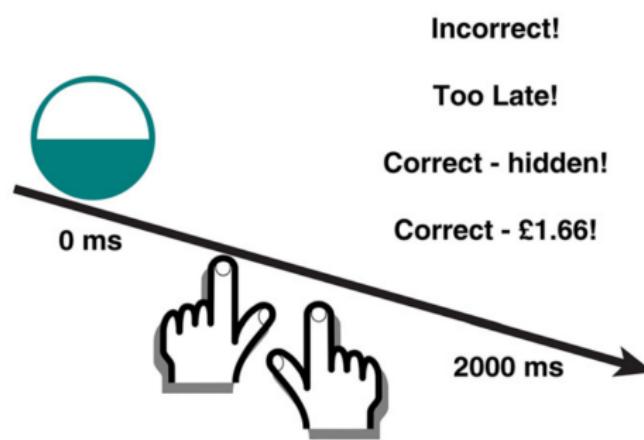
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 - Can formally prove that X indeed is a cause of Y
- ~ Robust against hidden confounding



Neural Dynamics of Probabilistic Reward Prediction



Neural Dynamics of Probabilistic Reward Prediction

A**B****C**

Motor training until stable performance

Reward learning
810 trials

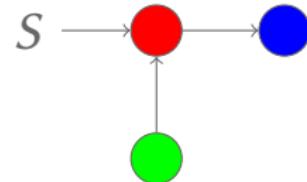
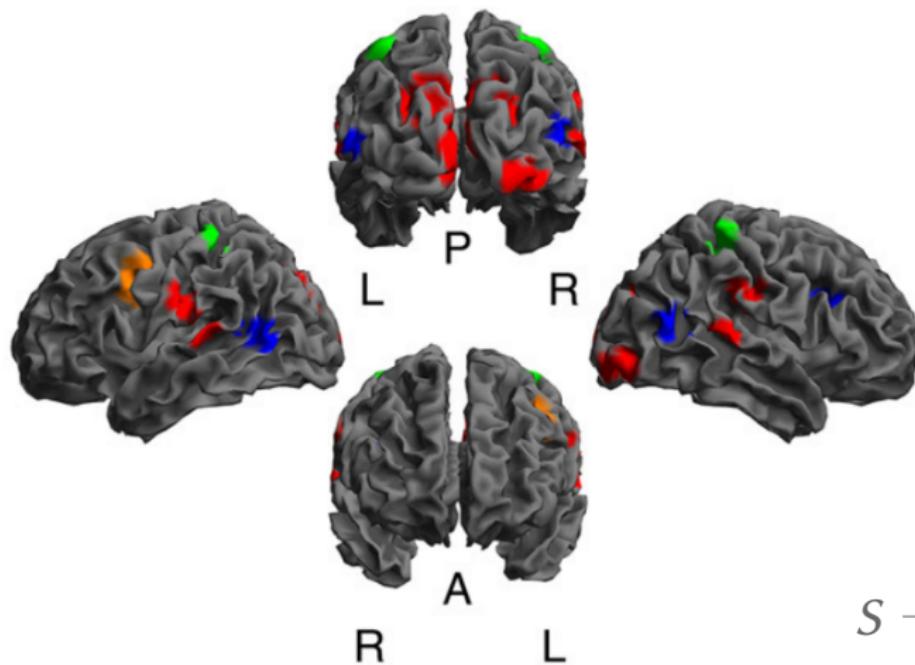
Refresher 1
180 trials

Refresher 2
180 trials

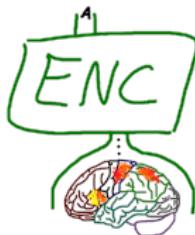
MEG
450 trials



Neural Dynamics of Probabilistic Reward Prediction



Causal interpretation of encoding and decoding models



$$X_i \not\perp C$$

“Significant variation explained by experimental condition?”

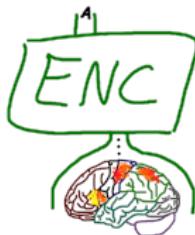


$$X_i \not\perp C | X_{\neg i}$$

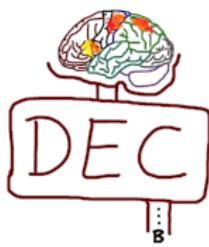
“Does removal impair decoding performance?”



Causal interpretation of encoding and decoding models

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

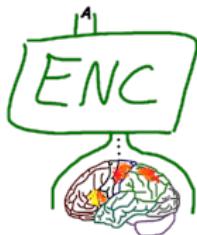
“Significant variation explained by experimental condition?”

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Causal interpretation of encoding and decoding models

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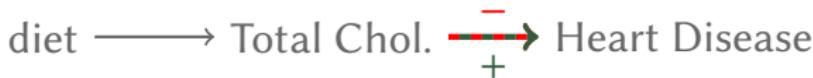
relevant feature $\xrightarrow{?}$ cognitive process



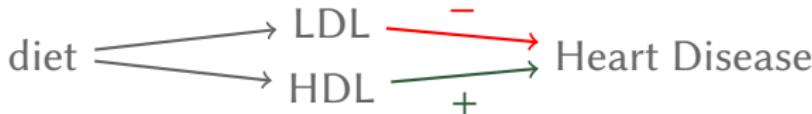
What else can go wrong? Cholesterol and Heart Disease



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Macro-variables can be problematic.



Causal inference: assumptions & data \rightsquigarrow causal hypotheses



Causal inference: assumptions & data \leadsto causal hypotheses

- 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 

